Feedback on Emerging Corporate Policies*

Sean Cao [a], Itay Goldstein [b], Jie He [c], and Yabo Zhao [d]

[a] University of Maryland
[b] University of Pennsylvania
[c] University of Georgia
[d] Chinese University of Hong Kong, Shenzhen

This version: May 2024

Abstract

We explore the role of market feedback in navigating emerging corporate policies on AI/green technologies. By assembling and analyzing a comprehensive sample of corporate disclosures in which managers discuss their forward-looking investment plans on AI/green technologies, we find that firms adjust such investments upward (downward) in response to favorable (unfavorable) market reactions to the corresponding disclosures. This association is more likely due to managerial learning from the market than alternative explanations based on omitted underlying fundamentals: It gets stronger when market reactions are unfavorable, when outside market participants are more knowledgeable about emerging technologies, and when managers have stronger incentives to promote investments in such fields. Such learning is absent for non-emerging-technology investment plans where managers have domain knowledge. Further, we find that following the market feedback on emerging corporate policies is rewarded by superior long-run operating and stock performance, especially when the feedback is unfavorable. We also find different learning patterns for AI and green technologies regarding peer firms' market feedback. Overall, our paper illustrates the usefulness of tapping the wisdom of the crowd when venturing into uncharted areas and sheds new light on what type of information managers learn from the stock market in different contexts of corporate policies.

Key words: Emerging Technologies, Artificial Intelligence, Carbon Emissions, Green Investment, Feedback, Managerial Learning

---

* We gratefully acknowledge helpful comments from Jawad Addoum, Jennie Bai, Brad Barber, Qi Chen, Jaewon Choi, Caroline Flammer, Matt Gustafson, Zhiguo He, Harrison Hong, Andrew Karolyi, Sophia Kazinnik, Jiasun Li, Pedro Matos, Ting Xu, Scott Yonker, as well as conference participants at the 2024 MFA annual meeting, 2023 Cornell ESG Investing Research Conference, the 2023 Columbia Burton Accounting Conference, the 2023 Journal of Accounting, Auditing and Finance (JAAF) Symposium, and seminar participants at George Mason University, Australian National University, Alliance Bernstein, Balyasny Asset Management, Bank of Japan, Erasmus University Rotterdam, Florida International University, Goethe University Frankfurt, Hitotsubashi University, University of Hong Kong, IE Business School, Lancaster University, Macquarie University, Norwegian School of Economics, National Taiwan University, Renmin University, Technical University of Munich, University of Auckland, University of California Davis, University of California Irvine, University of Georgia, University of New South Wales, University of Texas at Dallas, University of Technology Sydney, University of Sydney, and Wolfe Research.

1. Introduction

How do firms make decisions about investments in new technologies involving large uncertainties? What sources of information do they rely on for such decisions? These are some of the oldest questions in Economics, which are crucial for understanding the drivers for technological adoption and economic transformation. A prominent source of information, studied extensively in Financial Economics, is the financial market, which is known to aggregate the opinions of a diverse body of different investors. A growing strand of literature has argued that informational feedback from the financial market can help guide the decision making of corporate managers in the real sector.[1]

In this paper, we build on the insights from this literature and provide new evidence on how firms use market feedback to guide their decisions on investment in prominent emerging technologies. Specifically, we examine how firms adjust their investments in artificial intelligence (AI) and green (i.e., climate/environment related) technologies in response to the stock market reaction to their announcements of such investment plans. The motivation for focusing on AI and green technologies is threefold. First, these two technologies have been in the frontier of economic development in recent years, yet for any individual firm contemplating moving into such technological space, there are great risks and uncertainties. Firms have to assess the desirability and optimal strategies of these emerging-technology-related investments without past records to learn from and with limited models of the costs and benefits involved.[2] Moreover, even after the initiation of such investments, market trends, regulatory intervention, and technology development might all evolve in unexpected directions.[3] Hence, given the centrality of these technologies and the uncertainties involved, it is of paramount importance to understand how firm managers update priors about them, and what role market feedback plays during this process.[4]

---

[1] See, e.g., Chen, Goldstein, and Jiang (2007), Luo (2005), Edmans, Jayaraman, and Schneemeier (2017), Dessaint, Foucault, Fresard, and Matray (2019), and Jayaraman and Wu (2020) for empirical evidence, and Bond, Edmans, and Goldstein (2012) and Goldstein (2023) for reviews of this literature.

[2] For example, only 20% of the approximately 3,000 AI-aware C-level executives surveyed by McKinsey in 2017 admitted implementing AI-related technology on a large scale or incorporating it into their core businesses. Many of them said that poor or uncertain returns on such investment are the primary reasons that prevent them from adopting the technology. Similarly, recent literature has found that green sustainable energy investment also tends to be associated with higher risk and lower short-term returns (e.g., Lopez, Garcia, and Rodriguez, 2007).

[3] See, e.g., Acemoglu, Hanley, and Kerr (2016), Albrizio and Costa (2012), and Blyth et. al (2007).

[4] While managers can seek opinions from their friends/contacts in the industry or other professionals such as consulting companies, investment bankers, or financial analysts (e.g., Cookson, Niessner, and Schiller, 2023; Bae, Biddle, and Park, 2022), such feedback is likely limited in either scope or relevance, as these outsiders have no stakes in the focal firm and can only offer suggestions from their own (and sometimes conflicting) perspectives.

Second, despite the large empirical literature exploring the role of market feedback in corporate decision making, identifying a channel of *active* managerial learning remains a challenge. As pointed out by Goldstein (2023), different pieces of empirical evidence have provided the academic community with greater confidence in this channel, but none is fully conclusive, leaving room for additional evidence in different empirical settings. The setting we study here, observing the short-window market reaction to a firm's specific announcements on AI/green investment plans and then tracking how its corresponding investments evolve in response, enables us to achieve a degree of precision in identifying managers' active learning from the market, which is not typically attainable in this literature.

Third, while the literature on the feedback effect of financial markets focuses on finding evidence for the presence of feedback, it has paid less attention to *what specific* information managers learn from the market. This has been identified as an important direction for future research (Goldstein, 2023). Moreover, the lack of evidence on what specifically managers attempt to learn has been used as criticism against the feedback literature more broadly.[5] By analyzing how managers learn from the market reaction to specific announcements of AI/green investment plans, our paper helps fill this gap in the literature. Our analysis sheds new light not only by documenting that managers wish to get feedback when deciding on emerging technologies but also by drawing some differences in what is learnt about the different types of technologies.

We start by using textual analysis to identify firms' emerging-technology-related disclosure events based on their earnings conference calls and 8-K filings.[6] To focus on disclosures that are forward-looking in nature, we make sure the discussion of the AI/green investments in them is about future plans instead of ongoing projects. Figure 1 shows that over the period of 2010 to 2019, the annual fraction of major corporate disclosures discussing AI investment plans increases from about 6% to 11%, and that of disclosures discussing green investment plans increases from about 20% to 27%.

The core of our analysis is to examine whether firms' investments in AI and green technologies are positively associated with the stock market reaction to the mentioning of such

[5] For example, Gelsomin and Hutton (2023) argue that "To our knowledge, existing research fails to document what information managers extract from observing stock prices... The channel or mechanism of managerial learning remains empirically unexplored, as does the particular information managers are hypothesized to learn and use for their real investment decisions."

[6] Our findings are robust to examining these two types of disclosures separately. We also examine a firm's 10-K and 10-Q filings but find very little mentioning of emerging-technology-related investment plans there.

investment plans in their major corporate disclosures. Following Babina, Fedyk, He, and Hodson (2023, 2024), we measure the level of a firm's AI investment using its AI-related job postings. In a similar vein, we follow Darendeli, Law, and Shen (2022) to use the number of green-related job postings to capture the extent of a firm's green investment. [7] A larger number of corresponding job postings indicate the firm's stronger motive and commitment to invest in AI or green technology.

Using a sample of 41,263 AI-investment-related disclosures and 81,442 green-investment-related disclosures, we find that changes in firm-level AI and green investments from one year before to one year after a corresponding disclosure event are positively associated with the cumulative abnormal return (CAR) over a short window (i.e., 5 days) surrounding the event. This result suggests that firm managers adjust upward (downward) their emerging-technology-related investment when the stock market reacts favorably (unfavorably) to related discussions in their major corporate disclosures. The economic magnitude of this feedback effect is also nontrivial: A one standard-deviation increase in market reaction is associated with an increase in AI (green) job postings by around 0.8% (0.8%), which is about 9.2% (13.9%) of the mean increase in such postings. These associations remain robust even after we control for major ex-ante (i.e., pre-disclosure) firm characteristics, earnings surprises, disclosure tone/sentiment, contemporaneous changes in firms' overall (non-emerging-technology-related) investments from pre to post the event, as well as industry by year and/or firm fixed effects.

A usual concern in the feedback-effect literature is that observing a relation between market changes and follow-up corporate actions might not indicate a channel of active learning from the price, but rather just a passive reflection of an underlying fundamental that drives both the market price and the corporate actions. This issue is discussed in, for example, Chen, Goldstein, and Jiang (2007) and Foucault and Fresard (2014). Different papers in the literature have adopted different empirical strategies to deal with this concern with varying degrees of precision. In our context, the underlying fundamental could be the unobservable quality/prospects of the proposed investments

[7] We conduct robustness analyses by examining alternative measures of AI/green investment based on patenting outcomes or total greenhouse gas emissions and find consistent results.

in AI or green technologies, which can drive a positive association between the stock market reaction and the follow-up corporate investments without one affecting the other.[8]

We believe that the logic for this alternative explanation is indeed compelling when one considers a positive market response, which is followed by a positive change in investment. This is because such cases indicate that both the market and the corporate managers are reacting to the same underlying fundamental in the same direction. However, the logic for this alternative explanation breaks down when it comes to negative market reactions to the AI/green-related disclosures. Given that the disclosures in our sample are by and large about expanding or launching new activities,[9] such cases imply that the market and firm managers disagree on the importance/value of expanding emerging technology investments. Hence, an analysis of firms' investment adjustments following negative market reactions would show whether our baseline results above are driven by a passive reflection of underlying fundamentals that affect both the market response and corporate actions.

Interestingly, nearly half of our sample disclosures are followed by negative market reactions, suggesting that investors do not view such expansion plans favorably. More importantly, in these "market disapproval" cases, we observe an even stronger positive association between investment changes and market responses. That is, the tendency of a firm to cut down on its emerging-technology investment following a negative market reaction is even stronger than its tendency to expand following a positive market reaction. This finding is unlikely attributable to a passive reflection in both market prices and corporate investments. Rather it points more strongly in the direction of active learning from the price.[10]

Another concern in interpreting the results is that other components of the disclosures, such as information about general investment opportunities, management quality, or other firm fundamentals, could correlate with firms' subsequent AI/green investment behaviors while

[8] Another possible underlying fundamental could be firm managers' over-optimism in AI/green technologies, which is somehow shared by the marginal investors due to the "buzzwords" feature of corresponding announcements (Chava et al., 2022).

[9] Based on our manual reading of companies' AI/green-investment-related disclosures in our sample, almost all of them are about the plans to launch/expand rather than to stop/reduce the investment in such technologies, indicating managers' positive attitude towards such activities.

[10] It is worth noting that we do not take a stand on whether the feedback effect on emerging corporate policies should be stronger when the market reaction is positive or negative. The theory of Edmans, Goldstein, and Jiang (2015) predicts that in some cases speculators will have lower incentives to trade on negative information than on positive information, which means that negative information will less likely show up in the price. This, however, does not imply that managers should react less to negative price changes than to positive price changes.

generating market reactions in the same direction. This non-learning-based explanation is plausible because major corporate disclosures typically contain a large amount of information other than that related to emerging technology investment plans. We adopt two approaches to mitigate this concern. First, we exploit the granular time stamp information contained in earnings conference call transcripts to examine hourly stock price reaction during the hour when managers discuss their emerging-technology-related investment plans in conference calls. Presumably, such an instantaneous stock price change is more likely triggered by the news about emerging corporate policies than by confounding information contained in such disclosures. We continue to find the same positive investment-price association using this hourly announcement return measure. In contrast, we don't find a significant association between AI/green investment adjustments and the cumulative abnormal stock return from the beginning hour of the same earnings conference call until the "AI/green investment disclosure" hour. Second, we confirm our baseline findings using a subsample of "focused" 8-K filings with only one item (that mentions emerging-technology investment plans). Such focused 8-K filings are essentially material press releases that likely contain information exclusively about the plans of firms' emerging corporate policies, which alleviates the concern that our results are driven by confounding information components in corporate disclosures.

To further tie our results to market feedback, we explore cross-sectional variation in the documented relation between market reactions and subsequent corporate investment changes. First, we examine whether our baseline results are stronger when outside market participants, such as institutional investors, possess more expertise in the relevant emerging technologies, and find supporting evidence. Second, we show that the AI investment adjustment in response to market reaction is more pronounced when a firm faces greater technology peer pressure (as defined in Cao et al., 2018). Similarly, the association between the green investment adjustment and market reaction is stronger after the announcement of the Paris Agreement in December 2015, a landmark event that markedly increases market attention to environmental issues and corporate green actions. Taken together, these results show that the feedback effect is more pronounced when the market possesses more valuable information/insights about emerging technologies or when firm managers have stronger incentives to enhance investments in these fields.

We provide additional tests to strengthen the inference about managers learning on their plans for emerging-technology investments. First, we examine whether the documented feedback effect is weaker when the technologies mentioned in corporate disclosures are non-emerging in nature (e.g., traditional data analysis techniques such as linear regressions, time series analysis, or Monte Carlo simulation methods). For such conventional technologies, the market might possess less incremental knowledge compared to that of firm managers, and thus may not provide useful feedback to guide firms' investment decisions. Consistent with this prediction, we find that managers do not significantly change their conventional-technology-related job postings in response to the market feedback on the disclosure of investment plans in these areas. Second, we examine whether the feedback effect on emerging corporate policies still exists when the related discussions in the disclosures are *not about investment plans* but only referring to these technologies in a general way. Interestingly, we do not find a significant feedback effect for such disclosures. This suggests that our baseline-test announcement returns, which are followed by subsequent investment adjustments, are unlikely driven by the market's sentiment towards the risks, nature, or prospects of these emerging technologies per se. Instead, they are more likely driven by the market's reaction to firms' specific investment plans in these areas. Third, we find that firms' *past* (i.e., *pre-disclosure*) investment adjustments in emerging technologies are not positively associated with the market reactions, which further supports the notion that firms are actively responding to the market feedback on the proposed investment. Fourth, we find that firms' investment adjustments in emerging technologies are only related to the market reactions in the narrow announcement window but not in other 5-day windows immediately before or after the same disclosure event (such as days [-7, -3] or days [3, 7]).

We further check whether a firm's peers (e.g., those operating in the same product market) learn from the focal firm's market reaction. If the market reaction to emerging-technology-related disclosures is mostly idiosyncratic, i.e., only useful to the focal firm's investment planning, then we would not expect to see the firm's peers act on such feedback. If, however, the market possesses more industry-specific knowledge about emerging-technology-related investments and incorporates such insights into the announcement returns, then peer firms would also learn from the stock price movement around the focal firm's disclosures (Foucault and Frésard, 2014). Interestingly, we find that peer firms only learn from the market feedback on green-related investments but not that on AI-related investments. This may be because green-related investments are more industry specific (and less idiosyncratic) than the AI-related investments due to greater regulatory interventions on sector-wise environment-related activities and/or stronger investor preferences towards ESG issues.

In the final part of our paper, we explore whether following the wisdom of the crowd from the market improves firms' long-run performance. It is worth noting that managers' reluctance to follow the market feedback can be either rational or irrational. If their reluctance is largely rational and thus shareholder-value maximizing, then we should not expect to find any performance difference between feedback-following and non-following. If, however, managers' unwillingness to use external information from the market is largely irrational due to either incapabilities or behavioral biases, then following the feedback ought to be associated with better long-run performance than not following. We find that following the feedback indeed leads to better long-term operating and stock performance than not following, suggesting that ignoring the useful information contained in the stock price is sub-optimal for firm value. More interestingly, we observe such performance gaps only when the market feedback is negative, which alleviates a reverse causality concern that firms with more resources and better performance are able to invest more in emerging technologies following positive market feedback.

