

Market Feedback about Emerging Technologies

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Abstract

How do firms make decisions on investments in emerging technologies? We find that firms adjust AI/green investments in response to market reactions to announcements of such emerging-technology investment plans. Through a battery of tests, we show that this pattern is more likely due to active managerial learning from the market than alternative explanations such as a passive reflection of underlying fundamentals that drive both market reactions and corporate actions. Firms are more likely to act on feedback about emerging technologies than about other investments, particularly when market participants have more expertise in these areas and when firms face greater uncertainty.

Keywords: Emerging Technologies, Artificial Intelligence, Green Investment, Feedback, Managerial Learning
JEL codes: G14, G31, D22, E22, J23

1 Introduction

The emergence of new technologies confronts firms with difficult decisions on resource allocation. Contemplating investments in these emerging technologies, firm managers have to assess the opportunities in a constantly changing environment without past records to learn from and with limited models of the costs and benefits involved. In recent years, we have seen two such emerging technologies – artificial intelligence (AI) and green (i.e., climate/environment-related) technologies – rising to huge prominence and increasingly capturing the attention of firm managers. How did they decide whether and how to invest in these technologies? What sources of information did they rely on for such decisions? Having better answers to these questions is crucial not only for understanding firms’ investment behaviors but also for understanding modern societies’ technological transformation more broadly. After all, the collective decisions of different firms determine the extent of emerging technology investment and the scope of economic transformation that could follow.

In this paper, we look at a primary source of information – the stock market – and investigate how it has been used in the process of emerging technology investment. Financial markets are thought to be a powerful source of information since they aggregate the opinions of a diverse body of investors, and are both forward-looking and quickly responsive to announcements and economic developments. A growing strand of literature has argued that informational feedback from the financial markets can help guide the decision-making of corporate managers.¹ Building on these insights, we examine how firms use information from the stock market when deciding on their investments in AI and green technologies.

To identify the information from the market, we measure the stock market’s reaction to firms’ announcements of upcoming investments in AI and green technologies. We then study how firms

¹See, e.g., [Chen, Goldstein, and Jiang \(2007\)](#), [Luo \(2005\)](#), [Bakke and Whited \(2010\)](#), [Edmans, Goldstein, and Jiang \(2012\)](#), [Bai, Philippon, and Savov \(2016\)](#), [Zuo \(2016\)](#), [Edmans, Jayaraman, and Schneemeier \(2017\)](#), [Dessaint, Foucault, Frésard, and Matray \(2019\)](#), and [Jayaraman and Wu \(2020\)](#) for empirical evidence. [Bond, Edmans, and Goldstein \(2012\)](#) and [Goldstein \(2023\)](#) provide reviews of the empirical and theoretical literatures discussing some of the main tensions and implications that emerge from market feedback.

adjust their investments in these emerging technologies in response to this market reaction. Our analysis begins with the development of a unique dataset of firms’ disclosures of planned investments in AI and green technologies based on their earnings conference calls and 8-K filings.² For the purpose of identifying such disclosures, we use the “anchor-phrase” method of textual analysis in the fashion of [Hoberg and Maksimovic \(2015, 2022\)](#), [Hoberg and Moon \(2017\)](#), and [Frésard, Hoberg, and Phillips \(2020\)](#). To focus on disclosures that are forward-looking in nature, we ensure that the discussion of the AI/green investments is about future plans instead of ongoing projects. Our sample includes 40,317 AI-related and 80,730 green-related disclosures announced between 2010 and 2019, during which the fraction of earnings conference calls and 8-K filings discussing such investment plans grew substantially.

In order to assess subsequent firms’ decisions, we use measures that are directly correlated with firms’ green and AI investments. Following [Babina, Fedyk, He, and Hodson \(2023, 2024\)](#), we measure the level of a firm’s planned AI investment using its demand for AI skills in its 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 planned green investment. A larger number of AI/green job postings indicate the firm’s stronger motive and commitment to invest in these technologies, as the successful implementation of such investment projects entails corresponding skills and human capital.³

Our baseline results demonstrate that changes in firm-level AI and green investments from one year before to one year after a corresponding announcement are positively correlated with the cumulative abnormal return (CAR) over a short window (i.e., 5 days) surrounding the disclosure event. This result is consistent with the idea that firm managers adjust upward (downward) their emerging-technology investments when the stock market reacts favorably (unfavorably) to related discussions in their major corporate disclosures. The economic magnitude of this feedback effect is meaningful:

²We also examine a firm’s 10-K and 10-Q filings but find very little mentioning of emerging-technology investment plans there.

³Our results are robust to examining alternative measures of AI/green investment that are based on outcomes, such as the number of AI/green patents generated or total greenhouse gas emissions.

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 9.5% (14.2%) of the mean increase in such postings.

However, when interpreting a positive correlation between a stock return and a firm’s subsequent action, one has to be cautious before attributing it to managers’ active learning from the market price. After all, such a correlation can also point to a passive reflection of an underlying fundamental that drives both the market price and the corporate action. This issue is discussed at length in the market-feedback literature, going back to [Chen, Goldstein, and Jiang \(2007\)](#) and in more recent papers such as [Foucault and Frésard \(2014\)](#). In our context, the underlying fundamental could be the unobservable quality/prospects of the proposed AI or green technology investments, which can drive both the stock market reaction and the follow-up corporate action in the same direction without one affecting the other.

While the passive reflection channel is plausible when dealing with positive market reactions, it becomes less compelling as an explanation in the face of negative market reactions, which happen in nearly half of our sample. In these cases, the active learning channel remains the most plausible explanation. To see this, note that the disclosures in our sample are almost exclusively about expanding AI and green projects or launching new ones. There could be two interpretations for negative reactions to these expansion announcements. First, they may indicate that the market disagrees with the managers that such expansion is desirable. In this case, observing lower AI and green investments after a stronger negative reaction necessarily points to an active updating of prior beliefs by the managers. If the managers had planned lower investments from the start, there would not have been a reason for the more negative stock price reaction given the market’s unfavorable opinion of investment expansions. Second, a negative market reaction could also indicate that the market, despite being favorable towards the expansion plans, is disappointed that the disclosed expansion scale/scope is too small. Here, observing a smaller (yet still positive) expansion ex post

may be consistent with the passive reflection channel. However, if we see an actual reduction in AI or green investments relative to the pre-disclosure year, this must indicate that there has been some active learning by the managers based on the market reaction. Otherwise, one could not explain why the firm starts by disclosing expansion plans but ends up contracting such investments.

Overall, our results based on the subsample of disclosures with negative market reactions point to the presence and importance of active managerial learning from the market feedback, as opposed to just a passive reflection of information in both market reactions and firm actions. Interestingly, in the subsample of negative market reactions, we observe an even stronger positive relation between the market reaction to the disclosure and the subsequent investment adjustment (henceforth “investment-price association”) than in the subsample of positive market reactions. While this finding is not a necessary condition for active managerial learning, it certainly points to the prevalence of learning from negative feedback, which is key in identifying that managers learn from the market regarding emerging technology investments. Exploring the reasons for the stronger effect of negative feedback is an interesting avenue for future research. One thing to note is that there is no tension in this finding relative to the theory of [Edmans, Goldstein, and Jiang \(2015\)](#). Their model predicts that in some cases, speculators will have lower incentives to trade on negative information than on positive information, making negative information 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.

Another challenge for our empirical setting is that major corporate disclosures typically contain a large amount of information other than that related to emerging-technology investment plans. One could then wonder about the extent to which market reaction is tied to these particular plans. We adopt two approaches to address this challenge. First, we exploit the granular timestamp for information contained in earnings conference call transcripts to examine hourly stock price reaction during the hour when managers discuss their emerging-technology investment plans. Presumably, such an

instantaneous stock price change is more likely triggered by the news of the announced plans rather than confounding information from other parts of the conference calls. We continue to find a positive relation between the subsequent corporate action and this hourly announcement return measure. In contrast, there is no significant relation when we examine the “pre-hour” price movement, i.e., the cumulative return from the beginning hour of the same conference call until the “AI/green investment disclosure” hour. Second, we run the baseline analysis for a subsample of “focused” 8-K filings that discuss only emerging-technology investment plans, and the positive investment-price association persists.

Theories of market feedback predict that managers will rely more on the information in market prices when the market is more likely to possess new relevant information and when the managers face more uncertainty about the prospects of the proposed investments. To test these hypotheses, we explore cross-sectional variation in managers’ opportunities and incentives to learn from the market about AI/green technologies. Consistent with the theory, we find that the positive investment-price association is stronger when outside market participants, such as institutional investors, have more expertise in emerging technologies, and when managers express more concerns over the uncertainty about the proposed investments in their disclosures. These results lend further support to the story of active learning from the market.

An important question regarding the implication of our analyses and its relation to the literature is whether disclosures of future investments in emerging technologies play a unique role in eliciting feedback from the market. To shed light on this, we analyze other types of disclosures and check if they also induce a significant association between the market reaction and subsequent corporate actions. First, we examine corporate disclosures on investments in technologies that are more conventional in nature, such as traditional data analysis techniques that include linear regressions, time series analysis, or Monte Carlo simulation methods. 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. This result shows that external information about emerging technologies is particularly valuable given that managers have very little experience in these uncharted areas and face a lot of uncertainty about them. Second, we examine disclosures that include discussions about emerging technologies without mentioning any investment plans. We do not find a significant investment-price association for such disclosures either, suggesting that learning is more effective when there is a particular investment plan in mind. We also conduct placebo tests of various kinds to increase confidence in our inference. For example, we show that a firm's pre-disclosure trends in emerging-technology investment do not covary with the announcement return over the $[-2, 2]$ window. Further, firms' investment adjustments in emerging technologies around the disclosure event are not related to CARs over alternative 5-day windows such as $[-7, -3]$ or $[3, 7]$.

The literature on the feedback effect of financial markets has demonstrated that feedback is not limited to firms learning from their own prices, but rather peers can also learn from the prices of each other (Foucault and Frésard, 2014). Hence, we check whether a firm's peers learn from the focal firm's market reaction to the disclosure of emerging-technology investment plans. Interestingly, we find that peer firms learn from the focal firm's market feedback only on green investments but not on AI investments. This indicates that green investments may be more affected by industry factors, while AI investments may be more affected by firm-specific factors. This is an interesting theme to explore in future research.

The last part of our analysis explores whether following the feedback of the market improves firms' long-run performance. It is important to remember that a priori some managers may be reluctant to follow the market feedback for different reasons. If their reluctance is largely rational due to better information, then we should not expect to find any performance differences between feedback followers and non-followers. If, however, the unwillingness to use external information from the market is due to managerial biases, then following the feedback ought to be associated with better long-run

performance. Our analysis points to the latter: Following the feedback indeed leads to better long-term operating and stock performance. Importantly, we observe these performance gaps between feedback followers and non-followers only when the market feedback is negative. This alleviates a reverse causality concern that firms with more resources and better performance potential are able to invest more in emerging technologies following positive market feedback. Rather, the result suggests that managers who do not ignore negative feedback are helping their firms achieve higher long-term value.

