Feedback on Emerging Corporate Policies*

Sean Cao
Robert H. Smith School of Business
University of Maryland
scao824@umd.edu

Itay Goldstein
Wharton School
University of Pennsylvania
itayg@wharton.upenn.edu

Jie (Jack) He
Terry College of Business
University of Georgia
jiehe@uga.edu

Yabo Zhao
School of Management and Economics
Shenzhen Finance Institute
Chinese University of Hong Kong, Shenzhen
zhaoyabo@cuhk.edu.cn

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Abstract

We explore the role of market feedback in facilitating emerging corporate policies on AI/green technologies. By assembling and analyzing a comprehensive sample of corporate press releases and disclosures in which managers discuss their emerging-technology-related investment plans, we find that firms adjust their AI/green investments upward (downward) in response to favorable (unfavorable) market reactions to such disclosures. This association is more likely due to managerial learning from the market than other alternative explanations, as it gets stronger when market reactions are unfavorable, when outside market participants are more knowledgeable about emerging technologies, and when managers have stronger incentives to promote investments in such fields. The documented investment adjustment is also absent when managers consider non-emerging-technology investment plans. Further, we find that such learning is rewarded by superior long-run operating and stock performance, especially when the feedback is unfavorable. Overall, our paper illustrates the usefulness of tapping the wisdom of the crowd when venturing into uncharted areas and sheds new light on how managerial learning from the market differs across various types of corporate investment.

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

1. Introduction

Firms are constantly facing new challenges, but the recent rise in the prominence of new technologies – specifically artificial intelligence (AI) and green (i.e., climate/environment related) technologies – and the decisions firms need to make on investing in them have been exceptional. In the area of climate changes, firms have to grapple not only with their own exposure to physical climate threats, but also with the regulatory risk that new environment-friendly measures might be enforced and with the technological risk that green innovations might render the firms' current equipment/technology obsolete. Similarly, while AI technologies such as automation, machine learning, or big data analytics impose threats to companies operating with traditional business models, they offer first-mover advantages to new technology adopters. Against those uncertain benefits, investments in these rapidly growing fields entail significant upfront costs and a serious commitment of corporate resources, yet do not deliver immediate returns in terms of cash flows or profits.[1] Moreover, even after the initiation of such investments, market trends, regulatory intervention, and technology development might all evolve in undesirable directions.[2] Hence, firms have to assess the desirability of such investments without any past records to learn from and with limited models of the costs and benefits involved.

With these uncertainties and risks in mind, corporate insiders (i.e., managers and boards of directors) naturally need to look for external sources of information. While they can seek opinions from their friends/contacts in the industry or other professionals such as consulting companies, investment bankers, or financial analysts (e.g., Cookson, Niessner, and Schiller, 2022; Bae, Biddle, and Park, 2022), such feedback is likely limited in both scope and relevance, as these outsiders have no stakes in the focal firm and can only offer suggestions from their own (and sometimes conflicting) perspectives. A prominent alternative information source is the market, which is known to aggregate the opinions of a diverse body of different investors. A growing strand of literature has documented that informational feedback from the financial markets can help guide the decision making of corporate managers in the real sector (e.g., Chen, Goldstein, and Jiang, 2007; Luo, 2005; Edmans, Jayaraman, and Schneemeier, 2017; Dessaint et al., 2019; Jayaraman

[1] For example, only 20% of the approximately 3,000 AI-aware C-level executives surveyed by McKinsey in 2017 admitted implementing AI-related technology on a large scale or incorporating it into their core businesses. Many of them said that poor or uncertain returns on such investment are the primary reasons that prevent them from adopting the technology. Similarly, recent literature has found that green sustainable energy investment also tends to be associated with higher risk and lower short-term returns (e.g., Lopez, Garcia, and Rodriguez, 2007).
[2] See, e.g., Acemoglu, Hanley, and Kerr (2016), Albrizio and Costa (2012), and Blyth et. al (2007).

and Wu, 2020). We postulate that such learning can be particularly relevant in the case of AI and green technologies, given the uncertainties involved and the lack of other sources of information. Hence, in this paper, we examine whether managers actively tap the wisdom of the crowd from stock markets when they venture into such emerging technologies.[3] Our hypothesis is that firms' investments in AI and green technologies would be positively associated with the stock market reaction to the mentioning of such investment plans in their major corporate disclosures. Aside from identifying a market-based solution to guide firms' emerging corporate policies, this study can also push the literature by highlighting *when* managers learn and *what information* they learn from the market (Goldstein, 2022).

We use textual analysis to identify firms' emerging-technology-related disclosures based on their earnings conference calls and material press releases contained in the 8-K filings.[4] To focus on disclosures that are forward-looking in nature, we make sure the discussion of the AI/green investments in them is about future plans instead of ongoing projects. Figure 1 shows that over the period of 2006 to 2019, the annual fraction of major corporate disclosures discussing AI investment plans increases from about 6% to 11%, and that of disclosures discussing green investment plans increases from about 17% to 27%. Following Babina, Fedyk, He, and Hodson (2022a, b), we measure the level of a firm's AI investment using its AI-related job postings. A larger number of such postings indicate the firm's stronger motive and commitment to invest in AI. To capture the extent of a firm's green investment, we use the amount of its Green House Gas (GHG) emissions.[5] A lower amount of GHG emission indicates that firms have increased their investment in green (i.e., environmentally friendly) technology adoption.

Using a sample of 48,181 AI-investment-related disclosures and 106,650 green-investment-related disclosures, we find that changes in firm-level AI and green investments from

[3] Even though firms sometimes make green (or other ESG) investments to pursue objectives other than shareholder value maximization, managers might still cherish stock market feedback on such investment plans as long as they care about stock prices and the market as a whole possesses incremental knowledge about such emerging corporate policies.
[4] Our findings are robust when we examine earnings conference calls and 8-K filings separately. We also examine a firm's 10-K and 10-Q filings but find very little mentioning of emerging-technology-related investment plans in these disclosures.
[5] We acknowledge that green investment is broader than controlling the amount of GHG emissions, such as efforts to affect toxic material emissions, resources recycling, and so on. However, we focus on GHG emission to capture green investment outcomes because it is one of the most widely used measures that have drawn a lot of attention from investors (see, e.g., Azar et al., 2021; Bolton and Kacperczyk, 2021; Hsu, Liang, and Matos, 2021; and Atta-Darkua et al., 2023). In our robustness section, we examine alternative measures of green investment based on patenting outcomes or job postings and find consistent results.

one year before to one year after a disclosure event are positively associated with the cumulative abnormal return (CAR) over a short window (i.e., 5 days) surrounding the event. This result suggests that firm managers adjust upward (downward) their emerging-technology-related investment when the stock market reacts favorably (unfavorably) to related discussions in their major corporate disclosures. The economic magnitude of this feedback effect is also nontrivial: A one standard-deviation increase in market reaction is associated with an increase in AI job postings by around 0.8% (about 9% of the mean increase in such postings) and a decrease in Green House Gas emissions by around 8.1% (about 10.7% of the mean decrease in such emissions). These associations remain robust even after we control for major ex ante (i.e., pre-disclosure) firm characteristics, contemporaneous changes in firms' overall (non-emerging-technology-related) investments from pre to post the disclosure event, industry by year fixed effects, and firm fixed effects.

A common concern when testing theories of market feedback is that the positive relation between the market's reaction and the subsequent corporate investment might reflect an anticipation effect. This means that, upon seeing the corporate disclosure on emerging technologies, the market anticipates managers to increase their investment in these areas and reacts positively under the belief that these investments are good.[6] Hence, no active feedback from the market to the firm needs to be involved. While this is a compelling alternative, the logic of such anticipation effect breaks down when it comes to negative market reactions to the corporate disclosure (i.e., when the market and firm managers *disagree* on the importance/value of emerging corporate policies). Indeed, we find that nearly half of the disclosures, with the mentioning of increasing or expanding AI/green investments, are followed by negative market reactions. It suggests that investors do not view such investments positively. More importantly, when the market reaction is negative, we observe an even stronger positive association between investment changes and announcement returns. This observation directly contradicts the prediction of the anticipation explanation and instead demonstrates more active learning.