Our paper contributes to different strands of literature. First, considering AI and green investments, we are the first to assemble a comprehensive sample of AI/green-investment-related corporate disclosures, and to document the trend and extent of such active feedback seeking by firm managers. Given that these disclosures are largely voluntary in nature, it sheds light on what concrete actions managers can take to actively seek market feedback. Future studies can also leverage them to examine firms' strategic disclosure behaviors regarding their emerging corporate policies, which adds to the literature on information dissemination (Frankel et al., 1999; Matsumoto et al., 2011; Zhao, 2017; Gibbons et al., 2021).

Second, our paper contributes to the literature documenting the huge uncertainty (and thus the lack of relevant information) facing managers who consider venturing into unknown and risky areas such as the development of emerging technologies (e.g., Lopez, Garcia, and Rodriguez, 2007). Our findings indicate that one useful market-based solution to mitigate the ex-ante concerns over such technologies' inherent uncertainty as well as to improve the ex-post investment efficiency is to actively seek and utilize the feedback from outside market participants and thus benefit from the wisdom of the crowd. This result has important practical implications, as it not only helps guide the decision making of firm managers in an era of fast technological growth, but also shapes the overall flow of corporate resources into the development of new technologies in the economy.

Third, our paper opens new dialogues for future research on *what kind of information* managers actually learn from the market by examining and comparing managerial learning behavior across different investment types (i.e., AI, green, and conventional-technology-based investments) and across feedback seekers (i.e., focal firms and peer firms), while most of the empirical feedback literature to date has been focusing on *whether* such learning is going on (e.g., Chen, Goldstein, and Jiang, 2007; Luo, 2005; Bakke and Whited, 2010; Edmans, Goldstein, and Jiang, 2012; Betton et al., 2014; Bai, Philippon, and Savov, 2016; Zuo, 2016; Dessaint et al., 2019; Jayaraman and Wu, 2020; Banerjee et al., 2023; Cao et al., 2023). By analyzing how managers respond to the market reaction to specific announcements of AI/green investment plans, our findings shed direct light on what specific information managers learn from the market.

Finally, we demonstrate that managerial learning is context-based. For example, such learning does not exist for non-emerging corporate policies (e.g., investment plans on conventional technologies). Furthermore, our evidence indicates that the market feedback effect differs even *within* emerging-technology-related investments. For example, while managers adjust both types of investments following negative market reactions, this response is only significant for AI-related investments (but not for green-related investments) following positive market reactions. For another, the peer learning effect only manifests in green-related but not AI-related investments. These results suggest that insights from the prior literature on managerial learning in the context of other investment types (such as capital expenditures or acquisitions) might not be directly applicable to the context of emerging-technology investments. For example, two closely related studies to ours are Luo (2005) and Jayaraman and Wu (2020), who also adopt event-study approaches instead of traditional investment-Q type of analyses. Luo (2005) shows that market reactions to mergers and acquisitions announcements positively predict the consummation of the deals. Similarly, Jayaraman and Wu (2020) find that managers learn from stock price reactions to their capital expenditures forecasts. Complementing these analyses, we study managerial learning in a different empirical setting – managers seek market feedback to guide their investments in emerging technologies by voluntarily discussing such investment plans in their major corporate disclosures.[11]

2. Data, Variable, and Sample Construction

Our empirical analyses use data from several sources. Earnings conference calls are extracted from Thomson Reuters' StreetEvents and 8-K filings are from the SEC's EDGAR database. Firms' job postings are obtained from the Lightcast (formerly known as the Burning Glass Technologies) database. Institutional holding data comes from the Thomson Reuters 13F database. We obtain firms' stock prices and quarterly financial information from the Center for Research in Security Prices (CRSP) and the CRSP/Compustat Merged Quarterly database, respectively.

2.1 Corporate disclosures about emerging-technology-related investment plans

We begin our sample construction with firms' major corporate disclosures including their earnings conference calls (as covered by StreetEvents) and 8-K filings from 2006 to 2019. To identify managers' AI/green-investment-related disclosures, we construct four lists of keywords (e.g., see the examples in Appendix B1). The one on AI technology is obtained by combining those in Babina et al. (2023, 2024), Abis and Veldkamp (2024), Cao et al. (2023), Gofman and Jin (2024), and Cockburn et al. (2018). The list of green technology keywords is obtained by supplementing the dictionaries in Engle et al. (2020) and Sautner et al. (2023) with manually identified green-technology related keywords from the Sustainability Accounting Standards Board (SASB) Standards as well as those extracted from firms' annual CSR reports and press releases by adopting a word-embedding approach as in Li et al. (2021) and Cao et al. (2023, 2024).[12] Similarly, the list of investment related keywords is constructed by supplementing those in Ball, Hoberg, and Maksimovic (2015) and Hoberg and Maksimovic (2015) with words about decision making or business investment in the Oxford Dictionary. We also include manually identified investment related keywords in the corporate disclosures (earnings conference calls and 8-K filings), as well

[11] A contemporaneous working paper by Aretz, Ilyas, and Kankanhalli (2022) also examines the nature of information managers learn from the market using a different research design, but like most of the extant literature, it focuses on ordinary investment choices such as capital expenditures, R&D, and acquisitions. Goldstein, Liu, and Yang (2023) conduct a survey on Chinese firms and find that what managers try to learn about from their stock prices includes information related to macroeconomic and industry conditions, policy and regulatory implications, firms' competitive positions, as well as cost of capital, customers' demand, technology, etc.
[12] See SASB standards at https://www.sasb.org/standards/materiality-finder/?lang=en-us.

as keywords extracted from firms' annual CSR reports and press releases by adopting the same word-embedding approach described above.[13]

Finally, as our focus is on examining managers' potential learning from the market feedback, we want to limit our attention to only those disclosures that discuss future (i.e., intended or forthcoming) investment plans rather than past or ongoing projects in emerging technologies. While the disclosure of past/existing investment projects is often required as part of managers' fiduciary duty to investors, the disclosure of future investment plans is largely voluntary in nature and better captures managers' intention to actively seek market feedback.[14] Therefore, we construct a list of forward-looking keywords.[15] We then define a disclosure as AI/green-investment-related if it has the mentioning of AI/green technology specific keywords, investment related keywords, and forward-looking keywords (to ensure the description of the investment is about future plans instead of past or ongoing projects) in the same sentence within a given corporate disclosure (i.e., a conference call script or 8-K filing).

Appendix B1 presents examples of AI/green-investment-related disclosures for both 8-K filings (Panel A) and earnings conference calls (Panel B). Panel A describes the example of a focused 8-K filed by Ford Motor, which contains information only about one material event in item 8.01 – a news release of Ford's investment plan of $1 billion in Argo AI to develop autonomous vehicles in the next five years. Unlike earnings conference calls that tend to contain a large amount of information other than emerging-technology investment plans, this focused 8-K filing contains information exclusively about Ford's AI investment plans. In Section 3.2, we perform our baseline analysis only on a subsample of focused 8-K filings to alleviate the concern that the market might be reacting to omitted non-emerging-policy-related information in corporate disclosures. Panel B presents several examples for emerging-policy-related earnings conference calls, including the case of Alphabet's 2015 Annual Meeting of Stockholders Conference Call. As we can see, market participants (i.e., Alphabet's shareholders) are knowledgeable about the

[13] Words about decision making in the Oxford Dictionary are obtained from https://www.oxfordlearnersdictionaries.com/topic/preferences-and-decisions, and business investment words are from https://www.oxfordlearnersdictionaries.com/topic/business.

[14] Our analysis here follows the spirit of Dye and Sridhar (2002), Langberg and Sivaramakrishnan (2010), and Jayaraman and Wu (2020), who also differentiate between future and current investment.

[15] Specifically, we first obtain a list of forward-looking keywords from Li (2010), Muslu et al. (2015), Bozanic, Roulstone, and Van Buskirk (2018), Aljifri and Hussainey (2007), Hassanein and Hussainey (2015), Hassanein, Zalata, and Hussainey (2019), and Grewal (2019). Then, following Li et al. (2021) and Cao et al (2022), we use a word-embedding model to expand these keywords.

proposed renewable energy plan based on their own past working backgrounds and thus can provide useful feedback on the firm's investment. Interestingly, in this example, Alphabet's shareholders hold opposite views on the green-related investment plan. This suggests that it is necessary for managers to aggregate opinions from the market on such uncertain and controversial emerging corporate policies.

Figure 1 plots the time trend of the propensity of US public firms to discuss investment plans on emerging technologies in their earnings conference calls and 8-K filings from 2010 to 2019. The left y-axis denotes the propensity of AI-technology related disclosures, and the right y-axis denotes the propensity of green-technology related corporate disclosures. As we can see, there is a significant increase of emerging-technology-related disclosures over time: The propensity of AI-technology (green-technology) related disclosures increases from about 6% to 11% (from 20% to 27%).

In Figure 2, we examine the distribution of such disclosure growth across different industries. For each industry, the propensity of AI/green-investment-related disclosures is calculated as the number of corporate disclosures about AI/green investment plans in the industry over the sample period divided by the total number of corporate disclosures in that industry. As expected, companies in the utilities industry are particularly more likely to discuss green-related investment plans in their disclosures, followed by companies in mining, manufacturing, and construction industries. Meanwhile, companies in the service industry tend to discuss more AI-related investment plans in their conference calls and 8-K filings than those in other industries.

2.2 Firm-level AI investment

To capture the extent of a firm's AI investment, we follow Babina, Fedyk, He, and Hodson (2023, 2024) to examine its job postings that require AI-related skills. A larger number of AI-related postings indicate the firm's stronger motive and commitment to invest in AI. We obtain firms' job postings from Burning Glass (BG) Technologies (now named Lightcast). BG has one of the world's largest real-time, proprietary databases of job openings and career histories.[16] A potential concern of obtaining job postings from multiple sources is that multiple job postings can link to a single job vacancy. To alleviate this concern, BG employs a sophisticated two-step

[16] It collects job posting information from more than 40,000 sources daily in more than 30 countries and covers over 197 million job postings in the US in 2007 and 2010-2020.

approach to deduplicate job postings and avoid double counting job vacancies.[17] According to its report, up to 80% of all jobs are deduplicated. The data provides detailed information for each job posting including the job title, required skills, occupation, and the employer.

We focus on non-internship job postings with non-missing employer names and at least one required (i.e., AI-related) skill. To match BG employers to firms in the Compustat and CRSP merged database (CCM), we apply a fuzzy name matching approach after removing non-letter and non-number symbols from the name strings and stripping out their common endings such as "Inc", "Co", and "LLC". We match 52 million (around 27% out of 197 million) BG job postings to firms in the CCM database, which is consistent with prior statistics showing that publicly listed firms account for approximately 26% of overall US employment (Davis et al., 2006).[18]

To identify AI-related job postings and calculate a firm-level AI hiring measure, we follow Babina et al. (2023, 2024) and take three steps. First, for each skill s required by any job postings in the BG data, we calculate the skill's AI-relevance score as the number of job postings that require both the skill s and at least one of the four basic AI skills (i.e., artificial intelligence (AI), machine learning (ML), natural language processing (NLP), and computer vision (CV)), divided by the total number of job postings requiring at least the skill s.[19] This relevance score measures how correlated a skill s is with AI core skills. The higher the score, the more AI-related the skill s is. Second, for each job posting, we measure its AI-relatedness as the average AI-relevance score across all skills required for the job. Third, for each firm, we measure its AI-technology investment adjustment in a year ($\Delta AI\ Job\ Postings$) as the change in the natural logarithm of one plus the weighted sum of AI-related job postings by the firm from the year before an AI-related disclosure to the year after. The weight of each job posting is its AI-relatedness obtained in the second step.

2.3 Firm-level green investment

To measure a firm's investment in green technology, we follow Darendeli, Law, and Shen (2022) to examine its job postings that require green skills. The intuition is that a larger number of green job postings indicate that a firm has dedicated more resources to investing in green (i.e.,

[17] See more details about the deduplication approach at https://kb.emsidata.com/faq/how-does-emsi-burning-glass-handle-duplicate-postings/#.
[18] The 27% matching rate is slightly lower than that in Babina et al. (2023), who match BG job postings to Compustat firms (without requiring their stock listing status).
[19] We thank the authors of Cao, Jiang, Yang, and Zhang (2023) and Babina, Fedyk, He, and Hodson (2023, 2024) for sharing with us the processed AI-relevance score of skills.

environmentally friendly) technology adoption. We again focus on non-internship job postings from BG with non-missing employer names and at least one required skill. Following Darendeli, Law, and Shen (2022), we take three steps to calculate a firm-level green hiring measure. First, for each skill s, we label it as "green" if it belongs to the "Environment" skill cluster family in Burning Glass taxonomy. Second, for each job posting, we measure its green-relatedness as the number of required green skills divided by the total number of skills required in the job. Third, for each firm, we measure its green-technology investment adjustment in a year ($\Delta Green\, Job\, Postings$) as the change in the natural logarithm of one plus the weighted sum of green job postings by the firm from the year before a green-related disclosure to the year after. The weight of each job posting is its green-relatedness obtained in the second step above.

Although AI and green job postings are an important and timely reflection of firms' strong motive and commitment of investing in these emerging areas, we acknowledge that they might capture only one aspect of the related investment in human capital – online job postings.[20] Also, these measures do not reveal whether such job positions are eventually filled. Hence, in Section 5.3, we use the development of AI/green patents and firms' greenhouse gas (GHG) emissions as alternative measures of AI/green investment. The intuition is that a larger number (smaller amount) of AI/green patents (GHG emissions) indicate that a firm has increased its investment in AI/green technologies, which in turn generate a larger number of patents (lower GHG emission). We obtain patent data from the United States Patent and Trademark Office (USPTO) and corporate carbon emission data from Trucost, which collects firms' carbon emission data from publicly available sources and covers a wide spectrum of firms around the world.

2.4 Sample, summary statistics, and variable construction

The unit of observation for our analysis is an AI/green-investment-related corporate disclosure (earnings conference call or 8-K filing). Since our primary measure of AI/green investment is calculated based on the BG job posting database, which has consecutive coverage only starting from 2010, we limit our sample to between 2010 and 2019. We also exclude a related disclosure if the firm's financial information at the nearest quarter end prior to the disclosure is

[20] Although Burning Glass only covers online job postings, Hershbein and Kahn (2018) show that it has a better coverage of actual job postings than what is revealed by some national-level survey-based data, e.g., the Job Openings and Labor Turnover Survey conducted by the U.S. Bureau of Labor Statistics.

missing. We are left with a final sample of 41,263 AI-related disclosures made by 4,184 unique firms, and 81,442 green-technology related corporate disclosures covering 2,959 unique firms.

As described in the previous subsections, we measure a firm's AI/green-technology investment adjustment around a related disclosure as the change in AI/green job postings by the firm from the year before the disclosure to the year after. Table 1 Panel A (B) reports the number of such emerging-technology investment disclosures and firms' related investment adjustments surrounding them. As expected, an average firm exhibits an increase in its AI/green job postings, indicating an overall upward trend in the investment of these two emerging technologies. The independent variable of interest, FB, denoted for market feedback, is the five-day cumulative abnormal return surrounding the disclosure (i.e., [day -2, day 2]). Day 0 denotes the announcement date of a given corporate disclosure. The mean of FB is 0.3% for the AI-investment sample and 0.1% for the green-investment sample, with large standard deviations and interquartile ranges across the corresponding disclosures

We construct a set of quarterly firm characteristics that are likely to be correlated with AI/green investment adjustment. These control variables, measured at the nearest quarter end prior to emerging-technology-investment-related disclosures, include firm size (log of total sales in billion dollars), return on assets, R&D to sales ratio, market-to-book ratio, firm age, and cash reserve (cash holdings over assets). To account for the change in overall investment rate from the year prior to an emerging-technology-related corporate disclosure to the year after, we also control for the change in total job postings from the pre-disclosure year to the post-disclosure year. We include two additional control variables in our regressions, quarterly earnings surprise and disclosure sentiment. Earnings surprise is calculated as the actual earnings per share of the current quarter minus that of the same quarter in the previous year scaled by the latter. If the disclosure is an earnings conference call, earnings surprise is calculated for the corresponding conference call; otherwise, it is calculated for the nearest quarter prior to the disclosure date. Disclosure sentiment is calculated as the average of sentiment scores across sentences in the disclosure using a pre-trained natural language model.[21] All continuous variables are winsorized at the 1st and 99th percentiles to minimize the effects of outliers.

