Weathering AI: Artificial intelligence, climate change, and the Paris Agreement

Abstract

We explore the impact of artificial intelligence (AI) workforce adoption on shareholder value in the context of climate change, using stock market reactions to the Paris Agreement as a natural experiment. Leveraging an innovative dataset from Babina et al. (2024), which employs advanced textual analysis to measure AI-skilled employees, we provide empirical evidence that AI workforce adoption significantly enhances cumulative abnormal returns during this critical policy event. Firms with greater climate change exposure derive smaller benefits from AI adoption, likely because of competing priorities between investing in AI initiatives and addressing climate-related strategies. Moreover, AI adoption enhances R&D efforts, signaling strong innovation potential, but raises concerns about resource allocation in highly profitable firms. Finally, we demonstrate that abnormal returns attributable to AI workforce adoption predict long-term firm value, emphasizing AI's strategic importance in driving shareholder value and adaptability in a climate-conscious economy.

JEL Classification Codes: O33 (Technological Change: Choices and Consequences; Diffusion Processes), Q54 (Climate; Natural Disasters and Their Management; Global Warming), G32 (Financing Policy; Financial Risk and Risk Management; Capital and Ownership Structure), G14 (Information and Market Efficiency; Event Studies), Q55 (Environmental Economics: Technological Innovation), M54 (Labor Management)

Keywords: Artificial Intelligence, Climate Change, AI Workforce, Paris Agreement, Stock Market Reactions, Shareholder Value, R&D Investments, Climate Change Exposure

"AI is one of the most important things humanity is working on. It is more profound than electricity or fire."

— Sundar Pichai, Google CEO, speaking at a town hall event in San Francisco, January 2018

"We are the first generation that can end poverty, the last that can end climate change."

— Ban Ki-moon, UN Secretary General, remarks at the Catholic University of Leuven, Belgium, 2015

1. Introduction

Artificial intelligence (AI) is revolutionizing industries, creating new opportunities for growth, and forcing firms to rethink how they adapt to a world increasingly shaped by climate change (Agrawal et al., 2019; Belhadi et al., 2021; Lee et al., 2019). At the same time, the growing severity of climate-related risks—intensified by landmark policies like the Paris Agreement—demands that firms develop new strategies for resilience and long-term value creation (Bernstein et al., 2019; Giglio et al., 2021; Sautner et al., 2023). These two forces—rapid AI adoption and accelerating climate risk—have become defining features of modern business, with far-reaching implications for shareholder value and corporate strategy.

This study is driven by the urgent need to understand how AI workforce adoption shapes shareholder value during major climate policy shifts. We focus on the Paris Agreement as a major global policy event, using stock market reactions as a lens to assess whether AI-skilled employees enhance firm adaptability and investor confidence. With climate policy introducing new uncertainties and expectations, investors are increasingly attentive to how firms leverage advanced technologies to remain competitive and resilient. While existing research recognizes the promise of AI for innovation and operational efficiency (Agrawal et al., 2019; Mihet & Philippon, 2019), there is little direct evidence on its economic impact at moments of regulatory transformation, especially when climate risk is high.

This study is anchored by a direct comparison of two competing perspectives on the impact of AI workforce adoption in the climate policy context. On one hand, the "adaptation advantage hypothesis" suggests that AI adoption enhances firm resilience and adaptability to climate change, leading to more favorable outcomes for shareholders.[1] On the other hand, the "AI burden hypothesis" argues that heavy investment in AI may divert critical resources away from targeted climate strategies, potentially resulting in negative investor reactions during periods of major policy change. By explicitly contrasting these two views, our analysis is designed to reveal whether AI workforce adoption is perceived by investors as a strategic asset or a potential liability in the evolving landscape shaped by climate risk and regulatory transformation.

Drawing on detailed measures of AI workforce adoption (Babina et al., 2024), our analysis shows that firms with higher shares of AI-skilled employees experience more favorable market reactions to the Paris Agreement. However, this benefit diminishes for firms facing greater climate risk, underscoring the challenge of balancing technology investments with the immediate demands of climate adaptation. We further find that the value investors place on AI adoption is shaped by internal firm characteristics, such as R&D investment, profitability, and leverage—offering new insights into when AI is seen as a strategic advantage.

[1] A growing body of research suggests several mechanisms by which AI adoption may help firms adapt to climate change and mitigate climate risks. AI-driven analytics can enable firms to better predict and manage physical climate risks (e.g., extreme weather), optimize resource allocation, and strengthen supply chain resilience (Babina et al., 2024; Sautner et al., 2023). AI also supports compliance by automating regulatory monitoring and reporting, while fostering innovation in energy efficiency and emissions reduction (Mihet & Philippon, 2019; Brynjolfsson et al., 2021). At the firm level, an AI-skilled workforce enhances adaptability by equipping employees with tools for rapid scenario analysis, climate risk modeling, and the integration of climate data into strategic planning. These capabilities may allow firms to proactively address evolving climate challenges, comply with policy, and capitalize on emerging opportunities in a low-carbon economy.

Importantly, the positive stock market reactions to AI workforce adoption are not fleeting: they are predictive of sustained improvements in firm value, measured by Tobin's q, in the years following the Paris Agreement. This underscores the long-term importance of building AI talent for resilience and growth in a climate-conscious economy.

This paper makes several significant contributions to the intersection of artificial intelligence (AI) and climate change, offering valuable insights into how technological adoption influences firm performance during critical policy events. First, it enriches the growing body of literature on the economic implications of climate change by examining how AI adoption interacts with climate-focused regulatory and market dynamics (Bernstein et al., 2019; Chatjuthamard, Mook Lee, et al., 2024; Chindasombatcharoen et al., 2024; Choi et al., 2020; Nordhaus, 2019; Painter, 2020; Sautner et al., 2023; Seltzer et al., 2022; Stroebel & Wurgler, 2021; Treepongkaruna et al., 2024). By leveraging the Paris Agreement as a global exogenous event, our study highlights how technological preparedness and adaptability influence shareholder value in the context of climate policy shifts, adding to research on how firms navigate climate challenges.

Second, this paper contributes to recent literature leveraging textual analysis to extract insights into firm characteristics that are otherwise difficult to measure (Buehlmaier & Whited, 2018; Florackis et al., 2022; Li, 2010; Loughran & Mcdonald, 2011, 2016; Loughran & McDonald, 2020; Ongsakul et al., 2024, 2023; Ungpakorn et al., 2023; Wongsinhirun & Chatjuthamard, 2023). We employ the innovative AI workforce measure developed by Babina et al. (2024), which uses advanced textual analysis to quantify the presence of AI-skilled employees at the firm level. Our finding that this measure is significantly related to shareholder value during the Paris Agreement highlights its practical utility and underscores its importance as a tool for understanding the economic implications of AI adoption. This application not only demonstrates the robustness of the measure but also paves the way for future research on the intersection of AI workforce integration and financial performance.

Third, our findings contribute to the literature on firm-specific attributes and their interaction with technological adoption (Chen & Tajdini, 2024; Nafizah et al., 2024). This study shows that AI adoption complements R&D investments, signaling innovation potential, while raising resource allocation concerns for highly profitable firms—insights grounded in resource-based theory (Barney, 1991; Barney et al., 2021; Das & Teng, 2000; Hart, 1995), innovation theory (Schumpeter, 1942), and agency theory (Fama, 1980; Jensen & Meckling, 1976; Jiraporn et al., 2011). The analysis also highlights how leverage enhances the perceived value of AI adoption, as it signals managerial discipline (Chatjuthamard et al., 2022; Harris & Raviv, 1991; Harvey et al., 2004; Jiraporn & Gleason, 2007; Jiraporn & Liu, 2008; Titman & Wessels, 1988).

Fourth, this paper adds to the understanding of governance structures and their role in moderating market reactions to AI adoption. The findings suggest that traditional governance metrics, such as board independence and managerial ownership (Chatjuthamard et al., 2023; Duchin et al., 2010; Jensen & Meckling, 1976; Morck et al., 1988; Nguyen & Nielsen, 2010; Wongsinhirun et al., 2023), have limited influence on market perceptions of AI workforce adoption during climate-focused events. This highlights the need to rethink governance frameworks to better align with the strategic implications of technological and environmental objectives, contributing to the literature on dynamic governance in the context of innovation (Hillman et al., 2011; Samarawickrama, 2022).

Finally, our study breaks new ground by connecting short-term market reactions, as measured by cumulative abnormal returns (CARs), to long-term firm value, as measured by Tobin's q. This linkage provides evidence that market responses to AI workforce adoption during the Paris Agreement reflect genuine expectations of sustained economic benefits, bridging the gap between event-driven investor sentiment and broader performance outcomes. By tying these findings to the efficient market hypothesis and resource-based theory (Fama, 1970; Malkiel, 2003; Barney, 1991; Barney et al., 2021; Das & Teng, 2000; Hart, 1995), our study offers a robust theoretical framework for understanding how AI adoption drives shareholder value over time.

2. Pertinent information and prior research

This study explores the intersection of artificial intelligence (AI), climate change, and the regulatory implications of the Paris Agreement, emphasizing the strategic significance of AI workforce adoption in enhancing corporate resilience and shareholder value amidst climate-related risks and opportunities.

Artificial intelligence (AI) has become increasingly central to corporate strategy, with profound implications for economic productivity, innovation, and competitive advantage. AI technologies, characterized by their advanced predictive capabilities and scalability, enable firms to improve operational efficiencies and foster innovative outcomes, aligning AI with historical general-purpose technologies like electricity and the Internet (Agrawal et al., 2019; Brynjolfsson et al., 2021). Recent empirical evidence demonstrates that firms actively investing in AI experience accelerated growth in market value, sales, and employment, largely driven by product innovation (Babina et al., 2024). However, the critical driver behind the successful adoption of AI is not merely technology itself but the skilled workforce capable of leveraging AI systems effectively. Babina et al. (2024) emphasize this workforce dimension, utilizing advanced textual analysis of resume data to quantify the presence and impact of AI-skilled labor in firms, making a compelling case for why AI labor should be viewed as distinct and critical within broader AI adoption.

Climate change represents a systemic risk to global economies and financial markets, impacting firm performance, asset valuation, and investment strategies (Bernstein et al., 2019; Giglio et al., 2021). Companies exposed to significant climate risks—such as extreme weather events or stringent regulatory frameworks—often face higher capital costs, reduced valuations, and increased market scrutiny (Choi et al., 2020; Painter, 2020; Seltzer et al., 2022). Institutional investors increasingly incorporate climate vulnerability into their decision-making, viewing climate risk management as essential to sustained financial performance and stability (Krueger et al., 2020). Emerging literature using innovative textual analytics has further advanced our understanding of firm-specific climate risk, capturing nuanced variations in vulnerability through machine-learning methods applied to earnings call transcripts (Sautner et al., 2023). Such granular measures significantly enrich our comprehension of how firms' strategic and financial outcomes are influenced by climate-related challenges.

The Paris Agreement, adopted in December 2015, marked a turning point in global climate governance, mandating substantial reductions in greenhouse gas emissions and enhancing adaptation measures. As the most prominent international climate accord to date, the Paris Agreement significantly reshaped the regulatory and market environment, prompting firms worldwide to reassess their sustainability strategies and risk management frameworks (Lesnikowski et al., 2017; Streck et al., 2016). Prior research underscores the Paris Agreement's broad implications, highlighting how regulatory shifts under this framework impacted market valuations, corporate financing decisions, and investor expectations, especially for firms in environmentally sensitive industries (Chishti et al., 2024; Painter, 2020).

Critically, the intersection of AI adoption, climate risk management, and regulatory responses remains underexplored. Existing studies separately highlight AI's potential in boosting productivity (Babina et al., 2024), the economic consequences of climate risk (Giglio et al., 2021; Sautner et al., 2023), and the regulatory impacts of the Paris Agreement (Streck et al., 2016). Yet, an integrated assessment that directly investigates how AI workforce adoption specifically affects firm value and resilience during significant climate-related policy events, such as the adoption of the Paris Agreement, is lacking. This gap is particularly relevant because AI's analytical and predictive capabilities could significantly enhance firms' adaptive responses to climate change, improving their risk management capabilities and facilitating compliance with evolving regulatory demands.

Our study addresses this intersection explicitly by investigating whether and how the strategic adoption of AI-skilled labor influences shareholder value during the regulatory changes introduced by the Paris Agreement. By bridging literature on AI labor (Babina et al., 2024), climate risk management (Sautner et al., 2023), and international regulatory frameworks (Lesnikowski et al., 2017), we provide a comprehensive understanding of the strategic implications of AI workforce investments in navigating climate-induced uncertainties. This integrated perspective underscores the broader economic and strategic importance of AI labor within climate-conscious regulatory environments, extending the theoretical and empirical boundaries of existing research.

3. Hypothesis development

3.1. The adaptation advantage hypothesis

This hypothesis argues that companies with greater AI adoption witnessed more favorable market reactions to the Paris Agreement. This hypothesis posits that artificial intelligence (AI) is pivotal in addressing the multifaceted challenges posed by climate change by fostering innovation, enhancing operational efficiency, and mitigating associated risks. This hypothesis highlights AI's transformative role in reducing physical, transition, and operational risks while positioning firms to capitalize on the opportunities presented by the shift to a low-carbon economy (Deng et al., 2023; Liu et al., 2022; Roux et al., 2023; Shaik et al., 2024; Tao et al., 2024; Yang et al., 2024).

First, AI’s ability to analyze vast datasets and identify actionable insights supports the development of climate-friendly technologies, such as renewable energy systems, energy-efficient manufacturing processes, and smart grids. Firms investing in AI demonstrate heightened product innovation, evident in increased trademarks and patents, which positions them as leaders in climate resilience and sustainable economic growth (Babina et al., 2024; Bai et al., 2021; Choi & Kwon, 2023; Dehdarian & Tucci, 2021; Hötte & Jee, 2022; Rikap, 2022; Verendel, 2023). AI adoption not only supports green technology hiring and green patenting but also strengthens firms' ability to adapt to shifting regulatory landscapes (Chen et al., 2023; Fabrizi et al., 2018; Feng et al., 2024; Liang et al., 2023; Meng et al., 2020; Sautner et al., 2023; Wang et al., 2023).

Moreover, AI's predictive capabilities are instrumental in addressing physical risks associated with climate change, such as extreme weather events and environmental degradation. Machine learning models can forecast hurricanes, floods, and wildfires with precision, enabling firms to implement preemptive measures. Additionally, satellite imagery processed by AI can track deforestation, glacier melting, and rising sea levels, providing actionable insights for long-term risk mitigation (Giglio et al., 2021; A. Jones et al., 2023; Leal Filho et al., 2022; Sautner et al., 2023). AI also optimizes resource allocation during disaster management by identifying vulnerable regions and prioritizing aid delivery. These capabilities not only reduce the direct impact of climate disasters but also lower associated economic costs, enhancing firms' and communities' resilience (Cao, 2023; Huynh & Kiang, 2024; Sautner et al., 2023).