To further tie our results to market feedback, we explore cross-sectional variation in the documented relation between market reactions and subsequent corporate investment changes.

[6] Note that based on our manual reading of companies' AI/green-investment-related disclosures in our sample, almost all of them are about the plans to launch/expand rather than to stop/reduce the investment in such technologies. Hence, the market is more likely to anticipate an increase instead of a reduction in emerging-technology investment upon seeing the disclosures.

Following the spirit of studies in the market feedback literature (e.g., Dye and Sridhar, 2002, Chen et al., 2007, and Jayaraman and Wu, 2020), we examine whether our baseline results are stronger when outside market participants, such as institutional investors, possess more expertise in the relevant emerging technologies, and find supporting evidence. Further, we show that the AI investment adjustment in response to market reaction is more pronounced when a firm faces greater technology peer pressure (as defined in Cao et al., 2018). Similarly, the association between the green investment adjustment and market reaction is stronger after the announcement of the Paris Agreement in December 2015, a landmark event that markedly increases market attention to environmental issues and corporate green actions. Taken together, these results show that the feedback effect is more pronounced when the market possesses more valuable information/insights about emerging technologies or when firm managers have stronger incentives to enhance investments in these fields.

To shed more light on when and what information managers learn, we conduct a few additional tests that explore the nature and timing of emerging corporate policies. First, we examine whether the documented feedback effect is weaker when the technologies mentioned in corporate disclosures are non-emerging in nature (e.g., traditional data analysis techniques such as linear regressions, time series analysis, or Monte Carlo simulation methods). For such conventional technologies, the market might possess less incremental knowledge compared to that of firm managers, and thus may not provide useful feedback to guide firms' investment decisions. Consistent with this prediction, we find that managers do not significantly change their conventional-technology-related hiring in response to the market feedback on the disclosure of investment plans in these areas. Second, we examine whether the feedback effect on emerging corporate policies still exists when the related discussions in the disclosures are *not about investment plans* but only referring to these technologies in a general way. Interestingly, we do not find a significant feedback effect for such disclosures. This suggests that the observed announcement return, which is followed by subsequent investment adjustments, is unlikely driven by the market's sentiment towards the risks, nature, or prospects of these emerging technologies per se. Instead, it is more likely driven by the market's reaction to firms' specific investment plans in these areas. Third, we find that firms' *past* (i.e., *pre-disclosure*) investment adjustments in emerging technologies are not positively associated with the market reactions, which further supports the notion that firms are actively responding to the market feedback on the proposed investment. Our results are also robust to alternative measures of emerging-technology-related investments, such as changes in AI and green-related patent filings, and changes in job postings requiring green/climate-related skills (in the same fashion as our AI-related job postings).

Since major corporate disclosures contain a large amount of information, one might be concerned that the observed announcement returns capture market reactions to other components that correlate with subsequent AI/green investment behaviors, such as information about general investment opportunities, management quality, or other firm fundamentals. We adopt three approaches to mitigate this concern. First, we confirm our baseline findings using a subsample of "focused" 8-K filings with only one item (that mentions emerging-technology investment plans).[7] 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 the plans of firms' emerging corporate policies, which alleviates the concern that our results are driven by confounding information components. In the second approach, we construct a counterfactual "market reaction" to the non-emerging-technology-related parts of a sample disclosure. Specifically, for each AI/green-related disclosure in our sample, we match it to up to five non-AI/non-green related disclosure events of the same type (i.e., earnings conference call or 8-K filing) by the *same firm* with the closest textual similarity (following Hoberg and Phillips, 2016; Lang and Stice-Lawrence, 2015; and Brown and Tucker, 2011). Then we analyze how the firm's AI/green investment is associated with the "emerging-policy-related" market feedback (i.e., the difference between the actual market reaction of the focal disclosure event and the counterfactual market reaction). We find a significantly positive relation between a firm's AI/green investment adjustment and the emerging-policy-related market feedback, suggesting that our results are unlikely driven by the omitted yet investment-relevant parts of the corporate disclosures. Lastly, we find no significant adjustments in emerging technology investments surrounding these matched non-emerging-technology-related disclosures.

To explore what specific information managers learn about emerging corporate policies, we classify AI and green technologies into subcategories and examine which of them yields the strongest feedback effect. We first classify AI investment plans into those on robots/automation-

[7] Appendix B1 Panel A presents an example of focused 8-Ks: On February 10, 2017, Ford Motor filed a focused 8-K with only item 8.01 to announce its investment plan of $1 billion to develop a virtual driver system for the automaker's autonomous vehicles in the next five years.

related and data-related ones, and find that the feedback effects for both types of AI investments are of similar magnitudes. Then, following Sautner et al. (2022), we consider three subcategories within green investment: opportunity-, regulatory-, and physical-related, and find that our baseline results are stronger for opportunity-related green investment (such as growth opportunities in developing renewable energy or electric vehicles) and regulatory-related green investment (such as policy-orientated improvements of production processes), but absent for physical-related green investment (such as those triggered by natural disasters).

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

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

Overall, we think that our study makes three main contributions. First, to the best of our knowledge, we are the first to assemble a comprehensive sample of AI/green-investment-related corporate disclosures, and to document the trend and extent of such active feedback-seeking by firm managers. Given that these disclosures are largely voluntary in nature, future studies can leverage them to examine firms' strategic disclosure behaviors regarding their emerging corporate policies. Meanwhile, our analyses consider both the information outflow (via making specific disclosures) and inflow (via learning from the feedback), namely, the two-way information exchange between firm insiders and outsiders, which complements the large literature on how corporate disclosures, such as earnings conference calls and SEC filings, facilitate information dissemination (Frankel et al., 1999; Matsumoto et al., 2011; Zhao, 2017; Gibbons et al., 2021).

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

Third, our paper opens new dialogues for future research on *when* and *what* information managers actually learn from the market, while most of the empirical feedback literature to date has been focusing on *whether* such learning is going on (e.g., Chen, Goldstein, and Jiang, 2007; Luo, 2005; Bakke and Whited, 2010; Edmans, Goldstein, and Jiang, 2012; Betton et al., 2014; Bai, Philippon, and Savov, 2016; Zuo, 2016; Dessaint et al., 2019; Jayaraman and Wu, 2020; Banerjee et al., 2022; Cao et al. 2022).[8] In particular, we provide robust evidence that managers elicit and subsequently act on the feedback from financial markets regarding their emerging corporate policies (i.e., investment plans on AI and green technologies) that are highly uncertain and controversial, and about which the market can be more informed than managers. In contrast, such

[8] See Goldstein (2022) and Bond, Edmans, and Goldstein (2012) for comprehensive reviews of this literature.

learning does not exist for non-emerging corporate policies (e.g., investment plans on conventional technologies). More importantly, our evidence indicates that the market feedback effect differs even *within* emerging-technology-related investments. For one example, while managers adjust both types of investments following negative market reactions, this response is only significant for AI-related investments (but not for green-related investments) following positive market reactions. For another, the peer learning effect only manifests in green-related but not AI-related investments. These results suggest that insights from the prior literature on managerial learning in the context of one investment type (such as capital expenditures or acquisitions) might not be directly applicable to the context of another.[9]

2. Data, Variable, and Sample Construction

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

2.1 Corporate disclosures about emerging-technology-related investment plans

We begin our sample construction with firms' major corporate disclosures including their earnings conference calls (as covered by StreetEvents) and 8-K filings from 2006 to 2019. To identify managers' AI/green-investment-related disclosures, we construct four lists of keywords (e.g., see the examples in Appendix Table A1). The one on AI technology is obtained by combining those in Babina et al. (2022 a, b), Abis and Veldkamp (2022), Cao et al. (2022), Gofman and Jin (2022), and Cockburn et al. (2018). The list of green technology keywords is obtained by supplementing the dictionaries in Engle et al. (2020) and Sautner et al. (2022) with manually identified green-technology related keywords from the Sustainability Accounting Standards Board

[9] A contemporaneous working paper by Aretz, Ilyas, and Kankanhalli (2022) also examines the nature of information managers learn from the market using a different research design, but like most of the extant literature, it focuses on ordinary investment choices such as capital expenditures, R&D, and acquisitions.