Our paper contributes to several strands of literature. First, we contribute to the literature on the feedback effect from financial markets to corporate decisions. Existing empirical papers – e.g., [Chen, Goldstein, and Jiang \(2007\)](#), [Bakke and Whited \(2010\)](#), [Edmans, Goldstein, and Jiang \(2012\)](#), [Bai, Philippon, and Savov \(2016\)](#), [Edmans et al. \(2017\)](#), and [Dessaint et al. \(2019\)](#) – employ different strategies to examine whether active learning from the market plays a role in corporate decisions.⁴ These strategies include checking whether the sensitivity of investment to price is higher when prices contain more information that is new to decision-makers and looking at whether corporate decisions respond to noise in the price. The framework in our paper is closer to that in [Luo \(2005\)](#), [Zuo \(2016\)](#), and [Jayaraman and Wu \(2020\)](#), who look at market reactions to corporate announcements and subsequent corporate actions. In our analysis of AI and green technologies, we shed new light on what kind of information managers actually learn from the market.⁵ Establishing that managers exhibit a pattern of learning when it comes to emerging technologies, such as AI and green technologies, but not for traditional technologies, alongside other patterns of differential learning (e.g., managers learn from peers’ green feedback but not AI feedback) highlights what kind of feedback managers seek from the market. Moreover, the setting we study here – observing the short-window market reaction to a

⁴Recent studies also explore feedback from other sources such as social media (e.g., [Cookson, Niessner, and Schiller, 2024](#)).

⁵In a recent review of the literature, [Goldstein \(2023\)](#) points out that the literature needs more evidence on what type of information managers learn from the market. [Goldstein, Liu, and Yang \(2025\)](#) provide survey evidence, where, among other things, managers answer questions about what type of information they may glean from the market.

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 generally difficult to obtain in this literature.

Second, our paper contributes to a nascent body of Economics literature that studies the role of information frictions in barriers to technology adoption (e.g., [Conley and Udry, 2010](#); [Jack, 2011, 2013](#); [Bloom, Eifert, Mahajan, McKenzie, and Roberts, 2013](#); [Fafchamps, Islam, Malek, and Pakrashi, 2020](#); [Barrett, Islam, Mohammad Malek, Pakrashi, and Ruthbah, 2022](#)) and capital misallocation (e.g., [David, Hopenhayn, and Venkateswaran, 2016](#); [Tanaka, Bloom, David, and Koga, 2020](#); [Gondhi, 2023](#); [Charoenwong, Kimura, Kwan, and Tan, 2024](#)).⁶ For example, [Conley and Udry \(2010\)](#) and [Bloom et al. \(2013\)](#) find that farmers’ and textile manufacturers’ willingness to adopt new technologies is greatly hampered by their limited knowledge about or the inherent uncertainty associated with such technologies. On the other hand, [David et al. \(2016\)](#) show that the lack of relevant information often induces managers to make suboptimal investment decisions, leading to potential resource misallocation for the broader economy. Our paper illustrates that actively seeking and utilizing the feedback from stock market participants can significantly help alleviate the problem and improve the efficiency of capital allocation.

Third, to the best of our knowledge, our paper is the first to assemble a comprehensive sample of AI/green investment-related corporate disclosures and relate them to firms’ subsequent activities in these areas. These two technologies have been on the frontier of economic development in recent years, and it is of great importance to understand how decisions to invest in them are made, especially given all the uncertainties involved.⁷ Our paper helps fill the gap towards understanding these ongoing

⁶More broadly, this is related to the discussion on the impact of uncertainty on firm investment: e.g., [Smith \(1971\)](#), [Bernanke \(1983\)](#), [Dixit and Pindyck \(1994\)](#), [Bloom, Bond, and Van Reenen \(2007\)](#).

⁷For 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.

technological transformations by showing how the market guides investments in them. In that sense, it contributes to the broader literature on firms’ activities in the areas of AI and green technologies.⁸

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 Burning Glass Technologies) database. Institutional holding data come 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 investment plans

We begin our sample construction by assembling firms’ major corporate disclosures including their earnings conference calls (as covered by StreetEvents) and 8-K filings from 2010 to 2019. To identify managers’ AI/green investment-related disclosures, we adopt an “anchor-phrase” method of textual analysis following [Hoberg and Maksimovic \(2015, 2022\)](#), [Hoberg and Moon \(2017\)](#), and [Frésard et al. \(2020\)](#).⁹ Specifically, we construct four lists of keywords (see Internet Appendix A for examples). The AI technology keywords are obtained by combining those from [Babina et al. \(2023, 2024\)](#), [Abis and Veldkamp \(2024\)](#), [Cao et al. \(2024\)](#), [Gofman and Jin \(2024\)](#), and [Cockburn et al. \(2018\)](#). For green technology keywords, we augment the dictionaries from [Engle et al. \(2020\)](#) and [Sautner et al. \(2023\)](#) with

⁸See, e.g., [Babina et al. \(2023, 2024\)](#), [Abis and Veldkamp \(2024\)](#), [Cao, Jiang, Wang, and Yang \(2024\)](#), [Gofman and Jin \(2024\)](#), and [Cockburn, Henderson, and Stern \(2018\)](#) for AI technologies and [Engle, Giglio, Kelly, Lee, and Stroebel \(2020\)](#) and [Sautner, Van Lent, Vilkov, and Zhang \(2023\)](#) for green technologies.

⁹Distinct from the “bag-of-words” method of textual analysis, which simply counts the number of keywords, the anchor-phrase method uses textual proximity (i.e., multiple search terms within a specified distance in text) to provide context.

manually identified keywords from the Sustainability Accounting Standards Board (SASB) Standards, as well as those extracted from firms’ annual CSR reports and press releases using a word-embedding approach as in Hanley and Hoberg (2019) and Li, Mai, Shen, and Yan (2021).¹⁰ Similarly, we construct the list of investment-related keywords by supplementing those from Ball, Hoberg, and Maksimovic (2015) and Hoberg and Maksimovic (2015) with words related to decision-making or business investment from the Oxford Dictionary. We also include manually identified investment-related keywords in the corporate disclosures (earnings conference calls and 8-K filings) and use the same word-embedding approach above to extract relevant keywords from firms’ annual CSR reports and press releases.¹¹

Finally, as our focus is on examining managers’ potential learning from the market feedback, we 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 or existing investment projects is often required as part of managers’ fiduciary duty to investors, disclosures of future investment plans are largely voluntary in nature and more likely to reflect managers’ intention to actively seek market feedback.¹² Therefore, we construct a list of forward-looking keywords.¹³ We then define a disclosure as AI/green investment-related if it includes AI/green technology-specific keywords, investment-related keywords, and forward-looking keywords in the same sentence within a given corporate disclosure (i.e., a conference call script or 8-K filing).¹⁴

¹⁰See SASB standards at <https://www.sasb.org/standards/materiality-finder/?lang=en-us>.

¹¹Words 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>.

¹²Our 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.

¹³Specifically, we first obtain a list of forward-looking keywords from Li (2010), Mulsu, Radhakrishnan, Subramanyam, and Lim (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 Hanley and Hoberg (2019) and Li et al. (2021), we use a word-embedding model to expand these keywords.

¹⁴We also conduct a robustness test using the mentioning of the three sets of keywords within a 25-word window (rather than a sentence) to identify AI/green investment-related disclosures. As shown by Table A1 of Internet Appendix C, our main results continue to hold.

Internet Appendix B presents examples of AI/green investment-related disclosures for both 8-K filings (Panel A) and earnings conference calls (Panel B). Panel A describes an 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-technology-related information in corporate disclosures. Panel B presents several examples for emerging-technology-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 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 sometimes controversial emerging technology investments.

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

In Figure 2, we examine the distribution of such disclosures across different industries. As expected, companies in the utilities industry are particularly more likely to discuss green-related

investment plans in their conference calls and 8-K filings, followed by those in mining, manufacturing, and construction industries. Meanwhile, companies in the service industry tend to discuss more AI-related investment plans in their disclosures compared to those in other industries.

2.2 Firm-level AI investment

To capture the extent of a firm’s planned AI investment, we follow Babina, Fedyk, He, and Hodson (2023, 2024) to examine its demand for AI skills in its job postings. The central premise of this approach is that the successful adoption or implementation of AI technologies requires skilled workers with AI expertise. A larger number of AI-related job postings indicate a 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.¹⁵ ¹⁶ The data provide detailed information for each job posting, including 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 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-alphanumeric symbols from the name strings and stripping out their common endings such as “Inc”, “Co”, and “LLC”. We match 52 million BG job postings (around 27% of the total 197 million) 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, Haltiwanger, Jarmin, Miranda, Foote, and Éva Nagypál 2006).¹⁷

¹⁵It 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.

¹⁶A 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 approach to deduplicate job postings and avoid double counting job vacancies. According to its report, up to 80% of all jobs are deduplicated. See more details about the deduplication approach at <https://kb.emsidata.com/faq/how-does-ems-burning-glass-handle-duplicate-postings/#>.

¹⁷The 27% matching rate is slightly lower than that in Babina et al. (2024), who match BG job postings to

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 core 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 .¹⁸ 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 (ΔAI 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 investment-related disclosure to the year after.¹⁹ 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 planned investment in green technology, we follow Darendeli et al. (2022) to examine its job postings that require green skills. The underlying intuition is that a larger number of green job postings indicate that a firm has dedicated more resources to investing in green technologies. We again focus on non-internship job postings from BG with non-missing employer names and at least one required skill. Following Darendeli et al. (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

Compustat firms (without requiring their stock listing status).

¹⁸We thank the authors of Cao, Jiang, Yang, and Zhang (2023) and Babina et al. (2023, 2024) for sharing with us the processed AI-relevance score of skills.

¹⁹In untabulated analyses, we find qualitatively similar results using AI/green job postings within 90 days, 180 days, and 3 years since the AI/green disclosures to measure firms’ post-disclosure AI/green investment.

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 investment-related disclosure to the year after. The weight of each job posting is its green-relatedness obtained in the second step above.

One advantage of using these job-posting-based investment measures is that they provide an important and timely reflection of firms’ strong motive and commitment to invest in emerging technologies, which directly capture *managerial intentions* of venturing into such technological spaces and thus better suit our purpose of identifying possible feedback effects. This is in sharp contrast to alternative investment measures, such as the number of *actual* AI/green hires, which are shaped by the labor market frictions and labor supply decisions of workers in these fields.²⁰ Nevertheless, we acknowledge that our AI/green investment measures might capture only one aspect of the related investment in human capital – online job postings.²¹ Hence, to mitigate concerns over this limitation, in Table A2 of Internet Appendix C, 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) indicates that a firm has increased its investment in AI/green technologies, which in turn generate a larger number of patents (lower GHG emissions). Our main results continue to hold when examining these alternative measures of emerging technology investments.