[21] Specifically, we adopt a pre-trained sentiment analysis model that uses distilBERT embeddings and was trained over a mix of corpora, notably the Amazon review corpus and IMDB dataset. For each sentence of a disclosure, we rely on the above model to generate a sentiment score. We then average this score across all sentences within the

Table 1 reports the summary statistics of these control variables. For firms that make AI-investment-related disclosures, they on average have quarterly sales of \$1.07 billion, ROA of 1.6%, R&D to sales ratio of 21%, market-to-book ratio of 1.88, firm age of 18.7 years, cash reserve of 19.5% during the quarter prior to the disclosure announcement, and slightly negative earnings surprise of -0.004. These AI-investment-related disclosures have an average positive tone of 0.775. Further, for such firms, the average change in the log of total job postings from the pre-disclosure year to the post-disclosure year is 0.245. For firms making green-investment-related disclosures, they on average have quarterly sales of \$1.75 billion, ROA of 2.3%, R&D to sales ratio of 16.4%, market-to-book ratio of 1.7, firm age of 24.3 years, cash reserve of 14.4% during the quarter prior to the disclosure announcement, and earnings surprise of 0.011. These green-investment-related disclosures have an average positive tone of 0.870. Additionally, the average change in the log of total job postings from the pre-disclosure year to the post-disclosure year for these firms is 0.242.

3. Learning from the Market Feedback on Emerging Corporate Policies

3.1 Baseline model and results

To examine whether managers learn from financial markets when contemplating investments in emerging technologies, we start by analyzing the relationship between firms' investment adjustments in emerging technologies (i.e., AI and green investments) and the market reaction to the corporate disclosures of such investment plans. Specifically, we estimate the following regression:

$$\Delta Investment_{i,d,q} = \alpha + \beta_1 FB_{i,d,q} + \beta_2 Firm\ Characteristics_{i,q-1} + Fixed\ effects + \varepsilon_{i,d,q}\ , \quad (1)$$

where $\Delta Investment_{i,d,t}$ is the change in firm i's emerging-technology investment from the year prior to a corporate disclosure d in year-quarter q to the year after the disclosure. The main independent variable of interest, $FB_{i,d,q}$, refers to the five-day cumulative abnormal return surrounding the disclosure date of firm i's emerging-technology related corporate disclosure d made in quarter q. We control for various lagged firm characteristics (discussed in the previous section) at the nearest quarter end prior to the corporate disclosure and the sentiment of the disclosure. To isolate the effects of time-invariant firm characteristics or time-varying industry

disclosure. We standardize the score to be within the range of 0 to 1. A score of 0.5 indicates a neutral tone, and a score below (above) 0.5 indicates a negative (positive) tone.

trends, we also include *Firm fixed effects* and/or *Industry × Year fixed effects* in different model specifications. Standard errors are clustered at the firm level to account for within-firm correlations among the residuals.

Table 2 Panel A presents the baseline results regarding AI investment. We start with a parsimonious model in column (1) that only includes *FB*, the market reaction to the AI-investment-related corporate disclosure, as the independent variable. The coefficient of *FB* is 0.087 and significant at the 1% level. It suggests that a one standard-deviation increase in the market reaction is associated with an increase in firms' AI job postings by about 0.8% (=0.087×0.093), which is approximately 9.2% of the sample average change in AI investments. The positive association is robust to including various firm characteristics (column 2), earnings surprise, disclosure tone, and changes in total job postings as a proxy for total human capital investment changes (column 3), industry by year fixed effects (column 4), and firm and industry by year fixed effects (column 5).

The results of the feedback effect on green investments are presented in Table 2 Panel B. As can be seen, the coefficient of *FB* in column (1) of Panel B is 0.101 and significant at the 1% level, suggesting that a one standard-deviation increase in the market reaction to green-investment-related corporate disclosures is associated with an increase in firms' green job postings by around 0.8% (=0.101×0.078), which is approximately 13.9% of the sample average change in green investments. Similar to Panel A, columns (2) to (5) show that the coefficient of *FB* remains positive and statistically significant after the inclusion of various controls and different layers of fixed effects. To sum up, these results are consistent with our feedback hypothesis that managers adjust their AI/green investments upward (downward) in response to a positive (negative) market reaction to their AI/green-technology related corporate disclosures.

3.2 Non-feedback-based explanations

3.2.1 Omitted variables arising from underlying fundamentals

The documented positive association between firms' emerging-technology investment changes and market reactions to related corporate disclosures is consistent with our feedback hypothesis. However, there might be potential non-feedback-based explanations. A common concern when testing theories of market feedback is that the positive relation between the stock price movement and the subsequent corporate investment might be a passive reflection of an underlying fundamental that drives both instead of managers' active learning from the price. In our setting, the omitted underlying fundamental could be the unobservable quality/prospects of the proposed investments in AI or green technologies. Better projects' quality/prospects can trigger more favorable market reaction on the one hand and motivate managers to further expand their investments in these projects on the other hand, leading to a positive investment-price association without one affecting the other.

We acknowledge that the logic for this non-learning explanation is compelling when it comes to a positive market reaction, which is followed by an increase in investment. It indicates that both the market and the corporate managers are reacting to the same underlying fundamental in the same direction. However, the logic for this alternative explanation breaks down when considering negative market responses to the AI/green-investment-related disclosures. As the majority of corporate disclosures indicate an increase rather than a decrease in emerging technology investment (e.g., see the examples in Appendix B1), such cases with negative market reactions despite the mentioning of increasing such investment suggest that firm managers and the market perceive the underlying fundamental about the planned emerging technology projects differently. The idea is that rational managers would not voluntarily disclose bad news about their AI/green projects to begin with and thus would avoid disclosing any plans to cut down emerging-technology investments (which is consistent with our manual reading of in-sample disclosures). Put differently, when omitted private signals indicate poor prospects about firms' AI/green investment, which can trigger negative market reaction and motivate managers to reduce such investments, managers probably would not disclose and discuss such plans in the first place. Hence, an analysis of firms' investment adjustments following negative market reactions would show whether our baseline results above are driven by a passive reflection of underlying fundamentals that affect both the market response and corporate actions.

To that end, we split the sample of emerging-technology related corporate disclosures into two groups: one with positive market reactions and the other with negative market reactions. We then separately estimate our baseline regression in Equation (1) for the two subsamples. Table 3 presents the results. Several interesting patterns emerge. First, by comparing the number of observations in columns (1) and (2) for each panel, we can see that almost half of both AI and green investment-related disclosures have negative market reactions, despite the mentioning of increasing AI/green investment in almost all these corporate disclosures. This result suggests that investors do not always view such expansion plans favorably.

More importantly, in column (3) of both panels, we split the market reaction (*FB*) into two variables: *POSFB*, which denotes positive market reactions and zero otherwise; and *NEGFB*, which denotes negative market reactions and zero otherwise. The absolute magnitudes of the coefficients of *NEGFB* are significantly larger than those of *POSFB* in both panels (indicated by the F-tests at the bottom of the column), suggesting that the positive association between investment adjustments and market reactions is more prominent when the market reaction is *negative* (i.e., when the market and managers disagree on the plan of expanding emerging technology investment). This finding is unlikely attributable to a passive reflection in both market prices and corporate investments. Rather it demonstrates more strongly in the direction of active managerial learning from the price. We acknowledge that there are two implicit assumptions underlying our interpretation of this test result. First, rational managers are generally true to their intentions and do not systematically announce plans to expand AI/green investments when their private signals indicate poor prospects about such projects.[22] Second, the market reacts negatively to an emerging-technology related disclosure because it believes these announced investment plans are bad and the firms should cut down on them.[23]

It is also worth noting that our findings do not contradict the theory of Edmans, Goldstein, and Jiang (2015). Their paper predicts that in the presence of managerial learning from stock prices, it is less likely to observe negative market reactions than positive reactions, because if firms use market feedback to improve investment decisions and firm value, speculators with negative information would find it unprofitable to trade (while the same logic does not apply to traders with positive information). However, their theoretical model does not predict that *conditional on*

[22] Of course, one might argue that managers can strategically "cheap talk" by announcing expansion plans in emerging technology investments even if they obtain unfavorable private signals and thus plan to reduce such investments. However, this strategy is unlikely to be adopted by an average firm in our sample for two reasons, First, if the market is smart enough to see through the cheap talks, then lying will only backfire and will not happen in equilibrium. Second, if the market cannot detect lying but knows this is a pooling equilibrium where everyone discloses the same thing (i.e., expansion plans in emerging technology investment) regardless of their private signals or true investment plans, then it should not react to such uninformative disclosures (or at least should not react negatively), which is inconsistent with the large (particularly large negative) announcement returns we observe in our sample. Hence, most of the firms announcing an expansion plan in AI/green technologies are likely true to their intentions.

[23] Another possibility is that the negative market reactions are driven by the market's disappointment that the announced level of AI/green investment is not as high as what it expects. In other words, the market reacts negatively not because it disapproves emerging technology investment but because it thinks the planned level of expansion in such investments is insufficient. If this is true, we would expect to see the stock price to bounce back in the long run if a firm "acts against the feedback" by increasing its AI/green investment after getting negative market reactions. However, this is opposite to what we observe in the data: In untabulated analyses, we find that the cumulative abnormal return from the disclosure announcement date to 2 or 3 year later is significantly more negative for such firms than for firms that "follow the feedback" (i.e., cut down AI/green investment after getting negative market reactions).

negative price reaction, managers would learn less from it than in the case of positive reaction. In fact, whether managerial learning is stronger under positive or negative market reactions is an empirical question that depends on several competing economic forces. On the one hand, negative market reactions, as surprises, are more likely to grab the attention of insiders (managers or board of directors), inducing them to dig deeper into the reasons behind such feedback and to reflect more upon their proposed investment plans. This leads to a stronger learning effect, as what we find here in the context of emerging technology investments. On the other hand, negative market reactions might contain lower-quality information for managers to learn because traders with unfavorable views towards the investment plans would be reluctant to acquire useful information to begin with. This will result in a weaker learning effect, as what Jayaraman and Wu (2020) find in the context of ordinary capital expenditures.

3.2.2 Omitted variables arising from other components of the corporate disclosures

Because major corporate disclosures typically contain a large amount of information other than that related to emerging technology investment plans, another concern in interpreting the positive investment-price association documented in Section 3.1 is that other non-emerging-investment-related components of the disclosures could correlate with firms' subsequent AI/green investments and generate market reactions in the same direction (i.e., the parts in addition to the discussion of firms' future investment plans in emerging technologies). Examples of such omitted variables include information regarding general investment opportunities, management quality, or other firm fundamentals. Note that this alternative explanation should only bias against us finding a significant association between firms' investment adjustments and the market feedback if the patterns of the non-emerging-policy related information contained in our sample disclosures are largely random/idiosyncratic, i.e., not exhibiting any systematic patterns but only introducing noise into our estimation. Nevertheless, we still employ several methods to investigate its implication for our results.

Ideally, to fully address this concern, we need to divide the market reaction to a specific disclosure into two components: one driven by the discussions on emerging-technology-related investments (i.e., the "AI/green components") and the other by the rest of the information in the disclosure. However, such decomposition is impossible in practice. Hence, we adopt two approaches to alleviate this concern. In the first approach, we leverage the granular time stamp information contained in earnings conference call transcripts and examine stock price reaction within the hour during which managers discuss emerging-technology-related investment plans in conference calls. Presumably, such an instantaneous stock price change is more likely triggered by the discussion of emerging corporate policies than by other confounding information contained in such disclosures. We identify the granular time stamp of each sentence in an earnings conference call by using the start time of the call and its audio data. We obtain audio data from Seeking Alpha for the period of 2010 to 2017 and match it to the corresponding earnings conference call transcripts used in Section 3.1. The requirement for an earnings conference call to have both audio and transcript data reduces our sample size considerably. This step leaves us with around 6,300 (12,000) AI (green) investment-related earnings conference calls. We then calculate intraday stock returns using the trading data from the Wharton Research Data Services (WRDS) Consolidated Trades file, which are derived from the millisecond NYSE Trade and Quote (TAQ) database.

Table 4 presents the results, where the independent variable of interest, $FB_{Hour,}$ refers to a firm's stock price change in the hour when managers discuss AI/green-technology-related investment plans. We continue to find a significantly positive relation between a firm's AI/green investment adjustment and this hourly announcement return. In contrast, we do not find a significant association between AI/green investment adjustments and the cumulative stock return from the beginning hour of the same earnings conference call until the "AI/green investment disclosure" hour, or that from the end of the "AI/green investment disclosure" discussion until the conclusion of the conference call.

In the second approach, we perform our baseline tests using a subsample of "focused" 8-K filings with only one item (that mentions emerging technology investment plans). As each 8-K item links to one specific type of material events that firms are obliged to disclose to their investors, these focused 8-K filings with only one item are essentially material press releases that likely contain information exclusively about their emerging corporate policies. An example of focused 8-K filings is presented in Appendix B1 Panel A. As shown in Table 5, we continue to find a significantly positive relation between a firm's AI/green investment adjustment and the market reaction when we examine earnings conference calls and 8-K filings separately.[24] More importantly, Columns (3) of both panels show that our results persist in the subsample of focused

[24] Our baseline sample in Table 2 is at the firm–event date level. That is, we drop duplicates when a firm on a given event date has both earnings conference calls and 8-K filings. Due to the existence of multiple disclosures on the same day by the same firm, the sum of the number of observations in Columns (1) and (2) in Table 5 is larger than the number of observations in Table 2.

8-K filings (material press releases), suggesting that our results are unlikely driven by the omitted yet investment-relevant parts of the sample corporate disclosures.

3.3 Cross-sectional tests based on market participants' expertise and managerial incentives

To further tie to market feedback and explore the managerial learning channel for our baseline results, we perform three cross-sectional tests.

3.3.1 Market participants' expertise in emerging technologies

First, we exploit variation in outsiders' knowledge in related emerging technologies. If the positive association between emerging-technology investment adjustments and market reactions is indeed driven by managers learning from the market feedback, then the results should be more pronounced when market participants (i.e., outside investors) possess more information or knowledge about the emerging technologies and therefore can provide more insightful and valuable feedback for managers regarding the related investment plans (Dye and Sridhar, 2002, Chen et al., 2007, and Jayaraman and Wu, 2020).

To test this prediction, we examine one major type of market participants that can guide managers in the realm of emerging technology investments: institutional investors, given that they possess superior insights about emerging technologies and the firm, and can capitalize on such information by trading. We infer institutions' expertise from their portfolio holdings. To examine the expertise of institutions in AI technologies, we first classify AI industries as the top five 3-digit Cooperative Patent Classification (CPC) technology classes with the highest percentage of AI patents. AI patents are defined based on the AI prediction scores provided by the United States Patent and Trademark Office (USPTO) Artificial Intelligence Patent Dataset (AIPD). A patent is considered AI-related if any of its eight AI prediction scores – corresponding to the eight AI components identified by AIPD, namely, machine learning, evolutionary computation, NLP, speech, vision, knowledge processing, AI hardware, and planning and control – is above 50%. We then identify a firm as AI-related (and assign an AI-score of one to it) if its major patent technology area in a year is one of the five AI industries. Otherwise, the firm is assigned a zero AI-score. We measure an institution's expertise in AI technologies in a given quarter as the weighted average AI-score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Then, we take average of the institution's quarterly AI expertise score across the four quarters prior to a disclosure event. For each AI-investment-related disclosure, the focal firm's average institutional AI expertise score, *InstitutionAIExpertise*, is calculated as the value-weighted average of the institutional AI expertise score across all institutions, with the weight being the number of the focal firm's outstanding shares held by the institution at the nearest quarter end prior to the disclosure event.