Furthermore, the global shift toward decarbonization introduces significant regulatory and market uncertainties, which AI can help firms navigate effectively. By analyzing complex regulatory frameworks and modeling various scenarios, AI enables firms to anticipate and comply with evolving environmental regulations. AI's capacity to process high-dimensional data allows firms to evaluate their exposure to transition risks, such as carbon taxation or emission caps (Giglio et al., 2021; Hacker, 2023; Luers et al., 2024). In addition, the Paris Agreement brought heightened regulatory uncertainty, prompting investors to favor firms with adaptive capacities. AI investments signal such preparedness, enhancing market valuations and attracting capital (Pata et al., 2024; Salman et al., 2024). In sum, this hypothesis suggests that companies with higher levels of AI adoption experienced more favorable market reactions following the adoption of the Paris Agreement.

H1: Companies with greater AI workforce adoption experienced more favorable stock market reactions to the Paris Agreement.

3.2. The AI burden hypothesis

Conversely, this hypothesis argues that firms with substantial investments in AI experienced negative stock market reactions to the Paris Agreement. This outcome stems from concerns about resource allocation, strategic misalignment, and the relative advantages of firms that had not yet heavily adopted AI. The hypothesis highlights how the intersection of AI adoption and climate-focused regulatory frameworks could create perceptions of vulnerability rather than strength.

First, AI adoption is resource-intensive, requiring substantial investments in infrastructure, talent, and ongoing development. While these investments can drive innovation, they may also leave firms with fewer resources to implement climate-specific initiatives mandated or encouraged by the Paris Agreement. For example, measures such as transitioning to renewable energy or improving carbon efficiency demand significant capital and operational focus. Investors may have perceived AI-heavy firms as prioritizing technological advancement at the expense of immediate, impactful climate actions (Chishti et al., 2024; Lozo & Onishchenko, 2021; Sahil et al., 2023; Shaik et al., 2024). This resource trade-off becomes even more significant under the Paris Agreement, which heightened regulatory and social expectations for firms to demonstrate tangible progress in reducing emissions and improving sustainability. Firms perceived as over-allocated toward AI may have been viewed as less flexible and less prepared to meet these expectations, leading to a more cautious or negative market response.

Second**,** AI's application to general business processes does not inherently align with climate objectives. Without a clear demonstration of how AI investments support decarbonization or mitigate climate risks, firms risk appearing strategically misaligned. For instance, investors may have questioned whether AI-heavy firms were sufficiently prioritizing efforts to transition their operations in line with global sustainability goals (Vaio et al., 2020; Kulkov et al., 2024; Singh & Goyal, 2023; Spacey Martín et al., 2024).

Furthermore, the Paris Agreement may have been perceived as more advantageous to firms that had not yet adopted AI at scale. These firms, unburdened by the fixed costs and inertia associated with large AI investments, may have been viewed as more agile and able to reallocate resources dynamically toward climate initiatives. Investors may have seen these firms as better positioned to capitalize on Paris Agreement measures, such as subsidies for renewable energy adoption or incentives for carbon reduction, reinforcing the negative reaction to AI-heavy firms.

Finally, AI investments also raise societal and ethical concerns that may have contributed to negative market reactions. For example, the automation capabilities of AI could exacerbate job displacement, particularly in sectors undergoing transformations driven by climate-focused regulations. Automation technologies often replace labor, potentially amplifying social and economic disruptions. These concerns, when coupled with a perception of insufficient climate action, could have dampened enthusiasm for AI-heavy firms among socially conscious investors (Eilstrup-Sangiovanni & Hall, 2025; Girón & Ivanova, 2023).

H2: Companies with greater AI workforce adoption experienced less favorable stock market reactions to the Paris Agreement.

4. Sample selection and data description

4.1. Sample selection

Our analysis begins with a dataset provided by Babina et al. (2024), offering detailed insights into the AI workforce. Stock return data for the event study analysis is sourced from the Center for Research in Security Prices (CRSP), while company-specific characteristics are drawn from COMPUSTAT, with outliers handled through winsorization at the 1st and 99th percentiles. To evaluate market reactions to the signing of the Paris Agreement on Climate Change, we apply the standard event study methodology. Firm-specific exposure to climate change is measured using a unique metric developed by Sautner et al. (2021), derived from advanced textual analysis techniques. Information on board characteristics is obtained from Institutional Shareholder Services (ISS). Data on managerial ownership is sourced from the EXECUCOMP database, which reports the percentage of total equity held by the top five executives. The final dataset includes 1,501 publicly listed U.S. companies. The standard event study methodology is employed to evaluate market reactions to the signing of the Paris Agreement on Climate Change.[2] More

[2] If the event date falls on a non-trading day, it is adjusted to the next available trading day. As a result, although the Paris Agreement was announced on December 12, 2015, the event date is designated as December 14, 2015, the nearest subsequent trading day.

information about how we estimate the cumulative abnormal returns (CAR) is available in the Appendix.

4.2. Measuring the AI workforce

Recently developed by Babina et al., (2024), the dataset used to analyze the AI workforce leverages employee resume data, offering a detailed perspective on the availability and distribution of AI-specific talent. AI-skilled employees are a critical component of firms' ability to engage with and capitalize on AI, serving as the backbone of successful implementation. While computational resources and data infrastructure provide essential support, it is the specialized human capital in AI that enables firms to effectively utilize these tools.

The Cognism resume database is the primary data source for this analysis, containing extensive records of job histories, roles, and accomplishments for millions of individuals worldwide. Through this dataset, AI-skilled workers are identified by examining job titles, skills, and achievements such as patents, publications, and awards. For instance, resumes listing skills like "TensorFlow" or titles such as "Machine Learning Engineer" are categorized as AI-related. The methodology calculates an "AI-relatedness" score for each skill by analyzing its co-occurrence with core AI competencies like machine learning, natural language processing, and computer vision. Highly specialized terms such as "deep learning" receive high AI-relatedness scores, while general skills like "Microsoft Office" score significantly lower. A job is classified as AI-related if its average AI-relatedness score surpasses a predefined threshold, ensuring precision in identifying roles focused on AI technologies.

These classified roles are aggregated at the firm level, enabling the calculation of the proportion of AI-skilled employees relative to a company's total workforce. Rigorous validation, including manual inspections and correlation analyses with factors like increased R&D spending, ensures the accuracy of the classifications. This approach differentiates between roles that involve specific AI expertise and those associated with more generic data-related tasks, maintaining a clear focus on true AI integration.

This methodology offers a robust, data-driven framework for identifying AI-related roles and tracking their evolution over time. By relying on co-occurrence patterns of skills with core AI competencies, it avoids the limitations of traditional keyword-based approaches, which often rely on arbitrary classifications. Instead, it focuses on roles genuinely tied to AI, providing a more comprehensive understanding of AI workforce dynamics. Its scalability and adaptability across industries further enhance its applicability, capturing AI trends in diverse fields beyond technology. More detailed information about this methodology is available in Babina et al. (2024).

4.3. Climate change exposure

For firm-specific exposure to climate change, we utilize the dataset developed by Sautner et al. (2023), which provides firm-specific, time-varying indicators of climate change susceptibility derived from earnings conference call transcripts. Using an advanced machine learning approach, Sautner et al. (2023) identify climate change-related bigrams and calculate their frequency within the text by dividing the number of such bigrams by the total number of bigrams. This metric serves as a proxy for the frequency of climate-related events or shocks experienced by individual firms (Heo, 2021). Details regarding the metric's construction and methodology are elaborated in Sautner et al. (2023).

Earnings conference calls, where companies discuss quarterly or annual financial performance, have become a prominent platform for engaging with stakeholders, including analysts and investors. Managers often use these calls to emphasize their achievements during favorable periods and to address concerns during challenging times (Hossain et al., 2022). Given this dual purpose, conference calls offer a logical and effective source for measuring a firm's exposure to climate risks. As Hossain et al. (2022) note, this method has several distinct advantages, including its strong correlation with key economic indicators documented in the literature, such as public awareness of climate change (Sautner et al., 2023; Hossain et al., 2022).

While many climate-related studies rely on metrics such as carbon emissions, pollution levels, or natural disaster data, the measure introduced by Sautner et al. (2023) offers a broader and more inclusive assessment of climate risk. Traditional data sources like carbon emissions are often limited to firms that voluntarily disclose such information, excluding a significant number of polluters who opt not to report their emissions. In contrast, Sautner et al.'s (2023) methodology covers a much wider range of companies, making it a more comprehensive tool for assessing climate vulnerability (Hossain et al., 2022).

The widespread adoption of this innovative metric underscores its value. Several recent studies have incorporated it to better understand climate-related risks and their economic implications (Hossain et al., 2022; Heo, 2022; Chindasombatcharoen et al., 2024). By leveraging earnings call data, this approach captures various aspects of climate risk that are often overlooked by traditional measures, making it an increasingly preferred choice for contemporary climate finance research.

4.4. Empirical strategy

We estimate the following regression model to examine the effect of AI workforce adoption on stock market reactions to the Paris Agreement:

$$CAR_i\ (-1,+1) = \alpha + \beta_1\ (Share\ of\ AI\ Workers)_i + \beta_2\ (Controls)_i + Industry\ Fixed\ Effects + \varepsilon$$

where i indexes firms.

The dependent variable, cumulative abnormal return (CAR), is measured over the event window (–1, +1) to capture the immediate stock market response. Our empirical strategy employs ordinary least squares (OLS) regressions, and all regressions include industry fixed effects based on the first two digits of SIC codes. Robust standard errors are clustered by industry. Additional robustness checks, such as propensity score matching, entropy balancing, and instrumental-variable analysis, are performed as detailed in later sections.

Furthermore, to assess whether the effect of AI workforce adoption on market reactions varies with firms' climate change exposure, we include interaction terms in our regression models. Specifically, we interact the share of AI workers with overall climate change exposure as well as with key sub-dimensions such as physical risk, regulatory risk, and new opportunities. This approach allows us to test whether the relationship between AI workforce adoption and shareholder value depends on the type or intensity of climate-related risks and opportunities faced by the firm.

4.5. Additional variables

A comprehensive set of control variables is incorporated to address confounding influences. Firm size is included because larger firms typically have more resources and greater visibility, which may influence market reactions to policy events. Profitability is added to capture a firm's financial health, as profitable firms are often perceived as more capable of absorbing costs associated with climate policies or AI adoption. However, agency theory suggests that profitability may also raise concerns about resource misallocation (Jensen and Meckling, 1976).

We include leverage as it reflects a firm's financial risk profile and can moderate market reactions. High leverage can signal financial discipline but may also introduce perceptions of heightened risk (Myers, 1977). Capital expenditures are considered to account for long-term strategic investments, as firms with significant physical asset investments are often viewed as more committed to sustainable growth (Teece et al., 1997). Similarly, R&D investments are included as a proxy for innovation potential, complementing AI adoption and signaling a firm's adaptability and future growth prospects, consistent with innovation theory (Schumpeter, 1942).

Additional controls include advertising spending, which reflects brand equity and market visibility. High advertising spending may signal strategic intent and influence investor perceptions, as suggested by signaling theory (Spence, 1973). Dividends are incorporated to capture financial stability and management's confidence in future earnings, aligning with Lintner's (1956) insights on dividend relevance. Liquidity, measured by the current ratio, is included to evaluate a firm's ability to meet short-term obligations, which may be critical during policy shifts. Lastly, the effective tax rate accounts for regulatory exposure, as firms with higher tax burdens may respond differently to climate-related policy changes (Giglio et al., 2021).

We focus on CAR (-1, +1) as the primary dependent variable to capture immediate market reactions to the Paris Agreement. This narrow event window minimizes the influence of confounding factors and ensures that the results reflect the direct impact of the policy event. The variable definitions are shown in Table A1 in the Appendix and the summary statistics are available in Table 1.

5. Results

5.1. Baseline regression analysis

Table 2 evaluates the effect of AI workforce adoption on stock market reactions around the signing of the Paris Agreement, with the cumulative abnormal returns (CARs) serving as the dependent variable. The analysis primarily focuses on CAR (-1, +1), a narrow event window encompassing the day before, the day of, and the day after the agreement's announcement. By isolating a short time frame, CAR (-1, +1) captures investor sentiment directly associated with the Paris Agreement while reducing the influence of confounding factors.

To confirm the robustness of the results, we also examine CAR (-2, +2), a wider event window that includes two days before, the day of, and two days after the signing. While this broader window offers additional insights, it is more likely to encompass other market-moving events that could confound the effect of AI workforce adoption. As a result, CAR (-2, +2) is used as a supplementary check to validate the findings from the narrower CAR (-1, +1) window. Also, the clustering of standard errors by industry further strengthens the analysis, addressing potential within-industry correlations that could bias results.

The regression results in Table 2 reveal that the share of AI workers consistently shows a positive and significant effect, supporting the adaptation advantage hypothesis that AI adoption enhances firms' capacity to adapt to climate-focused policies. The results suggest that investors view AI-skilled labor as a strategic asset, reflecting its role in fostering resilience and innovation amid regulatory and operational shifts brought by the Paris Agreement.

We estimate the economic significance of the share of AI workers by calculating the standardized coefficient of the share of AI workers in Model 2 of Table 2 and find that a rise in the share of AI workers by one standard deviation results in an improvement in the stock market reactions by 4.7%. Therefore, the document effect is not only statistically significant, but it is also economically meaningful.

Our results are unlikely to be significantly influenced by endogeneity, as the analysis relies on an event study methodology that evaluates stock market reactions to the adoption of the Paris Agreement—a global policy event that is exogenous and beyond the control of individual firms. This setup minimizes concerns about reverse causality, as the Paris Agreement's signing represents an external shock to all firms rather than a firm-driven event. Nevertheless, as a precaution and to ensure the robustness of our findings, we conduct additional analyses.

5.2. Propensity score matching (PSM)

Table 3 employs propensity score matching (PSM) to confirm the robustness of our results and address potential endogeneity concerns. PSM is particularly advantageous because it allows for the creation of statistically comparable treatment and control groups, ensuring that the observed effect of AI workforce adoption is not driven by pre-existing differences between firms. By matching firms based on key characteristics, PSM effectively isolates the impact of the share of AI workers on stock market reactions.[3]

In Panel A, we classify firms in the top quartile of AI workforce share as the treatment group. For each treatment firm, we identify a matching control firm from the rest of the sample based on nine firm characteristics: the control variables used in the regression analysis. This approach ensures that the treatment and control groups are statistically identical in all aspects except for their share of AI workers.