(SASB) Standards as well as those extracted from firms' annual CSR reports and press releases by adopting a word-embedding approach as in Li et al. (2021) and Cao et al. (2022).[10] Similarly, the list of investment related keywords is constructed by supplementing those in Ball, Hoberg, and Maksimovic (2015) and Hoberg and Maksimovic (2015) with words about decision making or business investment in the Oxford Dictionary. We also include manually identified investment related keywords in the corporate disclosures (earnings conference calls and 8-K filings), as well as keywords extracted from firms' annual CSR reports and press releases by adopting the same word-embedding approach described above.[11]

Finally, as our focus is on examining managers' potential learning from the market feedback, we want to limit our attention to only those disclosures that discuss future (i.e., intended or forthcoming) investment plans rather than past or ongoing projects in emerging technologies. While the disclosure of past/existing investment projects is often required as part of managers' fiduciary duty to investors, the disclosure of future investment plans is largely voluntary in nature and better captures managers' intention to actively seek market feedback.[12] Therefore, we construct a list of forward-looking keywords.[13] We then define a disclosure as AI/green-investment-related if it has the mentioning of AI/green technology specific keywords, investment related keywords, and forward-looking keywords (to ensure the description of the investment is about future plans instead of past or ongoing projects) in the same sentence within a given corporate disclosure (i.e., a conference call script or 8-K filing).

Appendix B1 presents examples of AI/green-investment-related disclosures for both 8-K filings (Panel A) and earnings conference calls (Panel B). Panel A describes the example of a focused 8-K filed by Ford Motor, which contains information only about one material event in item 8.01 – a news release of Ford's investment plan of $1 billion in Argo AI to develop autonomous vehicles in the next five years. Unlike earnings conference calls that tend to contain a large amount of information other than emerging-technology investment plans, this focused 8-K

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

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

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

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

filing contains information exclusively about Ford's AI investment plans. In Section 4.4, we perform our baseline analysis only on a subsample of focused 8-K filings to alleviate the concern that the market might be reacting to omitted non-emerging-policy-related information in corporate disclosures. Panel B presents several examples for emerging-policy-related earnings conference calls, including the case of Alphabet's 2015 Annual Meeting of Stockholders Conference Call. As we can see, market participants (i.e., Alphabet's shareholders) are knowledgeable about the proposed renewable energy plan based on their own past working backgrounds and thus can provide useful feedback on the firm's investment. Interestingly, in this example, Alphabet's shareholders hold opposite views on the green-related investment plan. This suggests that it is necessary for managers to aggregate opinions from the market on such uncertain and controversial emerging corporate policies.

Figure 1 plots the time trend of the propensity of US public firms to discuss investment plans on emerging technologies in their earnings conference calls and 8-K filings from 2006 to 2019. The left y-axis denotes the propensity of AI-technology related disclosures, and the right y-axis denotes the propensity of green-technology related corporate disclosures. As we can see, there is a significant increase of emerging-technology-related disclosures over time: The propensity of AI-technology (green-technology) related disclosures increases from about 6% to 11% (from 17% to 27%).

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

2.2 Firm-level AI investment

To capture the extent of a firm's AI investment, we follow Babina, Fedyk, He, and Hodson (2022a, b) to examine its job postings that require AI-related skills. A larger number of AI-related postings indicate the firm's stronger motive and commitment to invest in AI. We obtain firms' job postings from Burning Glass (BG) Technologies (now named Lightcast). BG has one of the world's largest real-time, proprietary databases of job openings and career histories.[14] A potential concern of obtaining job postings from multiple sources is that multiple job postings can link to a single job vacancy. To alleviate this concern, BG employs a sophisticated two-step approach to deduplicate job postings and avoid double counting job vacancies.[15] According to its report, up to 80% of all jobs are deduplicated. The data provides detailed information for each job posting including the job title, required skills, occupation, and the employer.

We focus on non-internship job postings with non-missing employer names and at least one required (i.e., AI-related) skill. To match BG employers to firms in the Compustat and CRSP merged database (CCM), we apply a fuzzy name matching approach after removing non-letter and non-number symbols from the name strings and stripping out their common endings such as "Inc", "Co", and "LLC". We match 52 million (around 27% out of 197 million) BG job postings to firms in the CCM database, which is consistent with prior statistics showing that publicly listed firms account for approximately 26% of overall US employment (Davis et al., 2006).[16]

To identify AI-related job postings and calculate a firm-level AI hiring measure, we follow Babina et al. (2022a, b) and take three steps. First, for each skill s required by any job postings in the BG data, we calculate the skill's AI-relevance score as the number of job postings that require both the skill s and at least one of the four basic AI skills (i.e., artificial intelligence (AI), machine learning (ML), natural language processing (NLP), and computer vision (CV)), divided by the total number of job postings requiring at least the skill s.[17] 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 as the change in the natural logarithm of one plus the weighted sum of AI-related job postings by the firm from the previous year to the current year. The weight of each job posting is its AI-relatedness obtained in the second step.

[14] It collects job posting information from more than 40,000 sources daily in more than 30 countries and covers over 197 million job postings in the US in 2007 and 2010-2020.
[15] See more details about the deduplication approach at https://kb.emsidata.com/faq/how-does-emsi-burning-glass-handle-duplicate-postings/#.
[16] The 27% matching rate is slightly lower than that in Babina et al. (2022b), who match BG job postings to Compustat firms (without requiring their stock listing status).
[17] We thank the authors of Cao, Jiang, Yang, and Zhang (2023) and Babina, Fedyk, He, and Hodson (2022a, b) for sharing with us the processed AI-relevance score of skills.

2.3 Firm-level green investment

To measure a firm's investment in green technology, we examine its greenhouse gas (GHG) emissions. The intuition is that a smaller amount of GHG emission indicates that a firm has increased its investment in green (i.e., environmentally friendly) technology adoption and therefore has lower GHG emission. We obtain corporate carbon emission data from Trucost, which collects firms' carbon emission data from publicly available sources and covers a wide spectrum of firms around the world.[18] There are three major scopes (categories/types) in a firm's GHG emissions. Scope 1 emissions are the direct emissions from sources that a firm owns or controls, e.g., emissions produced by the internal combustion engines of trucks owned by a trucking company. Scope 2 emissions arise from a firm's consumption of purchased electricity, steam, or other sources of energy related to its direct operations. And scope 3 encompasses all other emissions associated with a firm's operations that are not directly owned or controlled by the firm, including indirect emissions from the supply chain. Following Azar et al. (2021), we calculate a firm's annual GHG emission as the total amount of GHG emission (in equivalents of metric tons of CO_2) based on all three scopes.[19] Although GHG emissions are an important and timely reflection of firms' green investment outcomes, we acknowledge that it might capture only one aspect of green investment. Hence, in Section 5.4, we use the development of green patents as an alternative measure of green investment. Green patents cover a wider range of environmentally related issues, including air pollution, water pollution, resource recycling, and so on. However, unlike GHG emissions, the development of green patents takes time and thus might not capture a firm's green investment in a timely manner.

2.4 Sample 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 investment is based on the BG job posting database, which has consecutive coverage only starting from 2010, we limit our sample to 48,181 AI-related disclosures made by 4,568 unique firms between 2010 and 2019. Meanwhile, as we measure a firm's green investment as its GHG emission *reduction*, we require it to have non-zero GHG emission in the nearest year prior to a green-technology related

[18] It covers around 5,000 firms annually between 2006 and 2015, and over 14,000 firms annually between 2016 and 2020.