To examine the expertise of institutions in green technologies, we obtain the environmental score of firms from Refinitiv ESG Company Summary database, which considers three environmental categories: resource use, emissions, and innovation. We then measure an institution's expertise in green technologies in a given quarter as the weighted average environmental score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Next, we take average of the institution's quarterly green expertise score across the four quarters prior to a disclosure event. For each green-related corporate disclosure, the focal firm's average institutional green expertise score, *InstitutionGreenExpertise*, is then calculated as the value-weighted average of the institutional green expertise score across all its institutions. Each institution's weight is the number of the focal firm's outstanding shares held by the institution at the nearest quarter end prior to the disclosure event.

Table 6 presents the results of this test. Panel A studies AI investment and institutions' AI technology expertise. The independent variable of interest is the interaction term, *FB* × *InstitutionAIExpertise*. As can be seen, the coefficient of the interaction is positive and significant, suggesting that when outside investors are more informed about AI technologies, managers make larger AI investment adjustments in response to the market feedback on their AI investment disclosures. Panel B presents the results of green investment and institutions' green expertise. Similarly, the positive and significant coefficient of *FB* × *InstitutionGreenExpertise* shows that managers make more substantial green investment adjustments in response to market feedback when the firm's institutional investors possess greater expertise in green technologies. We acknowledge that these institutional investors could directly communicate with the firm about its emerging-technology-related investments instead of trading its stocks. However, such communication would only attenuate the role of market feedback and therefore bias against us finding evidence for managerial learning from the market.

3.3.2 Technology peer pressure

Second, we explore the variation of a firm's exposure to technology competition. Our hypothesis is that when a firm faces more technological competition from its peers, the managers would have stronger incentives to elicit feedback from the market, as this could provide valuable insights for investment decision-making, guide resource allocation, and ultimately help maintain the firm's competitive edge. To test this prediction, we follow Cao et al. (2018) to measure a firm's Technology Peer Pressure (TPP) as:

$$TPP_{i,t} = \log[1 + (\sum_{j \neq i} w_{i,j} \times G_{j,t})/G_{j,t}], \tag{2}$$

where *i* denotes the focal firm, *t* denotes the year, and *j* denotes the peer firm. The idea of *TPP* is to capture a firm's technological threat from its peer firms proxied by the latter's R&D expenditures. $G_{j,t}$ is peer firm *j*'s R&D stock in dollars at the end of year *t*. Following Bloom et al. (2013), it equals the sum of the firm's R&D expense reported in year *t* and that reported in year *t-1* with a 15% decay rate (i.e., $G_{j,t} = R\&D_{j,t} + (1 - 15\%)R\&D_{j,t-1}$). $w_{i,j}$ measures the closeness between focal firm *i* and peer firm *j* in the product market. Specifically, we first construct a product-market "presence" vector V_i for each firm, whose element is the fraction of the firm's total sales over the past two years that are derived from each 4-digit SIC industry. Then we calculate the cosine similarity between the vector of the focal firm and that of a peer firm and use it as the weight for that peer. That is, the closeness between firm *i* and peer *j*'s product-market "presence" vectors $w_{i,j}$ equals $\cos(\theta_{i,j}) = \frac{V_i V_j'}{\|V_i\| \cdot \|V_j\|}$.

Table 7 presents the results of the cross-sectional tests based on technology peer pressure. Column (1) examines firms whose TPP is above sample median in the year of the corporate disclosure, and Column (2) examines firms whose TPP is below sample median. As can be seen, the coefficient of *FB* is only positive and significant in column (1) when firms face high technology peer pressure, but small and insignificant in column (2). In column (3), we include an interaction term *FB* × *HighTPP* and examine it using the full sample of corporate disclosures. The positive and significant coefficient of the interaction term suggests that consistent with our expectation, managers react stronger to the market feedback on their AI investment plans when they face greater technological competition from the product market.

3.3.3 The Paris Agreement

Third, we explore the time-series variation in managers' incentives to learn about green technologies using the Paris Agreement, which was adopted on December 12, 2015. It is an international treaty on climate changes with a long-term goal to keep the rise in the average global temperature under 1.5 °C (2.7 °F). This agreement argues that global greenhouse gas emissions should be reduced as soon as possible, preferably to reach a net-zero status by the middle of the 21st century. The Paris Agreement drew significant public attention to environmental and climate change issues, which might exert heightened pressure on firm managers to ponder their green-technology investment plans. Therefore, we explore whether the feedback effect on green investment changes around this salient event.

Table 8 presents the cross-sectional analysis of a firm's green investment response to market feedback before and after the announcement of the Paris Agreement in December 2015. Column (1) includes green-investment-related corporate disclosures in 2015 and earlier; and Column (2) includes those announced in 2016 and later. The coefficients of *FB* are positive and significant in both columns, indicating that the positive correlation between firms' green investment adjustments and the market feedback exists both before and after the Paris Agreement, though the magnitude of the correlation is larger in the post-agreement period. In Column (3), we analyze the interaction terms between *FB* and two time dummies, *Before*, which indicates whether the disclosure announcement date is in 2015 and earlier, and *After*, which indicates whether the disclosure announcement date is in 2016 and later. The variables of interest are the two interaction terms. The more positive coefficient of $FB \times After$ suggests that firms adjust their green investment more in response to the market feedback on their green investment related corporate disclosures. These results are consistent with our prediction that firms learn more from the market feedback when heightened public attention incentivizes managers to pay greater attention to environmental and climate-change related issues.

4. More Facets of Managerial Learning

To shed further light on what kind of information managers learn from the market and strengthen the inference about managerial learning, we conduct several additional tests that explore the nature and timing of emerging corporate policies.

4.1 Investment response to conventional technology-related market feedback

First, we examine firms' investment response to the market feedback on conventional rather than emerging technology-related corporate disclosures. Following Abis and Veldkamp (2024), we define conventional technologies as traditional data analytics techniques such as linear regression, time series analysis, Monte Carlo simulation models, etc. Since such conventional technologies have been well-recognized and adopted by industrial firms for a long time, the market should possess little incremental knowledge beyond that of firm insiders and thus cannot provide useful feedback to guide related investment decisions. Hence, we expect that the feedback effect documented above becomes weaker or disappears entirely when the technologies mentioned in corporate disclosures are conventional and non-emerging in nature.

To identify conventional technology-related corporate disclosures, we first follow Abis and Veldkamp (2024) to compile a list of conventional-technology-related keywords. We then identify conventional-technology-related disclosures as earnings conference calls or 8-K filings that mention at least one conventional technology-related keyword, one investment related keyword, and one forward-looking keyword in the same sentence. To obtain a clean sample, we also exclude disclosures that mention emerging technologies (i.e., AI/green-related). To measure a firm's investment in conventional technologies, we follow the same spirit of our AI/green investment measure by examining its conventional-technology-related job postings.

Table 9 Panel A presents the results. The dependent variable, $\Delta\, Conventional\, Job\, Postings$, is defined as the change in the natural logarithm of one plus the weighted sum of conventional-related job postings by a firm from the year prior to a conventional-investment-related disclosure to the year after. Each job posting is weighted by the average conventional-technology-relevance score across all skills required for the job (following Abis and Veldkamp, 2024). As can be seen, the coefficients of FB are small and insignificant in all model specifications, suggesting that the investment response to market feedback on conventional technology-related investment plans is much weaker than that on emerging technology-related ones. However, it is worth noting that this result does not necessarily contradict the evidence from the extant market feedback literature because our measure of conventional investment is based on firms' job postings, which only capture one specific category of investment, namely, the intangible human capital investment. It does not speak to firms' adjustments of capital expenditures on physical assets, R&D investment, or other types of investments.

4.2 Feedback on non-investment-related emerging technology disclosures

Next, we examine whether the feedback effect on emerging corporate policies persists when the related discussions in the disclosures do *not pertain to investment plans* but only refer to AI/green technologies in a general way.

Specifically, we first identify earnings conference calls and 8-K filings that contain at least one sentence that includes both AI/green related keywords and forward-looking keywords while in the meantime contains no investment related keywords. In other words, these corporate disclosures only refer to emerging technologies in a general way but have nothing to do with firms' investment plans. Then we perform the same baseline regressions for these *non-investment-related* emerging technology disclosures.

Table 9 Panel B reports the results. In this test, the independent variable of interest, *NonInvFB*, is a firm's five-day cumulative abnormal return surrounding the date of a disclosure that mentions AI/green technologies but not investment plans. As can be seen, the coefficients of *NonInvFB* in both panels are small and insignificant, suggesting that there is no clear correlation between a firm's investment adjustment in emerging technologies and the market reaction to its discussion of emerging technologies in a general way. This result suggests that the observed announcement return, which is followed by subsequent investment adjustments, is unlikely driven by the market's sentiment towards the risks, nature, or prospects of these emerging technologies per se. Instead, it is more likely driven by the market's reaction to the firm's specific investment plans in these areas.

4.3 Pre-disclosure trends in emerging-technology investments

Another non-learning interpretation of our baseline results is the pre-event trends in emerging-technology-related investments. Firms that have already started adjusting (accelerating or slowing-down) their AI/green investment plans prior to the related disclosures would continue such investment policies afterwards. Meanwhile, the market simply reacts to these predetermined trends. This alternative interpretation can explain our results based on both positive and negative market feedback. For example, the market could view a firm's announced plan to increase its emerging-technology investment as incredible and react negatively upon seeing a slow-down pre-disclosure trend. In this case, learning does not play an important role in explaining our baseline results as the "parallel trends" assumption for firms with differential market reactions is violated.

To address this concern, we directly examine firms' past (i.e., pre-disclosure) investment trends in emerging technologies. If our finding is mainly driven by the pre-event trends in investment policies, we would expect a positive association between firms' *past* investment adjustments in emerging technologies and the market reaction. Table 10 presents the results. The sample of corporate disclosures in this test are the same as those in our baseline analysis. The dependent variable in columns (1) and (2), *Past ΔAI Job Postings*, is the change in the natural logarithm of one plus a firm's AI job postings from two years prior to an AI-related disclosure to one year prior to the event. And the dependent variable in columns (3) and (4), *Past ΔGreen Job Postings*, is similarly defined using firms' green job postings. The small and insignificant coefficients of *FB* in both panels suggest that firms' past investment trends in emerging technologies are not significantly correlated with the market reactions, which is inconsistent with this alternative interpretation based on pre-disclosure trends.

4.4 Emerging-technology investments and market reactions in non-disclosure windows

To strengthen the inference about managerial learning from market feedback to specific disclosures, we perform a placebo test by examining the association between emerging investment changes and cumulative abnormal returns in 5-day windows other than that surrounding the same disclosure event (i.e., days [-2, 2]). Specifically, we look at the 5-day cumulative abnormal return before or after the same disclosure event (i.e., days [-7, -3] or days [3, 7]).

Table 11 presents the results. The sample of corporate disclosures and the two main dependent variables, *ΔAI Job Postings* and *ΔGreen Job Postings*, are the same as those in our baseline analysis. In Panel A, *PlaceboFB[-7, -3]* is the five-day cumulative abnormal return from seven days to three days prior to the disclosure date (i.e., day 0) of a firm's emerging-technology related corporate disclosure. In Panel B, *PlaceboFB[3, 7]* is the five-day cumulative abnormal return from three days to seven days after such a disclosure date. The small and insignificant coefficients of *PlaceboFB[-7, -3]* and *PlaceboFB[3, 7]* in both panels suggest that firms' investment adjustments in emerging technologies are only related to the market reactions in the narrow announcement window but not in other 5-day windows immediately before or after the same disclosure event.

5. More Nuances of the Learning Channel and Robustness Tests

5.1 Investment response to peer firms' emerging-technology-related market feedback

Next, we examine whether a firm adjusts its emerging-technology investments based on the market reaction to its peer firms' emerging-technology-related corporate disclosures. If the market reaction to emerging-technology-related disclosures is mostly idiosyncratic, i.e., only useful to the focal firm's investment planning, then we would not expect to see the firm's peers act on such feedback. However, if the market possesses more industry-specific knowledge about emerging-technology-related investments and incorporates such insights into the announcement returns, then peer firms would also learn from the stock price movement around the focal firm's disclosures (Foucault and Frésard, 2014).

We define peer firms as those operating in the same product market as the focal firm (i.e., with TNIC-3 scores above the sample median, Hoberg and Philips, 2010, 2016), and conduct a pair-level analysis on the focal firm's investment response to the market feedback on each of its peer firms' emerging-technology-related corporate disclosures. Table 12 presents the results. The independent variable of interest in this test, *PeerFB*, is a peer firm's five-day cumulative abnormal return surrounding its emerging technology-related disclosure date. We further control for *FocalFB*, the focal firm's five-day cumulative abnormal return surrounding its *peer* firm's emerging technology-related disclosure date, and include pair fixed effects to account for time-invariant relationships/characteristics of a focal-peer-firm pair.

Interestingly, the coefficients of *PeerFB* are small and insignificant in Panel A when we examine AI investment, but are positive and statistically significant in Panel B when green investment is analyzed. These contrasting results suggest that focal firms only learn from their peers' market feedback on green-related investments but not that on AI-related investments. This may be because the former is more industry specific (and less idiosyncratic) than the latter due to greater regulatory interventions on sector-wise environmental-related activities and/or stronger investor preferences towards ESG issues.

5.2 Benefits of following the market feedback

We next explore whether tapping the wisdom of the crowd from the stock market is useful in creating firm value. Specifically, we compare the long-term performance of firms when they follow the market feedback on their disclosed emerging-technology investment plans and when they choose not to follow such feedback. It is worth noting that managers' reluctance to follow the market feedback can be either rational (and optimal for firm value) or irrational. If their reluctance is largely rational and thus shareholder-value maximizing, then we should not expect to find any performance difference between feedback-following and non-following (as both reactions are optimal decisions). If, however, managers' unwillingness to use external information from the market is largely irrational due to either their lack of skills/knowledge or behavioral biases, then following the feedback ought to be associated with better long-run performance than not following.

Ideally, to analyze the long-run consequence of following market feedback, we should compare a firm's performance when it follows a given market reaction with the same firm's performance when it does not follow the identical market feedback. However, this approach is not feasible because for a given market reaction, a firm can either be a follower or a non-follower but not both. We therefore exploit an alternative approach based on propensity score matching. Among the firms that make emerging-technology-related disclosures in our sample, we define a firm as a follower if it increases its emerging-technology investment following positive market feedback or decreases such investment following negative market feedback. The rest of firms in our sample comprise the pool of non-followers. To ensure the two groups are ex ante similar, we perform a propensity score matching as follows. For each follower, we match it to up to five non-followers in the same SIC 2-digit industry in the same year with the closest propensity score based on firm size, ROA, R&D ratio, market-to-book ratio, firm age, and the level of emerging-technology investment in the year prior to the corresponding disclosures.[25] We then compare the average performance of followers to that of matched non-followers in the three years after their emerging-technology-related disclosures.

Table 13 presents the results. As can be seen, following the market feedback is associated with higher average return on assets (ROA) and stock returns than non-followers in the three years after their emerging-technology-related disclosures, suggesting that ignoring the useful information signals contained in the stock price is sub-optimal for firm value. Nevertheless, one reasonable concern regarding this positive association is that firms with more resources and thus expecting better future performance might be more capable of investing in emerging technologies. The logic of such a reverse causality explanation is likely to break down when the market feedback is negative, because in such cases followers actually reduce/slow down their AI/green investment and it is hard to argue that firms with more resources (growth potential) are more capable of cutting down their emerging technology investment. Therefore, similar to Table 3, we further split the

[25] Such a matching procedure leads to the smaller number of observations for this test compared to that for our baseline test in Table 2.

sample of emerging-technology-related corporate disclosures into two groups: one with positive market reactions and the other with negative market reactions. We find that the observed performance gaps only show up in the presence of negative market feedback, which mitigates the above reverse causality concern.

Overall, the results in this section illustrate the benefits of tapping the wisdom of the crowd when venturing into uncharted waters, suggesting that learning from the stock market feedback is a useful market-based solution in the face of significant uncertainties and the resulting lack of information associated with emerging technology investments.

5.3 Robustness tests

Finally, we conduct additional robustness tests for our analyses using an alternative measure of AI investment, $\Delta AI\ Patents$, as well as alternative measures of green investment, $\Delta Green\ Patents$ and $\Delta Total\ GHG\ emissions$.