[3] Propensity Score Matching (PSM) provides significant benefits in research. Firstly, it minimizes selection bias by equating covariates across treatment and control groups, effectively simulating the conditions of a randomized experiment. This approach ensures that observed differences in outcomes are linked to the share of AI workers rather than unrelated firm attributes. Secondly, PSM improves result clarity by accounting for confounding factors such as company size, profitability, debt levels, and market conditions that could otherwise distort the analysis. By enhancing the comparability between treatment and control groups, PSM bolsters the robustness and credibility of the findings, making it a powerful method in observational studies (Chindasombatcharoen et al., 2024; Lennox et al., 2012; Rosenbaum & Rubin, 1983).

The results in Panel A show that, before matching, significant differences exist between the two groups across several characteristics, such as firm size, leverage, profitability, and R&D investments. These differences suggest that firms with higher shares of AI workers tend to be larger, less leveraged, more profitable, and more focused on research and development. However, after matching, these differences disappear, as indicated by the reduced pseudo R-squared from 0.211 pre-match to 0.021 post-match.[4] This outcome confirms that our matching procedure successfully eliminates observable differences between treatment and control firms, making them indistinguishable apart from their AI workforce share.

In Table 3, Panel B, we re-estimate the effect of AI workforce adoption on stock market reactions using the matched sample. The coefficient for the share of AI workers is 0.638 and highly significant (at the 1% level), indicating a strong positive effect of AI workforce adoption on cumulative abnormal returns. This result reinforces the findings from the baseline regression, demonstrating that firms with greater AI workforce adoption experience more favorable market reactions to the Paris Agreement. By using the matched sample, we ensure that this effect is not driven by confounding differences in firm characteristics, providing a more robust estimate.

5.3. Entropy balancing

Table 4 utilizes entropy balancing to ensure robustness by addressing potential imbalances between treatment and control groups. Entropy balancing is a weighting method that equalizes the

[4] The R-squared value reflects the extent to which variation in the treatment variable, in this case, the share of AI workers, is accounted for by the observable characteristics used during matching. Prior to matching, the R-squared value is relatively high because the significant disparities between treatment and control groups enable observable characteristics to explain much of the variability. After matching, however, the R-squared decreases as the process equalizes the treatment and control groups, ensuring that observable variables no longer systematically account for differences in AI workforce adoption. This adjustment makes the treatment and control groups statistically comparable, leaving less variation in the share of AI workers attributable to the covariates. The reduction in R-squared is an expected result of effective matching, signifying that observable imbalances have been addressed and the groups are now more comparable.

distributions of covariates across groups, ensuring that the comparison is statistically valid and free from biases related to observable characteristics. This approach retains all observations in the sample, enhancing statistical power while achieving a high degree of balance (Hainmueller, 2012; Hainmueller & Xu, 2013; Tübbicke, 2022).

The results in Table 4 confirm the positive effect of AI workforce adoption on stock market reactions to the Paris Agreement. The coefficient for the share of AI workers is 0.447 and statistically significant at the 5% level, further supporting the conclusion that firms with a higher proportion of AI-skilled employees experience stronger positive cumulative abnormal returns. The application of entropy balancing reinforces the robustness of this result by ensuring that observed effects are not confounded by differences in firm characteristics.

5.4. Instrumental-variable analysis (IV)

Table 5 employs instrumental-variable (IV) analysis to address potential endogeneity concerns and provide more reliable causal estimates of the effect of AI workforce adoption on stock market reactions. IV analysis is particularly advantageous in this context as it separates the exogenous variation in the independent variable (AI workforce adoption) from its potential correlation with unobserved factors, ensuring that the results more accurately reflect the causal impact (Angrist & Krueger, 2001; Hahn & Hausman, 2002; Larcker & Rusticus, 2010).

The first instrument used is the average share of AI workers within the same industry. This variable is justified because industry-level averages capture general trends in AI adoption that are likely to influence a firm's propensity to adopt AI, while remaining exogenous to firm-specific unobserved factors affecting stock market reactions. For instance, firms in industries with a high prevalence of AI-skilled employees may face competitive or normative pressures to adopt AI, but this industry-level AI prevalence is unlikely to directly affect an individual firm's stock returns following the Paris Agreement, beyond its influence on the firm's AI adoption decision.

The IV results are shown in Table 5. In Model 1, the first stage of the IV analysis estimates the relationship between the share of AI workers and the instrument (industry average of AI workers). The coefficient for the instrument is highly significant (0.891, $p<0.01$), confirming that industry-level AI adoption strongly predicts firm-level AI adoption. This result indicates that the chosen instrument is valid and provides sufficient variation in the endogenous variable (share of AI workers) to support the IV estimation. In the second stage, Model 2, the instrumented share of AI workers is used to estimate its effect on stock market reactions (CARs) to the Paris Agreement. The coefficient for the instrumented share of AI workers is 2.323, significant at the 5% level, indicating a robust positive effect of AI workforce adoption on cumulative abnormal returns.

To ensure robustness, we execute additional analysis by using two instruments simultaneously: the average share of AI workers in the same industry and the average share of AI workers in the same zip code. The inclusion of a second instrument enhances the robustness of the causal inference by providing additional variation to identify the effect of AI workforce adoption on stock market reactions.

The second instrument is the average share of AI workers within the same zip code. Using zip code averages as an instrument is justified because zip codes are assigned based on geographic and logistical efficiency for mail delivery, rather than firm-specific characteristics (Chintrakarn et al., 2017, 2015; Jiraporn et al., 2014)). This inherent randomness in zip code assignments ensures that the instrument is exogenous to individual firm decisions or attributes. Local zip code areas often represent natural clusters of economic activity and labor market conditions. For instance, firms in regions with a higher prevalence of AI-skilled employees may adopt AI due to the availability of local talent and supportive ecosystems. However, the regional concentration of AI workers is unlikely to directly affect a firm's stock market reaction to the Paris Agreement, beyond its role in influencing AI adoption.

In Model 3 (Table 5), the first stage of the IV analysis estimates the relationship between the share of AI workers and the two instruments. Both instruments—industry average and zip code average of AI workers—are significant predictors of firm-level AI adoption. The coefficient for the zip code average is 0.955 ($p<0.01$), indicating a strong association between local AI workforce prevalence and firm-specific AI adoption. The inclusion of this instrument captures regional factors that complement the industry-level variation provided by the first instrument, ensuring robust identification of exogenous variation in AI adoption.

Model 4 uses the instrumented share of AI workers from the first stage to estimate its effect on stock market reactions (CARs) to the Paris Agreement. The coefficient for the instrumented share of AI workers is 0.529 ($p<0.05$), confirming a significant positive effect of AI workforce adoption on cumulative abnormal returns. Importantly, the Hansen J-statistic is not statistically significant, suggesting that our instruments are acceptable. This result aligns with the adaptation advantage hypothesis, suggesting that firms with greater AI workforce adoption are better positioned to benefit from market confidence during climate policy shifts.

5.5. Oster's (2019) approach for testing coefficient stability

Oster's (2019) method tests how robust regression results are to omitted variable bias by assessing how much stronger unobservable factors would need to be compared to the observed controls to invalidate the findings. The key idea is that if adding more controls doesn't change the coefficient of interest significantly, it is unlikely that unobserved factors could overturn the results.

Using this approach, we find that unobservable factors would need to be 3.30 times as influential as the included controls to invalidate the effect of AI workforce adoption on stock market reactions to the Paris Agreement. This high threshold highlights the robustness of our results and suggests that omitted variables are unlikely to undermine the conclusions. The strength of this coefficient stability shows the validity of our findings, reinforcing the importance of AI workforce adoption in driving shareholder value during critical climate policy events.

5.6. The role of firm-specific exposure to climate change

Analyzing firm-specific exposure to climate change is critical for understanding how individual companies are impacted by and respond to the broader challenges of a changing climate. Climate change exposure reflects the degree to which a firm is affected by or involved in discussions and strategies related to climate change, which can shape financial performance, stakeholder perceptions, and strategic priorities. Unlike general measures, firm-specific metrics capture the unique vulnerabilities and opportunities faced by each company, providing a more precise understanding of their position within the evolving landscape of climate awareness Chatjuthamard, Chintrakarn, et al., 2024; Chatjuthamard, Lee, et al., 2024; Chindasombatcharoen et al., 2024; Likitapiwat et al., 2023; Ongsakul et al., 2024; Sautner et al., 2023; Treepongkaruna et al., 2024). This detailed perspective is particularly relevant in evaluating responses to major global events, such as the Paris Agreement. It helps to identify how firms with varying levels of climate engagement are perceived by investors and how this perception influences their market performance.

Sautner et al. (2023) measure firm-specific exposure to climate change by analyzing earnings conference call transcripts. Using advanced machine learning techniques, they identify climate-related bigrams (two-word phrases) and calculate their frequency in the text. This frequency is then normalized by dividing it by the total number of bigrams in the transcript. The resulting metric reflects how frequently climate-related topics are discussed during earnings calls, serving as a proxy for the firm's exposure to climate-related risks and events.

Table 6, Model 1, investigates how the interaction between the share of AI workers and firm-specific climate change exposure influences cumulative abnormal returns (CARs) surrounding the Paris Agreement. The negative and significant coefficient for the interaction term reveals a notable dynamic: while AI workforce adoption generally enhances investor confidence, its benefits appear to diminish for firms with higher levels of climate change exposure.

This result likely reflects the heightened expectations and scrutiny faced by firms with greater climate exposure. Companies more engaged in or vulnerable to climate change issues are often expected to demonstrate clear, actionable strategies for addressing these challenges. When such firms also invest heavily in AI, investors may question whether these resources are being effectively aligned with climate-related objectives. If AI adoption is perceived as being unrelated to—or insufficiently integrated into—climate risk mitigation strategies, it may dilute investor enthusiasm, even if AI adoption signals broader adaptability.

Additionally, higher climate change exposure may amplify concerns about resource allocation. Firms with significant climate-related challenges may be expected to prioritize direct investments in sustainability initiatives, such as renewable energy adoption or emissions reductions. If these firms allocate substantial resources to AI without a clear connection to their climate strategies, investors may view this as a potential misalignment of priorities, further diminishing the perceived benefits of AI.

According to Sautner et al. (2023), firm-specific climate change exposure can be divided into three dimensions: physical risk, regulatory risk, and new opportunities. These dimensions offer a comprehensive framework for understanding how climate change impacts firms differently and influences their financial and operational strategies. The first dimension, physical risk, refers to the direct effects of climate change on a firm's operations, assets, and supply chains. Extreme weather events such as hurricanes, floods, and wildfires can cause significant disruptions, damage infrastructure, and increase costs for firms. Companies with higher physical risk are more vulnerable to these environmental threats, which can reduce their resilience and, consequently, their attractiveness to investors.

The second dimension, regulatory risk, captures the challenges firms face in complying with climate-related policies and regulations. These risks arise from measures such as carbon taxes, emissions caps, or mandatory disclosures, which may impose additional costs or require operational adjustments. Firms operating in regions or industries subject to stringent climate policies are particularly exposed to regulatory risk, as compliance can directly affect their profitability and competitiveness. The third dimension, new opportunities, represents the potential benefits that climate change can create for firms. The transition to a low-carbon economy brings opportunities in areas such as renewable energy, sustainable products, and green technologies. Firms that can successfully position themselves to take advantage of these opportunities may gain new revenue streams, attract greater investor interest, and enhance their competitive edge.

To gain further insights, we examine the interaction between the share of AI workers and each specific dimension of climate change exposure. In Table 6, Models 2 through 4 explore the interaction between the share of AI workers and different dimensions of climate change exposure—physical risk, regulatory risk, and new opportunities. In Model 2, the positive but statistically insignificant interaction suggests that AI workforce adoption does not strongly influence market perceptions of a firm's ability to address physical risks from climate change. Similarly, Model 3 finds no significant effect for the interaction with regulatory risk, indicating that investors do not associate AI adoption with improved capacity to navigate regulatory uncertainties tied to the Paris Agreement. Model 4 shows a negative but insignificant interaction with new opportunities, suggesting that AI workforce adoption does not enhance investor perceptions of a firm's ability to capitalize on climate-driven opportunities.

The significant interaction between the share of AI workers and overall firm-specific climate change exposure, contrasted with the lack of significance for its specific components, highlights the holistic nature of investor perceptions when evaluating AI adoption in the context of climate change. Overall climate exposure serves as a broad indicator of a firm’s engagement with climate-related challenges, encapsulating the combined effects of physical risks, regulatory pressures, and emerging opportunities. This aggregate view resonates more strongly with investors, who may find it challenging to parse the distinct impacts of individual dimensions in isolation.

A key explanation lies in the theory of salience (Bordalo et al., 2012), which suggests that investors focus on prominent and easily interpretable metrics. Overall climate exposure is a salient indicator, offering a straightforward measure of a firm’s climate engagement and strategic adaptability. By contrast, individual dimensions like physical risk or regulatory compliance may be perceived as more complex and context-dependent, reducing their immediate relevance in shaping market reactions to events like the Paris Agreement.

Another contributing factor is the ambiguity surrounding the direct role of AI in addressing specific components of climate exposure. For example, while AI can assist in mitigating physical risks through predictive modeling and optimization, its tangible benefits in this domain may not be immediately apparent to investors. Similarly, the connection between AI adoption and regulatory risk management may seem indirect, as investors often expect regulatory compliance to be addressed through traditional measures like policy adaptation or legal frameworks rather than through technological innovation.

The significance of the interaction with overall exposure also aligns with theories of general-purpose technologies (GPTs), which emphasize the transformative potential of innovations like AI to enhance firm-level resilience and adaptability across multiple domains. Investors may view AI adoption as a signal of a firm's ability to tackle the multifaceted challenges posed by climate change. This broad perception contrasts with the more fragmented impact of AI on individual dimensions, which may require clearer connections to firm-specific climate strategies to gain investor recognition.

Finally, signaling theory (Spence, 1973) provides additional insights into these findings. A firm's investment in AI serves as a strong signal of its commitment to innovation and adaptability in the face of climate challenges. However, this signal may lose potency when applied to narrower components of climate exposure, such as regulatory or physical risks, which demand targeted strategies rather than general technological adoption. Without explicit alignment between AI investments and these specific dimensions, the benefits of AI adoption may not fully translate into enhanced market perceptions.