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

disclosure. We also exclude a related 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 106,650 green-technology related corporate disclosures covering 3,178 unique firms from 2006 to 2019.

Our goal is to examine whether managers learn from the market feedback when venturing into emerging technologies. In our main analysis, we use firms' AI job postings to measure their investment in AI technology and their total GHG emission to measure their investment in green technology. Specifically, based on the firm-level AI investment defined in Section 2.2, we construct $\Delta AI\ Job\ Postings$, a firm's AI investment adjustment surrounding an AI-investment-related disclosure, as the change in the natural logarithm of one plus the weighted number of AI job postings by the firm from the year prior to an AI-investment-related corporate disclosure to the year after the disclosure. Similarly, based on the firm-level green investment defined in Section 2.3, we construct $\Delta Total\ GHG\ emission$, a firm's green-technology investment adjustment surrounding a green-investment-related disclosure, as the change in the natural logarithm of one plus its total GHG emission from the year prior to the disclosure to the year after. As robustness checks, we also examine three alternative emerging-technology-related investment measures based on patent filings and the number of green-technology related job postings (see Section 5.4 for more details).

Table 1 Panel A (B) reports the number of AI (green)-investment-related disclosures and firms' related investment adjustments surrounding the emerging-technology-investment disclosures. The independent variable of interest, FB, denoted for feedback, is the five-day cumulative abnormal return surrounding the disclosure (i.e., [day -2, day 2]). Day 0 denotes the announcement date of a given corporate disclosure. As expected, an average firm exhibits an increase in its AI job postings and a decrease in its total GHG emissions, indicating an overall upward trend in the investment of these two emerging technologies.

Lastly, we construct a set of quarterly firm characteristics that are likely to be correlated with AI/green investment. These control variables, measured at the nearest quarter end prior to emerging-technology-investment-related disclosures, include firm size (log of total sales in billion dollars), return on assets, R&D to sales ratio, and cash reserve (cash holdings over assets). Table 1 reports the summary statistics of these characteristics. To account for the change in overall investment rate from the year prior to an emerging-technology-related corporate disclosure to the year after, we also control for the change in total job postings (the annual sales growth rate) from the pre-disclosure year to the post-disclosure year when estimating regressions for AI-related (green-related) investments. All continuous variables are winsorized at the 1st and 99th percentiles to minimize the effects of outliers. For firms that make AI-investment-related disclosures, they on average have quarterly sales of $1.117 billion, ROA of 1.6%, R&D to sales ratio of 19.6%, and cash reserve of 19.8% during the quarter prior to the disclosure announcement. Further, for such firms, the average change in the log of total job postings from the pre-disclosure year to the post-disclosure year is 0.245. For firms making green-investment-related disclosures, they on average have quarterly sales of $1.836 billion, ROA of 2.4%, R&D to sales ratio of 14.2%, and cash reserve of 14.3% during the quarter prior to the disclosure announcement. Additionally, these firms have an average annual sales growth of 2.4% from the pre-disclosure year to the post-disclosure year.

3. Learning from the Market Feedback on Emerging Corporate Policies

3.1 Baseline model and results

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

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

where $AdjInvestment_{i,d,t}$ is the change in firm i's emerging-technology investment from the year prior to a corporate disclosure d in year-quarter q to the year after the disclosure. The main independent variable of interest, $FB_{i,d,q}$, refers to the five-day cumulative abnormal return surrounding the disclosure date of firm i's emerging-technology related corporate disclosure d made in quarter q. We control for various lagged firm characteristics (discussed in the previous section) at the nearest quarter end prior to the corporate disclosure. To isolate the effects of time-invariant firm characteristics or time-varying industry trends, we also include *Firm fixed effects* and/or *Industry* × *Year fixed effects* in different model specifications. Standard errors are clustered at the firm level to account for within-firm correlations among the residuals.

Table 2 Panel A presents the baseline results regarding AI investment. We start with a parsimonious model in column (1) that only includes *FB*, the market reaction to the AI-investment-related corporate disclosure, as the independent variable. The coefficient of FB is 0.091 and significant at the 1% level. It suggests that a one standard-deviation increase in the market reaction is associated with an increase in firms' AI job postings by about 0.8% (=0.091×0.093), which is approximately 9.4% of the sample average change in AI investments (0.094=$e^{0.09} - 1$). The positive association is robust to including various firm characteristics (column 2), 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). These results suggest that managers seem to adjust their AI investments upward (downward) in response to a positive (negative) market reaction to their AI-investment-related corporate disclosures.

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 -0.998 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 a decrease in firms' GHG emissions by around 8.1% (=-0.998×0.081), which is approximately 10.7% of the sample average change in GHG emissions (-0.758=$e^{-1.418} - 1$). Similar to Panel A, columns (2) to (5) show that the coefficient of FB remains negative and statistically significant after the inclusion of firm characteristics, firms' contemporaneous sales growth (as a proxy for overall investment changes), and various layers of fixed effects. It is worth pointing out that, as described in Section 2.4, the dependent variable in our regressions captures the *change* in a firm's green investment. Therefore, the negative association here does not suggest the firm is divesting (expanding) its green technologies upon negative (positive) market reactions, but rather suggests that when the market feedback is more negative (positive), the firm slows down (speeds up) *its reduction* in GHG emissions, which is an overall trend in the economy. To sum up, these results are consistent with our feedback hypothesis that managers adjust their green investments upward (downward) in response to a positive (negative) market reaction to their green-technology related corporate disclosures.

3.2 An alternative non-feedback-based explanation – Anticipation of the market

The documented positive association between firms' emerging-technology investment changes and market reactions to related corporate disclosures is consistent with our feedback hypothesis. However, there might be potential non-feedback-based explanations. A common concern when testing theories of market feedback is that the positive relation between the market's reaction and the subsequent corporate investment might reflect an anticipation effect. That is, the market, upon seeing the corporate disclosure on emerging technologies, anticipates managers to increase their investment in such areas and reacts positively under the belief that these investments are good.[20] Hence, under this alternative explanation, the *larger increase* in investment the market anticipates (based on the enthusiasm in the related disclosure), the *more positive* the announcement return is. This leads to a positive correlation between actual investments in emerging technologies and the market reactions without any feedback or learning going on.

However, as the majority of corporate disclosures indicate an increase rather than a decrease in emerging technology investment (e.g., see the examples in Appendix B1), the anticipation story would predict that the market reactions to most of our sample disclosures are positive and that our baseline results are more prominent when the market reaction is positive (i.e., when the market and the firm agree on the value/importance of emerging technologies).

To test these two predictions, we split the sample of emerging-technology related corporate disclosures into two groups: one with positive market reactions and the other with negative market reactions. We then separately estimate our baseline regression in Equation (1) for the two subsamples. Table 3 presents the results. Several interesting patterns emerge. First, by comparing the number of observations in columns (1) and (2) for each panel, we can see that almost half of both AI and green investment-related disclosures have negative market reactions, which is inconsistent with the implications of the anticipation story.

Furthermore, 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, suggesting that the positive association between investment adjustments and market reactions is more prominent when the market reaction is *negative*. This contradicts the prediction of the anticipation explanation but demonstrates more active learning.

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

[20] Some studies (e.g., Chava et al., 2022) find that the market generally likes emerging technologies as firms mentioning "buzzwords" related to such technologies in their earnings conference calls tend to experience immediate stock price appreciation.