²⁰[Babina et al. \(2024\)](#) find a high correlation between measures of AI investments based on resume data (i.e., actual hires) and those based on the job posting data.

²¹Although 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.

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 disclosures made between 2010 and 2019. We also exclude a disclosure if the firm’s financial information at the nearest quarter end prior to the disclosure is missing. We are left with a final sample of 40,317 AI investment-related disclosures made by 4,119 unique firms, and 80,730 green investment-related corporate disclosures made by 2,947 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, but there is wide variation in these variables.²² The independent variable of interest, FB, denoted for market feedback, is the five-day cumulative abnormal return (i.e., stock return minus the S&P 500 index 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 adjustments. 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

²²Note that firms can have negative AI/green investment adjustments because the disclosed investment plans might be a continuation of existing projects or an expansion of related pilot programs, both of which require a positive pre-disclosure job posting level to begin with.

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 contemporaneous changes in the overall investment rate, 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.²³ All continuous variables are winsorized at the 1st and 99th percentiles to minimize the effects of outliers.

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 \$1.09 billion, ROA of 1.6%, R&D to sales ratio of 21%, market-to-book ratio of 1.88, firm age of 18.8 years, cash reserve of 19.4% 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 0.157. 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 0.246. For firms making green investment-related disclosures, they on average have quarterly sales of \$1.76 billion, ROA of 2.4%, 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 0.012. These green investment-related disclosures have an average positive tone of 0.153. 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 0.241.

²³Specifically, 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 that ranges between -1 and 1. A zero score indicates a neutral tone, and a score below (above) zero indicates a negative (positive) tone.

3 Testing the Learning Channel and Alternative Interpretations

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/green investments) and the market reactions to corporate disclosures of such investment plans. Specifically, we estimate the following regression:

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

where $\Delta Investment_{i,d,q}$ 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 investment-related corporate disclosure d made in year-quarter q .²⁴ 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 trends, we also include *Firm fixed effects* and/or *Industry $\times$ 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 includes only FB , the market reaction to the AI investment-related corporate disclosure, as the independent variable. The coefficient of FB is 0.090 and significant at

²⁴To mitigate the concern that the continuous measure of cumulative abnormal returns (CARs) might be subject to measurement errors, we also examine a binary measure of market reactions that equals one if the CARs are positive and zero otherwise. The untabulated analysis reveals that our baseline results are robust to using this alternative independent variable of interest.

the 1% level. It suggests that a one standard-deviation increase in the market reaction is associated with an approximate 0.8% ($=0.090 \times 0.093$) increase in firms' AI job postings, which is about 9.5% 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 0.102 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% ($=0.102 \times 0.078$), which is approximately 14.2% 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 hypothesis that managers adjust their AI/green investments upward (downward) in response to positive (negative) market reactions to their AI/green investment-related corporate disclosures.

3.2 Alternative explanation: Passive reflection of omitted underlying fundamentals

The documented positive investment-price association is consistent with our hypothesis on managerial learning from stock market feedback. However, there might be potential non-learning-based explanations. A common concern when testing theories of market feedback is that the positive correlation between the stock price movement and the subsequent corporate investment might be a passive reflection of an underlying fundamental 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/green technologies. Better projects' quality/prospects can trigger more favorable

market reactions on the one hand and motivate managers to further expand related investments on the other hand, leading to a positive investment-price association without one affecting the other.²⁵

We acknowledge that the logic for this non-learning-based 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 corporate managers are reacting to the same underlying fundamental in the same direction. However, this alternative explanation becomes less clear when we consider negative market responses to the AI/green investment-related disclosures. As almost all of our sample corporate disclosures indicate an increase rather than a decrease in emerging technology investments (e.g., see examples in Internet Appendix B), a negative market reaction to such expansion claims could have two possible interpretations.

3.2.1 The disagreement-based interpretation

First, it could suggest that firm managers and the market perceive the underlying fundamental about the planned projects differently. That is, the market reacts negatively because it disagrees with the managers that the AI/green investments have good prospects. Under this circumstance, if the managers are true to their intention when making the expansion disclosures, then observing lower AI/green investments after a stronger negative reaction necessarily points to an active updating of prior beliefs by the managers.²⁶

To test this prediction, 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

²⁵Another 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, Du, and Paradkar 2026).

²⁶Even if managers strategically announce expansion plans while privately planning for investment cuts, there is still no obvious reason for us to observe *lower* AI/green investments after a *stronger* negative reaction without any active learning going on.

3 presents the results. Several interesting patterns emerge. First, by comparing the number of observations in columns (1) and (2) of each panel, we can see that almost half of both AI and green investment-related disclosures are associated with negative market reactions, despite the mentioning of increasing AI/green investment in almost all these corporate disclosures. Second, 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, as indicated by the F-tests at the bottom of the column. This suggests that the positive association between investment adjustments and market reactions is more prominent when the market reaction is negative. This finding is unlikely to be attributable to a passive reflection of omitted underlying fundamentals under the disagreement-based interpretation of a negative market response (i.e., the market and managers disagree on the desirability of the announced expansion plans). Rather it demonstrates more strongly in the direction of active managerial learning from the price.

It is also worth noting that our findings in Table 3 do not contradict the theory of [Edmans et al. \(2015\)](#). 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 negative price reaction, managers would learn less from it than in the case of positive price reaction. In fact, whether managerial learning is stronger following 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, as 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 The disappointment-based interpretation

Second, the observed negative market reactions could also indicate the market’s disappointment of firms’ lackluster expansion plans. In other words, the market reacts negatively not because it disagrees with the proposed emerging technology investment plans, but because it thinks the proposed scale/scope of expansion is insufficient. Under this interpretation, firms whose announced AI/green investment plans fall shorter of market expectations would witness more negative stock market reactions. Meanwhile, such firms will follow their proposed plans and expand their actual AI/green investments to a smaller extent, leading to a positive investment-price association without any learning going on. This alternative story, however, cannot explain firms shrinking their investments after observing negative stock market reactions to their proposed expansion plans.

Thus, to examine the plausibility of the disappointment-based explanation, we replace the continuous measure of AI/green investment change (as in our baseline tests) in the regressions with an indicator variable that captures a firm’s decision to contract related investment. Specifically, *Cut* is defined to equal one if a firm’s AI/green-related job postings in the year after the disclosure are lower than those in the year prior, and zero otherwise. We then examine whether firms are more likely to shrink their AI/green investments in the face of more negative market reactions. If the disappointment story holds, firms receiving negative market reactions would still expand (albeit less than what the market expects), so we should not observe an increase in the probability of investment cuts.

Table 4 presents the analysis using only disclosures with negative market reactions. The negative and significant coefficients of FB in both panels show that firms facing more negative market feedback are more likely to shrink their AI/green investments rather than merely implement the “lackluster expansion plans”. These results suggest that the disappointment-based explanation is unlikely the primary driving force of our baseline results.

3.3 Other non-learning-based explanations

3.3.1 Confounding components of corporate disclosures

Because major corporate disclosures typically contain a large amount of information other than emerging technology investment plans, another concern in interpreting the positive investment-price association documented in Section 3.1 is that other components of the disclosures (i.e., parts other than the discussion of firms’ future investment plans in emerging technologies) might correlate with firms’ subsequent AI/green investments and generate market reactions in the same direction. Examples of such confounding factors include information regarding general investment opportunities, management quality, or other firm fundamentals. It is important to note that this alternative explanation should only bias against us finding a significant investment-price association if the patterns of such confounding information are largely idiosyncratic, i.e., they do not exhibit any systematic patterns but only introduce noise into our estimations. Nevertheless, we employ several methods to investigate its implication for our results.

Ideally, to fully address this concern, we should decompose the market reaction to a specific disclosure into two components: one driven by the discussions of emerging-technology investment plans (i.e., the “AI/green components”) and the other by the rest of the information contained in the same 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 timestamp of the information

contained in earnings conference call transcripts and examine stock price reactions within the hour during which managers discuss emerging-technology investment plans. Presumably, such an instantaneous stock price change is more likely triggered by the discussions of emerging-technology investment plans than by other confounding information contained in the disclosure. We identify the granular timestamp of each sentence in an earnings conference call using the start time of the call and its audio data. We obtain audio data from Seeking Alpha for the period of 2010-2017 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, leaving us with around 6,300 (AI) and 12,000 (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 5 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. Nor do we find such an association for the cumulative stock return 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 that contain only one item mentioning 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 technology investment plans. An example of focused

8-K filings is presented in Internet Appendix B Panel A. As shown in Table 6, we continue to find a significantly positive relation between a firm’s AI/green investment adjustment and the market reaction when examining earnings conference calls and 8-K filings separately.²⁷ More importantly, columns (3) of both panels show that the positive investment-price association continues to hold in the subsample of focused 8-K filings, suggesting that our baseline results are unlikely driven by omitted yet investment-relevant parts of the sample corporate disclosures.

3.3.2 Pre-disclosure trends in emerging-technology investments

One might argue that pre-disclosure trends in emerging-technology investments could lead to the observed positive investment-price association. Specifically, firms that have already started adjusting (accelerating or slowing-down) their AI/green investment plans prior to the related disclosures would continue such investment trends afterwards. Meanwhile, the market tracks firm movements in real time, generating investment signals and reacting to these predetermined trends. 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 slowdown pre-disclosure trend. In this case, managerial 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 explore this possibility, we directly examine firms’ past (i.e., pre-disclosure) investment trends in emerging technologies. If our findings are mainly driven by the pre-event investment trends, we would expect to observe a positive association between firms’ past investment adjustments in emerging technologies and the market reactions. Table A3 in Internet Appendix C presents the results. We find that firms’ past investment trends in emerging technologies (i.e., the changes

²⁷Our baseline sample in Table 2 is at the firm–event date level. That is, we drop duplicates when a firm has both earnings conference calls and 8-K filings on the same event date. 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 6 is larger than the number of observations in Table 2.

in AI/green hiring from two years prior to the relevant disclosures to one year before) are not significantly correlated with the market reactions to the disclosures, which is inconsistent with this alternative explanation based on pre-disclosure trends.

3.3.3 Other alternative explanations

Managerial ability: Unobservable but correctly perceived managerial ability might also drive the documented positive investment-price association. The idea is that the market may react more negatively (positively) to the announced expansion plans when the correctly perceived managerial ability to carry out such investments is poorer (superior). Meanwhile, firms with poorer (superior) managerial ability are likely to implement the ex-post emerging technology investments less (more) efficiently, leading to a positive investment-price association. However, such an explanation is unlikely to be the main driver of our baseline findings because our measure of AI/green investment uses job postings, which capture firms' ex-ante intention to invest in these emerging technologies instead of their managers' ability to implement such projects ex post.