Specifically, Δ*AI Patents* is calculated as the difference between the natural logarithm of one plus the number of AI patents generated during the N-year period (N=1, 2, 3) after an AI-related corporate disclosure, and that generated during the one-year period prior to the disclosure. AI patents are defined based on the AI prediction scores provided by the United States Patent and Trademark Office (USPTO) Artificial Intelligence Patent Dataset (AIPD). We define a patent to be an AI-related one if any of its eight AI prediction scores (corresponding to the eight AI components identified by AIPD, namely, machine learning, evolutionary computation, NLP, speech, vision, knowledge processing, AI hardware, and planning and control) is above 50%.

Similarly, Δ*Green Patents* is calculated as the difference between the natural logarithm of one plus the number of green patents generated during the N-year period (N=1, 2, 3) after a green-related corporate disclosure, and that generated during the one-year period prior to the disclosure. Following Cohen, Gurun, and Nguyen (2022) and Haščič, and Migotto (2015), we define green patents based on the list of IPC/CPC codes from the Organization for Economic Co-operation and Development (OECD).

Δ*Total GHG emission* is measured as the change in the natural logarithm of one plus a firm's total GHG emission from the year before a green-investment-related corporate disclosure to the year after. The intuition is that a smaller amount of GHG emission indicates that a firm has increased its investment in green (i.e., environmentally friendly) technology adoption and therefore has lower GHG emission. We obtain corporate carbon emission data from Trucost, which collects firms' carbon emission data from publicly available sources and covers a wide spectrum of firms around the world from 2006 to 2020. There are three major scopes (categories/types) in a firm's GHG emissions. Scope 1 emissions are the direct emissions from sources that a firm owns or controls, e.g., emissions produced by the internal combustion engines of trucks owned by a trucking company. Scope 2 emissions arise from a firm's consumption of purchased electricity, steam, or other sources of energy related to its direct operations. And scope 3 encompasses all other emissions associated with a firm's operations that are not directly owned or controlled by the firm, including indirect emissions from the supply chain. Following Azar et al. (2021), we calculate a firm's annual GHG emission as the total amount of GHG emission (in equivalents of metric tons of CO2) based on all three scopes.[26]

Table 14 presents the results. Columns (1) to (3) repeat the baseline regressions using $\Delta AI\ Patents$ as the dependent variable. The coefficients of FB remain significantly positive across all columns, which is consistent with the positive association between a firm's AI investment adjustments and the market feedback to AI technology-related corporate disclosures documented earlier. Columns (4) to (6) examine $\Delta Green\ Patents$, the change in firms' green patent applications over the next one-, two-, and three-year period after receiving the market feedback. The coefficients of FB remain positive and largely significant in all three columns. Column (7) examines $\Delta Total\ GHG\ emission$ as the dependent variable. The coefficient of FB is negative and statistically significant, suggesting that our baseline results are robust to using these alternative measures of emerging corporate policy changes.

6. Conclusion

This paper explores the role of market feedback when firms contemplate emerging corporate policies on AI and green technologies. We find that firms adjust their investments in AI/green technologies in response to the market reaction to the discussions of such plans in their corporate disclosures. Specifically, managers adjust their AI/green investments upward (downward) in response to a favorable (unfavorable) market reaction to the corresponding corporate disclosures. This association is stronger when the market reaction is negative, and unlikely to be driven by non-feedback-based explanations, the pre-disclosure trends in such investments, or the confounding effects of the non-AI/green-related component of the corporate

[26] In untabulated analysis, our findings are robust to considering only scope 1 emission or scope 1 and 2 emissions.

disclosures. We also find this association to be stronger when market participants (e.g., institutional investors) possess more expertise in emerging technologies, when the technology competition from peers is more intense, and when the market pays more attention to environmental issues such as after the announcement of the Paris Agreement. Finally, we document the benefits of following the market feedback on emerging corporate policies in terms of long-run operating and stock performance.

Our study, to the best of our knowledge, is the first to construct a comprehensive set of AI/green-investment-related corporate disclosures, and to document the trend and extent of such feedback-seeking behavior by firm managers in emerging corporate policies. Our findings suggest one potential solution to mitigate managers' ex-ante concerns and improve ex-post investment efficiency when they venture into unknown and risky areas such as emerging technologies – the active utilization of the wisdom of the crowd from outside market participants. Our analyses also shed new light on *what type of information* managers actually learn from the market. We provide the first piece of empirical evidence that managers elicit and subsequently act on the feedback from financial markets regarding their investment plans in green and AI technologies that are highly risky, controversial, and lacking track records in related investments. More importantly, our results show that managers' learning behavior varies not only *between* emerging- and non-emerging corporate policies, but also *within* different categories of emerging corporate policies.

References

Abis, Simona, and Laura Veldkamp, 2024, The Changing Economics of Knowledge Production, *Review of Financial Studies* 37: 89-118.

Acemoglu, Daron, Ufuk Akcigit, Douglas Hanley, and William Kerr, 2016, Transition to Clean Technology, *Journal of Political Economy* 124: 52-104.

Albrizio, Silvia, and Helia Costa, 2012, Policy Uncertainty and Investment in Low-Carbon Technology, *Working Paper*.

Aljifri, Khaled, and Khaled Hussainey, 2007, The Determinants of Forward-looking Information in Annual Reports of UAE Companies, *Managerial Auditing Journal* 22: 881-894.

Aretz, Kevin, Hassan Ilyas, and Gaurav Kankanhalli, 2022, Technological Progress, Managerial Learning, and the Investment-to-Stock Price Sensitivity, *Working Paper*.

Azar, José, Miguel Duro, Igor Kadach, and Gaizka Ormazabal, 2021, The Big Three and Corporate Carbon Emissions around the World, *Journal of Financial Economics* 142: 674-696.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson, 2024, Artificial Intelligence, Firm Growth, and Product Innovation, *Journal of Financial Economics* 151: 103745.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson, 2023, Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition, *NBER Volume on Technology, Productivity, and Economic Growth*, forthcoming.

Bae, Jihun, Gary C. Biddle, and Chul W. Park, 2022, Managerial Learning from Analyst Feedback to Voluntary Capex Guidance, Investment Efficiency, and Firm Performance, *Management Science* 68: 1-808.

Bai, Jennie, Thomas Philippon, and Alexi Savov, 2016, Have Financial Markets Become More Informative?, *Journal of Financial Economics* 122: 625-654,

Bakke, Tor-Erik, and Toni Whited, 2010, Which Firms Follow the Market? An Analysis of Corporate Investment Decisions, *Review of Financial Studies* 23: 1941-1980.

Ball, Christopher, Gerard Hoberg, and Vojislav Maksimovic, 2015, Disclosure, Business Change and Earnings Quality, *Working Paper*.

Banerjee, Suman, Shiyang Huang, and Vikram Nanda, and Steven Xiao, 2023, Managerial Overconfidence and Market Feedback Effects, *Management Science* 69: 7151-7882.

Betton, Sandra, B. Espen Eckbo, Rex Thompson, and Karin Thorburn, 2014, Merger Negotiations with Stock Market Feedback, *Journal of Finance* 69: 1705-1745.

Bloom, Nicholas, Mark Schankerman, and John Van Reenen, 2013, Identifying Technology Spillovers and Product Market Rivalry, *Econometrica* 81: 1347-1393.

Blyth, William, Richard Bradley, Derek Bunn, Charlie Clarke, Tom Wilson, and Ming Yang, 2007, Investment Risks under Uncertain Climate Change Policy, *Energy Policy* 35: 5766-5773.

Bond, Philip, Alex Edmans, and Itay Goldstein, 2012, The Real Effects of Financial Markets, *Annual Review of Financial Economics* 4: 339-360.

Bozanic, Zahn, Darren T. Roulstone, and Andrew Van Buskirk, 2018, Management Earnings Forecasts and Other Forward-looking Statements, *Journal of Accounting and Economics* 65: 1-20.

Cao, Sean, Wei Jiang, Junbo Wang, and Baozhong Yang, 2024, From Man vs. Machine to Man + Machine: The Art and AI of Stock Analyses, *Journal of Financial Economics,* forthcoming.

Cao, Sean, Wei Jiang, Baozhong Yang, Alan Zhang, 2023, How to Talk When a Machine is Listening? Corporate Disclosure in the Age of AI, *Review of Financial Studies* 36: 3603-3642.

Cao, Sean, Yongtae Kim, Angie Wang, and Houping Xiao, 2022, From Words to Syntax: Identifying Context-specific Information in Textual Analysis, *Working Paper*.

Cao, Sean, Guang Ma, Jennifer Wu Tucker, and Chi Wan, 2018, Technological Peer Pressure and Product Disclosure, *The Accounting Review* 93: 95-126.

Chava, Sudheer, Wendi Du, and Nikhil Paradkar, 2022, More than Buzzwords? Firms' Discussions of Emerging Technologies in Earnings Conference Calls, *Working Paper*.

Chen, Qi, Itay Goldstein, and Wei Jiang, 2007, Price Informativeness and Investment Sensitivity to Stock Price, *Review of Financial Studies* 20: 619-650.

Cockburn, Iain M., Rebecca Henderson, and Scott Stern, 2018, The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis, *The Economics of Artificial Intelligence: An Agenda*: 115-146.

Cohen, Lauren, Umit G. Gurun, and Quoc Nguyen, 2022, The ESG – Innovation Disconnect: Evidence from Green Patenting, *Working Paper*.

Cookson, J. Anthony, Marina Niessner, and Christoph Schiller, 2023, Can Social Media Inform Corporate Decisions? Evidence from Merger Withdrawals, *Journal of Finance*, forthcoming.

Darendeli, Alper, Kelvin K. F. Law, and Michael Shen, 2022, Green New Hiring, *Review of Accounting Studies* 27: 986-1037.

Davis, Steven J., John Haltiwanger, Ron Jarmin, Javier Miranda, Christopher Foote, and Eva Nagypal, 2006, Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms, *NBER Macroeconomics Annual* 21: 107-179.

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray, 2019, Noisy Stock Prices and Corporate Investment, *Review of Financial Studies* 32: 2625-2672.

Dye, Ronald A., and Sri S. Sridhar, 2002, Resource Allocation Effects of Price Reactions to Disclosures, *Contemporary Accounting Research* 19: 385-410.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2012, The Real Effects of Financial Markets: The Impact of Prices on Takeovers, *Journal of Finance* 67: 933-971.

Edmans, Alex, Itay Goldstein, and Wei Jiang, 2015, Feedback Effects, Asymmetric Trading, and the Limits to Arbitrage, *American Economic Review* 105: 3766-97.

Edmans, Alex, and Sudarshan Jayaraman, and Jan Schneemeier, 2017, The Source of Information in Prices and Investment-price Sensitivity, *Journal of Financial Economic*s 126: 74-96.

Engle, Robert F., Stefano Giglio, Bryan Kelly, Heebum Lee, and Johannes Stroebel, 2020, Hedging Climate Change News, *Review of Financial Studies* 33: 1184-1216.

Frankel, Richard, Marilyn Johnson, and Douglas J. Skinner, 1999, An Empirical Examination of Conference Calls as a Voluntary Disclosure Medium, *Journal of Accounting Research* 37: 133-150.

Foucault Thierry, and Laurent Frésard, 2014, Learning from Peers' Stock Prices and Corporate Investment, *Journal of Financial Economic*s 111: 554-577.

Gelsomin, Eric, and Amy Hutton, 2023, The Learning Hypothesis Revisited: A Discussion of Sani, Shroff and White (2023), *Journal of Accounting and Economics* 76: 101644.

Gibbons, Brian, Peter Iliev, and Jonathan Kalodimos, 2021, Analyst Information Acquisition via EDGAR, *Management Science* 67: 661-1328.

Gofman, Michael, and Zhao Jin, 2024, Artificial Intelligence, Education, and Entrepreneurship, *Journal of Finance* 79: 631-667.

Goldstein, Itay, 2023, Information in Financial Markets and Its Real Effects, *Review of Finance* 27: 1-32.

Goldstein, Itay, Bibo Liu, and Liyan Yang, 2023, Market Feedback: Evidence from the Horse's Mouth, *Working Paper*.

Grewal, Jyothika, 2019, Management and Disclosure of Corporate Sustainability Performance, *Working Paper*.

Haščič, Ivan, and Mauro Migotto, 2015, Measuring Environmental Innovation Using Patent Data, *OECD Environment Working Papers 89*.

Hassanein, Ahmed, and Khaled Hussainey, 2015, Is Forward-looking Financial Disclosure Really Informative? Evidence from UK Narrative Statements, *International Review of Financial Analysis* 41: 52-61.

Hassanein, Ahmed, Alaa Zalata, and Khaled Hussainey, 2019, Do Forward-looking Narratives Affect Investors' Valuation of UK FTSE All-shares Firms?, *Review of Quantitative Finance and Accounting* 52: 493-519.

Hershbein, Brad and Lisa B. Kahn, 2018, Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings, *American Economic Review* 108: 1737-72.

Hoberg, Gerard, and Vojislav Maksimovic, 2015, Redefining Financial Constraints: A Text-Based Analysis, *Review of Financial Studies* 28: 1312-1352.

Hoberg, Gerard, and Gordon Phillips, 2010, Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis, *Review of Financial Studies* 23: 3773-3811.

Hoberg, Gerard, and Gordon Phillips, 2016, Text-Based Network Industries and Endogenous Product Differentiation, *Journal of Political Economy* 124: 1423-1465.

Hsu, Po-Hsuan, Hao Liang, and Pedro Matos, 2021, Leviathan Inc. and Corporate Environmental Engagement, *Management Science,* forthcoming.

Jayaraman, Sudarshan, and Joanna Shuang Wu, 2020, Should I Stay or Should I Grow? Using Voluntary Disclosure to Elicit Market Feedback, *Review of Financial Studies* 33: 3854–3888.

Langberg, Nisan, and K. Sivaramakrishnan, 2010, Voluntary Disclosures and Analyst Feedback, *Journal of Accounting Research* 48: 603-646.

Li, Feng, 2010, The Information Content of Forward-Looking Statements in Corporate Filings—A Naïve Bayesian Machine Learning Approach, *Journal of Accounting Research* 48: 1049-1102.

Li, Kai, Feng Mai Rui Shen, and Xinyan Yan, 2021, Measuring Corporate Culture Using Machine Learning, *Review of Financial Studies* 34: 3265-3315.

Lopez, M. Victoria, Arminda Garcia, and Lazaro Rodriguez, 2007, Sustainable Development and Corporate Performance: A Study Based on the Dow Jones Sustainability Index, *Journal of Business Ethics* 75: 285-300.

Luo, Yuanzhi, 2007, Do Insiders Learn from Outsiders? Evidence from Mergers and Acquisitions, *Journal of Finance* 60: 1951-1982.

Matsumoto, Dawn, Maarten Pronk, and Erik Roelofsen, 2011, What Makes Conference Calls Useful? The Information Content of Managers' Presentations and Analysts' Discussion Sessions, *The Accounting Review* 86: 1383-1414.

Mulsu, Volkan, Suresh Radhakrishnan, K. R. Subramanyam, and Dongkuk Lim, 2015, Forward-Looking MD&A Disclosures and the Information Environment, *Management Science* 61: 931-948.

Sautner, Zacharias, Laurence van Lent, Grigory Vilkov, and Ruishen Zhang, 2023, Firm-level Climate Change Exposure, *Journal of Finance* 78: 1449-1498.

Zhao, Xiaofei, 2017, Does Information Intensity Matter for Stock Returns? Evidence from Form 8-K Filings, *Management Science* 63: 1271-1656.

Zuo, Luo, 2016, The Informational Feedback Effect of Stock Prices on Management Forecasts, *Journal of Accounting and Economics* 61: 391-413.