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

3.3.1 Market participants' expertise in emerging technologies

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

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

To examine the expertise of institutions in green technologies, we obtain the environmental score of firms from Refinitiv ESG Company Summary database, which considers three environmental categories: resource use, emissions, and innovation. We then measure an institution's expertise in green technologies in a given quarter as the weighted average environmental score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Next, we take average of the institution's quarterly green expertise score across the four quarters prior to a disclosure event. For each green-related corporate disclosure, the focal firm's average institutional green expertise score, *InstitutionGreenExpertise*, is then calculated as the value-weighted average of the institutional green expertise score across all its institutional blockholders (i.e., those holding 5% or more of the firm's outstanding shares). Each institutional blockholder's weight is the number of the focal firm's outstanding shares held by the institution at the nearest quarter end prior to the disclosure event.

Table 4 presents the results of the cross-sectional tests based on large institutional investors' expertise in emerging technologies. Panel A studies AI investment and institutions' AI technology expertise. The independent variable of interest is the interaction term, *FB* × *InstitutionAIExpertise*. As can be seen, the coefficient of the interaction is positive and significant, suggesting that when outside investors are more informed about AI technologies, managers make larger AI investment adjustments in response to the market feedback on their AI investment disclosures. Panel B presents the results of green investment and institutions' green expertise. Similarly, the negative and significant coefficient of *FB* × *InstitutionGreenExpertise* shows that managers make more substantial green investment adjustments in response to market feedback when the firm's blockholding institutions possess greater expertise in green technologies.

3.3.2 Technology peer pressure

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

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

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

Table 5 presents the results of the cross-sectional tests based on technology peer pressure. Column (1) examines firms whose TPP is above sample median in the year of the corporate disclosure, and Column (2) examines firms whose TPP is below sample median. As can be seen, the coefficient of *FB* is only positive and significant in column (1) when firms face high technology peer pressure, but small and insignificant in column (2). In column (3), we include an interaction term *FB* × *HighTPP* and examine it using the full sample of corporate disclosures. The positive and significant coefficient of the interaction term suggests that consistent with our expectation, managers react stronger to the market feedback on their AI investment plans when they face greater technological competition from the product market.

3.3.3 The Paris Agreement

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

Table 6 presents the cross-sectional analysis of a firm's green investment response to market feedback before and after the announcement of the Paris Agreement in December 2015. Column (1) includes green-investment-related corporate disclosures in 2015 and earlier; and Column (2) includes those announced in 2016 and later. The coefficients of *FB* are negative and significant in both columns, indicating that the positive correlation between firms' green investment adjustments and the market feedback exists both before and after the Paris Agreement, though the magnitude of the correlation is larger in the post-agreement period. In Column (3), we analyze the interaction terms between *FB* and two time dummies, *Before*, which indicates whether the disclosure announcement date is in 2015 and earlier, and *After*, which indicates whether the disclosure announcement date is in 2016 and later. The variables of interest are the two interaction terms. The more negative coefficient of *FB* × *After* suggests that firms adjust their green investment more in response to the market feedback on their green investment related corporate disclosures. These results are consistent with our prediction that firms learn more from the market feedback when heightened public attention incentivizes managers to pay greater attention to environmental and climate-change related issues.

4. More Facets of the Managerial Learning

To shed further light on when and what information managers learn from the market, we conduct three additional tests that explore the nature and timing of emerging corporate policies.

4.1 Investment response to conventional technology-related market feedback

First, we examine firms' investment response to the market feedback on conventional rather than emerging technology-related corporate disclosures. Following Abis and Veldkamp (2022), we define conventional technologies as traditional data analytics techniques such as linear regression, time series analysis, Monte Carlo simulation models, etc. Since such conventional technologies have been well-recognized and adopted by industrial firms for a long time, the market should possess little incremental knowledge beyond that of firm insiders and thus cannot provide useful feedback to guide related investment decisions. Hence, we expect that the feedback effect documented above becomes weaker or disappears entirely when the technologies mentioned in corporate disclosures are conventional and non-emerging in nature.

To identify conventional technology-related corporate disclosures, we first follow Abis and Veldkamp (2022) to compile a list of conventional-technology-related keywords. We then identify conventional-technology-related disclosures as earnings conference calls or 8-K filings that mention at least one conventional technology-related keyword, one investment related keyword, and one forward-looking keyword in the same sentence. To obtain a clean sample, we also exclude disclosures that mention emerging technologies (i.e., AI-related). To measure a firm's investment in conventional technologies, we follow the same spirit of our AI investment measure by examining its conventional-technology-related job postings.

Table 7 Panel A presents the results. The dependent variable, $\Delta\, Conventional\, Job\, Postings$, is defined as the change in the natural logarithm of one plus the weighted sum of conventional-related job postings by a firm from the year prior to a conventional-investment-related disclosure to the year after. Each job posting is weighted by the average conventional-technology-relevance score across all skills required for the job (following Abis and Veldkamp, 2022). As can be seen, the coefficients of *FB* are small and insignificant in all model specifications, suggesting that the investment response to market feedback on conventional technology-related investment plans is much weaker than that on emerging technology-related ones. However, it is worth noting that this result does not necessarily contradict the evidence from the extant market feedback literature because our measure of conventional investment is based on firms' job postings, which only capture one specific category of investment, namely, the intangible human capital investment. It does not speak to firms' adjustments of capital expenditures on physical assets, R&D investment, or other types of investments.

4.2 Feedback on non-investment-related emerging technology disclosures

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

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

Table 7 Panel B reports the results. In this test, the independent variable of interest, *NonInvFB*, is a firm's five-day cumulative abnormal return surrounding the date of a disclosure that mentions AI/green technologies but not investment plans. As can be seen, the coefficients of *NonInvFB* in both panels are small and insignificant, suggesting that there is no clear correlation between a firm's investment adjustment in emerging technologies and the market reaction to its discussion of emerging technologies in a general way. This result suggests that the observed announcement return, which is followed by subsequent investment adjustments, is unlikely driven by the market's sentiment towards the risks, nature, or prospects of these emerging technologies per se. Instead, it is more likely driven by the market's reaction to the firm's specific investment plans in these areas.

4.3 Pre-disclosure trends in emerging-technology-related investments

An alternative interpretation of our baseline results is that firms that have already started adjusting their emerging-technology-related investment plans *prior to* the related disclosures would continue such investment policies afterwards, while the market simply reacts to these predetermined investment policies. In this case, learning does not play an important role in explaining our baseline results as the "parallel trends" assumption for firms with differential market reactions is violated.

To address this concern, we examine firms' *past* (i.e., *pre-disclosure*) investment adjustments in emerging technologies. If our finding is mainly driven by the pre-event trends in investment policies, we would expect a positive association between firms' past investment adjustments in emerging technologies and the market reaction. Table 7 Panel C presents the results. The sample of corporate disclosures in this test are the same as those in our baseline analysis. The dependent variable in Panel C, columns (1) and (2), $Past\ \Delta\ AI\ Job\ Postings$, is the change in the natural logarithm of one plus a firm's AI job postings from two years prior to an AI-related disclosure to one year prior to the event. And the dependent variable in Panel C, columns (3) and (4), *Past* Δ *Total GHG emission*, is similarly defined using total GHG emission. The small and insignificant coefficients of *FB* in both panels suggest that firms' past investment adjustments in emerging technologies are not significantly correlated with the market reactions, indicating a lack of pre-event trends in investment adjustments.

4.4 Non-emerging-policy information in corporate disclosures

One may argue that the corporate disclosures in our sample (i.e., earnings conference calls and 8-K filings) contain a large amount of information in addition to the discussion of firms' future investment plans in emerging technologies. Therefore, it is unclear whether the market is reacting to firms' emerging-technology-related investment plans or other components of the disclosures that correlate with subsequent AI/green investment behaviors (e.g., information regarding general investment opportunities, past investment success, management quality, or other firm fundamentals). Note that this alternative explanation should only bias against us finding a significant association between firms' investment adjustments and the market feedback if the patterns of the non-emerging-policy related information contained in our sample disclosures are largely random/idiosyncratic, i.e., not exhibiting any systematic patterns but only introducing noise into our estimation. Nevertheless, we still employ a few methods to investigate its implication for our results.