Financial constraints: One may wonder whether firms increase (decrease) their ex-post AI/green investment because of relaxed (tightened) financial constraints induced by positive (negative) stock price movements and the corresponding drop (rise) in their cost of capital. If so, firms would (1) also adjust non-emerging-technology investments following the same stock price movements, and (2) adjust their emerging-technology investments in response to stock price movements during other non-disclosure windows in the same fashion. Hence, to mitigate concerns over this possibility, we perform two falsification tests in Internet Appendix Tables A4 and A5. We find no significant associations: (1) between non-emerging-technology investment adjustments (i.e., changes in job postings not requiring AI/green skills) and market reactions to emerging-technology-investment disclosures, or (2) between AI/green investment adjustments and market reactions during other 5-day non-disclosure

windows immediately before or after the same disclosure event (such as days [-7, -3] or days [3, 7]). These results are inconsistent with the implications of the financial-constraint-based explanation.²⁸

4 Cross-sectional Tests

Theories of market feedback predict that managers will rely more on the information in market prices when the market is more likely to possess new relevant information and when the managers face more uncertainty about the prospects of the proposed investments. To test these hypotheses and further tie our baseline findings to the managerial learning channel, we explore cross-sectional variations in managers’ opportunities and incentives to learn.

4.1 Managers’ opportunities to learn: Market participants’ expertise

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

To test this prediction, we examine one major type of market participant that can guide managers in the realm of emerging technology investments: institutional investors. These investors, generally perceived to be sophisticated, likely possess valuable insights about emerging technologies and the investing firms, and can capitalize on such information by trading. We infer institutions’

²⁸We conduct two more untabulated analyses to examine this explanation. First, in a cross-sectional test, we do not find that our baseline results vary with firms’ ex-ante financial constraints measured by the KZ index (Kaplan and Zingales 1997). Second, in a placebo test, we do not find firms’ green (AI) investment adjustments are significantly related to the market reaction to their AI (green) disclosures. These results are inconsistent with the financial constraint explanation.

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.²⁹ We then classify a firm as AI-related and assign it an AI score of one if its major patent technology area in a given year falls within one of the top 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 scores 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 scores of firms from the Refinitiv ESG Company Summary database, which considers three environmental categories: resource use, emissions, and innovation. We measure an institution’s expertise in green technologies in a given quarter as the weighted average environmental score of all firms 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 the 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 scores across all its institutions. Each institution’s weight is the number of the focal firm’s outstanding shares held by the institution

²⁹AI 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%.

at the nearest quarter end prior to the disclosure event.

Table 7 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, $FB \times InstitutionAIExpertise$. As can be seen, the coefficient of the interaction term is positive and significant, suggesting that when outside investors have more domain knowledge about AI technologies, managers make larger AI investment adjustments in response to the market feedback on their AI investment disclosures. Panel B examines green investment and institutions' green expertise, and finds similar results. We acknowledge that these institutional investors could directly communicate with a firm about its emerging-technology 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.

4.2 Managers' incentives to learn: Uncertainty about the disclosed investment plans

Second, we consider managerial incentives to learn from the market. Firms face critical challenges when making investment decisions under uncertainty (Dixit and Pindyck 1994; Bloom 2009). We hypothesize that managers are more likely to learn from the market feedback and adjust their investments in emerging technologies when they are more uncertain about the proposed investment plans or when such investments are riskier. To test this prediction, we leverage the verbal content in corporate disclosures to assess the extent of uncertainty and risk associated with the proposed investment plans. Specifically, we adopt a similar textual analysis method based on a list of keywords about uncertainty and risk obtained from Loughran and McDonald (2011), Cookson, Moon, and Noh (2024), and Cao, Yang, and Zhang (2025). Internet Appendix A presents examples of these keywords. We then define managers' uncertainty about the proposed investment plans (*Uncertainty*) as the number of uncertainty and risk keywords in the sentences disclosing the firm's emerging technology

investment plans scaled by the total number of words in those sentences. A higher value of this ratio indicates greater managerial incentives to learn from the market because managers are more uncertain about their proposed investment plans or deem such investments riskier.

Table 8 presents the results of this test. Panels A and B study AI and green investments, respectively. The positive and significant coefficients of the interaction term $FB \times Uncertainty$ in both panels suggest that when managers are more uncertain about AI/green technologies or deem such investments riskier, they adjust their AI/green investments more in response to the market feedback on their emerging-technology investment-related disclosures.³⁰

5 When Do Managers Learn and When They Do Not

An important question regarding the implication of our analyses and its relation to the literature is whether disclosures of future investments in emerging technologies play a unique role in eliciting feedback from the market. Another interesting question is whether firms learn only from their own market feedback or from that of peer firms as well. To shed light on these questions, we conduct several additional tests that explore when and what managers learn.

5.1 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, and Monte Carlo simulation models. Since these conventional technologies have

³⁰We further explore the variation in managers' incentives to learn based on firms' heterogeneous exposure to technology competition and the market's attention to environmental/climate-related issues (i.e., the Paris Agreement). As shown by Internet Appendix C, Tables A6 and A7, firms learn more from the market feedback when facing greater technology competition from their product market peers and after the passage of the Paris Agreement, which heightens public attention and incentivizes managers to pay greater attention to environmental-related issues.

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 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, $\Delta \textit{Conventional Job Postings}$, is defined as the change in the natural logarithm of one plus the weighted sum of conventional-technology-related job postings by a firm from the year prior to a conventional technology-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 investment plans is much weaker than that for emerging-technology 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. Rather it suggests that external information about emerging technologies is particularly valuable given that managers have very little experience in these uncharted areas and face a lot of uncertainty about them.

5.2 Investment response to non-investment-related emerging-technology feedback

Next, we examine whether the feedback effect on emerging technology investments 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. We then 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 AI/green investment adjustment and the market reaction to its general discussions of these emerging technologies. This result suggests that the documented positive investment-price association 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, indicating that managerial learning is more effective when there is a particular investment plan in mind.

5.3 Investment response to peer firms’ emerging-technology market feedback

The literature on the feedback effect of financial markets has demonstrated that feedback is not limited to firms learning from their own prices, but rather peers can also learn from the prices of each other (Foucault and Frésard 2014). Hence, we further 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 such disclosures is mostly idiosyncratic, i.e., only useful to the focal firm’s investment planning, then we would not expect peer firms to act on such feedback. However, if the market possesses more macro- or industry-specific knowledge about emerging-technology 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.

We define peer firms as those operating in the same product market as the focal firm, i.e., firms with TNIC-3 scores above the sample median (Hoberg and Phillips 2010, 2016). We then 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 10 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.

6 Benefits of Following the Market Feedback

Finally, we explore whether following the stock market feedback is useful in creating firm value. Specifically, we compare the long-term performance of firms when they follow the market feedback 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 consequences 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 that 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.³¹ 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 11 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-following in the three years after their emerging-technology-related disclosures. This suggests that ignoring the useful information contained in stock prices 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, making it 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 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 that managers who do not ignore negative feedback when venturing into uncharted waters are helping their firms achieve higher long-term value. It suggests that learning from stock market feedback is a useful market-based solution in the face of significant uncertainties associated with emerging technology investments.

³¹Such a matching procedure leads to the smaller number of observations for this test compared to our baseline test in Table 2.

7 Conclusion

This paper explores the role of market feedback when firms contemplate emerging technology investments in AI and green technologies. We find that firms adjust their investments in AI/green technologies upward (downward) in response to favorable (unfavorable) market reactions to the announcements of such plans in their corporate disclosures. This association is stronger when the market reaction is negative, and unlikely to be driven by non-learning-based explanations, such as omitted fundamentals, market disappointment, confounding effects from non-AI/green-related components of the corporate disclosures, financial constraints, or pre-disclosure trends in such investments. We also find this association to be stronger when market participants possess more domain knowledge in emerging technologies, and when managers are more uncertain about the proposed investments. Finally, we document the benefits of following the market feedback on emerging technology investments in terms of long-run operating and stock performance.

To the best of our knowledge, we are 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 technology investments. Our findings suggest that actively seeking and utilizing the feedback from stock market can help mitigate managers' ex-ante concerns and improve ex-post investment efficiency when they venture into unknown and risky areas such as emerging technologies. Our analyses also shed new light on *what kind 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 AI and green technologies that are highly risky, controversial, and lacking track records in related investments. More importantly, our results indicate that managers' learning behaviors vary not only *between* emerging and non-emerging technology investments, but also *within* different categories of emerging technology investments.

References

- Abis, S., and L. Veldkamp. 2024. The Changing Economics of Knowledge Production. *Review of Financial Studies* 37:89–118.
- Aljifri, K., and K. Hussainey. 2007. The Determinants of Forward-looking Information in Annual Reports of UAE Companies. *Managerial Auditing Journal* 22:881–894.
- Babina, T., A. Fedyk, A. He, and J. Hodson. 2023. Firm Investments in Artificial Intelligence Technologies and Changes in Workforce Composition. NBER Volume on Technology, Productivity, and Economic Growth.
- Babina, T., A. Fedyk, A. He, and J. Hodson. 2024. Artificial Intelligence, Firm Growth, and Product Innovation. *Journal of Financial Economics* 151:103745.
- Bai, J., T. Philippon, and A. Savov. 2016. Have Financial Markets Become More Informative? *Journal of Financial Economics* 122:625–654.
- Bakke, T. E., and T. Whited. 2010. Which Firms Follow the Market? An Analysis of Corporate Investment Decisions. *Review of Financial Studies* 23:1941–1980.
- Ball, C., G. Hoberg, and V. Maksimovic. 2015. Disclosure, Business Change and Earnings Quality. Working Paper.
- Barrett, C. B., A. Islam, A. Mohammad Malek, D. Pakrashi, and U. Ruthbah. 2022. Experimental Evidence on Adoption and Impact of the System of Rice Intensification. *American Journal of Agricultural Economics* 104:4–32.
- Bernanke, B. S. 1983. Irreversibility, Uncertainty, and Cyclical Investment. *Quarterly Journal of Economics* 98:85–106.
- Bloom, N. 2009. The Impact of Uncertainty Shocks. *Econometrica* 77:623–685.
- Bloom, N., S. Bond, and J. Van Reenen. 2007. Uncertainty and Investment Dynamics. *Review of Economic Studies* 74:391–415.
- Bloom, N., B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts. 2013. Does Management Matter? Evidence from India. *Quarterly Journal of Economics* 128:1–51.
- Bond, P., A. Edmans, and I. Goldstein. 2012. The Real Effects of Financial Markets. *Annual Review of Financial Economics* 4:339–360.
- Bozanic, Z., D. T. Roulstone, and A. Van Buskirk. 2018. Management Earnings Forecasts and Other Forward-looking Statements. *Journal of Accounting and Economics* 65:1–20.