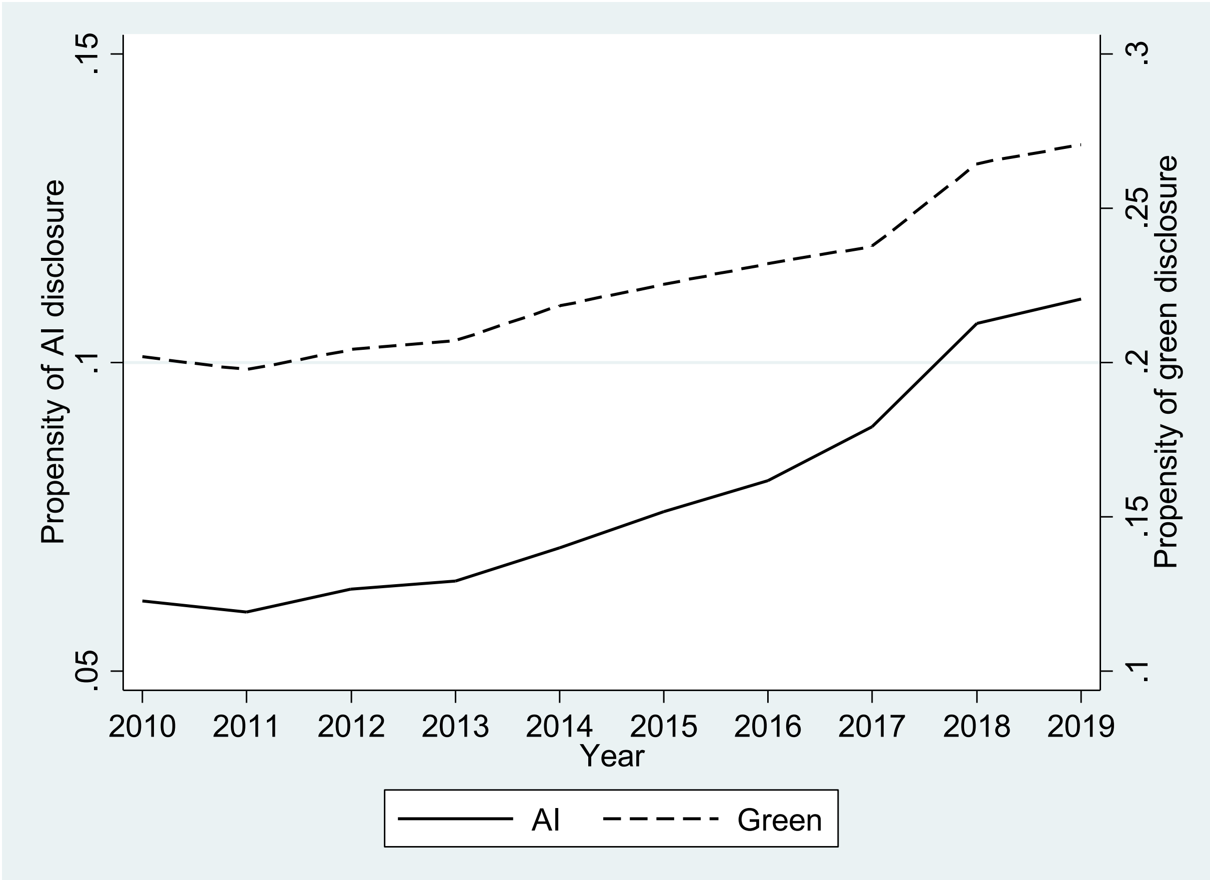

Figure 1: Time trend of emerging-technology related disclosure propensity

This figure plots the propensity of US public firms to discuss investment plans on emerging technologies in their earnings conference calls and 8-K filings from 2010 to 2019. The solid line denotes the number of AI-technology related disclosures divided by the total number of earnings conference calls and 8-K filings in a year. The dashed line denotes the number of green-technology related disclosures divided by the total number of earnings conference calls and 8-K filings in a year.

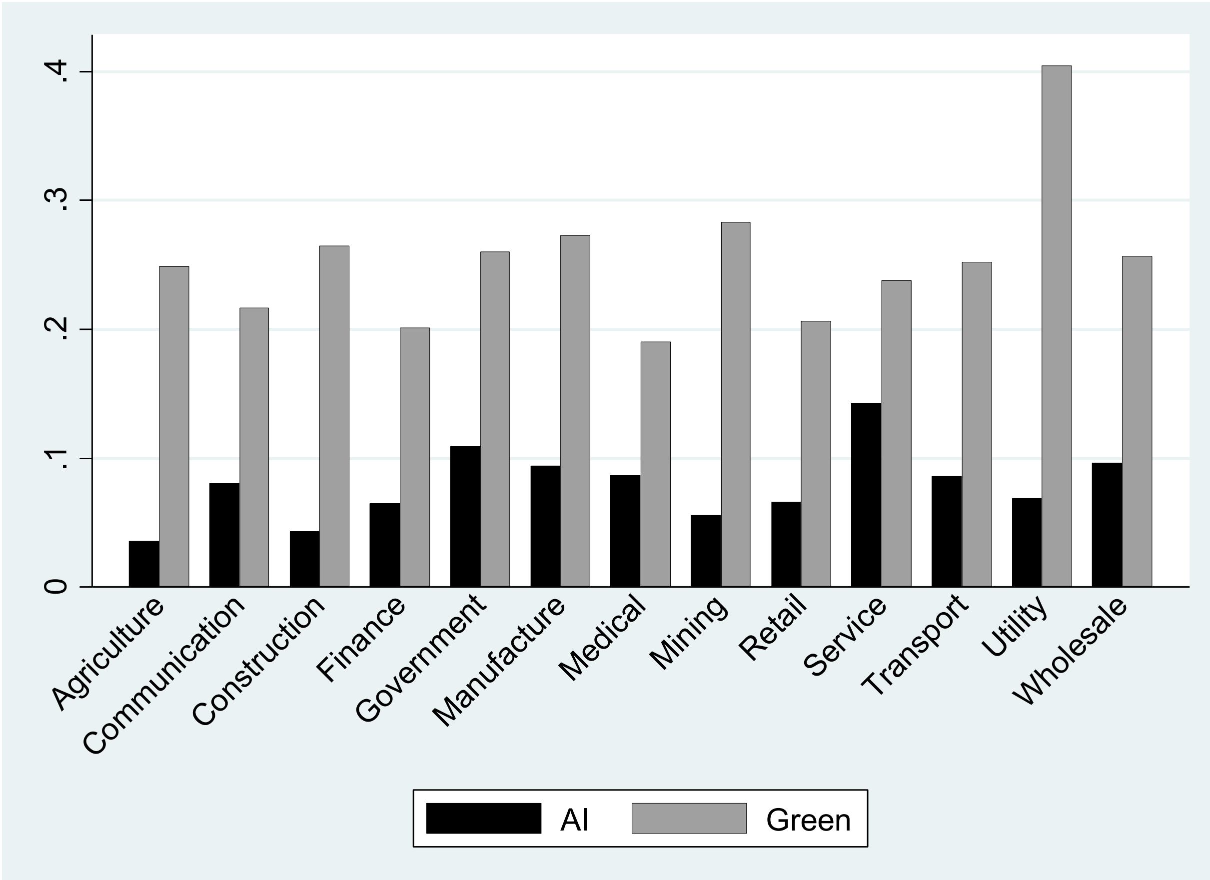

Figure 2: Industry distribution of emerging-technology related disclosure propensity

This figure plots the propensity of US public firms to discuss investment plans on emerging technologies across different industries. The black bar denotes the propensity to discuss AI-related investment plans, which is the number of AI-technology related disclosures in an industry over our sample period divided by the total number of conference calls and 8-K filings in that industry. The grey bar denotes the propensity to discuss green-related investment plans, which is the number of green-technology related disclosures in an industry over our sample period divided by the total number of earnings conference calls and 8-K filings in that industry.

Table 1: Summary statistics

This table presents summary statistics. Panels A and B present the descriptive statistics of the samples of AI-investment-related and green-investment-related disclosures between 2010 and 2019, respectively. Δ*AI Job Postings* (Δ*Green Job Postings*) is the change in the natural logarithm of one plus the weighted sum of AI-related (green-related) job postings by a firm from the year prior to an AI-investment-related (green-investment-related) corporate disclosure to the year after the disclosure. *FB* is a firm's market feedback on the AI/green-investment-related disclosure, i.e., the five-day ([-2, 2]) cumulative abnormal return surrounding the disclosure date (day *0*). *Firm Size* is the natural logarithm of the firm's quarterly sales (in $millions). *ROA* is the firm's quarterly operating income before depreciation divided by its total assets. *R&D ratio* is the firm's quarterly research and development expenses divided by its total sales. *Market-to-book Ratio* is the firm's market value of assets divided by its book value. *Firm Age* is the number of years since listing recorded in Compustat. *Cash Reserve* is the firm's quarterly cash and short-term investments divided by its total assets. All these firm characteristics are calculated at the nearest quarter end before the disclosure date. *Earning Surprise* is the actual earnings per share of the current quarter minus that of the same quarter in the previous year scaled by the latter. If the disclosure is an earnings conference call, *Earning Surprise* is calculated for the quarter corresponding to the conference call; otherwise, it is calculated for the nearest quarter prior to the disclosure date. *Disclosure Tone* is the sentiment of the disclosure calculated as the average sentiment score across sentences in the disclosure. Δ *Total Job Postings* is measured as the change in the natural logarithm of one plus the total number of job postings by the firm in a year from the year prior to an AI or green-investment-related disclosure to the year after the disclosure. All variables have been winsorized at their 1st and 99th percentiles.

Panel A: AI-investment-related corporate disclosures								
Variable	Obs	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
ΔAI Job Postings	41,263	0.088	0.333	-0.794	-0.004	0.000	0.167	1.445
FB	41,263	0.003	0.093	-0.291	-0.040	0.001	0.044	0.317
Firm Size	41,263	5.264	2.153	0.000	3.931	5.409	6.766	9.242
ROA	41,263	0.016	0.055	-0.303	0.007	0.025	0.040	0.161
R&D Ratio	41,263	0.210	0.841	0.000	0.000	0.000	0.109	6.102
Market-to-book Ratio	41,263	1.880	1.678	0.211	0.939	1.308	2.212	12.388
Firm Age	41,263	18.654	14.963	0.000	6.250	15.500	26.500	57.500
Cash Reserve	41,263	0.195	0.212	0.000	0.037	0.112	0.281	0.931
Earning Surprise	40,317	-0.004	1.410	-6.375	-0.278	0.000	0.222	7.000
Disclosure Tone	41,263	0.775	0.163	0.502	0.523	0.869	0.889	0.993
ΔTotal Job Postings	41,263	0.245	0.979	-2.303	-0.067	0.000	0.486	4.385
Panel B: Green-investment-related corporate disclosures								
Variable	Obs	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
ΔGreen Job Postings	81,442	0.057	0.420	-1.269	0.000	0.000	0.114	1.702
FB	81,442	0.001	0.078	-0.251	-0.034	0.001	0.039	0.247
Firm Size	81,442	6.340	1.806	0.000	5.343	6.523	7.589	9.242
ROA	81,442	0.023	0.042	-0.303	0.014	0.027	0.040	0.161
R&D Ratio	81,442	0.164	0.792	0.000	0.000	0.000	0.040	6.102
Market-to-book Ratio	81,442	1.695	1.545	0.211	0.841	1.167	1.930	12.388
Firm Age	81,442	24.265	16.805	0.000	10.250	20.750	37.500	57.500
Cash Reserve	81,442	0.144	0.183	0.000	0.026	0.073	0.181	0.931
Earning Surprise	80,730	0.011	1.399	-6.850	-0.251	0.000	0.246	6.778
Disclosure Tone	81,442	0.870	0.095	0.523	0.873	0.898	0.912	0.997
ΔTotal Job Postings	81,442	0.242	0.917	-2.048	-0.076	0.000	0.460	4.234

Table 2: Investment response to emerging-technology-related market feedback: Baseline analysis
This table presents the baseline analysis of a firm's investment response to emerging-technology-related market feedback. Panels A and B study AI-related and green-related investments, respectively. In Panel A, the dependent variable is Δ*AI Job Postings*. In Panel B, the dependent variable is Δ*Green Job Postings*. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure (i.e., [-2, 2] with disclosure date as day 0). *Firm FE* are indicators for each firm. *Industry* × *Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI Investment					
	Dependent Variable: ΔAI Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.087***	0.084***	0.067***	0.070***	0.053***
	(4.49)	(4.36)	(4.26)	(4.47)	(3.29)
Firm Size		0.021***	0.022***	0.024***	0.023***
		(10.85)	(13.81)	(13.03)	(3.04)
ROA		-0.053	-0.103	-0.117*	-0.029
		(-0.74)	(-1.61)	(-1.84)	(-0.33)
R&D Ratio		-0.005	-0.001	0.003	0.005
		(-1.60)	(-0.48)	(1.18)	(1.23)
Market-to-book Ratio		0.010***	0.009***	0.006***	0.002
		(4.66)	(4.67)	(3.34)	(0.70)
Firm Age		-0.001***	-0.000**	-0.000*	-0.003
		(-4.12)	(-2.36)	(-1.85)	(-0.75)
Cash Reserve		0.094***	0.087***	0.059***	0.045
		(5.19)	(5.77)	(3.48)	(1.37)
Earning Surprise			0.001	-0.000	-0.001
			(0.85)	(-0.08)	(-1.20)
Disclosure Tone			0.021*	0.022*	0.008
			(1.83)	(1.88)	(0.60)
ΔTotal Job Postings			0.215***	0.212***	0.215***
			(37.84)	(38.51)	(34.40)
Firm FE	No	No	No	No	Yes
Industry × Year FE	No	No	No	Yes	Yes
Observations	41,263	41,263	40,317	40,291	39,521
R-squared	0.001	0.017	0.411	0.444	0.551

Panel B: Green Investment					
	Dependent Variable: ΔGreen Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.101***	0.097***	0.058**	0.046**	0.048**
	(3.62)	(3.49)	(2.18)	(2.31)	(2.51)
Firm Size		0.014***	0.019***	0.017***	0.035***
		(5.97)	(8.55)	(9.38)	(4.19)
ROA		0.082	0.089	0.062	-0.064
		(1.10)	(1.27)	(0.98)	(-0.57)
R&D Ratio		0.012**	0.017***	0.012***	0.007
		(2.57)	(3.80)	(3.41)	(1.32)
MtB		-0.002	-0.004*	-0.004**	-0.003
		(-1.19)	(-1.91)	(-2.32)	(-0.84)
Firm Age		-0.000*	-0.000	-0.000	-0.010
		(-1.70)	(-0.05)	(-0.73)	(-1.25)
Cash Reserve		-0.004	-0.008	-0.019	0.069*
		(-0.17)	(-0.41)	(-1.12)	(1.82)
Earning Surprise			0.003	0.002*	0.005***
			(1.52)	(1.65)	(3.19)
Disclosure Tone			-0.053**	-0.005	0.004
			(-2.57)	(-0.22)	(0.21)
ΔTotal Job Postings			0.173***	0.160***	0.166***
			(21.83)	(46.75)	(47.25)
Firm FE	No	No	No	No	Yes
Industry × Year FE	No	No	No	Yes	Yes
Observations	81,442	81,442	80,730	80,730	80,596
R-squared	0.000	0.004	0.145	0.206	0.290

Table 3: Investment response to emerging-technology-related market feedback: Positive and negative market reactions

This table presents the analyses of a firm's investment response to emerging-technology-related market feedback when the reaction is either positive or negative. Panels A and B study AI-related and green-related investments, respectively. In Panel A, the dependent variable is Δ*AI Job Postings*. In Panel B, the dependent variable is Δ*Green Job Postings*. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. The sample in Column (1) of each panel includes corporate disclosures with positive market reactions (i.e., *FB*>0), and that in Column (2) includes disclosures with negative market reactions (i.e., *FB*<0). All other variables are defined as in Table 1 and Table 2. Column (3) includes all corporate disclosures in our baseline analysis in Table 2. *PosFB* equals *FB* if *FB*>0, and zero otherwise. *NegFB* equals *FB* when *FB*<0, and zero otherwise. Standard errors are clustered by firm. F-statistics and corresponding p-value testing the difference between coefficients of *PosFB* and *NegFB* are reported. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment				Panel B: Green investment			
Dependent Var.	ΔAI Job Postings			Dependent Var.	ΔGreen Job Postings		
Subsample	Positive FB	Negative FB	Full	Subsample	Positive FB	Negative FB	Full
	(1)	(2)	(3)		(1)	(2)	(3)
FB	0.039***	0.078**		FB	-0.034	0.080*	
	(3.06)	(2.48)			(-0.75)	(1.79)	
PosFB			0.021**	PosFB			-0.009
			(2.00)				(-0.24)
NegFB			0.070***	NegFB			0.105***
			(2.93)				(2.90)
F-stat			3.04	F-stat			3.27
P-value			0.081	P-value			0.071
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Firm FE	Yes	Yes	Yes
Ind. × Year FE	Yes	Yes	Yes	Ind. × Year FE	Yes	Yes	Yes
Observations	19,792	18,521	39,521	Observations	40,992	39,206	80,596
R-squared	0.591	0.578	0.551	R-squared	0.334	0.332	0.290