Ideally, to fully address this concern, we need to divide the market reaction to a specific disclosure into two components: one driven by the discussions on emerging-technology-related investments (i.e., the "AI/green components") and the other by the rest of the information in the disclosure. However, such decomposition is difficult in practice. Hence, we adopt three approaches to alleviate this concern. In the first approach, we perform our baseline tests using a subsample of "focused" 8-K filings with only one item (that mentions emerging technology investment plans). As each 8-K item links to one specific type of material events that firms are obliged to disclose to their investors, these focused 8-K filings with only one item are essentially material press releases that likely contain information exclusively about their emerging corporate policies. An example of focused 8-K filings is presented in Appendix B1 Panel A. As shown in Table 8, we continue to find a significantly positive relation between a firm's AI/green investment adjustment and the market reaction when we examine earnings conference calls and 8-K filings separately. More importantly, Columns (3) of both panels show that our results persist in the subsample of focused 8-K filings (material press releases), suggesting that our results are unlikely driven by the omitted yet investment-relevant parts of the sample corporate disclosures.

In the second approach, we use a matching method to compare similar disclosures with and without the mentioning of emerging corporate policies. Specifically, for each AI/green related disclosure in our sample, we match it to up to five non-AI/non-green related disclosures of the same type (i.e., earnings conference call or 8-K filing) by *the same firm* with the closest textual similarity based on the non-emerging-policy parts (following Hoberg and Phillips, 2016; Lang and Stice-Lawrence, 2015; and Brown and Tucker, 2011).[21] Then we calculate a *counterfactual "market reaction"* to the non-emerging-policy component of the focal disclosure as the average market reactions of the matched non-emerging-technology-related disclosures. We use the difference between the actual announcement return of the focal disclosure and its counterfactual "market reaction" (i.e., the *emerging-policy-related* market reaction) to capture the market reaction to the AI/green component of the focal disclosure. The identifying assumption here is that the market reaction to the matched non-emerging-technology related disclosures by the same firm with similar information content captures the unobservable component of the market reaction that responds to the non-emerging-policy parts of the focal disclosure.

Table 9 presents the results. The independent variable of interest, *EmergingFB*, is the difference between the focal firm's actual market reaction (i.e., the five-day CAR) surrounding a given sample disclosure and the average "counterfactual" market reaction to matched firms' non-AI/green investment related disclosures. As can be seen, we continue to find a significantly positive relation between a firm's AI/green investment and the emerging-policy-related market feedback, suggesting that our results are unlikely driven by confounding information components in our sample disclosures.

Lastly, as shown in Appendix Table A2, we also find that there are no significant AI/green investment adjustments surrounding the above matched non-emerging-technology-related disclosures. This further highlights the important role played by the emerging-policy-related information contained in our sample disclosures.

5. More Nuances of the Learning Channel and Robustness Tests

5.1 Heterogeneous market feedback across emerging technology subcategories

To shed further light on what specific information managers learn about emerging corporate policies, we classify AI and green technologies into finer subcategories and examine which of them yields the strongest feedback effect.

[21] We require that a matched disclosure's textual similarity to the focal one is at least 0.5. In untabulated analysis, we verify that our results are robust to using 0.4 and 0.6 as alternative thresholds. The purpose of imposing this filter is to make sure the identified matched disclosures are indeed similar enough to the focal one.

In Table 10 Panel A, we explore subcategories of AI technologies. We sort AI-related corporate disclosures into two subcategories, namely, those focusing on robotic and non-robotic technologies, respectively. Robotic technologies are those involving the development/usage of robots or automation techniques. For each AI-related corporate disclosure, we measure its relatedness with robotic technologies by calculating the cosine similarity between a corporate disclosure vector and a robotic technology vector. Each element of the vectors corresponds to an AI-related keyword, which can be either robotic or non-robotic related. The value of an element in the corporate disclosure vector equals the number of times that a given keyword appears in the corporate disclosure. The value of an element in the robotic (non-robotic) technology vector equals one if the keyword is classified as robotic (non-robotic), and zero otherwise. We then classify the corporate disclosure into the robotic (non-robotic) category if its relatedness with the robotic (non-robotic) technologies is higher. The positive and significant coefficients of *FB* in both columns of Panel A suggest that firms' AI investment response to market feedback is similarly strong for both robotic and non-robotic technology-related corporate disclosures.

In Table 10 Panel B, we explore subcategories of green technologies. Following Sautner, van Lent, Vilkov, and Zhang (2022), we sort green-related corporate disclosures into three subcategories, namely, those discussing technological opportunities, regulatory interventions, and physical threats, respectively. To do so, we first sort green-related keywords into three sub-lists of keywords following the categories defined by Sautner, van Lent, Vilkov, and Zhang (2022). Each sub-list corresponds to one of the three subcategories (namely, opportunity-, regulatory-, or physical-related). Then, similar to the classification of AI-related corporate disclosures, for each green-related corporate disclosure, we measure its relatedness with each of the three subcategories by calculating the cosine similarity between a corporate disclosure vector and a subcategory vector. Each element of the vectors corresponds to a green-related keyword, which can belong to each of the three subcategories. The value of an element in the corporate disclosure vector equals the number of times a given green keyword appears in the corporate disclosure. The value of an element in the subcategory vector equals one if the green keyword belongs to that subcategory, and zero otherwise. We then classify the corporate disclosure into a particular subcategory that it has the highest relatedness with.

Table 10 Panel B presents the results. The negative and statistically significant coefficients of *FB* in columns (1) and (2) suggest that firms' green investment response to market feedback is more pronounced for opportunity- and regulatory-related green corporate disclosures, but much more muted for physical-related ones.

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

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

We define peer firms as those operating in the same four-digit SIC industry as the focal firm, and conduct a pair-level analysis on the focal firm's investment response to the market feedback on each of its peer firms' emerging-technology-related corporate disclosures. Table 11 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 *FB*, 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 negative and statistically significant in Panel B when green investment is analyzed. These contrasting results suggest that focal firms only learn from their peers' market feedback on green-related investments but not that on AI-related investments. This may be because the former is more industry specific (and less idiosyncratic) than the latter due to greater regulatory interventions on sector-wise environmental-related activities and/or stronger investor preferences towards ESG issues.

5.3 Benefits of following the market feedback

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

Ideally, to analyze the long-run consequence of following market feedback, we should compare a firm's performance when it follows a given market reaction with the same firm's performance when it does not follow the identical market feedback. However, this approach is not feasible because for a given market reaction, a firm can either be a follower or a non-follower but not both. We therefore exploit an alternative approach based on propensity score matching. Among the firms that make emerging-technology-related disclosures in our sample, we define a firm as a follower if it increases its emerging-technology investment following positive market feedback or decreases such investment following negative market feedback. The rest of firms in our sample comprise the pool of non-followers. To ensure the two groups are ex ante similar, we perform a propensity score matching as follows. For each follower, we match it to up to five non-followers in the same SIC 2-digit industry in the same year with the closest propensity score based on firm size, ROA, R&D ratio, market-to-book ratio, firm age, and the level of emerging-technology investment in the year prior to the corresponding disclosures. 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 12 presents the results. As can be seen, following the market feedback is associated with higher average return on assets (ROA) and stock returns than non-followers in the three years after their emerging-technology-related disclosures, suggesting that ignoring the useful information signals contained in the stock price is sub-optimal for firm value. Nevertheless, one reasonable concern regarding this positive association is that firms with more resources and thus expecting better future performance might be more capable of investing in emerging technologies. The logic of such a reverse causality explanation is likely to break down when the market feedback is negative, because in such cases followers actually reduce/slow down their AI/green investment and it is hard to argue that firms with more resources (growth potential) are more capable of cutting down their emerging technology investment. Therefore, similar to Table 3, we further split the sample of emerging-technology-related corporate disclosures into two groups: one with positive market reactions and the other with negative market reactions. We find that the observed performance gaps only show up in the presence of negative market feedback, which mitigates the above reverse causality concern.