- Cao, S., W. Jiang, J. Wang, and B. Yang. 2024. From Man vs. Machine to Man + Machine: The Art and AI of Stock Analyses. *Journal of Financial Economics* 160:103910.
- Cao, S., W. Jiang, B. Yang, and A. 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, S., B. Yang, and A. Zhang. 2025. Managerial Risk Assessment and Fund Performance: Evidence from Textual Disclosure. Working Paper.
- Charoenwong, B., Y. Kimura, A. Kwan, and E. Tan. 2024. Capital Budgeting, Uncertainty, and Misallocation. *Journal of Financial Economics* 153:103779.
- Chava, S., W. Du, and N. Paradkar. 2026. Walking the Tech Talk? Hype, Credibility, and Investments in Emerging Technologies. Working Paper.
- Chen, Q., I. Goldstein, and W. Jiang. 2007. Price Informativeness and Investment Sensitivity to Stock Price. *Review of Financial Studies* 20:619–650.
- Cockburn, I. M., R. Henderson, and S. Stern. 2018. The Impact of Artificial Intelligence on Innovation: An Exploratory Analysis. In *The Economics of Artificial Intelligence: An Agenda*, pp. 115–146.
- Conley, T. G., and C. R. Udry. 2010. Learning about a New Technology: Pineapple in Ghana. *American Economic Review* 100:35–69.
- Cookson, J. A., S. K. Moon, and J. Noh. 2025. Speculative and Informative: Lessons from Market Reactions to Speculation Cues. *Review of Corporate Finance Studies* p. cfaf021.
- Cookson, J. A., M. Niessner, and C. Schiller. 2024. Can Social Media Inform Corporate Decisions? Evidence from Merger Withdrawals. *Journal of Finance* Forthcoming.
- Darendeli, A., K. K. F. Law, and M. Shen. 2022. Green New Hiring. *Review of Accounting Studies* 27:986–1037.
- David, J. M., H. A. Hopenhayn, and V. Venkateswaran. 2016. Information, Misallocation, and Aggregate Productivity. *Quarterly Journal of Economics* 131:943–1005.
- Davis, S. J., J. Haltiwanger, R. Jarmin, J. Miranda, C. Foote, and Éva Nagypál. 2006. Volatility and Dispersion in Business Growth Rates: Publicly Traded versus Privately Held Firms. *NBER Macroeconomics Annual* 21:107–179.
- Dessaint, O., T. Foucault, L. Frésard, and A. Matray. 2019. Noisy Stock Prices and Corporate Investment. *Review of Financial Studies* 32:2625–2672.
- Dixit, A. K., and R. S. Pindyck. 1994. *Investment under Uncertainty*. Princeton University Press.

- Dye, R. A., and S. S. Sridhar. 2002. Resource Allocation Effects of Price Reactions to Disclosures. *Contemporary Accounting Research* 19:385–410.
- Edmans, A., I. Goldstein, and W. Jiang. 2012. The Real Effects of Financial Markets: The Impact of Prices on Takeovers. *Journal of Finance* 67:933–971.
- Edmans, A., I. Goldstein, and W. Jiang. 2015. Feedback Effects, Asymmetric Trading, and the Limits to Arbitrage. *American Economic Review* 105:3766–3797.
- Edmans, A., S. Jayaraman, and J. Schneemeier. 2017. The Source of Information in Prices and Investment-price Sensitivity. *Journal of Financial Economics* 126:74–96.
- Engle, R. F., S. Giglio, B. Kelly, H. Lee, and J. Stroebe. 2020. Hedging Climate Change News. *Review of Financial Studies* 33:1184–1216.
- Fafchamps, M., A. Islam, M. A. Malek, and D. Pakrashi. 2020. Can Referral Improve Targeting? Evidence from an Agricultural Training Experiment. *Journal of Development Economics* 144:102436.
- Foucault, T., and L. Frésard. 2014. Learning from Peers’ Stock Prices and Corporate Investment. *Journal of Financial Economics* 111:554–577.
- Frésard, L., G. Hoberg, and G. Phillips. 2020. Innovation Activities and Integration through Vertical Acquisitions. *Review of Financial Studies* 33:2937–2976.
- Gofman, M., and Z. Jin. 2024. Artificial Intelligence, Education, and Entrepreneurship. *Journal of Finance* 79:631–667.
- Goldstein, I. 2023. Information in Financial Markets and Its Real Effects. *Review of Finance* 27:1–32.
- Goldstein, I., B. Liu, and L. Yang. 2025. Market Feedback: Evidence from the Horse’s Mouth. *Journal of Financial Economics* Forthcoming.
- Gondhi, N. 2023. Rational Inattention, Misallocation, and The Aggregate Economy. *Journal of Monetary Economics* 136:50–75.
- Grewal, J. 2019. Management and Disclosure of Corporate Sustainability Performance. Working Paper.
- Hanley, K. W., and G. Hoberg. 2019. Dynamic Interpretation of Emerging Risks in the Financial Sector. *Review of Financial Studies* 32:4543–4603.
- Hassanein, A., and K. Hussainey. 2015. Is Forward-looking Financial Disclosure Really Informative? Evidence from UK Narrative Statements. *International Review of Financial Analysis* 41:52–61.
- Hassanein, A., A. Zalata, and K. 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, B., and L. B. Kahn. 2018. Do Recessions Accelerate Routine-Biased Technological Change? Evidence from Vacancy Postings. *American Economic Review* 108:1737–1772.
- Hoberg, G., and V. Maksimovic. 2015. Redefining Financial Constraints: A Text-Based Analysis. *Review of Financial Studies* 28:1312–1352.
- Hoberg, G., and V. Maksimovic. 2022. Product Life Cycles in Corporate Finance. *Review of Financial Studies* 35:4249–4299.
- Hoberg, G., and S. K. Moon. 2017. Offshore Activities and Financial vs Operational Hedging. *Journal of Financial Economics* 125:217–244.
- Hoberg, G., and G. Phillips. 2010. Product Market Synergies and Competition in Mergers and Acquisitions: A Text-Based Analysis. *Review of Financial Studies* 23:3773–3811.
- Hoberg, G., and G. Phillips. 2016. Text-Based Network Industries and Endogenous Product Differentiation. *Journal of Political Economy* 124:1423–1465.
- Jack, B. K. 2011. Market Inefficiencies and the Adoption of Agricultural Technologies in Developing Countries. White paper, J-PAL (MIT) and CEGA, UC Berkeley.
- Jack, B. K. 2013. Constraints on the Adoption of Agricultural Technologies in Developing Countries. Literature Review, J-PAL (MIT) and CEGA, UC Berkeley.
- Jayaraman, S., and J. S. Wu. 2020. Should I Stay or Should I Grow? Using Voluntary Disclosure to Elicit Market Feedback. *Review of Financial Studies* 33:3854–3888.
- Kaplan, S. N., and L. Zingales. 1997. Do Investment-Cash Flow Sensitivities Provide Useful Measures of Financing Constraints? *Quarterly Journal of Economics* 112:169–215.
- Langberg, N., and K. Sivaramakrishnan. 2010. Voluntary Disclosures and Analyst Feedback. *Journal of Accounting Research* 48:603–646.
- Li, F. 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, K., F. Mai, R. Shen, and X. Yan. 2021. Measuring Corporate Culture Using Machine Learning. *Review of Financial Studies* 34:3265–3315.
- Loughran, T., and B. McDonald. 2011. When is a Liability not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *Journal of Finance* 66:35–65.
- Luo, Y. 2005. Do Insiders Learn from Outsiders? Evidence from Mergers and Acquisitions. *Journal of Finance* 60:1951–1982.

- Mulsu, V., S. Radhakrishnan, K. R. Subramanyam, and D. Lim. 2015. Forward-Looking MDA Disclosures and the Information Environment. *Management Science* 61:931–948.
- Sautner, Z., L. Van Lent, G. Vilkov, and R. Zhang. 2023. Firm-level Climate Change Exposure. *Journal of Finance* 78:1449–1498.
- Smith, R. G. E. 1971. Uncertainty, Information and Investment Decisions. *Journal of Finance* 26:67–82.
- Tanaka, M., N. Bloom, J. M. David, and M. Koga. 2020. Firm Performance and Macro Forecast Accuracy. *Journal of Monetary Economics* 114:26–41.
- Zuo, L. 2016. The Informational Feedback Effect of Stock Prices on Management Forecasts. *Journal of Accounting and Economics* 61:391–413.

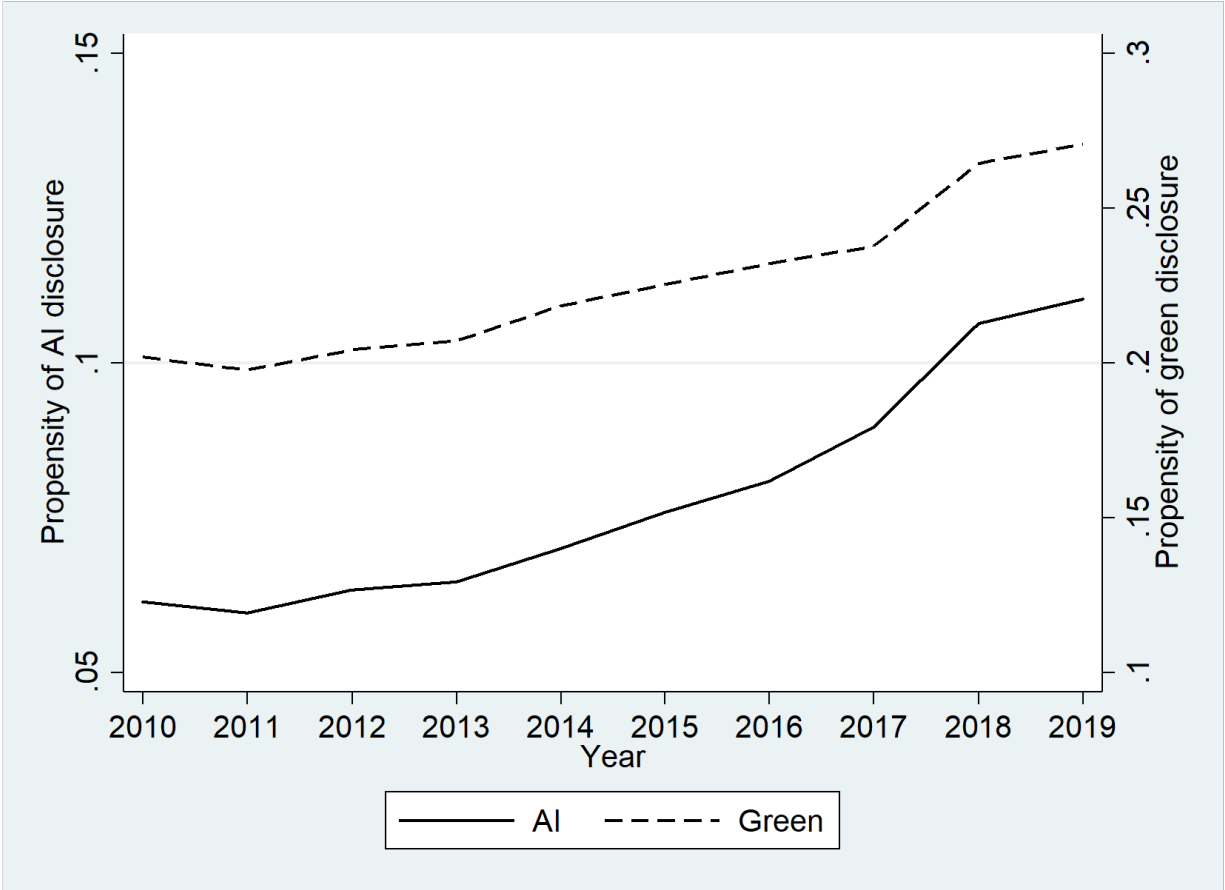


Figure 1: Time trend of the propensity to disclose emerging-technology investment plans

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 investment-related disclosures divided by the total number of earnings conference calls and 8-K filings in a given year. The dashed line denotes the number of green investment-related disclosures divided by the total number of earnings conference calls and 8-K filings in a given year.