5.7. The role of climate change sentiment

According to Sautner et al. (2023), climate change sentiment represents the tone or attitude of discussions surrounding climate-related issues, capturing whether a firm's narrative is positive, negative, or neutral. This is distinct from climate change exposure, which measures the degree to which a firm is impacted by or engaged with climate-related risks and opportunities. While exposure reflects the firm's involvement in addressing climate challenges, sentiment provides insights into how these challenges and opportunities are perceived and communicated by stakeholders. Sentiment focuses on the framing of climate discussions, offering a qualitative dimension that complements the quantitative aspect of exposure.

Following Sautner et al. (2023), we use the climate change sentiment measure to capture the net tone of climate-related discussion by integrating both positive and negative sentiment in each of the three key dimensions: physical risk sentiment, regulatory risk sentiment, and opportunity sentiment. Physical risk sentiment captures the tone and language used when discussing the direct physical impacts of climate change (e.g., extreme weather). Regulatory risk sentiment reflects attitudes toward climate-related regulations and policy developments. Opportunity sentiment measures the framing of climate change as a source of potential business opportunities. These sentiment measures provide a nuanced view of how firms communicate about different aspects of climate change and allow us to assess whether investor responses to AI workforce adoption are conditioned by these specific types of climate-related sentiment.

Table 7 examines how the interaction between the share of AI workers and climate change sentiment affects cumulative abnormal returns (CARs) around the Paris Agreement. The results reveal important nuances in the market's perception of AI adoption within the context of climate sentiment. For overall climate change sentiment, the interaction term is negative but statistically insignificant, indicating that investors do not strongly link the general tone of climate discussions with the perceived benefits of AI adoption. This could stem from the broad nature of sentiment metrics, which may not directly convey actionable strategies or specific outcomes.

However, the interaction between AI adoption and sentiment related to physical risks is both positive and statistically significant, suggesting that firms with strong AI adoption and positive discussions about managing physical climate risks experience enhanced market reactions. This aligns with the idea that AI's capabilities in predictive modeling and data analysis can directly address physical risks, such as extreme weather events, which resonates positively with investors.

Conversely, the interactions with sentiment around regulatory risks and new opportunities are not statistically significant. This implies that while AI may play a role in navigating regulatory challenges or capitalizing on climate-driven opportunities, investors may perceive these areas as requiring more direct or specialized strategies beyond general AI adoption. Regulatory risk management often involves compliance frameworks and legal expertise, while new opportunities may demand targeted environmental innovations, which AI alone may not sufficiently signal.

In summary, the results emphasize the importance of climate sentiment in shaping market perceptions, particularly in contexts where AI adoption aligns closely with specific challenges like physical risks. However, the lack of significance in other dimensions suggests that firms must clearly articulate how AI investments contribute to actionable climate strategies to fully leverage investor confidence. By aligning AI adoption with tangible outcomes, firms can enhance the perceived value of their climate-related initiatives.

5.8. Interactions with firm-specific characteristics

Table 8 examines how the interaction between the share of AI workers and firm-specific attributes—R&D investments, profitability, leverage, and capital expenditures—affects cumulative abnormal returns (CARs) around the Paris Agreement. Firm characteristics such as resources, financial health, and management practices shape how investors perceive the value of AI adoption, particularly in addressing climate-related challenges.

Resource-based theory (Barney, 1991) suggests that firms with substantial internal resources, like high R&D spending, are better positioned to benefit from AI, enhancing adaptability and competitive advantage. Similarly, innovation theory (Schumpeter, 1942) underscores the impact of combining AI with a firm's innovative capabilities. Agency theory (Jensen & Meckling, 1976) and signaling theory (Spence, 1973) indicate that leverage can reassure investors about managerial discipline, while profitability may raise concerns over resource misallocation. The dynamic capabilities framework (Teece, Pisano, and Shuen, 1997) highlights the importance of aligning strategic investments, such as capital expenditures and AI adoption, with changing environmental and market conditions.

Empirically, Model 1 shows a strong positive interaction between the share of AI workers and R&D, supporting the notion that investors view this combination as a signal of long-term value creation (Schumpeter, 1942). Model 2 finds a negative interaction with profitability, suggesting investor skepticism toward profitable firms adopting AI, possibly due to agency concerns over misaligned priorities (Jensen & Meckling, 1976).[5] Model 3's positive interaction with leverage is consistent with agency and signaling theories (Jensen & Meckling, 1976; Spence, 1973), indicating that financial discipline strengthens confidence in AI investments. Model 4 shows that capital

[5] One possible interpretation, grounded in agency theory (Jensen & Meckling, 1976), is that profitable firms are often viewed as having more slack resources and managerial discretion. In these cases, investors may worry that additional investments—including in advanced technologies like AI—are not subject to sufficient discipline and may be at greater risk of being directed toward projects with lower strategic urgency or unclear climate impact. By contrast, for firms with lower profitability or more constrained resources, AI investments may signal a disciplined, targeted effort to improve operational efficiency, adaptability, and long-term competitiveness—attributes especially valued in the face of climate-related uncertainty. Thus, the negative moderation by profitability does not contradict the overall positive impact of AI workforce adoption, but rather highlights that the incremental value of such investments depends on how they interact with a firm's financial context and perceived managerial discipline.

expenditures and AI adoption together enhance perceived adaptability, consistent with the dynamic capabilities perspective (Teece, Pisano, and Shuen, 1997). Overall, these results underscore that AI adoption is most valued when it complements strong internal resources or signals efficient management, but may be questioned in resource-rich firms if not clearly linked to climate strategies.

5.9. The role of corporate governance

Table 9 explores how corporate governance moderates the relationship between AI workforce adoption and cumulative abnormal returns (CARs) around the Paris Agreement. Corporate governance is a critical factor in shaping strategic decisions, resource allocation, and investor confidence. Strong governance structures are expected to enhance the alignment of managerial actions with shareholder interests, particularly during significant policy shifts. By examining attributes such as board independence, gender diversity, and managerial ownership, Table 9 evaluates whether governance mechanisms influence the perceived value of AI adoption in the context of climate-related challenges.

The decision to focus on corporate governance is supported by key theoretical frameworks. Agency theory (Jensen and Meckling, 1976) posits that governance mechanisms like independent directors and managerial ownership help mitigate conflicts of interest between managers and shareholders, ensuring efficient resource utilization. Moreover, resource dependence theory (Pfeffer & Salancik, 1978) highlights the role of diverse and independent boards in providing external expertise and fostering strategic adaptability. Governance structures that enhance oversight and decision-making may amplify the benefits of AI workforce adoption, signaling greater preparedness to navigate climate-related risks and opportunities.

The results, however, reveal complex dynamics. The interaction between the share of AI workers and the percentage of independent directors is positive but not statistically significant. This finding suggests that while independent boards enhance oversight, their role in influencing the market's perception of AI adoption during climate policy events may be limited. Independent directors are often more effective in addressing traditional governance concerns than in facilitating complex technological strategies like AI adoption.

Similarly, the interaction between the share of AI workers and the percentage of female directors is negative and not significant. Although gender-diverse boards have been associated with better decision-making and innovation (Adams & Ferreira, 2009; Pattanaporn Chatjuthamard et al., 2021; Ongsakul et al., 2020; Papangkorn et al., 2021; Post & Byron, 2015), their influence on the perceived benefits of AI adoption during climate policy shifts appears minimal. This may reflect the broader challenge of linking board diversity to specific strategic outcomes, such as leveraging AI in the context of climate change.

The interaction with managerial ownership is also negative and not significant. While managerial ownership can align incentives with shareholder interests, it may also lead to entrenchment, reducing strategic flexibility (Morck et al., 1988). In the case of AI adoption, this balance may explain why managerial ownership does not significantly moderate the market's perception of technological investments during climate-related events.

5.10. The effect of the abnormal returns attributable to AI workforce adoption on subsequent firm value

Table 10 examines whether the abnormal returns attributable to AI workforce adoption in response to the Paris Agreement can predict subsequent firm value, as measured by Tobin's q. This analysis is particularly significant in the context of climate change, as it evaluates whether market reactions during a landmark policy event translate into sustained economic benefits for firms. The Paris Agreement's focus on emissions reductions and sustainability has created a global environment where technological adaptability and innovation are crucial. By linking short-term market reactions to long-term firm value, Table 10 sheds light on the economic implications of AI adoption as a tool for addressing climate-related challenges and opportunities.

We begin by estimating the predicted cumulative abnormal return from Model 2 in Table 2, which reflects the impact of AI workforce adoption, and then run the following analysis.

$$(\textit{Tobin's } q)_{2016} = \alpha + \beta_1 \, (\textit{Predicted CAR}(-1, +1)) + \beta_2 \, (\textit{Controls})_{2015} + \textit{Industry Fixed Effects} + \varepsilon$$

Understanding whether CAR (-1, +1) predicts future firm value is vital because it demonstrates whether investors correctly anticipate the long-term benefits of AI adoption in the context of climate change. According to the efficient market hypothesis (EMH) (Fama, 1970), stock prices reflect all available information, including expectations about a firm's ability to adapt to the demands of a low-carbon economy. Moreover, resource-based theory (Barney, 1991) suggests that firms leveraging unique resources, such as AI-skilled employees, are better positioned to gain a competitive advantage in the shifting regulatory and market landscapes driven by climate policies like the Paris Agreement.

The results in Table 10 strongly support the link between AI workforce adoption and long-term firm value. The coefficient for predicted CAR (-1, +1) is positive and highly significant in both models. These findings indicate that firms with higher abnormal returns during the Paris Agreement event window achieve greater subsequent firm value, reflecting investor recognition of AI's role in addressing climate-focused challenges. The persistence of this relationship over multiple years highlights the enduring impact of AI adoption as a strategic asset.

In the first model, the significant effect of CAR (-1, +1) on Tobin's q in 2016 suggests that firms with greater AI workforce adoption are perceived as better equipped to innovate and adapt to the regulatory and operational changes introduced by the Paris Agreement. This aligns with the intensified global focus on sustainability, where AI plays a critical role in managing risks and exploring green opportunities. In the second model, the consistent positive effect over the 2016–2018 period demonstrates that the market's initial optimism is not fleeting but instead translates into sustained economic benefits. This finding supports dynamic capabilities theory (Teece, Pisano, and Shuen, 1997), which emphasizes the role of technological resources like AI in enabling firms to adapt and thrive in rapidly changing environments.

These results demonstrate the importance of AI adoption not only in signaling short-term adaptability during major climate policy events but also in contributing to long-term firm value in the low-carbon economy. Firms with greater AI workforce adoption are likely to gain a competitive edge through enhanced innovation, operational efficiency, and resilience to climate-related risks. These results strongly corroborate Babina et al. (2024), who also document the beneficial effect of AI workforce adoption on firm value. In addition, our findings align with the objectives of the Paris Agreement, where technological investments are integral to the transition toward sustainable business practices. By connecting short-term market reactions to subsequent firm performance, Table 10 highlights the strategic value of AI as a cornerstone of climate resilience and sustainable growth.

5.11. The U.S. withdrawal from the Paris agreement

To deepen our understanding of how AI workforce adoption influences firm value in varying climate policy environments, we conduct an additional event study centered on the U.S. withdrawal from the Paris Agreement. This analysis serves as a critical complement to our main investigation of the Agreement's adoption, enabling us to assess not only how the market rewards AI adoption during periods of strong climate policy support, but also how it responds when such policy momentum falters or reverses.

The U.S. withdrawal stands as a highly relevant policy shock. Announced on June 1, 2017, this move signaled a dramatic shift in federal climate strategy and reduced regulatory commitment to climate action, raising questions about the future of climate governance and corporate adaptation in the United States. Importantly, the process was drawn out: while the intent to withdraw was declared in 2017, the official notification was submitted in November 2019, and the withdrawal did not become effective until November 2020. Thus, although the announcement generated immediate debate and uncertainty, it did not precipitate abrupt regulatory change for U.S. firms.

Our analysis reveals a noteworthy asymmetry: while firms with a larger AI workforce experienced significant positive market reactions to the adoption of the Paris Agreement, their stock price responses to the withdrawal announcement were statistically insignificant. That is, investors did not penalize or reward firms with greater AI capabilities in the wake of the policy reversal (results available upon request).

Several factors likely contribute to this muted response. First, the withdrawal was widely anticipated—Trump had made his intentions explicit during his campaign—so the market likely priced in this shift well in advance of the official announcement. Second, AI investments may be perceived by investors as conferring broad, enduring value that extends beyond climate adaptation, making them less sensitive to fluctuations in U.S. policy. Third, the lengthy, multi-year withdrawal process allowed both firms and markets to gradually adjust their expectations and strategies, dampening any immediate reaction. Lastly, any potential negative effects of weakened U.S. climate policy may have been offset by ongoing global momentum toward climate action, reinforcing the idea that AI capabilities remain strategically valuable even as domestic policy ebbs and flows.

Collectively, these findings suggest that the market rewards AI workforce adoption most strongly in times of advancing climate policy, but views such investments as resilient assets whose value is not easily undermined by individual policy reversals.

5.12. Practical managerial implications

The findings of this study provide valuable insights for corporate managers, investors, policymakers, and board members as they navigate the integration of artificial intelligence (AI) within climate-focused strategies.

Managers should recognize that AI workforce adoption enhances shareholder value by signaling innovation and adaptability. However, for firms with high climate exposure, investors may be wary of resource misallocation if AI investments are not clearly tied to climate strategies. Managers must demonstrate how AI contributes to sustainability goals, such as emissions tracking and risk management, to alleviate these concerns. Highlighting AI's role in addressing climate risks can improve investor confidence and market perception. Investors can use these insights to assess how AI adoption influences long-term firm value in the context of climate risks. Firms with higher AI workforce adoption show stronger market reactions, particularly when aligned with innovation efforts like R&D. However, investors should be cautious with firms that adopt AI without clearly linking it to climate actions, as this could signal misaligned priorities.

Policymakers should consider incentivizing AI-driven climate solutions. Since AI adoption enhances firm adaptability to climate policies, governments could offer tax incentives or grants for AI projects focused on reducing emissions and managing climate risks. Supporting AI innovations in sustainability would encourage more firms to adopt these technologies in meaningful ways. Board members must ensure that AI investments are aligned with climate strategies. Traditional governance metrics, such as board independence, have limited influence on market reactions to AI adoption during climate events. Boards should demand clear reporting on how AI investments contribute to climate resilience and shareholder value.

Firms in high-exposure industries, such as energy and manufacturing, should focus on integrating AI into climate-specific solutions like risk modeling and carbon footprint reduction. Conversely, firms with strong R&D programs are better positioned to benefit from AI adoption. Leveraging AI for climate-related innovations can enhance both shareholder value and long-term competitive advantage. Overall, firms should align AI strategies with climate goals to maximize investor confidence and long-term growth, especially in an era of heightened climate awareness.