Table 4: Investment response to emerging-technology-related market feedback – Intraday stock price changes for earnings conference calls

This table presents the analysis of a firm's investment response to intraday stock price changes for earnings conference calls that announce emerging-technology-related investment plans. Columns (1) and (2) study AI-related and green-related investments, respectively. In column (1), the dependent variable is Δ*AI Job Postings*. In column (2), the dependent variable is Δ*Green Job Postings*. FB_{Hour} is the firm's stock price change in the hour when managers discuss their emerging-technology-related investment plans. $Return_{PreHour}$ is the firm's stock price change from the beginning of the earnings conference call until the time that managers start disclosing their emerging-technology-related investment plans. $Return_{PostHour}$ is the firm's stock price change from the end of the hour during which managers disclose their emerging-technology-related investment plans until the end of the earnings conference call. *Firm FE* are indicators for each firm. *Industry* × *Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent variable:	ΔAI Job Postings	ΔGreen Job Postings
	(1)	(2)
FB_{Hour}	0.260**	0.146*
	(1.99)	(1.70)
$Return_{PreHour}$	-0.208	-0.029
	(-0.74)	(-0.12)
$Return_{PostHour}$	0.107	0.080
	(0.65)	(0.89)
Firm Size	0.043*	0.023
	(1.86)	(1.25)
ROA	-0.043	-0.237
	(-0.16)	(-0.99)
R&D Ratio	-0.005	0.009
	(-0.30)	(0.66)
Market-to-book Ratio	-0.002	-0.006
	(-0.21)	(-0.92)
Firm Age	0.035***	-0.005
	(2.78)	(-0.38)
Cash Reserve	0.140	-0.096
	(1.53)	(-1.17)
Earning Surprise	-0.000	0.001
	(-0.10)	(0.32)
Disclosure Tone	0.001	-0.012
	(0.02)	(-0.40)
ΔTotal Job Postings	0.300***	0.150***
	(18.17)	(10.92)
Firm FE	Yes	Yes
Industry × Year FE	Yes	Yes
Observations	4,953	10,738
R-squared	0.660	0.487

Table 5: Subsample analysis of earnings conference calls and focused 8-K filings

This table presents the analysis of a firm's investment response to emerging-technology-related market feedback using subsamples of earnings conference calls and 8-K filings separately. Panels A and B study AI-related and green-related investments respectively. In Panel A, the dependent variable is Δ*AI Job Postings*. In Panel B, the dependent variable is Δ*Green Job Postings*. The subsamples of emerging-technology-related disclosures are earnings conference calls, 8-K filings, and "focused" 8-K filings that have only one item in Columns (1), (2), and (3), respectively. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure (i.e., [-2, 2] with disclosure date as day 0). *Firm FE* are indicators for each firm. *Industry × Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment				Panel B: Green investment			
Dep. Var.	ΔAI Job Postings			Dep. Var.	ΔGreen Job Postings		
	Conference Call	8K	Stand-alone 8K		Conference Call	8K	Stand-alone 8K
	(1)	(2)	(3)		(1)	(2)	(3)
FB	0.083***	0.056***	0.067*	FB	0.073**	0.077**	0.114***
	(2.96)	(2.98)	(1.81)		(2.06)	(2.47)	(3.04)
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Firm FE	Yes	Yes	Yes
Ind×Year FE	Yes	Yes	Yes	Ind×Year FE	Yes	Yes	Yes
Obs.	16,991	28,493	8,682	Obs.	49,314	66,334	33,948
R-squared	0.583	0.576	0.677	R-squared	0.314	0.318	0.388

Table 6: Cross-sectional tests based on investors' AI/green related expertise

This table presents the cross-sectional analyses of baseline regressions based on institutional investors' expertise in emerging technologies. We infer institutions' expertise from their portfolio holdings. Panel A examines AI-related investments and the expertise of institutions in AI technologies. We first classify AI industries as the top five 3-digit Cooperative Patent Classification (CPC) technology classes with the highest percentage of AI patents. AI patents are defined based on the AI prediction scores provided by the United States Patent and Trademark Office (USPTO) Artificial Intelligence Patent Dataset (AIPD). We define a patent to be an AI-related one if any of its eight AI prediction scores (corresponding to the eight AI components identified by AIPD, namely, machine learning, evolutionary computation, NLP, speech, vision, knowledge processing, AI hardware, and planning and control) is above 50%. We then identify a firm as AI-related (and assign an AI-score of one to it) if its major patent technology area in a year is one of the five AI industries. Otherwise, the firm is assigned a zero AI-score. We measure an institution's expertise in AI technologies in a given quarter as the weighted average AI-score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Then, we take average of the institution's quarterly AI expertise score across the four quarters prior to a disclosure event. For each AI-investment-related disclosure, the focal firm's average institutional AI expertise score, *InstitutionAIExpertise*, is calculated as the value-weighted average of the institutional AI expertise score across all institutional investors, with the weight being the number of the focal firm's outstanding shares held by the institution at the quarter end immediately prior to the disclosure event. Panel B examines green-related investments and the expertise of institutions in green technologies. We measure an institution's expertise in green technologies in a given quarter as the weighted average environmental score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Next, we take average of the institution's quarterly green expertise score across the four quarters prior to a disclosure event. For each green-related corporate disclosure, the focal firm's average institutional green expertise score, *InstitutionGreenExpertise*, is then calculated as the value-weighted average of the institutional green expertise score across all its institutional investors. Each institutional investor's weight is the number of the focal firm's outstanding shares held by the institution at the quarter end immediately prior to the disclosure event. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment	
Dependent Variable:	ΔAI Job Postings
	(1)
FB × InstitutionAIExpertise	0.305***
	(3.22)
FB	-0.024
	(-0.90)
InstitutionAIExpertise	0.010
	(0.38)
Controls	Yes
Firm FE	Yes
Industry × Year FE	Yes
Observations	39,521
R-squared	0.551

Panel B: Green investment	
Dependent Variable:	ΔGreen Job Postings
	(1)
FB × InstitutionGreenExpertise	0.184**
	(2.03)
FB	-0.055
	(-1.11)
InstitutionGreenExpertise	-0.035
	(-0.71)
Controls	Yes
Firm FE	Yes
Industry × Year FE	Yes
Observations	80,596
R-squared	0.290

Table 7: Cross-sectional tests based on firms' exposure to technology competition

This table presents the cross-sectional analyses of a firm's AI investment response to market feedback based on its exposure to technology competition. The dependent variable is Δ *AI Job Postings*. Following Cao et al. (2018), we measure a firm's technology peer pressure (*TPP*) as the weighted average of peer firms' R&D stock relative to its own R&D stock. The weight is the closeness between the focal firm and a peer firm in the product market space spanned by 4-digit SIC industries. Specifically, we first construct a product-market "presence" vector for each firm, whose element is the fraction of the firm's total sales over the past two years that are derived from each 4-digit SIC industry. Then we calculate the cosine similarity between the vector of the focal firm and that of a peer firm and use it as the weight for that peer. Column (1) examines firms whose *TPP* is above sample median in the year of the corporate disclosure, and Column (2) examines firms whose *TPP* is below sample median. In Column (3), *HighTPP* is a dummy variable that equals one if the firm's *TPP* is above the sample median in the disclosure year, and zero otherwise. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Dependent Variable: ΔAI Job Postings		
Sample	High TPP	Low TPP	Full
	(1)	(2)	(3)
FB	0.079***	-0.002	0.000
	(3.90)	(-0.08)	(0.01)
FB × HighTPP			0.077**
			(2.46)
HighTPP			-0.017
			(-1.49)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	21,994	17,272	39,521
R-squared	0.597	0.582	0.552

Table 8: Cross-sectional tests based on the Paris Agreement

This table presents the cross-sectional analysis of a firm's green investment response to market feedback before and after the announcement of the Paris Agreement in December 2015. The dependent variable is Δ*Green Job Postings*. The announcement of the Paris Agreement draws significant attention to environmental issues. Column (1) includes green-investment-related corporate disclosures in 2015 and earlier; and Column (2) includes those announced in 2016 and later. In Column (3), *After* is a dummy variable that equals one if the disclosure announcement date is in 2016 and later, and zero otherwise. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	ΔGreen Job Postings		
Sample	Before (<=Year 2015)	After (>=Year 2016)	Full
	(1)	(2)	(3)
FB	-0.003	0.070***	-0.015
	(-0.07)	(3.26)	(-0.38)
FB × After			0.088**
			(1.97)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	32,889	47,659	80,596
R-squared	0.360	0.318	0.290

Table 9: More facets of the managerial learning

This table presents the analysis of more facets of the managerial learning by exploring the nature and timing of emerging corporate policies. Panel A presents the analysis of a firm's investment response to conventional-technology-related market feedback. Following Abis and Veldkamp (2024), we first compile a list of conventional-technology-related keywords. The sample of conventional-technology-related corporate disclosures are then defined as earnings conference calls or 8-K filings with at least one sentence that includes: (1) one or more conventional-technology-related keywords, (2) one or more forward-looking keywords, and (3) one or more investment related keywords in the same sentence. We exclude corporate disclosures that are AI-related. A firm's investment in conventional technologies is measured by its conventional-technology-related job postings. The dependent variable, Δ *Conventional Job Postings*, is defined as the difference between the natural logarithm of one plus the weighted sum of conventional-related job postings by a firm in the year after a conventional-investment-related corporate disclosure and the natural logarithm of one plus the weighted sum of conventional-related job postings by the firm in the year prior to the disclosure. Each job posting is weighted by the average conventional-technology-relevance score across all skills required for the job (following Abis and Veldkamp, 2024). Panel B examines the associations between AI/green investment changes and announcement returns when the related discussions in the disclosures only refer to the emerging technologies in a general way but are not about investment plans. The sample consists of earnings conference calls and 8-K filings with at least one sentence that includes both AI/green related keywords and forward-looking keywords, but without any investment-related keywords in the same sentence. In Panel B, the dependent variable is Δ*AI Job Postings* in Columns (1) and (2) and is Δ*Green Job Postings* in Columns (3) and (4). *FB* is a firm's five-day cumulative abnormal return surrounding the AI/green-investment-related disclosure date. *NonInvFB* is a firm's five-day cumulative abnormal return surrounding the date of a disclosure that mentions AI/green technologies but no investment plans. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Investment response to conventional-technology-related market feedback					
	Dependent Variable: ΔConventional Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.015	0.014	0.003	0.009	0.008
	(1.19)	(1.08)	(0.23)	(0.77)	(0.61)
Firm Size		0.010***	0.010***	0.011***	0.003
		(5.57)	(5.92)	(6.28)	(0.60)
ROA		-0.014	-0.010	-0.013	0.042
		(-0.41)	(-0.28)	(-0.38)	(0.81)
R&D Ratio		0.003**	0.003**	0.005***	0.001
		(2.25)	(2.43)	(3.25)	(0.37)
Market-to-book Ratio		-0.000	-0.001	-0.000	0.000
		(-0.31)	(-0.81)	(-0.39)	(0.13)
Firm Age		0.000	0.000	-0.000	-0.011***
		(0.22)	(0.40)	(-0.01)	(-2.60)
Cash Reserve		0.037***	0.039***	0.026*	0.023
		(2.79)	(2.95)	(1.80)	(0.83)
Earning Surprise			0.001	0.001	0.001
			(0.97)	(0.85)	(0.58)
Disclosure Tone			-0.010	0.001	0.029*
			(-0.87)	(0.04)	(1.71)
ΔTotal Job Postings			0.045***	0.042***	0.042***
			(11.18)	(12.00)	(10.12)
Firm FE	No	No	No	No	Yes
Industry × Year FE	No	Yes	Yes	Yes	Yes
Observations	20,193	15,746	15,063	15,020	14,339
R-squared	0.000	0.009	0.066	0.155	0.275

Panel B: Feedback to non-investment-related disclosures				
Dependent Variable:	ΔAI Job Postings		ΔGreen Job Postings	
	(1)	(2)	(3)	(4)
NonInvFB	0.028	0.011	0.024	0.010
	(0.91)	(0.65)	(0.52)	(0.25)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
Observations	6,759	5,674	7,032	6,325
R-squared	0.370	0.660	0.119	0.465

Table 10: A placebo test on past (pre-disclosure) investment changes

This table presents the analysis of the association between firms' past (i.e., pre-disclosure) AI/green investment changes and the market reactions to their AI/green-investment-related disclosures. The dependent variable in columns (1) and (2), *Past ΔAI Job Postings*, is the difference between the natural logarithm of one plus the weighted sum of AI-related job postings by the firm in the year before the corporate disclosure and the natural logarithm of one plus the weighted sum of AI-related job postings by the firm two years prior to the disclosure. In columns (3) and (4), the dependent variable in *Past ΔGreen Job Postings*, is the difference between the natural logarithm of one plus the weighted sum of green job postings by the firm in the year before the corporate disclosure and the natural logarithm of one plus the weighted sum of green job postings by the firm two years prior to the disclosure (i.e., two years prior to the disclosure). *FB* is a firm's five-day cumulative abnormal return surrounding the AI/green-investment-related disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Past ΔAI Job Postings		Past ΔGreen Job Postings	
	(1)	(2)	(3)	(4)
FB	0.000	-0.011	-0.042	-0.018
	(0.00)	(-0.67)	(-1.27)	(-0.56)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
Observations	39,673	38,879	79,128	78,993
R-squared	0.445	0.596	0.207	0.353

Table 11: A placebo test on non-disclosure windows

This table presents the analysis of a firm's investment response to the firm's stock market changes in 5-day windows other than the one surrounding the disclosure date. In Panel A, *PlaceboFB[-7,-3]* is the firm's five-day cumulative abnormal return from seven days prior to the disclosure date to three days before. In Panel B, *PlaceboFB[3,7]* is the firm's five-day cumulative abnormal return from three days after the disclosure date to seven days after. Δ*AI Job Postings* is the change in the natural logarithm of one plus the weighted sum of AI-related job postings by a firm from the year prior to an AI-investment-related corporate disclosure to the year after the disclosure. Δ*Green Job Postings* is the change in the natural logarithm of one plus the weighted number of green job postings by a firm from the year prior to a green-investment-related corporate disclosure to the year after the disclosure. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Cumulative abnormal market reactions in pre-disclosure short window				
Dependent Variables	ΔAI Job Postings		ΔGreen Job Postings	
	(1)	(2)	(3)	(4)
PlaceboFB[-7, -3]	-0.013	-0.020	-0.010	0.005
	(-0.50)	(-0.76)	(-0.19)	(0.13)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
Observations	40,313	39,513	80,728	80,594
R-squared	0.411	0.550	0.145	0.290

Panel B: Cumulative abnormal market reactions in post-disclosure short window				
Dependent Variables	ΔAI Job Postings		ΔGreen Job Postings	
	(1)	(2)	(3)	(4)
PlaceboFB[3, 7]	0.005	-0.014	0.008	-0.017
	(0.20)	(-0.52)	(0.17)	(-0.38)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
Observations	40,313	39,516	80,725	80,591
R-squared	0.411	0.550	0.145	0.290

Table 12: Investment response to peer firms' emerging-technology-related market feedback