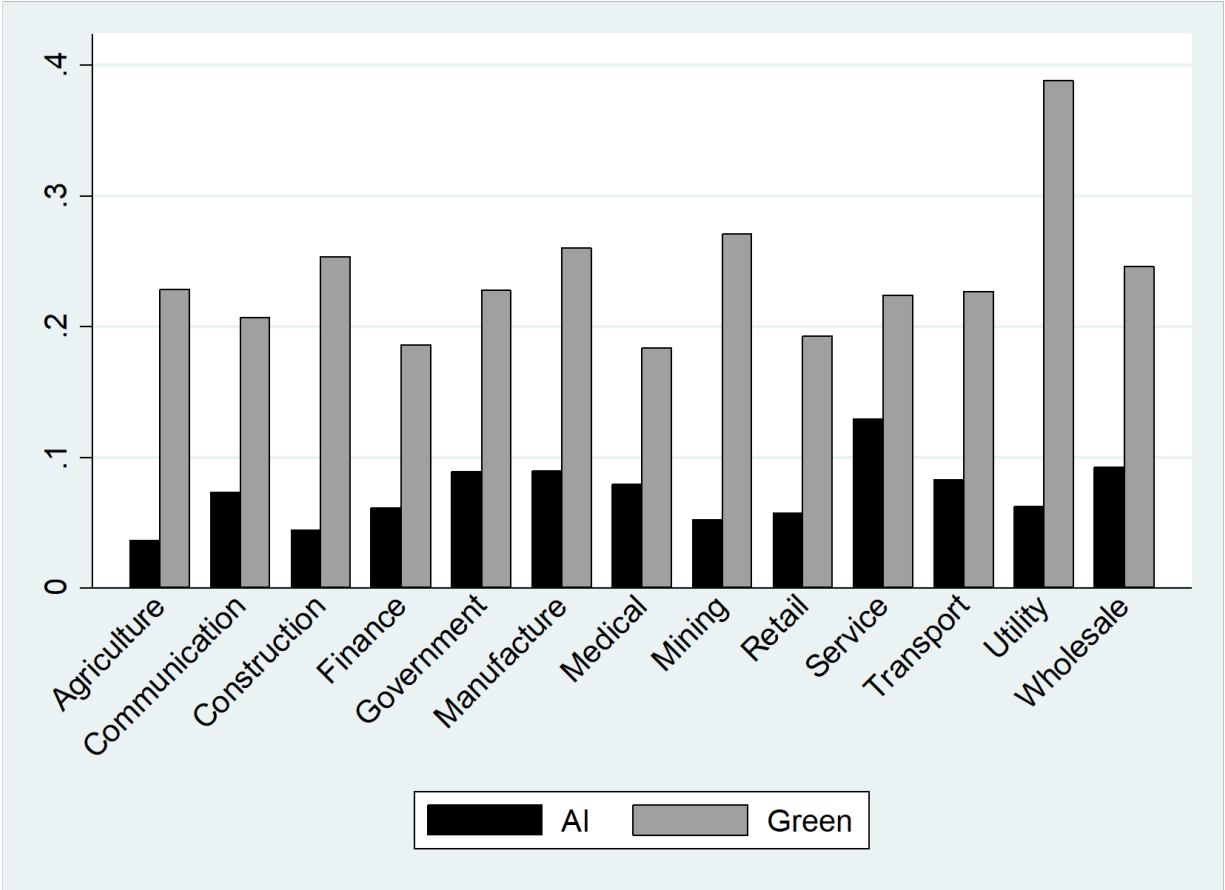


Figure 2: Industry distribution of emerging-technology investment-related disclosures

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

Table 1: Summary statistics

This table presents summary statistics for the samples of AI investment-related disclosures (Panel A) and green investment-related disclosures (Panel B) between 2010 and 2019. $\Delta AI \text{ Job Postings}$ 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. Each job posting is weighted by the average AI-relevance score across all skills required for the job. Following Babina et al. (2023, 2024), the AI-relevance score of each skill s is calculated as the number of job postings requiring both the skill s and at least one of the four basic AI skills (i.e., artificial intelligence, machine learning, natural language processing, and computer vision) divided by the total number of job postings requiring that skill s . $\Delta Green \text{ Job Postings}$ is the change in the natural logarithm of one plus the 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. 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). $Firm \text{ Size}$ 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. $R\&D \text{ ratio}$ is the firm's quarterly research and development expenses divided by its total sales. MtB is the firm's market value of assets divided by its book value. $Firm \text{ Age}$ is the number of years since listing recorded in Compustat. $Cash \text{ Reserve}$ is the firm's quarterly cash and short-term investments divided by its total assets. All firm characteristics are calculated at the nearest quarter end before the disclosure date. $Earning \text{ Surprise}$ is the actual earnings per share (EPS) for the current quarter minus the EPS for the same quarter in the previous year scaled by the previous year's same quarter value. If the disclosure is an earnings conference call, Earning Surprise is calculated at the disclosure date; otherwise, it is calculated at the nearest quarter end prior to the disclosure. $Disclosure \text{ Tone}$ is the sentiment of the disclosure. $\Delta Total \text{ Job Postings}$ 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
Δ AI Job Postings	40,317	0.089	0.334	-0.794	-0.004	0.000	0.170	1.445
FB	40,317	0.003	0.093	-0.291	-0.040	0.002	0.044	0.317
Firm Size	40,317	5.307	2.142	0.000	3.997	5.452	6.800	9.242
ROA	40,317	0.016	0.054	-0.303	0.008	0.025	0.040	0.161
R&D Ratio	40,317	0.209	0.837	0.000	0.000	0.000	0.108	6.102
MtB	40,317	1.881	1.670	0.211	0.941	1.313	2.219	12.388
Firm Age	40,317	18.835	14.992	0.000	6.250	15.750	27.000	57.500
Cash Reserve	40,317	0.194	0.211	0.000	0.037	0.111	0.277	0.931
Earning Surprise	40,317	-0.004	1.410	-6.375	-0.278	0.000	0.222	7.000
DisclosureTone	40,317	0.157	0.200	-0.795	0.000	0.175	0.306	0.982
Δ Total Job Postings	40,317	0.246	0.977	-2.303	-0.068	0.000	0.483	4.385
Panel B: Green-investment-related corporate disclosures								
Variable	Obs	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Δ Green Job Postings	80,730	0.056	0.419	-1.256	0.000	0.000	0.116	1.669
FB	80,730	0.001	0.078	-0.257	-0.035	0.001	0.038	0.248
Firm Size	80,730	6.350	1.803	0.000	5.358	6.532	7.597	9.242
ROA	80,730	0.024	0.042	-0.303	0.014	0.027	0.040	0.161
R&D Ratio	80,730	0.164	0.792	0.000	0.000	0.000	0.040	6.102
MtB	80,730	1.695	1.545	0.211	0.841	1.167	1.930	12.388
Firm Age	80,730	24.338	16.806	0.000	10.250	21.000	37.500	57.500
Cash Reserve	80,730	0.144	0.183	0.000	0.026	0.073	0.181	0.931
Earning Surprise	80,730	0.012	1.417	-7.000	-0.251	0.000	0.246	7.000
DisclosureTone	80,730	0.153	0.187	-0.987	0.000	0.154	0.279	0.912
Δ Total Job Postings	80,730	0.241	0.915	-2.074	-0.076	0.000	0.459	4.220

Table 2: Investment response to emerging-technology market feedback: Baseline analysis

This table presents the baseline analysis of a firm's investment response to the market feedback on its emerging-technology-related corporate disclosures. Panels A and B study AI-related and green-related investments, respectively. In Panel A, the dependent variable is $\Delta AI \text{ Job Postings}$. In Panel B, the dependent variable is $\Delta Green \text{ Job Postings}$. FB is the firm's five-day cumulative abnormal return surrounding the disclosure (i.e., $[-2, 2]$ with the disclosure date as day 0). $Firm \text{ FE}$ are indicators for each firm. $Industry \times Year \text{ FE}$ 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: $\Delta AI \text{ Job Postings}$				
	(1)	(2)	(3)	(4)	(5)
FB	0.090*** (4.47)	0.088*** (4.43)	0.066*** (4.16)	0.069*** (4.41)	0.052*** (3.23)
Firm Size		0.021*** (10.45)	0.021*** (13.46)	0.023*** (12.94)	0.023*** (3.00)
ROA		-0.062 (-0.85)	-0.104 (-1.63)	-0.119* (-1.88)	-0.032 (-0.36)
R&D Ratio		-0.006* (-1.81)	-0.002 (-0.65)	0.003 (0.97)	0.005 (1.21)
MtB		0.010*** (4.66)	0.008*** (4.30)	0.006*** (3.16)	0.002 (0.69)
Firm Age		-0.001*** (-3.96)	-0.000** (-2.47)	-0.000* (-1.95)	-0.000 (-0.08)
Cash Reserve		0.097*** (5.23)	0.085*** (5.65)	0.058*** (3.40)	0.045 (1.37)
Earning Surprise			0.001 (0.79)	-0.000 (-0.11)	-0.001 (-1.21)
Disclosure Tone			0.046*** (4.85)	0.031*** (3.43)	0.015* (1.74)
$\Delta \text{Total Job Postings}$			0.215*** (37.81)	0.212*** (38.51)	0.215*** (34.41)
Firm FE	No	No	No	No	Yes
Industry $\times$ Year FE	No	No	No	Yes	Yes
Observations	40,317	40,317	40,317	40,291	39,521
R-squared	0.001	0.017	0.412	0.444	0.551