Finally, our results indicate that AI workforce adoption drives not only short-term market reactions but also long-term firm value, offering critical insights for managers and other stakeholders. For managers, this highlights the importance of viewing AI as a strategic, long-term investment rather than a short-term technological trend. Integrating AI into core business processes and sustainability initiatives can help firms enhance their adaptability to evolving climate policies and maintain competitive advantages over time. For investors and policymakers, these findings reinforce the idea that firms with AI-driven innovation capabilities are better positioned to achieve sustainable growth. Boards should also recognize that AI adoption has lasting impacts on firm performance and ensure that it aligns with long-term value creation strategies, particularly in the context of climate-related risks and opportunities.

6. Conclusions

Climate change and artificial intelligence (AI) are rapidly emerging as critical factors in shaping the global economy and corporate strategies. Climate change presents systemic risks to businesses and financial markets, while AI is transforming industries by enhancing decision-making, operational efficiency, and innovation potential (Giglio et al., 2021; Agrawal, Gans, and Goldfarb, 2019). Our study emphasizes the connection between AI workforce adoption and shareholder value, using an event study framework centered on the Paris Agreement, a landmark climate policy event. Leveraging a novel dataset developed by Babina et al. (2024), we examine how AI-skilled employees contribute to firms' resilience and adaptability, as reflected in stock market reactions, providing critical insights into the value AI adoption generates for shareholders in the context of climate change.

Our results reveal a significant and robust positive effect of AI workforce adoption on stock market reactions to the Paris Agreement. These findings remain consistent across a range of robustness checks, including propensity score matching, entropy balancing, and instrumental-variable analysis, showing the reliability of the results. Furthermore, our findings reveal a significant interaction between AI adoption and firm-specific climate change exposure, indicating that the benefits of AI adoption may decline for firms with higher climate exposure. This effect is likely driven by concerns over resource allocation, as firms face competing priorities between AI investments and climate-focused initiatives. Also, the results on climate change sentiment show that positive sentiment about physical risks enhances the market's response to AI workforce adoption, emphasizing AI’s role in addressing tangible climate challenges. However, sentiment related to regulatory risks and new opportunities has no significant effect.

Interactions with firm-specific attributes provide additional insights. For example, AI adoption complements R&D investments, signaling innovation potential, but raises concerns about resource allocation for highly profitable firms. Similarly, the positive interaction with leverage highlights how financial discipline may enhance the perceived value of AI adoption. Governance characteristics, such as board independence and managerial ownership, show limited influence on the market’s perception of AI adoption during climate policy shifts, suggesting that traditional governance metrics may require stronger alignment with technological and environmental strategies.

Finally, we demonstrate that the abnormal returns attributable to AI workforce adoption during the Paris Agreement predict subsequent firm value, as measured by Tobin’s q. This finding emphasizes that market reactions to AI adoption are not merely short-term but reflect genuine expectations of sustained economic benefits, supporting theories like the efficient market hypothesis and resource-based theory.

These findings provide actionable insights for corporate managers. Firms should align AI investments with their climate strategies to maximize investor confidence and long-term value creation. Communicating how AI adoption addresses both climate risks and opportunities is crucial, particularly for firms with high climate exposure. Additionally, integrating governance structures to support technological and environmental goals can further enhance the strategic value of AI adoption. By leveraging AI as a tool for climate resilience, firms can position themselves as leaders in the low-carbon economy.

Table 1: Summary statistics

This table displays the descriptive statistics for the sample. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. For ease of presentation, we scale firm-specific exposure to climate change and its components by multiplying each measure by 1,000. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

Variable	Mean	SD	25th	Median	75th
Stock Market Reactions					
CAR (-1,+1)	-0.013	0.044	-0.032	-0.008	0.009
CAR (-2,+2)	-0.011	0.063	-0.035	-0.009	0.014
AI Workforce					
Share of AI Workers	0.002	0.004	0.000	0.000	0.001
Firm Characteristics					
Firm Size	7.074	1.872	5.787	6.967	8.302
Profitability	0.024	0.184	0.007	0.066	0.112
Leverage	0.272	0.259	0.036	0.231	0.415
Capital Expenditures	0.042	0.043	0.014	0.028	0.056
R&D Investments	0.057	0.101	0.000	0.009	0.079
Advertising Spending	0.014	0.033	0.000	0.000	0.010
Dividends	0.014	0.027	0.000	0.000	0.020
Current Ratio	2.579	2.298	1.243	1.966	3.070
Effective Tax Rate	0.144	0.530	0.000	0.234	0.354
Climate Change					
Climate Change Exposure	0.733	1.455	0.096	0.279	0.663
Physical	0.010	0.092	0.000	0.000	0.000
Regulatory	0.032	0.223	0.000	0.000	0.000
New Opportunities	0.265	0.730	0.000	0.068	0.221
Corporate Governance					
Ln (Board Size)	2.294	0.198	2.197	2.303	2.398
% Independent Directors	79.939	10.902	75.000	83.333	88.889
% Female Directors	15.400	10.553	10.000	14.286	22.222
% Managerial Ownership	2.672	5.270	0.291	0.803	2.262

Table 2: The effect of AI worker adoption on shareholder value around the adoption of the Paris Agreement

This table presents the regression results. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)	(3)	(4)
	CAR (-1,+1)	CAR (-1,+1)	CAR (-2,+2)	CAR (-2,+2)
Share of AI Workers	**0.517****	**0.487***	**0.628****	**0.388***
	(2.226)	**(1.734)**	**(2.057)**	**(1.953)**
Firm Size		0.002***		0.002**
		(3.715)		(2.215)
Profitability		0.042*		0.017
		(1.678)		(0.621)
Leverage		-0.022***		-0.017**
		(-4.114)		(-2.401)
Capital Expenditures		-0.037		-0.018
		(-0.755)		(-0.256)
R&D Investments		0.023		0.037
		(0.647)		(0.812)
Advertising Spending		0.058		0.066
		(1.559)		(1.342)
Dividends		-0.088		-0.153*
		(-1.389)		(-1.988)
Current Ratio		0.001		0.001
		(0.804)		(0.700)
Effective Tax Rate		0.003**		0.002
		(2.054)		(0.940)
Constant	-0.014***	-0.027***	-0.012***	-0.026***
	(-37.500)	(-5.537)	(-23.387)	(-2.671)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,498	1,498	1,497	1,497
Adjusted R-squared	0.032	0.082	0.035	0.044

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Propensity score matching (PSM)

This table presents the regression results with propensity score matching. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

Panel A: Diagnostic testing

	Pre-Match	Post-Match
	(1)	(2)
	Treatment (High Share of AI Workers)	Treatment (High Share of AI Workers)
Firm Size	0.282***	0.101
	(4.541)	(1.369)
Profitability	1.613***	-0.465
	(3.009)	(-0.775)
Leverage	-1.046**	-0.206
	(-2.029)	(-0.607)
Capital Expenditures	-0.559	1.749
	(-0.204)	(0.494)
R&D Investments	9.503***	-0.810
	(5.105)	(-0.482)
Advertising Spending	2.827	-0.178
	(0.837)	(-0.047)
Dividends	-2.150	-3.875
	(-0.893)	(-1.356)
Current Ratio	0.046	-0.016
	(1.486)	(-0.540)
Effective Tax Rate	0.056	0.056
	(0.405)	(0.249)
Constant	-2.525***	-1.249
	(-5.154)	(-1.622)
Industry Fixed Effects	Yes	Yes
Pseudo R-squared	0.211	0.021
Observations	1,224	745

Robust z-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Propensity score matching (PSM) (Continued)

Panel B: Regression analysis

	(1)
	CAR (-1,+1)
Share of AI Workers	**0.638*****
	(4.223)
Firm Size	0.004***
	(4.316)
Profitability	-0.023
	(-1.350)
Leverage	-0.002
	(-0.350)
Capital Expenditures	-0.078*
	(-1.735)
R&D Investments	-0.039
	(-1.120)
Advertising Spending	0.054*
	(1.815)
Dividends	0.002
	(0.032)
Current Ratio	0.001
	(0.730)
Effective Tax Rate	0.006***
	(3.149)
Constant	-0.035***
	(-3.807)
Industry Fixed Effects	Yes
Observations	745
Adjusted R-squared	0.066

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 4: Entropy Balancing

This table presents the regression results with entropy balancing. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)
	CAR (-1,+1)
Share of AI Workers	**0.447****
	(2.214)
Firm Size	0.003***
	(5.891)
Profitability	0.005
	(0.382)
Leverage	-0.003
	(-0.528)
Capital Expenditures	-0.027
	(-0.764)
R&D Investments	-0.010
	(-0.473)
Advertising Spending	0.030*
	(1.983)
Dividends	-0.088**
	(-2.191)
Current Ratio	0.001
	(1.441)
Effective Tax Rate	0.009***
	(8.716)
Constant	-0.030***
	(-6.459)
Industry Fixed Effects	Yes
Observations	1,498
Adjusted R-squared	0.038

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: Instrumental-variable analysis (IV)

This table presents the regression results with an instrumental-variable analysis. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)	(3)	(4)
	First Stage	Second Stage	First Stage	Second Stage
	Share of AI Workers	CAR (-1,+1)	Share of AI Workers	CAR (-1,+1)
Share of AI Workers (Industry Average)	**0.891*****		**0.244*****	
	(9.537)		**(3.132)**	
Share of AI Workers (Instrumented)		**2.323****		**0.529****
		(2.564)		**(2.239)**
Share of AI Workers (Zip Code Average)			**0.955*****	
			(10.518)	
Firm Size	0.000**	0.002***	0.000*	0.002***
	(2.121)	(3.834)	(1.942)	(4.006)
Profitability	0.001	0.042**	-0.000	0.044**
	(0.566)	(2.068)	(-0.065)	(2.259)
Leverage	-0.001*	-0.019***	0.000	-0.022***
	(-1.872)	(-3.804)	(0.411)	(-4.314)
Capital Expenditures	0.003*	-0.053	0.000	-0.055
	(1.701)	(-1.615)	(0.194)	(-1.667)
R&D Investments	0.010**	0.010	0.001	0.033
	(2.468)	(0.351)	(0.947)	(1.307)
Advertising Spending	0.005**	0.044	0.001	0.051
	(2.625)	(1.108)	(0.711)	(1.290)
Dividends	-0.003	-0.067	-0.000	-0.077
	(-0.683)	(-1.128)	(-0.221)	(-1.312)
Current Ratio	0.000	0.001	0.000	0.000
	(0.541)	(0.677)	(0.334)	(0.529)
Effective Tax Rate	-0.000	0.004**	-0.000	0.004**
	(-0.853)	(2.327)	(-0.242)	(2.160)
Constant	-0.002*	-0.026***	-0.001***	-0.025***
	(-1.945)	(-5.567)	(-2.949)	(-4.962)
Observations	1,501	1,501	1,501	1,501
Adjusted R-squared	0.145	0.061	0.560	0.059
F-Statistics	90.96***	-	279.96***	-
Hansen J-Statistics	-	-	-	1.604

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Interactions with climate change exposure

This table presents the regression results with interactions with climate change exposure. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)	(3)	(4)
	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)
Share of AI Workers × Climate Change Exposure	**-333.733****			
	(-2.378)			
Climate Change Exposure	**2.388***			
	(1.970)			
Share of AI Workers × Physical Risk		**7,569.827**		
		(0.850)		
Physical Risk		**5.225**		
		(0.888)		
Share of AI Workers × Regulatory Risk			**2,677.047**	
			(0.830)	
Regulatory Risk			**-0.968**	
			(-0.149)	
Share of AI Workers × New Opportunities				**-464.666**
				(-1.376)
New Opportunities				**6.351*****
				(3.285)
Share of AI Workers	0.779***	0.476*	0.478	0.614**
	(3.666)	(1.736)	(1.636)	(2.410)
Firm Size	0.002***	0.002***	0.002***	0.002***
	(3.790)	(3.725)	(3.653)	(3.682)
Profitability	0.043*	0.042	0.042*	0.043*
	(1.748)	(1.669)	(1.687)	(1.747)
Leverage	-0.022***	-0.022***	-0.022***	-0.022***
	(-4.097)	(-4.202)	(-4.086)	(-4.140)
Capital Expenditures	-0.043	-0.037	-0.037	-0.048
	(-0.902)	(-0.758)	(-0.763)	(-1.069)
R&D Investments	0.026	0.023	0.023	0.026
	(0.742)	(0.641)	(0.651)	(0.749)
Advertising Spending	0.060	0.057	0.057	0.062
	(1.639)	(1.542)	(1.548)	(1.654)
Dividends	-0.091	-0.089	-0.088	-0.087
	(-1.444)	(-1.405)	(-1.369)	(-1.365)
Current Ratio	0.001	0.001	0.001	0.001
	(0.840)	(0.820)	(0.796)	(0.820)
Effective Tax Rate	0.003**	0.003**	0.003**	0.003**
	(2.100)	(2.053)	(2.058)	(2.063)
Constant	-0.030***	-0.028***	-0.027***	-0.029***
	(-6.190)	(-5.556)	(-5.512)	(-5.774)
Industry Fixed Effects	Yes	Yes	Yes	Yes

Observations	1,498	1,498	1,498	1,498
Adjusted R-squared	0.085	0.081	0.081	0.089

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: Interactions with climate change sentiment

This table presents the regression results with interactions with climate change sentiment. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)	(3)	(4)
	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)
Share of AI Workers × Climate Change Sentiment	**-565.738**			
	(-0.935)			
Climate Change Sentiment	**0.928**			
	(0.594)			
Share of AI Workers × Physical Risk Sentiment		**59,984.690*** **		
		(6.513)		
Physical Risk Sentiment		**-4.349**		
		(-0.798)		
Share of AI Workers × Regulatory Risk Sentiment			**1,317.338**	
			(0.674)	
Regulatory Risk Sentiment			**0.244**	
			(0.040)	
Share of AI Workers × New Opportunities Sentiment				**1,119.425**
				(0.742)
New Opportunities Sentiment				**5.696*** **
				(2.851)
Share of AI Workers	0.561***	0.491*	0.492*	0.401**
	(3.166)	(1.749)	(1.742)	(2.254)
Firm Size	0.002***	0.002***	0.002***	0.002***
	(3.739)	(3.725)	(3.712)	(3.710)
Profitability	0.042*	0.042	0.042*	0.043*
	(1.692)	(1.639)	(1.684)	(1.744)
Leverage	-0.022***	-0.022***	-0.022***	-0.022***
	(-4.123)	(-4.068)	(-4.082)	(-4.361)
Capital Expenditures	-0.038	-0.038	-0.037	-0.048
	(-0.784)	(-0.782)	(-0.757)	(-1.051)
R&D Investments	0.024	0.022	0.023	0.026
	(0.676)	(0.618)	(0.655)	(0.760)
Advertising Spending	0.057	0.058	0.058	0.063
	(1.552)	(1.571)	(1.563)	(1.660)
Dividends	-0.088	-0.091	-0.089	-0.091
	(-1.382)	(-1.469)	(-1.386)	(-1.380)
Current Ratio	0.001	0.001	0.001	0.001
	(0.805)	(0.802)	(0.803)	(0.818)
Effective Tax Rate	0.003**	0.003**	0.003**	0.003**
	(2.056)	(2.009)	(2.056)	(2.050)
Constant	-0.028***	-0.027***	-0.027***	-0.029***
	(-5.613)	(-5.583)	(-5.608)	(-5.734)
Industry Fixed Effects	Yes	Yes	Yes	Yes