This table presents the pair-level analysis of a firm's investment response to each of its product market peers' emerging-technology-related market feedback. For each emerging-technology-related corporate disclosure of a firm, we analyze the AI/green investment response to its market feedback by each of the firm's product market peers (those with TNIC-3 scores above sample median). Panels A and B study AI-related and green-related investment, respectively. In Panel A, the dependent variable is Δ*AI Job Postings*. In Panel B, the dependent variable is Δ*Green Job Postings*. *PeerFB* is each peer firm's five-day cumulative abnormal return surrounding its emerging-technology-investment-related disclosure date. *FocalFB* is the focal firm's five-day cumulative abnormal return surrounding its peer's emerging-technology-investment-related disclosure date. *Firm FE* are indicators for each focal firm. *Pair FE* are indicators for each pair of a focal firm and its peer firm. *Industry* × *Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1. Standard errors are double clustered by focal firm and peer firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment			
	Dependent Variable: ΔAI Job Postings		
	(1)	(2)	(3)
PeerFB	0.002	0.001	0.001
	(1.32)	(0.91)	(1.13)
FocalFB		0.008	0.006
		(1.65)	(1.21)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	No
Industry × Year FE	Yes	Yes	Yes
Pair FE	No	No	Yes
Observations	1,226,178	1,226,018	1,225,789
R-squared	0.457	0.457	0.520

Panel B: Green investment			
	Dependent Variable: ΔGreen Job Postings		
	(1)	(2)	(3)
PeerFB	0.008**	0.007**	0.007**
	(2.13)	(1.97)	(2.12)
FocalFB		0.020	0.012
		(1.03)	(0.73)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	No
Industry × Year FE	Yes	Yes	Yes
Pair FE	No	No	Yes
Observations	1,823,274	1,823,104	1,822,906
R-squared	0.250	0.250	0.368

Table 13: Long-run performance of following the market feedback

This table presents the analysis of comparing the long-term performance of a firm when it follows emerging-technology-related market feedback and that when it does not follow the feedback. Panels A and B study the performance outcomes of AI-related and green-related investments respectively. The dependent variable in Columns (1) to (3) is the average return on assets (ROA) of the firm in the three years after an emerging-technology-related disclosure. The dependent variable in Columns (4) to (6) is the average stock return of the firm in the three years after an emerging-technology-related disclosure. In Panel A, *Follow* is a dummy variable that equals one if the firm increases its AI job postings (i.e., Δ *AI Job Postings*>0) following positive market feedback or decreases its AI job postings ((i.e., Δ *AI Job Postings*<0)) following negative market feedback, and zero otherwise. In Panel B, *Follow* is a dummy variable that equals one if the firm increases its green job postings (i.e., Δ*Green Job Postings*>0) following positive market feedback or decreases its green job postings (i.e., Δ*Green Job Postings*<0) following negative market feedback, and zero otherwise. *Firm FE* are indicators for each focal firm. *Industry* × *Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment						
Dependent Variables	$ROA_{t+1\rightarrow t+3}$			$Return_{t+1\rightarrow t+3}$		
Sample	Full	Negative CAR	Positive CAR	Full	Negative CAR	Positive CAR
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	0.002*	0.005**	-0.002	-0.007	0.024*	-0.010
	(1.83)	(2.14)	(-0.62)	(-1.35)	(1.86)	(-0.99)
Firm Size	0.004	-0.004	0.009*	-0.074***	-0.057**	-0.084***
	(0.91)	(-0.70)	(1.81)	(-4.12)	(-2.39)	(-3.94)
R&D ratio	-0.013*	-0.007	-0.016	-0.028	-0.040	-0.038
	(-1.91)	(-1.20)	(-1.49)	(-0.89)	(-1.04)	(-0.92)
Cash Reserve	-0.014	-0.037*	-0.007	-0.188***	-0.276***	-0.153**
	(-0.98)	(-1.67)	(-0.45)	(-2.96)	(-2.86)	(-2.20)
Sale Growth	-0.003	-0.002	-0.005**	0.007	-0.021	0.029**
	(-1.50)	(-0.69)	(-1.98)	(0.70)	(-1.14)	(2.22)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	13,278	4,382	8,084	13,278	4,382	8,084
R-squared	0.941	0.955	0.948	0.691	0.810	0.662

Panel B: Green investment						
Dependent Variables	$\mathrm{ROA}_{t+1\to t+3}$			$\mathrm{Return}_{t+1\to t+3}$		
Sample	Full	Negative CAR	Positive CAR	Full	Negative CAR	Positive CAR
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	0.001	0.020***	-0.001	0.052*	0.056**	0.013
	(0.92)	(3.17)	(-0.20)	(1.94)	(2.10)	(0.37)
Firm Size	-0.004	0.002	-0.009*	-0.026**	-0.040***	0.005
	(-1.33)	(0.48)	(-1.83)	(-2.06)	(-4.39)	(0.32)
R&D ratio	0.001	-0.002	0.004	0.022*	0.054***	0.017
	(0.13)	(-0.35)	(0.66)	(1.96)	(2.98)	(1.24)
Cash Reserve	0.032**	0.012	0.076***	-0.135**	-0.036	-0.292*
	(2.25)	(0.78)	(2.81)	(-2.14)	(-0.80)	(-1.80)
Sale Growth	0.002	-0.001	0.003	0.005	0.014*	-0.004
	(0.92)	(-0.29)	(0.91)	(0.68)	(1.69)	(-0.37)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,456	15,362	6,666	22,456	15,362	6,666
R-squared	0.923	0.935	0.942	0.596	0.648	0.770

Table 14: Alternative measures of emerging-technology investments

This table presents robustness tests of the baseline analysis using alternative measures of emerging-technology investments. In Columns (1) to (3), the dependent variable, Δ *AI Patents*, is the difference between the natural logarithm of one plus the number of AI patents generated during the N-year period (N=1, 2, 3) after an AI-investment-related corporate disclosure, and that generated during the one-year period prior to the disclosure. AI patents are defined based on the AI prediction scores provided by the United States Patent and Trademark Office (USPTO) Artificial Intelligence Patent Dataset (AIPD). We define a patent to be an AI-related one if any of its eight AI prediction scores (corresponding to the eight AI components identified by AIPD, namely, machine learning, evolutionary computation, NLP, speech, vision, knowledge processing, AI hardware, and planning and control) is above 50%. In Columns (4) to (6), the dependent variable, Δ *Green Patents*, is the difference between the natural logarithm of one plus the number of green patents generated during the N-year period (N=1, 2, 3) after a green-investment-related corporate disclosure, and that generated during the one-year period prior to the disclosure. Green patents are defined based on the list of IPC/CPC codes from the Organization for Economic Co-operation and Development (OECD). In Column (7), the dependent variable is Δ*Total GHG emission*, measured as the change in the natural logarithm of one plus a firm's total greenhouse gas (GHG) emissions (measured in equivalents of metric tons of CO_2) from the year prior to a green-investment-related corporate disclosure to the year after the disclosure. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Δ AI Patents			Δ Green Patents			Δ Total GHG emission
	1-year	2-year	3-year	1-year	2-year	3-year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FB	0.050***	0.053**	0.046*	0.007***	0.008**	0.006	-0.596***
	(2.74)	(2.53)	(1.86)	(2.59)	(2.05)	(1.46)	(-2.84)
Firm Size	0.009	0.010	0.011	0.002	0.003	0.005	-0.138
	(0.59)	(0.47)	(0.48)	(1.46)	(1.20)	(1.31)	(-1.14)
ROA	0.111	0.206	0.413**	-0.022	-0.016	-0.043	-2.589*
	(0.93)	(1.30)	(2.49)	(-1.54)	(-0.78)	(-1.52)	(-1.82)
R&D Ratio	-0.008	-0.012	0.008	-0.001	-0.001	-0.002	-0.007
	(-0.97)	(-1.08)	(0.77)	(-1.56)	(-1.13)	(-1.55)	(-0.07)
Market-to-book Ratio	0.006	0.004	0.002	0.001	0.000	-0.000	0.130***
	(0.92)	(0.47)	(0.21)	(1.15)	(0.13)	(-0.40)	(2.82)
Firm Age	-0.002	-0.002	0.004	0.001	0.001	0.000	-1.595***
	(-0.56)	(-0.48)	(0.69)	(1.62)	(0.93)	(0.35)	(-38.95)
Cash Reserve	-0.014	-0.063	-0.111*	-0.003	-0.013	-0.017	0.839*
	(-0.25)	(-0.84)	(-1.68)	(-0.45)	(-1.29)	(-1.23)	(1.79)
Sales Growth	-0.004	-0.007	-0.005	-0.001	-0.002	-0.003	0.153**
	(-0.47)	(-0.61)	(-0.36)	(-1.22)	(-1.39)	(-1.43)	(2.26)
Earning Surprise	0.001	0.001	-0.002	-0.000	0.000	0.000	0.121***
	(0.69)	(0.47)	(-0.84)	(-0.64)	(0.11)	(0.11)	(2.60)
Disclosure Tone	-0.034	-0.044	-0.062*	-0.001	-0.005	-0.008	1.012***
	(-1.37)	(-1.26)	(-1.65)	(-0.14)	(-0.73)	(-0.95)	(5.70)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,187	26,235	18,103	111,102	105,110	92,760	88,089
R-squared	0.629	0.702	0.737	0.393	0.443	0.583	0.601

Appendix Table A1: Examples of AI/green technology, investment, and forward-looking keywords

AI technology	Green technology	Investment	Forward-looking
Artificial Intelligence	Renewable Energy	Capital Investment	Anticipate
Computer Vision	Electric Vehicle	Capital Spending	Forecast
Machine Learning	Solar Energy	To Be Early On	Expect
Natural Language Processing	Greenhourse Gas	Clinical Trial	Plan
Neural Network	Carbon Emission	Research Development	Outlook
Image Recognition	Energy Regulatory	Collaborative Partner	Going To
Deep Learning	Bioeconomy	Product Line	Aim To
Reinforcement Learning	Clean Energy	Joint Venture	Opportunity
Bayesian Network	Climate Change	Expected Completed	Look Forward
Supervised Learning	Carbon Neutral	Business Development	Move Forward
Automatic Speech Recognition	Water Discharge	Plant Seed	Future
Sentiment Classification	Carbon Tax	See An Opportunity	Potentially
Word2Vec	Global Warm	Take A Chance	Target
Torch	Carbon Dioxide	Collaboration	Promise
Random Forest	Environmental-friendly	Training Program	Prospect

Appendix B1: Examples of AI/green-investment-related corporate disclosures

Panel A: Focused 8-K filings

On February 10, 2017, Ford Motor Company made a news release concerning its investment in Argo AI in item 8.01**:**

Item 8.01. Other Events.

Our news release dated February 10, 2017 concerning our investment in Argo AI is filed as Exhibit 99 to this Report and incorporated by reference herein.

Item 9.01. Financial Statements and Exhibits.

EXHIBITS*

Designation	Description	Method of Filing
Exhibit 99	News release dated February 10, 2017 concerning Argo AI	Filed with this Report

In exhibit 99, Ford further elaborated on its vision and enthusiasm for the investment.

San Francisco, Feb. 10, 2017 – Ford Motor Company (NYSE: F) today announces it is investing $1 billion during the next five years in Argo AI, an artificial intelligence company, to develop a virtual driver system for the automaker's autonomous vehicle coming in 2021 - and for potential license to other companies.

Founded by former Google and Uber leaders, Argo AI is bringing together some of the most experienced roboticists and engineers working in autonomy from inside and outside of Ford. The team of experts in robotics and artificial intelligence is led by Argo AI founders Bryan Salesky, company CEO, and Peter Rander, company COO. Both are alumni of Carnegie Mellon National Robotics Engineering Center and former leaders on the self-driving car teams of Google and Uber, respectively.

"The next decade will be defined by the automation of the automobile, and autonomous vehicles will have as significant an impact on society as Ford's moving assembly line did 100 years ago," said Ford President and CEO Mark Fields. "As Ford expands to be an auto and a mobility company, we believe that investing in Argo AI will create significant value for our shareholders by strengthening Ford's leadership in bringing self-driving vehicles to market in the near term and by creating technology that could be licensed to others in the future."

The current team developing Ford's virtual driver system - the machine-learning software that acts as the brain of autonomous vehicles - will be combined with the robotics talent and expertise of Argo AI. This innovative partnership will work to deliver the virtual driver system for Ford's SAE level 4 self-driving vehicles.

Ford will continue to lead on development of its purpose-built autonomous vehicle hardware platform, as well as on systems integration, manufacturing, exterior and interior design, and regulatory policy management.

Panel B: Earnings conference calls

AI-investment-related disclosures:

eBay Inc., Q2 2016 Earnings Call by Devin N. Wenig - President, Chief Executive Officer & Director "I think that when I look out to the future, we're also planting seeds, because I think that the impact of AI will be much more significant on commerce eventually. I think that when we see now the way large scale datasets are being used by algorithms through things like GPUs and the cloud, to me AI is going to be the next platform revolution. And just like eBay was early on the Internet, was early on mobile. *I want us to be early on AI.* …When I look out a few years, it's going to be significant for a massive improvement to personalization for consumers and targeting to sellers. So, *we're building that capability now*, possibly a little bit in advance of when that platform revolution comes."

eBay Inc., Q4 2016 Earnings Conference Call "We have delivered against our financial commitments…. The strong revenue performance also e*nabled us to invest more significantly in our product and technology*, planting seeds *in the areas of AI and machine learning* that will provide the foundation of our future. *We intend to drive even more progress* against our key objectives, and this is reflected in our guidance, which implies meaningful *growth acceleration in our marketplace platform*."

Procter & Gamble Company, Q3 2017 Earnings Call "We're *digitizing our manufacturing operations and automating with robotics using*, for example, *collaborative robots* to automate activities like palletizing, and *autonomous vehicles* to move materials and pallets within our operations. We see an opportunity for additional $1 billion of savings from transportation, warehousing and other cost of goods sold."

Green-investment-related disclosures:

Duke Energy Corporation, Q4 2016 Earnings Call: "I want to spend the next few minutes *offering insight into our long-term vision* for Duke Energy…. Our industry is undergoing transformation, from increasing customer and stakeholder expectations to rapid technology development and new public policy requirements….. *We will invest at areas* that position us well for this transformation; strengthening and modernizing our energy grid, *generating cleaner energy through natural gas and renewables*…. We will generate cleaner energy through natural gas and renewables, *investing $11 billion as we move to a lower-carbon future*. … Let me spend a few minutes on each investment area…. *Our next major investment platform focuses on generating cleaner energy*…… *In the next 10 years, we will invest $11 billion*, increasing new, highly-efficient natural gas generation to 35% of our portfolio, and cleaner renewable energy sources to approximately 10%."

Exxon Mobil Corporation, Exxon Mobil Corporation 2017 Analyst Meeting: "Very pleased to be here this morning to share our business' strategies and *our investment plans*… One of *our long-standing imperatives is the development and application of new technologies*. We have a commitment to fundamental science, *spending about $1 billion annually on research and development*. Through this sustained investment, ExxonMobil continues to develop and deploy new technologies that add significant value…. T*echnology is also helping us to address the risk posed by climate change.* As society looks for affordable energy solutions with lower greenhouse gas emissions, advancement in technology will be critical.…. *Our plan is to* selectively invest in projects that add the most value and are resilient in lower price environments."

Alphabet Inc., 2015 Annual Meeting of Stockholders Conference Call: ***Shareholder question/criticize the project:*** "*This proposal asks that management tell Google shareholders if their investments in renewables makes economic sense. Management says its goal is a 100% renewable like electricity, but they* *don't explain why this is in the best interest of Google's owners, that's us*. We ask management to compare buying power from the local power suppliers with Google's investments in renewable but intermittent sources of electricity. … *I started my career in energy about 60 years ago*, and worked on making it, saving it, moving it and with a few others *invented the main method for converting biomass into electricity* used in California. …Please vote yes on this proposal, so we can find out if Google is spending our dollars wisely." ***Shareholder support the project:*** "Good morning. My name is Abigail Shaw from NorthStar Asset Management in Boston. *I'd like to take this opportunity to commend Google for its good work on and commitment to renewable energy*. The final two shareholder proposals on today's docket seem to disagree but what is quickly becoming a fundamental truth. *Action in favor of the environment is good business*. … *Further supporting climate change policy is a smart way to safeguard the company's investments*… Google clearly understands the importance of committing to cleaner our energy. It is both good for business and good for the future of our world."