Panel B: Green Investment					
	Dependent Variable: Δ Green Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.102*** (3.64)	0.098*** (3.50)	0.057** (2.17)	0.045** (2.28)	0.047** (2.49)
Firm Size		0.014*** (5.89)	0.019*** (8.64)	0.017*** (9.34)	0.035*** (4.20)
ROA		0.091 (1.21)	0.097 (1.38)	0.063 (1.00)	-0.064 (-0.57)
R&D Ratio		0.012** (2.49)	0.017*** (3.84)	0.012*** (3.39)	0.007 (1.33)
MtB		-0.002 (-1.19)	-0.004** (-1.98)	-0.004** (-2.33)	-0.003 (-0.85)
Firm Age		-0.000 (-1.62)	-0.000 (-0.08)	-0.000 (-0.75)	-0.010 (-1.22)
Cash Reserve		-0.002 (-0.08)	-0.008 (-0.37)	-0.019 (-1.11)	0.069* (1.83)
Earning Surprise			0.003 (1.56)	0.002* (1.66)	0.004*** (3.21)
Disclosure Tone			-0.004 (-0.31)	0.005 (0.57)	0.003 (0.35)
Δ Total Job Postings			0.173*** (21.88)	0.159*** (46.90)	0.165*** (47.39)
Firm FE	No	No	No	No	Yes
Industry $\times$ Year FE	No	No	No	Yes	Yes
Observations	80,730	80,730	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 market feedback: Positive and negative market reactions

This table presents the analyses of a firm's investment response to emerging-technology 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 $\Delta AI \text{ Job Postings}$. In Panel B, the dependent variable is $\Delta Green \text{ Job Postings}$. FB is the firm's five-day cumulative abnormal return surrounding the disclosure date. The sample for column (1) of each panel includes corporate disclosures with positive market reactions (i.e., $FB > 0$), whereas the sample for column (2) includes disclosures with negative market reactions (i.e., $FB < 0$). 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. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. F-statistics and corresponding p-values testing the difference between the coefficients of $POSFB$ and $NEGFB$ are reported. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment				Panel B: Green investment			
Dependent Var.	$\Delta AI \text{ Job Postings}$			Dependent Var.	$\Delta Green \text{ Job Postings}$		
Subsample	Positive FB	Negative FB	Full	Subsample	Positive FB	Negative FB	Full
	(1)	(2)	(3)		(1)	(2)	(3)
FB	0.039*** (3.06)	0.078** (2.48)		FB	-0.033 (-0.56)	0.079* (1.80)	
PosFB			0.022** (2.06)	PosFB			-0.008 (-0.21)
NegFB			0.071*** (2.95)	NegFB			0.103*** (2.86)
F-stat			3.033	F-stat			3.125
P-value			0.082	P-value			0.077
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Firm FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Industry $\times$ 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 negative market feedback: Alternative explanation based on market disappointment

This table presents the analyses of a firm's investment expansion/shrinkage decisions in response to emerging-technology market feedback under negative market reactions. The sample includes AI/green investment-related disclosures with negative market feedback. Panels A and B study AI-related and green-related investments, respectively. The dependent variable *Cut* is a dummy variable that equals one if a firm's AI/green-related job postings in the year after the disclosure are lower than those in the year prior, 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.

Panel A: AI investment		Panel B: Green investment	
Dependent Var.	Cut	Dependent Var.	Cut
Sample	Negative FB	Sample	Negative FB
	(1)		(1)
FB	-0.192*** (-3.43)	FB	-0.092** (-1.97)
Controls	Yes	Controls	Yes
Firm FE	Yes	Firm FE	Yes
Industry $\times$ Year FE	Yes	Industry $\times$ Year FE	Yes
Observations	18,521	Observations	39,206
R-squared	0.561	R-squared	0.419

Table 5: Investment response to emerging-technology market feedback – Hourly market reaction

This table presents the analysis of a firm’s investment response to emerging-technology market feedback using the hourly stock price change following the announcement of its emerging-technology investment plans during earnings conference calls. Columns (1) and (2) study AI-related and green-related investments, respectively. In column (1), the dependent variable is $\Delta AI \text{ Job Postings}$. In column (2), the dependent variable is $\Delta Green \text{ Job Postings}$. FB_{Hour} is the firm’s stock price change in the hour right after the managerial disclosure of their emerging-technology investment plans. $Return_{PreHour}$ is the firm’s stock price change from the beginning of the earnings conference call until the time the managers disclose their emerging-technology investment plans. $Return_{PostHour}$ is the firm’s stock price change from the closing of the managerial disclosure of their emerging-technology investment plans until the end of the earnings conference call. 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:	$\Delta AI \text{ Job Postings}$	$\Delta Green \text{ Job Postings}$
	(1)	(2)
FB_{Hour}	0.260** (1.99)	0.146* (1.70)
$Return_{Pre}$	-0.208 (-0.74)	-0.029 (-0.12)
$Return_{Post}$	0.107 (0.65)	0.080 (0.89)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry $\times$ Year FE	Yes	Yes
Observations	4,953	10,738
R-squared	0.660	0.487

Table 6: Subsample analysis of earnings conference calls and 8-K filings

This table presents the analysis of a firm's investment response to emerging-technology 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 $\Delta AI \text{ Job Postings}$. In Panel B, the dependent variable is $\Delta Green \text{ Job Postings}$. Columns (1), (2), and (3) examine earnings conference calls, 8-K filings, and "focused" 8-K filings that have only one item, respectively. FB is the firm's five-day cumulative abnormal return surrounding the disclosure (i.e., $[-2, 2]$ with the disclosure date as day 0). 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				Panel B: Green investment			
Dependent Var.: $\Delta AI \text{ Job Postings}$				Dependent Var.: $\Delta Green \text{ Job Postings}$			
	Conference Call	8K	Stand- alone 8K		Conference Call	8K	Stand- alone 8K
	(1)	(2)	(3)		(1)	(2)	(3)
FB	0.083*** (2.96)	0.056*** (2.98)	0.067* (1.81)	FB	0.073** (2.06)	0.077** (2.47)	0.114*** (3.04)
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Firm FE	Yes	Yes	Yes
Ind. $\times$ Year FE	Yes	Yes	Yes	Ind. $\times$ Year FE	Yes	Yes	Yes
Observations	16,991	28,493	8,682	Observations	49,314	66,334	33,948
R-squared	0.583	0.576	0.677	R-squared	0.314	0.318	0.388

Table 7: Cross-sectional tests based on investors’ expertise in emerging technologies

This table presents cross-sectional tests 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 it an AI-score of one 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 the average of the institution’s quarterly green expertise score across the four quarters prior to a disclosure event. For each green investment-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		Panel B: Green investment	
Dependent Var.: Δ AI Job Postings		Dependent Var.: Δ Green Job Postings	
	(1)		(1)
FB $\times$ InstitutionAIExpertise	0.305*** (3.22)	FB $\times$ InstitutionGreenExpertise	0.184** (2.03)
FB	-0.024 (-0.90)	FB	-0.055 (-1.11)
InstitutionAIExpertise	0.010 (0.38)	InstitutionGreenExpertise	-0.035 (-0.71)
Controls	Yes	Controls	Yes
Firm FE	Yes	Firm FE	Yes
Industry $\times$ Year FE	Yes	Industry $\times$ Year FE	Yes
Observations	39,521	Observations	80,596
R-squared	0.551	R-squared	0.290

Table 8: Cross-sectional tests based on managers' uncertainty about their investment plans

This table presents cross-sectional tests based on managers' uncertainty about their investment plans in emerging technologies. FB is a firm's five-day cumulative abnormal return surrounding the disclosure date. $Uncertainty$ is measured as the number of uncertainty and risk-related keywords in the sentences disclosing the firm's emerging-technology investment plans scaled by the total number of words in those sentences. It is standardized to have zero mean and unit variance. 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		Panel B: Green investment	
Dependent Var.	Δ AI Investment	Dependent Var.	Δ Green Investment
	(1)		(1)
$FB \times Uncertainty$	0.042*** (2.67)	$FB \times Uncertainty$	0.043** (2.13)
FB	0.051*** (3.19)	FB	0.040** (2.16)
$Uncertainty$	0.000 (0.02)	$Uncertainty$	-0.002 (-0.71)
Controls	Yes	Controls	Yes
Firm FE	Yes	Firm FE	Yes
Industry $\times$ Year FE	Yes	Industry $\times$ Year FE	Yes
Observations	39,521	Observations	80,596
R-squared	0.551	R-squared	0.290

Table 9: When managers do not learn: Conventional technology and non-investment-related feedback

This table examines more facets of managerial learning by exploring other types of disclosures and subsequent corporate actions. 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 investment-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/green-related. A firm’s investment in conventional technologies is measured by its conventional technology-related job postings. The dependent variable, $\Delta \textit{Conventional Job Postings}$, is defined as the difference between the natural logarithm of one plus the weighted sum of conventional technology-related job postings by a firm in the year after a conventional technology investment-related corporate disclosure and the natural logarithm of one plus the weighted sum of conventional technology-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 $\Delta \textit{AI Job Postings}$ in columns (1) and (2) and is $\Delta \textit{Green Job Postings}$ 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 Var.	Δ Conventional Job Postings			
	(1)	(2)		
FB	0.003 (0.23)	0.008 (0.61)		
Controls	Yes	Yes		
Firm FE	No	Yes		
Industry $\times$ Year FE	No	Yes		
Observations	15,063	14,339		
R-squared	0.066	0.275		
Panel B: Investment response to non-investment-related emerging-technology market feedback				
Dependent Var.	Δ AI Job Postings		Δ Green Job Postings	
	(1)	(2)	(3)	(4)
NonInvFB	0.028 (0.91)	0.011 (0.65)	0.024 (0.52)	0.010 (0.25)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry $\times$ 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: Investment response to peer firms' emerging-technology market feedback

This table presents the pair-level analysis of a firm's investment response to each of its peers' emerging-technology market feedback. For each emerging-technology investment-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 (i.e., firms with TNIC3 scores above the sample median). Panels A and B study AI-related and green-related investment, respectively. In Panel A, the dependent variable is $\Delta AI \text{ Job Postings}$. In Panel B, the dependent variable is $\Delta Green \text{ Job Postings}$. $PeerFB$ is each peer firm's five-day cumulative abnormal return surrounding its emerging-technology investment-related disclosure date. FB is the focal firm's five-day cumulative abnormal return surrounding its peer's emerging-technology investment-related disclosure date. $Firm \text{ FE}$ are indicators for each focal firm. $Pair \text{ FE}$ are indicators for each pair of a focal firm and its peer firm. $Industry \times Year \text{ FE}$ 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 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 Var.: $\Delta AI \text{ Job Postings}$		
	(1)	(2)	(3)
PeerFB	0.002 (1.32)	0.001 (0.91)	0.001 (1.13)
FB		0.008 (1.65)	0.006 (1.21)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	No
Industry $\times$ 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 Var.: $\Delta Green \text{ Job Postings}$		
	(1)	(2)	(3)
PeerFB	0.008** (2.13)	0.007** (1.97)	0.007** (2.12)
FB		0.020 (1.03)	0.012 (0.73)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	No
Industry $\times$ 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 11: Benefits of following market feedback: Long-run performance

This table presents the analysis of comparing the long-term performance of a firm when it follows emerging-technology 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 investment-related disclosure. The dependent variable in columns (4) to (6) is the average raw stock return of the firm in the three years after the same disclosure. In Panel A, Follow is a dummy variable that equals one if the firm increases its AI job postings (i.e., $\Delta AI \text{ Job Postings} > 0$) following positive market feedback or decreases its AI job postings (i.e., $\Delta AI \text{ Job Postings} < 0$) 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., $\Delta Green \text{ Job Postings} > 0$) following positive market feedback or decreases its green job postings (i.e., $\Delta Green \text{ Job Postings} < 0$) following negative market feedback, and zero otherwise. *Firm FE* are indicators for each focal firm. *Industry $\times$ 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 Var.	ROA			Return		
Sample	Full	Negative FB	Positive FB	Full	Negative FB	Positive FB
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	0.002* (1.85)	0.006** (2.13)	-0.001 (-0.34)	-0.009 (-1.41)	0.019* (1.80)	-0.015 (-1.15)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10,481	3,619	6,252	10,481	3,619	6,252
R-squared	0.945	0.974	0.953	0.653	0.800	0.695
Panel B: Green investment						
Dependent Var.	ROA			Return		
Sample	Full	Negative FB	Positive FB	Full	Negative FB	Positive FB
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	-0.000 (-0.11)	0.012*** (2.34)	-0.010 (-1.64)	0.013* (1.69)	0.050** (2.15)	0.027 (0.92)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	17,127	11,223	5,433	17,127	11,223	5,433
R-squared	0.927	0.942	0.946	0.695	0.757	0.775

Internet Appendix for Market Feedback about Emerging Technologies

This internet appendix is organized as follows.