Observations	1,498	1,498	1,498	1,498
Adjusted R-squared	0.081	0.083	0.080	0.089

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8: Interaction with firm-specific characteristics

This table presents the regression results with interactions with firm-specific characteristics. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)	(3)	(4)
	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)
Share of AI Workers × R&D Investments	**5.516*** **			
	(2.983)			
Share of AI Workers × Profitability		**-3.941*** **		
		(-3.961)		
Share of AI Workers × Leverage			**3.568*** **	
			(7.266)	
Share of AI Workers × Capital Expenditures				**20.851*** **
				(3.342)
Share of AI Workers	-0.338	0.148	-0.115	-0.336
	(-1.194)	(0.653)	(-0.585)	(-0.982)
Firm Size	0.002***	0.003***	0.002***	0.002***
	(3.867)	(4.125)	(3.602)	(3.795)
Profitability	0.043*	0.054**	0.044*	0.044*
	(1.769)	(2.201)	(1.798)	(1.758)
Leverage	-0.023***	-0.023***	-0.028***	-0.022***
	(-4.338)	(-4.747)	(-5.932)	(-4.136)
Capital Expenditures	-0.037	-0.038	-0.035	-0.064
	(-0.743)	(-0.761)	(-0.725)	(-1.188)
R&D Investments	0.010	0.025	0.022	0.025
	(0.255)	(0.694)	(0.635)	(0.691)
Advertising Spending	0.057	0.052	0.055	0.052
	(1.531)	(1.398)	(1.486)	(1.394)
Dividends	-0.089	-0.093	-0.089	-0.087
	(-1.454)	(-1.538)	(-1.470)	(-1.401)
Current Ratio	0.001	0.001	0.001	0.001
	(0.960)	(1.065)	(0.823)	(0.919)
Effective Tax Rate	0.003*	0.003*	0.004**	0.003**
	(1.990)	(1.923)	(2.105)	(2.054)
Constant	-0.027***	-0.029***	-0.025***	-0.027***
	(-5.403)	(-5.979)	(-4.979)	(-5.370)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Observations	1,498	1,498	1,498	1,498
Adjusted R-squared	0.085	0.092	0.088	0.086

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: The role of corporate governance

This table presents the regression results with interactions with corporate governance. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)	(3)
	CAR (-1,+1)	CAR (-1,+1)	CAR (-1,+1)
Share of AI Workers × % Independent Directors	**0.027**		
	(1.245)		
Share of AI Workers × % Female Directors		**-0.062**	
		(-1.337)	
Share of AI Workers × % Managerial Ownership			**-0.010**
			(-0.154)
% Managerial Ownership			-0.000
			(-0.513)
Ln (Board Size)	0.005	0.006	
	(0.612)	(0.705)	
% Independent Directors	0.000	0.000	
	(0.014)	(0.691)	
% Female Directors	0.000	0.000	
	(0.037)	(0.594)	
Share of AI Workers	-1.871	1.361*	0.481
	(-0.967)	(1.688)	(1.020)
Firm Size	-0.000	-0.000	0.001
	(-0.230)	(-0.253)	(1.258)
Profitability	0.069*	0.070*	0.060**
	(1.888)	(1.897)	(2.459)
Leverage	-0.014	-0.014	-0.016**
	(-1.481)	(-1.466)	(-2.305)
Capital Expenditures	0.113	0.107	0.048
	(1.365)	(1.282)	(0.796)
R&D Investments	0.067**	0.064**	0.025
	(2.047)	(2.031)	(0.611)
Advertising Spending	0.107	0.105	-0.006
	(1.331)	(1.303)	(-0.112)
Dividends	-0.127**	-0.132**	-0.084
	(-2.390)	(-2.391)	(-1.607)
Current Ratio	-0.001	-0.001	-0.000
	(-0.763)	(-0.877)	(-0.448)
Effective Tax Rate	-0.001	-0.001	0.001
	(-0.440)	(-0.364)	(0.503)
Constant	-0.024	-0.030	-0.022**
	(-1.039)	(-1.282)	(-2.175)
Industry Fixed Effects	Yes	Yes	Yes
Observations	574	574	757
Adjusted R-squared	0.130	0.132	0.068

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: The effect of the abnormal return attributable to AI workforce adoption on subsequent firm value

This table presents the regression results investigating the impact of the abnormal return to subsequent firm value. All firm-level variables, unless otherwise indicated, are measured annually. Stock market reaction variables are calculated using daily returns. The share of AI workers is defined as the proportion of AI-skilled employees at the firm, measured annually using resume data following Babina et al. (2024), and is treated as a continuous variable in all analyses. Control variables are defined in Appendix Table A1. Robust standard errors are clustered by industry.

	(1)	(2)
	$(\text{Tobin's q})_{2016}$	$(\text{Average Tobin's q})_{2016\text{-}2018}$
CAR (-1, +1) (Predicted)	**165.102*** **	**185.090*** **
	(4.377)	**(5.182)**
Firm Size	-0.584***	-0.632***
	(-3.179)	(-3.454)
Profitability	-3.732***	-4.734***
	(-3.147)	(-4.500)
Leverage	4.667***	5.076***
	(4.059)	(4.576)
Capital Expenditures	8.007***	8.794***
	(4.141)	(4.099)
R&D Investments	-1.288	-1.819**
	(-1.491)	(-2.429)
Advertising Spending	-7.189***	-7.300**
	(-2.686)	(-2.596)
Dividends	23.884***	25.290***
	(4.685)	(5.582)
Current Ratio	0.101*	0.103*
	(1.939)	(1.812)
Effective Tax Rate	-0.330**	-0.399***
	(-2.422)	(-2.671)
Constant	5.625***	6.176***
	(4.481)	(4.996)
Industry Fixed Effects	Yes	Yes
Observations	1,379	1,381
Adjusted R-squared	0.233	0.240

Robust t-statistics in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix

Table A1: Variable definitions

With the exception of stock market reactions, all variables are based on annual data.

Variable	Definition
Stock Market Reactions	
CAR (-1,+1)	Cumulative abnormal returns from Day -1 to Day +1
CAR (-2,+2)	Cumulative abnormal returns from Day -2 to Day +2
AI Workforce	
Share of AI Workers	Proportion of AI workers developed by Babina et al. (2024)
Firm-specific Characteristics	
Firm Size	Ln (Total Assets)
Profitability	EBIT/Total Assets
Leverage	Total Debt/Total Assets
Capital Expenditures	Capital Expenditures/Total Assets
Advertising Intensity	Advertising Expense/Total Assets
R&D Investments	R&D Expense/Total Assets
Dividend	Dividends/Total Assets
Current Ratio	Current Assets/Current Liabilities
Effective Tax Rate	Tax Expense/Pre-tax Income
Climate Change	
Climate Change Exposure	Firm-specific climate change exposure developed by Sautner et al (2023)
Physical	Firm-specific climate change exposure due to physical risk
Regulatory	Firm-specific climate change exposure due to regulatory risk
New Opportunities	Firm-specific climate change exposure due to new business opportunities.
Board Attributes	
% of Independent Directors	Percentage of independent directors on the board
% of Female Directors	Percentage of female directors on the board
Ln (Board Size)	Natural log of board size
% Managerial Ownership	Total percentage of equity held by the top five executives

Event study estimation

We analyze market responses to the adoption of the Paris Agreement on climate change using a traditional event study approach. The estimation period extends from 300 days to 46 days prior to the event date, t. We estimate the predicted return ($E(r_{i,t})$) using the market model based on the CRSP equally-weighted index as the benchmark market index ($r_{m,t}$). Our proxy for the stock market reactions is the cumulative abnormal return (CAR) over the event windows (–1, 1).[6] Specifically,

$$CAR_{i,t}\,(-1,+1) = \sum_{t=-1}^{t=+1}\left(r_{i,t} - E(r_{i,t})\right)$$

where $r_{i,t}$ denotes raw return on a stock i on the event day t and $E(r_{i,t}) = \hat{\alpha}_i + \hat{\beta}_i \times r_{m,t}$ respectively.

To enhance the reliability of our findings, we apply strict criteria to exclude potential confounding events overlapping with the Paris Agreement's adoption. Specifically, we focus on quarterly earnings announcements, given extensive evidence of abnormal returns associated with these events (Watts, 1978). As a result, firms that reported quarterly earnings within two business days of the agreement's signing are excluded from our analysis.

[6] If an event date falls on a non-trading day, it is adjusted to the nearest subsequent trading day. Thus, the event date for the adoption of the Paris Agreement is set to December 14, 2015, although the announcement was made on December 12, 2015. For the estimation window, a minimum of 100 non-missing return observations is required. The CRSP equally-weighted index is constructed by giving equal weight to each stock within the index, ensuring that no single stock disproportionately influences the index's performance. The index value is based on the overall performance of all included stocks, with periodic rebalancing to maintain the equal weight distribution. There must be no missing returns within the event window. For example, estimating the Cumulative Abnormal Return (CAR) for the window (-1, +1) requires three non-missing returns within that period.

We also evaluate the impact of financial analysts' revisions on stock market dynamics. A wealth of research in finance and accounting underscores the influential role of sell-side analysts' reports in shaping investor behavior. Positive abnormal returns often follow analyst upgrades (in earnings forecasts, price targets, and recommendations), while downgrades typically yield negative abnormal returns. To address this, we analyze three critical indicators: analyst recommendations, price targets, and annual EPS estimates. Leveraging I/B/E/S data, we compare these metrics with their prior values from the same analyst and brokerage, issued at least a year earlier. Companies experiencing revisions in any of these metrics within two business days of the Paris Agreement's adoption are removed from our dataset.

Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, *40*(S1), S293–S340. https://doi.org/10.1086/718327

Adams, R. B., & Ferreira, D. (2009). Women in the boardroom and their impact on governance and performance. *Journal of Financial Economics*, *94*(2), 291–309. https://doi.org/10.1016/j.jfineco.2008.10.007

Aghion, P., Jones, B. F., & Jones, C. I. (2017). *Artificial intelligence and economic growth*. *23928*. https://doi.org/10.7208/9780226613475-011

Agrawal, A., Gans, J., & Goldfarb, A. (2019). *The economics of artificial intelligence: An agenda*. University of Chicago Press. https://books.google.com/books?hl=en&lr=&id=4GyVDwAAQBAJ&oi=fnd&pg=PR7&dq=%E2%80%A2%09Agrawal,+A.,+Gans,+J.,+%26+Goldfarb,+A.+(2019).+The+Economics+of+Artificial+Intelligence:+An+Agenda.+University+of+Chicago+Press.&ots=3U4dh7qYtv&sig=uls4IxZnW0Z_ZvFQh5-TCMp9JEM

Angrist, J. D., & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, *15*(4), 69–85. https://doi.org/10.1257/jep.15.4.69

Armstrong, C. S., Core, J. E., & Guay, W. R. (2014). Do independent directors cause improvements in firm transparency? *Journal of Financial Economics*, *113*(3), 383–403. https://doi.org/10.1016/j.jfineco.2014.05.009

Babina, T., Fedyk, A., He, A., & Hodson, J. (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics*, *151*(103745), 103745. https://doi.org/10.1016/j.jfineco.2023.103745

Bai, Y., Chou, L., & Zhang, W. (2021). Industrial innovation characteristics and spatial differentiation of smart grid technology in China based on patent mining. *Journal of Energy Storage*, *43*(103289), 103289. https://doi.org/10.1016/j.est.2021.103289

Barnea, A., Haugen, R. A., & Senbet, L. W. (1981). An equilibrium analysis of debt financing under costly tax arbitrage and agency problems. *The Journal of Finance*, *36*(3), 569. https://doi.org/10.2307/2327519

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, *17*(1), 99–120. https://doi.org/10.1177/014920639101700108

Barney, J. B., Ketchen, D. J., Jr, & Wright, M. (2021). Resource-based theory and the value creation framework. *Journal of Management*, *47*(7), 1936–1955. https://doi.org/10.1177/01492063211021655

Belhadi, A., Mani, V., Kamble, S. S., Khan, S. A. R., & Verma, S. (2021). Artificial intelligence-driven innovation for enhancing supply chain resilience and performance under the effect of supply chain dynamism: an empirical investigation. *Annals of Operations Research*, *333*(2–3), 1–26. https://doi.org/10.1007/s10479-021-03956-x

Bernstein, A., Gustafson, M. T., & Lewis, R. (2019). Disaster on the horizon: The price effect of sea level rise. *Journal of Financial Economics*, *134*(2), 253–272. https://doi.org/10.1016/j.jfineco.2019.03.013

Binder, J. (1998). The event study methodology since 1969. *Review of Quantitative Finance and Accounting*, *11*(2), 111–137. https://doi.org/10.1023/a:1008295500105

Bolton, P., & Kacperczyk, M. (2021). Do investors care about carbon risk? *Journal of Financial Economics*, *142*(2), 517–549. https://doi.org/10.1016/j.jfineco.2021.05.008

Bordalo, P., Gennaioli, N., & Shleifer, A. (2012). Salience theory of choice under risk. *The Quarterly Journal of Economics*, *127*(3), 1243–1285. https://doi.org/10.1093/qje/qjs018

Brown, S. J., & Warner, J. B. (1985). Using daily stock returns: The case of event studies. *Journal of Financial Economics*, *14*(1), 3–31. https://doi.org/10.1016/0304-405X(85)90042-X

Brynjolfsson, E., Rock, D., & Syverson, C. (2019). Artificial intelligence and the modern productivity paradox. *The Economics of Artificial Intelligence*. https://doi.org/10.7208/chicago/9780226613475.003.0001

Brynjolfsson, Erik, Rock, D., & Syverson, C. (2021). The productivity J-curve: How intangibles complement general purpose technologies. *American Economic Journal Macroeconomics*, *13*(1), 333–372. https://doi.org/10.1257/mac.20180386