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

5.4 Robustness tests

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

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

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

Δ *Green Job Postings* is measured as the difference between the natural logarithm of one plus the weighted sum of green-related job postings by a firm in the year after a green-investment-related corporate disclosure and the natural logarithm of one plus the weighted sum of green-related job postings by the firm in the year prior to the disclosure. Each job posting is weighted by the average green-relevance score across all skills required for the job. The green-relevance score of each skill in the job postings is one if it belongs to the Environment skill cluster family provided by the Burning Glass database, and zero otherwise (Darendeli, Law, and Shen, 2022).

Table 13 presents the results. Columns (1) to (3) repeat the baseline regressions using $\Delta\, AI\ Patents$ as the dependent variable. The coefficients of FB remain significantly positive across all columns, which is consistent with the positive association between a firm's AI investment adjustments and the market feedback to AI technology-related corporate disclosures documented earlier. Columns (4) to (6) examine $\Delta\, Green\ Patents$, the change in firms' green patent applications over the next one-, two-, and three-year period after receiving the market feedback. The coefficients of FB remain positive and largely significant in all three columns. Column (7) examines $\Delta\, Green\ Job\ Postings$ as the dependent variable. The coefficient of FB is positive and statistically significant, suggesting that our baseline results are robust to using these alternative measures of emerging corporate policy changes.

6. Conclusion

This paper explores whether learning from the market feedback is useful when firms contemplate emerging corporate policies on AI and green technologies. We find that firms adjust their investments in AI/green technologies in response to the market reaction to the discussions of such plans in their corporate disclosures. Specifically, managers adjust their AI/green investments upward (downward) in response to a favorable (unfavorable) market reaction to the corresponding corporate disclosures. This association is stronger when the market reaction is negative, and unlikely to be driven by non-feedback-based explanations, such as the anticipation of the market about firms' emerging technology investment plans, the pre-disclosure trends in such investments, or the confounding effects of the non-AI/green-related component of the corporate disclosures. We also find this association to be stronger when market participants (e.g., institutional blockholders) possess more expertise in emerging technologies, when the technology competition from peers is more intense, and when the market pays more attention to environmental issues such as after the announcement of the Paris Agreement. Finally, we document the benefits of following the market feedback on emerging corporate policies in terms of long-run operating and stock performance.

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

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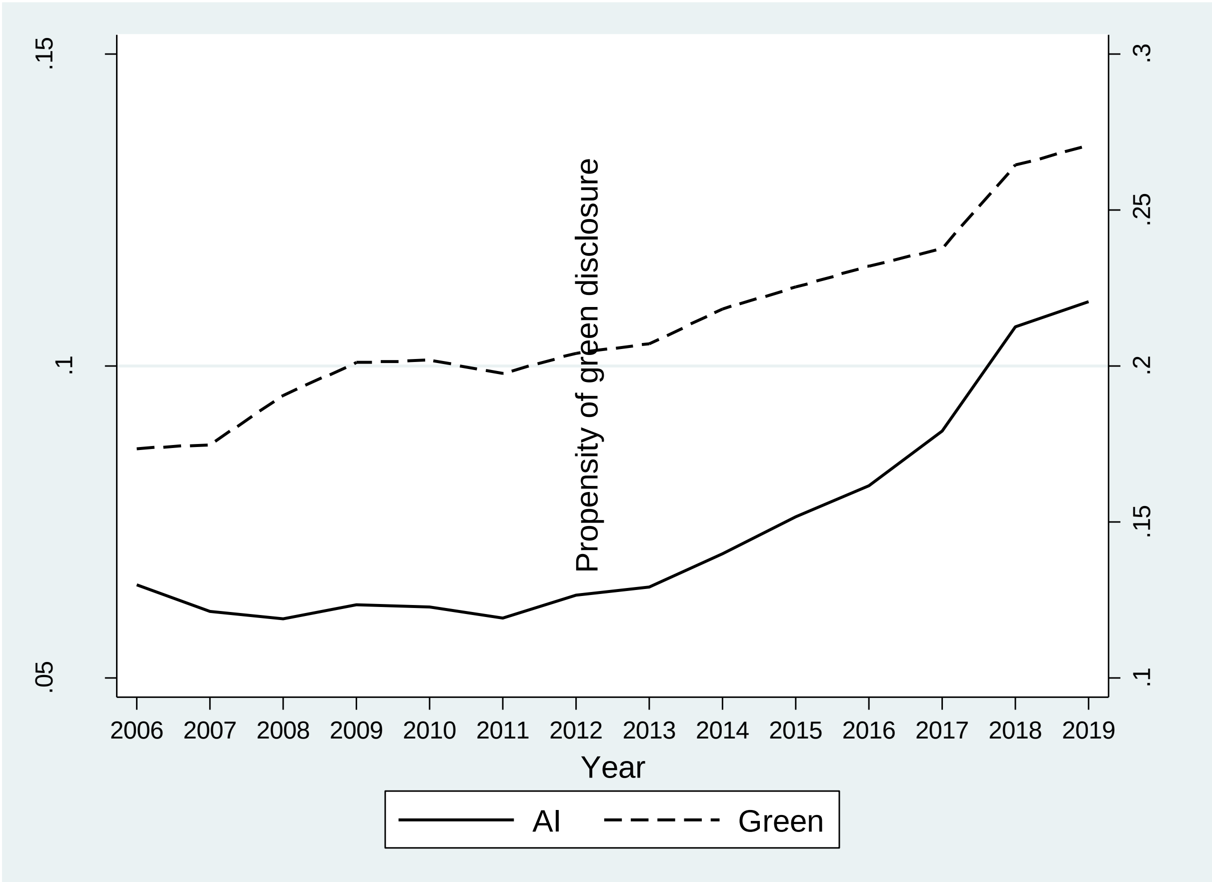

Figure 1: Time trend of emerging-technology related disclosure propensity

This figure plots the propensity of US public firms to discuss investment plans on emerging technologies in their earnings conference calls and 8-K filings from 2006 to 2019. The solid line denotes the number of AI-technology related disclosures divided by the total number of earnings conference calls and 8-K filings in a year. The dashed line denotes the number of green-technology related disclosures divided by the total number of earnings conference calls and 8-K filings in a year.