Appendix A	Examples of AI/green technology, investment, forward-looking, and uncertainty keywords
Appendix B	Examples of AI/green investment-related corporate disclosures
Appendix C	Additional tables
	Table A1: Alternative way of defining emerging-technology investment-related disclosures using 25-word windows
	Table A2: Alternative measures of emerging-technology investments
	Table A3: Pre-disclosure investment changes and emerging-technology market feedback
	Table A4: Non-emerging-technology investments and emerging-technology market feedback
	Table A5: Investment response to market reactions in other 5-day windows
	Table A6: Cross-sectional tests based on firms' exposure to technology competition
	Table A7: Cross-sectional tests based on the Paris Agreement

Appendix A: Examples of AI/green technology, investment, forward-looking, and uncertainty keywords

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

Appendix B: 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*

<u>Designation</u>	<u>Description</u>	<u>Method of Filing</u>
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 enabled 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.”

Ford Motor, Corporate Conference Call on February 2017 “I think this really builds on our ten years of working on autonomous vehicles, building on an incredible team of autonomous vehicle hardware and software developers. . . . We plan to build the best team, and this structure allows us to extend competitive equity that will allow employees to participate in the upside of Argo AI. ...We need to recruit the best people, and we will be hiring teams in those three markets.”

iRobot, Q4 2018 Earnings Conference Call “It is certainly a case of timing because of the challenges of attracting all of the talent that we would love to hire. We’ve been certainly building into our 2019 plan, new programs that we believe will help address the hiring challenges that we saw in 2018 and get us back to a place where talent does not slow us down. iRobot hires some of the best experts in artificial intelligence, machine learning, digital object recognition, mapping and navigation that exists on the planet. And so we certainly compete with other top tech companies for this top talent. And I think that in ’18, the growth in our strategic direction and the technology content of our robots left us a little bit short against our hiring plans, causing us to go and make some additional investments in how we source talent for ’19.”

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. . . . Technology 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.”

Appendix C: Additional Tables

Appendix Table A1: Alternative way of defining emerging-technology investment-related disclosures using 25-word windows

This table presents robustness tests using the mentioning of the three sets of keywords within a 25-word window (rather than a sentence) to identify AI/green technology investment-related disclosures. Panels A and B study AI-related and green-related investments, respectively. In Panel A, the dependent variable is ΔAI Job Postings. In Panel B, the dependent variable is $\Delta Green$ 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 $\times$ 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. Model specifications in columns (1) to (5) correspond to those of 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)	(2)	(3)	(4)	(5)
FB	0.093*** (5.47)	0.093*** (5.55)	0.067*** (5.06)	0.070*** (5.28)	0.056*** (4.24)
Firm FE	No	No	No	No	Yes
Industry $\times$ Year FE	No	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Observations	56,328	56,021	56,021	56,000	55,265
R-squared	0.001	0.015	0.403	0.428	0.525
Panel B: Green Investment					
	Dependent Variable: $\Delta Green$ Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.091*** (3.00)	0.088*** (2.91)	0.057** (1.96)	0.045** (2.27)	0.051*** (2.61)
Firm FE	No	No	No	No	Yes
Industry $\times$ Year FE	No	No	No	Yes	Yes
Controls	No	Yes	Yes	Yes	Yes
Observations	100,781	100,586	100,586	100,584	100,454
R-squared	0.000	0.002	0.117	0.175	0.255

Appendix Table A2: 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, 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, 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. Following [Cohen, Gurun, and Nguyen \(2025\)](#) and [Haščić and Migotto \(2015\)](#), 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 Total GHG emissions, 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 CO₂) from the year prior to a green investment-related corporate disclosure to the year after the disclosure. Corporate carbon emission data is obtained from Trucost that collects firms' carbon emission data from publicly available sources and covers a wide spectrum of firms around the world. 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, Duro, Kadach, and Ormazabal \(2021\)](#), a firm's annual GHG emission is calculated as the total amount of GHG emission (in equivalents of metric tons of CO₂) based on all three scopes.* *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 Var.:	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*** (2.73)	0.052** (2.44)	0.045* (1.80)	0.007** (2.53)	0.007* (1.93)	0.006 (1.29)	-0.378** (-2.84)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,239	26,280	18,134	111,460	105,435	93,029	64,908
R-squared	0.628	0.702	0.736	0.393	0.443	0.583	0.702

Appendix Table A3: Pre-disclosure investment changes and emerging-technology market feedback

This table presents the analysis of the associations 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 Δ AI 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 Δ Green 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 Var.	Past Δ AI Job Postings		Past Δ Green Job Postings	
	(1)	(2)	(3)	(4)
FB	0.000 (0.00)	-0.011 (-0.67)	-0.042 (-1.27)	-0.018 (-0.56)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry $\times$ 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

Appendix Table A4: Non-emerging-technology investments and emerging-technology market feedback

This table presents the analysis of firms' non-emerging-technology investment adjustments in response to the stock market changes surrounding their emerging-technology-related disclosures. FB is the firm's five-day cumulative abnormal return surrounding the disclosure (i.e., $[-2, 2]$ with the disclosure date as day 0). $\Delta Non-AI \text{ Job Postings}$ is the change in the natural logarithm of one plus the weighted sum of non-AI-related job postings by a firm from the year prior to an AI investment-related corporate disclosure to the year after the disclosure. $\Delta Non-Green \text{ Job Postings}$ is the change in the natural logarithm of one plus the weighted number of non-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.

Dependent Var.	$\Delta Non-AI \text{ Job Postings}$		$\Delta Non-Green \text{ Job Postings}$	
	(1)	(2)	(3)	(4)
FB	-0.000 (-0.07)	0.002 (0.39)	-0.003 (-0.28)	0.006 (0.57)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry $\times$ Year FE	No	Yes	No	Yes
Observations	40,317	39,521	80,730	80,596
R-squared	0.987	0.990	0.964	0.972

Appendix Table A5: Investment response to market reactions in other 5-day windows

This table presents the analysis of a firm's AI/green investment response to the firm's stock market changes in other windows other than surrounding the emerging-technology investment-related 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 (i.e., day 0) 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. $\Delta AI \text{ Job Postings}$ 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. $\Delta Green \text{ Job Postings}$ 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 returns in pre-disclosure short window				
Dependent Var.	$\Delta AI \text{ Job Postings}$		$\Delta Green \text{ Job Postings}$	
	(1)	(2)	(3)	(4)
PlaceboFB[-7, -3]	-0.013 (-0.50)	-0.020 (-0.76)	-0.010 (-0.19)	0.005 (0.13)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry $\times$ 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 returns in post-disclosure short window				
Dependent Var.	$\Delta AI \text{ Job Postings}$		$\Delta Green \text{ Job Postings}$	
	(1)	(2)	(3)	(4)
PlaceboFB[3, 7]	0.005 (0.20)	-0.014 (-0.52)	0.008 (0.17)	-0.017 (-0.38)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry $\times$ 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

Appendix Table A6: 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 AI Job Postings. Following [Cao, Ma, Tucker, and Wan \(2018\)](#), we measure a firm's technology peer pressure (TPP) as:

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

where i denotes the focal firm, t denotes the year, and j denotes the peer firm. $G_{j,t}$ is peer firm j 's R&D stock in dollars at the end of year t . Following [Bloom, Schankerman, and Van Reenen \(2013\)](#), 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 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 closeness and the weight for that peer. Column (1) examines firms whose TPP is above the sample median in the year of the corporate disclosure, and column (2) examines firms whose TPP is below the 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 Var.	Δ AI Job Postings		
	High TPP	Low TPP	Full
	(1)	(2)	(3)
Sample			
FB	0.079*** (3.90)	-0.002 (-0.08)	0.000 (0.01)
FB $\times$ HighTPP			0.077** (2.46)
HighTPP			-0.017 (-1.49)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes
Observations	21,994	17,272	39,521
R-squared	0.597	0.582	0.552

Appendix Table A7: 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 Paris Agreement 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, which draws significant public attention to environmental and climate change issues, 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 dependent variable is $\Delta Green\ Job\ Postings$. 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.

Dependent Var. Sample	$\Delta Green\ Job\ Postings$		
	Before ($\leq$ Year 2015)	After ($\geq$ Year 2016)	Full
	(1)	(2)	(3)
FB	-0.003 (-0.07)	0.070*** (3.26)	-0.015 (-0.38)
FB $\times$ After			0.088** (1.97)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry $\times$ Year FE	Yes	Yes	Yes
Observations	32,889	47,659	80,596
R-squared	0.360	0.318	0.290

Reference

- [A1] Azar, J., M. Duro, I. Kadach, and G. Ormazabal. 2021. The Big Three and Corporate Carbon Emissions around the World. *Journal of Financial Economics* 142:674–696.
- [A2] Bloom, N., M. Schankerman, and J. Van Reenen. 2013. Identifying Technology Spillovers and Product Market Rivalry. *Econometrica* 81:1347–1393.
- [A3] Cao, S., G. Ma, J. W. Tucker, and C. Wan. 2018. Technological Peer Pressure and Product Disclosure. *The Accounting Review* 93:95–126.
- [A4] Cohen, L. H., U. G. Gurun, and Q. H. Nguyen. 2025. The ESG – Innovation Disconnect: Evidence from Green Patenting. *Management Science* Forthcoming.
- [A5] Haščič, I., and M. Migotto. 2015. Measuring Environmental Innovation Using Patent Data. OECD Environment Working Papers 89.