Buehlmaier, M. M. M., & Whited, T. M. (2018). Are financial constraints priced? Evidence from textual analysis. *The Review of Financial Studies*, *31*(7), 2693–2728. https://doi.org/10.1093/rfs/hhy007

Cao, L. (2023). AI and data science for smart emergency, crisis and disaster resilience. *International Journal of Data Science and Analytics*, *15*(3), 231–246. https://doi.org/10.1007/s41060-023-00393-w

Chatjuthamard, P., Kijkasiwat, P., & Jiraporn, P. (2023). The takeover market's effect on managerial ownership: evidence from hostile takeover susceptibility. *Management Research*. https://www.emerald.com/insight/content/doi/10.1108/MRR-03-2022-0164/full/html

Chatjuthamard, Pattanaporn, Chintrakarn, P., & Jiraporn, P. (2022). The effect of hostile takeover threats on capital structure: Evidence from half a century. *SSRN Electronic Journal*. https://doi.org/10.2139/ssrn.4227361

Chatjuthamard, Pattanaporn, Chintrakarn, P., Jiraporn, P., & Lee, S. M. (2024). Climate change, tax avoidance, and shareholder value: Evidence from the Paris Agreement. *International Review of Finance*. https://doi.org/10.1111/irfi.12454

Chatjuthamard, Pattanaporn, Jiraporn, P., & Lee, S. M. (2021). Does board gender diversity weaken or strengthen executive risk-taking incentives? *PloS One*, *16*(10), e0258163. https://doi.org/10.1371/journal.pone.0258163

Chatjuthamard, Pattanaporn, Mook Lee, S., Kim, Y. S., Jiraporn, P., & Potosky, D. (2024). Climate change and shareholder value: Evidence from textual analysis and Trump's unexpected victory. *Journal of Business Research*, *180*(114728), 114728. https://doi.org/10.1016/j.jbusres.2024.114728

Chen, J., & Tajdini, S. (2024). A moderated model of artificial intelligence adoption in firms and its effects on their performance. *Information Technology and Management*. https://doi.org/10.1007/s10799-024-00422-5

Chen, W., Zou, W., Zhong, K., & Aliyeva, A. (2023). Machine learning assessment under the development of green technology innovation: A perspective of energy transition. *Renewable Energy*, *214*, 65–73. https://doi.org/10.1016/j.renene.2023.05.108

Chindasombatcharoen, P., Chatjuthamard, P., Jiraporn, P., & Wongsinhirun, N. (2024). Climate change exposure and the takeover market: A text-based analysis. *Business Strategy and the Environment*. https://doi.org/10.1002/bse.3935

Chintrakarn, P., Jiraporn, P., Jiraporn, N., & Davidson, T. (2017). Estimating the effect of corporate social responsibility on firm value using geographic identification. *Asia-Pacific Journal of Financial Studies*, *46*(2), 276–304. https://doi.org/10.1111/ajfs.12170

Chintrakarn, P., Jiraporn, P., Tong, S., & Chatjuthamard, P. (2015). Estimating the effect of entrenched boards on firm value using geographic identification. *Finance Research Letters*, *12*, 109–116. https://doi.org/10.1016/j.frl.2014.11.002

Chishti, M. Z., Xia, X., & Dogan, E. (2024). Understanding the effects of artificial intelligence on energy transition: The moderating role of Paris Agreement. *Energy Economics*, *131*(107388), 107388. https://doi.org/10.1016/j.eneco.2024.107388

Choi, D., Gao, Z., & Jiang, W. (2020). Attention to Global Warming. *The Review of Financial Studies*, *33*(3), 1112–1145. https://doi.org/10.1093/rfs/hhz086

Choi, K. H., & Kwon, G. H. (2023). Strategies for sensing innovation opportunities in smart grids: In the perspective of interactive relationships between science, technology, and business. *Technological Forecasting and Social Change*, *187*(122210), 122210. https://doi.org/10.1016/j.techfore.2022.122210

Corrado, C. J. (2011). Event studies: A methodology review. *Accounting & Finance*. https://doi.org/10.1111/j.1467-629X.2010.00375.x

Das, T. K., & Teng, B.-S. (2000). A resource-based theory of strategic alliances. *Journal of Management*, *26*(1), 31–61. https://doi.org/10.1177/014920630002600105

De Bruyn, A., Viswanathan, V., Beh, Y. S., Brock, J. K.-U., & Von Wangenheim, F. (2020). Artificial intelligence and marketing: Pitfalls and opportunities. *Journal of Interactive Marketing*, *51*(1), 91–105. https://doi.org/10.1016/j.intmar.2020.04.007

Dehdarian, A., & Tucci, C. L. (2021). A complex network approach for analyzing early evolution of smart grid innovations in Europe. *Applied Energy*, *298*(117143), 117143. https://doi.org/10.1016/j.apenergy.2021.117143

Deng, Y., Jiang, W., & Wang, Z. (2023). Economic resilience assessment and policy interaction of coal resource oriented cities for the low carbon economy based on AI. *Resources Policy*, *82*(103522), 103522. https://doi.org/10.1016/j.resourpol.2023.103522

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review.

Journal of Business Research, *121*, 283–314. https://doi.org/10.1016/j.jbusres.2020.08.019

Diaz-Rainey, I., Gehricke, S. A., Roberts, H., & Zhang, R. (2021). Trump vs. Paris: The impact of climate policy on U.S. listed oil and gas firm returns and volatility. *International Review of Financial Analysis*, *76*(101746), 101746. https://doi.org/10.1016/j.irfa.2021.101746

Duchin, R., Matsusaka, J. G., & Ozbas, O. (2010). When are outside directors effective?☆. *Journal of Financial Economics*, *96*(2), 195–214. https://doi.org/10.1016/j.jfineco.2009.12.004

Dwivedi, Y. K., Hughes, L., Ismagilova, E., Aarts, G., Coombs, C., Crick, T., Duan, Y., Dwivedi, R., Edwards, J., Eirug, A., Galanos, V., Ilavarasan, P. V., Janssen, M., Jones, P., Kar, A. K., Kizgin, H., Kronemann, B., Lal, B., Lucini, B., … Williams, M. D. (2021). Artificial Intelligence (AI): Multidisciplinary perspectives on emerging challenges, opportunities, and agenda for research, practice and policy. *International Journal of Information Management*, *57*(101994), 101994. https://doi.org/10.1016/j.ijinfomgt.2019.08.002

Eilstrup-Sangiovanni, M., & Hall, N. (2025). *Climate activism, digital technologies, and organizational change*. Cambridge University Press. https://doi.org/10.1017/9781009483544

Enholm, I. M., Papagiannidis, E., Mikalef, P., & Krogstie, J. (2022). Artificial intelligence and business value: A literature review. *Information Systems Frontiers: A Journal of Research and Innovation*, *24*(5), 1709–1734. https://doi.org/10.1007/s10796-021-10186-w

Fabrizi, A., Guarini, G., & Meliciani, V. (2018). Green patents, regulatory policies and research network policies. *Research Policy*, *47*(6), 1018–1031. https://doi.org/10.1016/j.respol.2018.03.005

Fama, E. (1970). Efficient capital markets: A Review of Theory and empirical work. *Journal of Finance*, *25*, 383–417. https://doi.org/10.1111/J.1540-6261.1970.TB00518.X

Fama, E. F. (1980). Agency problems and the theory of the firm. *The Journal of Political Economy*, *88*(2), 288–307. https://doi.org/10.1086/260866

Feng, F., Li, J., Zhang, F., & Sun, J. (2024). The impact of artificial intelligence on green innovation efficiency: Moderating role of dynamic capability. *International Review of Economics & Finance*, *96*(103649), 103649. https://doi.org/10.1016/j.iref.2024.103649

Florackis, C., Louca, C., Michaely, R., & Weber, M. (2022). Cybersecurity risk. *The Review of Financial Studies*, *36*(1), 351–407. https://doi.org/10.1093/rfs/hhac024

Giglio, S., Maggiori, M., Rao, K., Stroebel, J., & Weber, A. (2021). Climate Change and Long-Run Discount Rates: Evidence from Real Estate. *The Review of Financial Studies*, *34*(8), 3527–3571. https://doi.org/10.1093/rfs/hhab032

Ginglinger, E., & Moreau, Q. (2019). Climate Risk and Capital Structure. In *Université Paris-Dauphine Research*. https://doi.org/10.2139/ssrn.3327185

Girón, A., & Ivanova, A. (2023). Climate action, institutional investors, and just transition. *Journal of Economic Issues*, *57*(2), 575–585. https://doi.org/10.1080/00213624.2023.2202142

Grennan, J., & Michaely, R. (2019). *Artificial intelligence and the future of work: Evidence from analysts*. https://scholar.google.com/citations?user=U7dGAyMAAAAJ&hl=en&oi=sra

Hacker, P. (2023). Sustainable AI Regulation. In *arXiv [cs.CY]*. arXiv. https://kluwerlawonline.com/journalarticle/Common+Market+Law+Review/61.2/COLA2024025

Hahn, J., & Hausman, J. (2002). A new specification test for the validity of instrumental variables. *Econometrica: Journal of the Econometric Society*, *70*(1), 163–189. https://doi.org/10.1111/1468-0262.00272

Hainmueller, J. (2012). Entropy Balancing for Causal Effects: A Multivariate Reweighting Method to Produce Balanced Samples in Observational Studies. *Political Analysis: An Annual Publication of the Methodology Section of the American Political Science Association*, *20*(1), 25–46. https://doi.org/10.1093/pan/mpr025

Hainmueller, J., & Xu, Y. (2013). *Ebalance: A Stata Package for Entropy Balancing*. https://doi.org/10.2139/ssrn.1943090

Harris, M., & Raviv, A. (1991). The theory of capital structure. *The Journal of Finance*, *46*(1), 297–355. https://doi.org/10.1111/j.1540-6261.1991.tb03753.x

Hart, S. L. (1995). A natural-resource-based view of the firm. *Academy of Management Review*, *20*(4), 986–1014. https://doi.org/10.5465/amr.1995.9512280033

Harvey, C. R., Lins, K. V., & Roper, A. H. (2004). The effect of capital structure when expected agency costs are extreme. *Journal of Financial Economics*, *74*(1), 3–30. https://doi.org/10.1016/j.jfineco.2003.07.003

Heo, Y. (2021). Climate Change Exposure and Firm Cash Holdings. In *Available at SSRN 3795298*. https://doi.org/10.2139/ssrn.3795298

Hillman, K., Nilsson, M., Rickne, A., & Magnusson, T. (2011). Fostering sustainable technologies: a framework for analysing the governance of innovation systems. *Science and Public Policy*, *38*(5), 403–415. https://doi.org/10.3152/030234211X12960315267499

Hossain, A., Masum, A.-A., Saadi, S., Benkraiem, R., & Das, N. (2022). Firm-level climate change risk and CEO equity incentives. *British Journal of Management*. https://doi.org/10.1111/1467-8551.12652

Hötte, K., & Jee, S. J. (2022). Knowledge for a warmer world: A patent analysis of climate change adaptation technologies. *Technological Forecasting and Social Change*, *183*(121879), 121879. https://doi.org/10.1016/j.techfore.2022.121879

Huynh, B. Q., & Kiang, M. V. (2024). AI for anticipatory action: Moving beyond climate forecasting. *Proceedings of the AAAI Symposium Series*, *2*(1), 78–84. https://doi.org/10.1609/aaaiss.v2i1.27652

Jensen, M. C. (1986). Agency Costs of Free Cash Flow, Corporate Finance, and Takeovers. *The American Economic Review*, *76*(2), 323–329. http://www.jstor.org/stable/1818789

Jensen, M. C., & Meckling, W. H. (1976). Theory of the firm: Managerial behavior, agency costs and ownership structure. *Journal of Financial Economics*, *3*(4), 305–360. https://doi.org/10.1016/0304-405X(76)90026-X

Jiraporn, P., & Gleason, K. C. (2007). Capital structure, shareholder rights, and corporate governance. *Journal of Financial Research*, *30*(1), 21–33. https://doi.org/10.1111/j.1475-6803.2007.00200.x

Jiraporn, P., Jiraporn, N., Boeprasert, A., & Chang, K. (2014). Does corporate social responsibility (CSR) improve credit ratings? Evidence from geographic identification. *Financial Management*, *43*(3), 505–531. https://doi.org/10.1111/fima.12044

Jiraporn, P., Kim, J.-C., & Kim, Y. S. (2011). Dividend payouts and corporate governance quality: An empirical investigation. *Financial Review*, *46*(2), 251–279. https://doi.org/10.1111/j.1540-6288.2011.00299.x

Jiraporn, P., & Liu, Y. (2008). Capital Structure, Staggered Boards, and Firm Value. *Financial Analysts Journal*, *64*(1), 49–60. https://doi.org/10.2469/faj.v64.n1.7

Jones, A., Kuehnert, J., Fraccaro, P., Meuriot, O., Ishikawa, T., Edwards, B., Stoyanov, N., Remy, S. L., Weldemariam, K., & Assefa, S. (2023). AI for climate impacts: applications in flood risk. *Npj Climate and Atmospheric Science*, *6*(1), 1–8. https://doi.org/10.1038/s41612-023-00388-1

Jones, C. I., & Tonetti, C. (2020). Nonrivalry and the economics of data. *American Economic Review*, *110*(9), 2819–2858. https://doi.org/10.1257/aer.20191330

Kim, D., & Starks, L. T. (2016). Gender Diversity on Corporate Boards: Do Women Contribute Unique Skills? *The American Economic Review*, *106*(5), 267–271. https://doi.org/10.1257/aer.p20161032

Kochhar, R. (1996). Explaining firm capital structure: The role of agency theory vs. Transaction cost economics. *Strategic Management Journal*, *17*(9), 713–728. https://doi.org/10.1002/(sici)1097-0266(199611)17:9<713::aid-smj844>3.0.co;2-9

Kothari, S. P., & Warner, J. B. (2007). Econometrics of event studies. In *Handbook of empirical corporate finance* (pp. 3–36). Elsevier. https://www.sciencedirect.com/science/article/pii/B9780444532657500159

Krueger, P., Sautner, Z., & Starks, L. T. (2020). The Importance of Climate Risks for Institutional Investors. *The Review of Financial Studies*, *33*(3), 1067–1111. https://doi.org/10.1093/rfs/hhz137

Kulkov, I., Kulkova, J., Rohrbeck, R., Menvielle, L., Kaartemo, V., & Makkonen, H. (2024). Artificial intelligence - driven sustainable development: Examining organizational, technical, and processing approaches to achieving global goals. *Sustainable Development*, *32*(3), 2253–2267. https://doi.org/10.1002/sd.2773

Larcker, D. F., & Rusticus, T. O. (2010). On the use of instrumental variables in accounting research. *Journal of Accounting and Economics*, *49*(3), 186–205. https://doi.org/10.1016/j.jacceco.2009.11.004

Leal Filho, W., Wall, T., Rui Mucova, S. A., Nagy, G. J., Balogun, A.-L., Luetz, J. M., Ng, A. W., Kovaleva, M., Safiul Azam, F. M., Alves, F., Guevara, Z., Matandirotya, N. R., Skouloudis, A., Tzachor, A., Malakar, K., & Gandhi, O. (2022). Deploying artificial intelligence for climate change adaptation. *Technological Forecasting and Social Change*, *180*(121662), 121662. https://doi.org/10.1016/j.techfore.2022.121662

Lee, J., Suh, T., Roy, D., & Baucus, M. (2019). Emerging technology and business model innovation: The case of artificial intelligence. *Journal of Open Innovation Technology Market and Complexity*, *5*(3), 44. https://doi.org/10.3390/joitmc5030044

Lennox, C. S., Francis, J. R., & Wang, Z. (2012). Selection models in accounting research. *The Accounting Review*, *87*(2), 589–616. https://doi.org/10.2308/accr-10195

Lesnikowski, A., Ford, J., Biesbroek, R., Berrang-Ford, L., Maillet, M., Araos, M., & Austin, S. E. (2017). What does the Paris Agreement mean for adaptation? *Climate Policy*, *17*(7), 825–831. https://doi.org/10.1080/14693062.2016.1248889

Li, F. (2010). Textual analysis of corporate disclosures: A survey of the literature. *Journal of Accounting Literature*, *29*(1), 143–165. https://www.cuhk.edu.hk/acy2/workshop/20110215FengLI/Paper1.pdf

Liang, P., Sun, X., & Qi, L. (2023). Does artificial intelligence technology enhance green transformation of enterprises: based on green innovation perspective. *Environment Development and Sustainability*, *26*(8), 21651–21687. https://doi.org/10.1007/s10668-023-04225-6

Likitapiwat, T., Jiraporn, P., & Treepongkaruna, S. (2023). Weathering exchange rates: estimating the effect of climate change vulnerability on foreign currency hedging using a text-based approach. *Journal of Accounting Literature*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/JAL-06-2023-0107

Lintner, J. (1956). Distribution of Incomes of corporations among dividends, Retained Earnings and taxes. *The American Economic Review*, *46*, 97–113. https://www.jstor.org/stable/1910664

Liu, J., Liu, L., Qian, Y., & Song, S. (2022). The effect of artificial intelligence on carbon intensity: Evidence from China's industrial sector. *Socio-Economic Planning Sciences*, *83*(101002), 101002. https://doi.org/10.1016/j.seps.2020.101002

Loughran, T., & Mcdonald, B. (2011). When is a liability not a liability? Textual analysis, dictionaries, and 10-ks. *The Journal of Finance*, *66*(1), 35–65. https://doi.org/10.1111/j.1540-6261.2010.01625.x

Loughran, T., & Mcdonald, B. (2016). Textual analysis in accounting and finance: A survey. *Journal of Accounting Research*, *54*(4), 1187–1230. https://doi.org/10.1111/1475-679x.12123

Loughran, T., & McDonald, B. (2020). Textual Analysis in Finance. *Annual Review of Financial*. https://doi.org/10.1146/annurev-financial-012820-032249

Lozo, O., & Onishchenko, O. (2021). The potential role of the artificial intelligence in combating climate change and natural resources management: political, legal and ethical challenges. *J Nat Resour*, *4*(3), 111–131. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3951302

Luers, A., Koomey, J., Masanet, E., Gaffney, O., Creutzig, F., Lavista, F. J., & Horvitz, E. (2024). Will AI accelerate or delay the race to net-zero emissions? *Nature*, *628*(8009), 718–720. https://www.nature.com/articles/d41586-024-01137-x

Malkiel, B. G. (2003). The efficient market hypothesis and its critics. *The Journal of Economic Perspectives: A Journal of the American Economic Association*, *17*(1), 59–82. https://doi.org/10.1257/089533003321164958

McCarthy, J., Minsky, M., Rochester, N., & Shannon, C. (2006). A proposal for the Dartmouth summer research project on artificial intelligence, August 31, 1955. *AI Magazine*, *27*(4), 12–14. https://doi.org/10.1609/aimag.v27i4.1904

Meng, F., Xu, Y., & Zhao, G. (2020). Environmental regulations, green innovation and intelligent upgrading of manufacturing enterprises: evidence from China. *Scientific Reports*, *10*(1), 14485. https://doi.org/10.1038/s41598-020-71423-x

Mihet, R., & Philippon, T. (2019). The economics of big data and artificial intelligence. In *Disruptive Innovation in Business and Finance in the Digital World* (pp. 29–43). Emerald Publishing Limited. https://doi.org/10.1108/s1569-376720190000020006

Morck, R., Shleifer, A., & Vishny, R. W. (1988). Management ownership and market valuation: An empirical analysis. *Journal of Financial Economics*, *20*, 293–315. https://doi.org/10.1016/0304-405X(88)90048-7

Myers, S. C. (1977). Determinants of corporate borrowing. *Journal of Financial Economics*, *5*(2), 147–175. https://doi.org/10.1016/0304-405x(77)90015-0

Nafizah, U. Y., Roper, S., & Mole, K. (2024). Estimating the innovation benefits of first-mover and second-mover strategies when micro-businesses adopt artificial intelligence and machine learning. *Small Business Economics*, *62*(1), 411–434. https://doi.org/10.1007/s11187-023-00779-x

Nguyen, B. D., & Nielsen, K. M. (2010). The value of independent directors: Evidence from sudden deaths☆. *Journal of Financial Economics*, *98*(3), 550–567. https://doi.org/10.1016/j.jfineco.2010.07.004

Nordhaus, W. (2019). Climate change: The ultimate challenge for economics. *American Economic Review*, *109*(6), 1991–2014. https://doi.org/10.1257/aer.109.6.1991

Ongsakul, V., Chintrakarn, P., Papangkorn, S., & Jiraporn, P. (2024). Climate change exposure and dividend policy: evidence from textual analysis. *International Journal of Accounting & Information Management*, *ahead-of-print*(ahead-of-print). https://doi.org/10.1108/IJAIM-07-2023-0170

Ongsakul, V., Jiraporn, P., & Kim, Y. S. (2020). The effect of earnings management on shareholder value and the role of board gender diversity: Evidence from terrorism. *Pacific Accounting Review*, *32*(3), 323–334. https://doi.org/10.1108/par-09-2019-0110

Ongsakul, V., Papangkorn, S., & Jiraporn, P. (2023). Estimating the effect of climate change exposure on firm value using climate policy uncertainty: A text-based approach. *Journal of Behavioral and Experimental Finance*, 100842. https://doi.org/10.1016/j.jbef.2023.100842

Oster, E. (2019). Unobservable Selection and Coefficient Stability: Theory and Evidence. *Journal of Business & Economic Statistics: A Publication of the American Statistical Association*, *37*(2), 187–204. https://doi.org/10.1080/07350015.2016.1227711

Painter, M. (2020). An inconvenient cost: The effects of climate change on municipal bonds. *Journal of Financial Economics*, *135*(2), 468–482. https://doi.org/10.1016/j.jfineco.2019.06.006

Papangkorn, S., Chatjuthamard, P., Jiraporn, P., & Chueykamhang, S. (2021). Female directors and firm performance: Evidence from the Great Recession. *International Review of Finance*, *21*(2), 598–610. https://doi.org/10.1111/irfi.12275

Pata, U. K., Si Mohammed, K., Serret, V., & Kartal, M. T. (2024). Assessing the influence of climate risk, carbon allowances, and technological factors on the ESG market in the European union. *Borsa Istanbul Review*, *24*(4), 828–837. https://doi.org/10.1016/j.bir.2024.04.013

Pfeffer, J., & Salancik, G. R. (1978). The external control. *New York*. https://books.google.com/books?hl=en&lr=&id=zuZ3HEi4dXIC&oi=fnd&pg=PA233&d

q=Pfeffer+%26+Salancik,+1978&ots=vGtjIm1yIN&sig=-vU5hdTdE1SjlRFT7GXX544Y5t8

Post, C., & Byron, K. (2015). Women on boards and firm financial performance: A meta-analysis. *Academy of Management Journal*, *58*(5), 1546–1571. https://doi.org/10.5465/amj.2013.0319

Rikap, C. (2022). Becoming an intellectual monopoly by relying on the national innovation system: the State Grid Corporation of China's experience. *Research Policy*, *51*(4), 104472. https://doi.org/10.1016/j.respol.2021.104472

Rosenbaum, P. R., & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, *70*(1), 41–55. https://doi.org/10.1093/biomet/70.1.41

Roux, M., Chowdhury, S., Kumar Dey, P., Vann Yaroson, E., Pereira, V., & Abadie, A. (2023). Small and medium-sized enterprises as technology innovation intermediaries in sustainable business ecosystem: interplay between AI adoption, low carbon management and resilience. *Annals of Operations Research*. https://doi.org/10.1007/s10479-023-05760-1

Sahil, K., Mehta, P., Kumar Bhardwaj, S., & Dhaliwal, L. K. (2023). Development of mitigation strategies for the climate change using artificial intelligence to attain sustainability. In A. Srivastav, A. Dubey, A. Kumar, S. Kumar Narang, & M. Ali Khan (Eds.), *Visualization Techniques for Climate Change with Machine Learning and Artificial Intelligence* (pp. 421–448). Elsevier. https://doi.org/10.1016/b978-0-323-99714-0.00021-2

Salman, M., Wang, G., Qin, L., & He, X. (2024). G20 roadmap for carbon neutrality: The role of Paris agreement, artificial intelligence, and energy transition in changing geopolitical landscape. *Journal of Environmental Management*, *367*(122080), 122080. https://doi.org/10.1016/j.jenvman.2024.122080

Samarawickrama, M. (2022). AI governance and ethics framework for sustainable AI and sustainability. In *arXiv [cs.CY]*. arXiv. http://arxiv.org/abs/2210.08984

Sautner, Z., Van Lent, L., Vilkov, G., & Zhang, R. (2023). Firm-level climate change exposure. *The Journal of Finance*. https://doi.org/10.1111/jofi.13219

Schumpeter, J. A. (1942). *Capitalism, Socialism, and Democracy.* Harper & Brothers.

Seltzer, L. H., Starks, L., & Zhu, Q. (2022). *Climate Regulatory Risk and Corporate Bonds* (No. 29994). National Bureau of Economic Research. https://doi.org/10.3386/w29994

Shaik, A. S., Alshibani, S. M., Jain, G., Gupta, B., & Mehrotra, A. (2024). Artificial intelligence (AI)-driven strategic business model innovations in small- and medium-sized enterprises. Insights on technological and strategic enablers for carbon neutral businesses. *Business Strategy and the Environment*, *33*(4), 2731–2751. https://doi.org/10.1002/bse.3617

Singh, S., & Goyal, M. K. (2023). Enhancing climate resilience in businesses: The role of artificial intelligence. *Journal of Cleaner Production*, *418*(138228), 138228. https://doi.org/10.1016/j.jclepro.2023.138228

Spacey Martín, R., Ranger, N., Schimanski, T., & Leippold, M. (2024). Harnessing AI to assess corporate adaptation plans on alignment with climate adaptation and resilience goals. *Available at SSRN 4878341*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4878341

Spence, M. (1973). Job Market Signaling. *Quarterly Journal of Economics*, *87*, 355–374. https://doi.org/10.2307/1882010

Streck, C., Keenlyside, P., & von Unger, M. (2016). The Paris Agreement: A new beginning. *Journal for European Environmental & Planning Law*, *13*(1), 3–29. https://doi.org/10.1163/18760104-01301002

Stroebel, J., & Wurgler, J. (2021). What do you think about climate finance? *Journal of Financial Economics*, *142*(2), 487–498. https://doi.org/10.1016/j.jfineco.2021.08.004

Tao, W., Weng, S., Chen, X., ALHussan, F. B., & Song, M. (2024). Artificial intelligence-driven transformations in low-carbon energy structure: Evidence from China. *Energy Economics*, *136*(107719), 107719. https://doi.org/10.1016/j.eneco.2024.107719

Teece, D. J., Pisano, G., & Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, *18*(7), 509–533. https://doi.org/10.1002/(sici)1097-0266(199708)18:7<509::aid-smj882>3.0.co;2-z

Titman, S., & Wessels, R. (1988). The determinants of capital structure choice. *The Journal of Finance*, *43*(1), 1–19. https://doi.org/10.1111/j.1540-6261.1988.tb02585.x

Treepongkaruna, S., Jiraporn, P., Kyaw, K., & Padungsaksawasdi, C. (2024). Climate change exposure and corporate culture: A text-based approach. *International Review of Economics & Finance*, *95*(103497), 103497. https://doi.org/10.1016/j.iref.2024.103497

Tübbicke, S. (2022). Entropy Balancing for continuous treatments. *Journal of Econometric Methods*, *11*(1), 71–89. https://doi.org/10.1515/jem-2021-0002

Ungpakorn, S., Chatjuthamard, P., Jiraporn, P., & Phiromswad, P. (2023). Infectious diseases, dividend policy, and independent directors: Evidence from textual analysis. *PloS One*, *18*(2), e0281109. https://doi.org/10.1371/journal.pone.0281109

Verendel, V. (2023). Tracking artificial intelligence in climate inventions with patent data. *Nature Climate Change*, *13*(1), 40–47. https://doi.org/10.1038/s41558-022-01536-w

Wang, Q., Sun, T., & Li, R. (2023). Does artificial intelligence promote green innovation? An assessment based on direct, indirect, spillover, and heterogeneity effects. *Energy & Environment*. https://doi.org/10.1177/0958305x231220520

Wongsinhirun, N., & Chatjuthamard, P. (2023). Corporate culture and board gender diversity: Evidence from textual analysis. *International Review Of*. https://www.sciencedirect.com/science/article/pii/S1057521923000509

Wongsinhirun, Nopparat, Chatjuthamard, P., Chintrakarn, P., & Jiraporn, P. (2023). Tax avoidance, managerial ownership, and agency conflicts. *Finance Research Letters*, 104937. https://doi.org/10.1016/j.frl.2023.104937

Yang, S., Wang, J., Dong, K., Dong, X., Wang, K., & Fu, X. (2024). Is artificial intelligence technology innovation a recipe for low-carbon energy transition? A global perspective. *Energy (Oxford, England)*, *300*(131539), 131539. https://doi.org/10.1016/j.energy.2024.131539