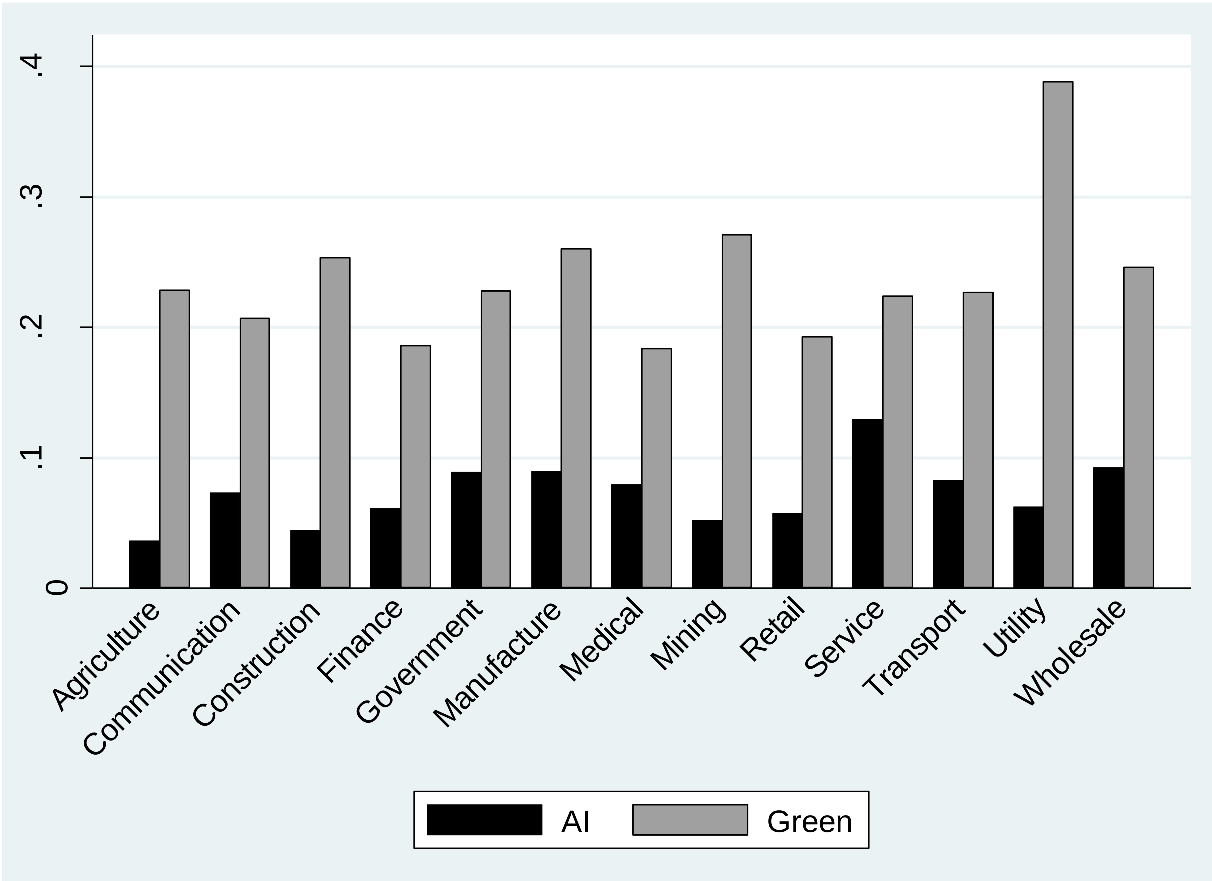

Figure 2: Industry distribution of emerging-technology related disclosure propensity

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

Table 1: Summary statistics

This table presents summary statistics. Panel A presents the descriptive statistics of the sample of AI-investment-related disclosures between 2010 and 2019. Panel B presents the descriptive statistics of the sample of green-investment-related disclosures between 2006 and 2019. Δ *AI Job Postings* is the change in the natural logarithm of one plus the weighted sum of AI-related job postings by a firm from the year prior to an AI-investment-related corporate disclosure to the year after the disclosure. Each job posting is weighted by the average AI-relevance score across all skills required for the job. Following Babina et al. (2022a, b), the AI-relevance score of each skill *s* in the job postings is calculated as the number of job postings requiring *both* skill *s* and at least one of the four basic AI skills (i.e., artificial intelligence (AI), machine learning (ML), natural language processing (NLP), and computer vision (CV)) divided by the total number of job postings requiring at least skill *s*. Δ *Total GHG emission* is 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. *FB* is a firm's market feedback on the AI/green-investment-related disclosure, i.e., the five-day ([-2, 2]) cumulative abnormal return surrounding the disclosure date (day *0*). *Firm Size* is the natural logarithm of the firm's quarterly sales (in $millions). *ROA* is the firm's quarterly operating income before depreciation divided by its total assets. *R&D ratio* is the firm's quarterly research and development expenses divided by its total sales. *Cash 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. Δ *Total Job Postings* is measured as the change in the natural logarithm of one plus the total number of job postings by the firm in a year from the year prior to an AI-investment-related disclosure to the year after the disclosure. *Sales Growth* in Panel B is the annual percentage change of the firm's sales from the pre-disclosure year to the post-disclosure year. All variables have been winsorized at their 1^{st} and 99^{th} percentiles.

Panel A: AI-investment-related corporate disclosures

Variable	Obs	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Δ AI Job Postings	48,181	0.090	0.339	-0.799	-0.004	0.000	0.170	1.473
FB	48,181	0.003	0.093	-0.289	-0.039	0.002	0.044	0.323
Firm Size	48,181	5.298	2.159	0.000	3.948	5.424	6.815	9.242
ROA	48,181	0.016	0.054	-0.303	0.006	0.024	0.039	0.161
R&D ratio	48,181	0.196	0.793	0.000	0.000	0.000	0.112	6.102
Cash Reserve	48,181	0.198	0.211	0.000	0.039	0.116	0.287	0.931
Δ Total Job Postings	48,181	0.245	0.976	-2.303	-0.063	0.000	0.481	4.369

Panel B: Green-investment-related corporate disclosures

Variable	Obs	Mean	Std. Dev.	Min	Q1	Median	Q3	Max
Δ Total GHG emission	106,650	-1.418	4.564	-16.213	-0.264	0.048	0.343	8.527
FB	106,638	0.001	0.081	-0.289	-0.035	0.001	0.038	0.302
Firm Size	106,650	6.440	1.759	0.000	5.460	6.602	7.662	9.242
ROA	106,650	0.024	0.040	-0.303	0.014	0.027	0.040	0.161
R&D ratio	106,650	0.142	0.720	0.000	0.000	0.000	0.040	6.102
Cash Reserve	106,650	0.143	0.177	0.000	0.027	0.075	0.184	0.931
Sales Growth	106,453	0.054	0.327	-0.962	-0.042	0.021	0.092	3.367

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

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

Panel A: AI Investment

	Dependent Variable: Δ AI Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.091***	0.087***	0.062***	0.066***	0.049***
	(4.98)	(4.79)	(4.26)	(4.57)	(3.40)
Firm Size		0.018***	0.020***	0.022***	0.019***
		(10.41)	(15.07)	(14.11)	(2.73)
ROA		0.020	-0.042	-0.067	0.032
		(0.31)	(-0.81)	(-1.28)	(0.38)
R&D ratio		-0.005	-0.001	0.003	0.006
		(-1.60)	(-0.49)	(1.15)	(1.35)
Cash Reserve		0.142***	0.129***	0.088***	0.029
		(8.00)	(9.18)	(5.51)	(0.97)
Δ Total Job Postings			0.220***	0.216***	0.219***
			(40.13)	(40.64)	(36.71)
Firm FE	No	No	No	No	Yes
Industry × Year FE	No	No	No	Yes	Yes
Observations	48,181	48,181	48,181	48,157	47,322
R-squared	0.001	0.014	0.414	0.443	0.544

Panel B: Green Investment					
	Dependent Variable: Δ Total GHG emission				
	(1)	(2)	(3)	(4)	(5)
FB	-0.998***	-1.044***	-1.054***	-0.442**	-0.485***
	(-3.92)	(-4.13)	(-4.16)	(-2.24)	(-2.80)
Firm Size		-0.015	-0.012	-0.258***	-0.288***
		(-0.64)	(-0.50)	(-10.60)	(-2.72)
ROA		2.831***	3.187***	2.133**	0.843
		(2.60)	(2.91)	(2.29)	(0.63)
R&D ratio		-0.046	-0.072	0.037	0.044
		(-0.68)	(-1.08)	(0.62)	(0.45)
Cash Reserve		1.075***	1.110***	0.961***	1.317***
		(4.78)	(4.92)	(3.99)	(3.01)
Sales Growth			0.427***	0.165***	0.027
			(5.05)	(2.58)	(0.44)
Firm FE	No	No	No	No	Yes
Industry × Year FE	No	No	No	Yes	Yes
Observations	106,638	106,638	106,566	106,546	106,409
R-squared	0.000	0.002	0.003	0.434	0.584

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

This table presents the analyses of a firm's investment response to emerging-technology-related market feedback when the reaction is either positive or negative. Panels A and B study AI-related and green-related investments, respectively. In Panel A, the dependent variable is Δ *AI Job Postings*. In Panel B, the dependent variable is Δ *Total GHG emission*. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. The sample in Column (1) of each panel includes corporate disclosures with positive market reactions (i.e., *FB*>0), and that in Column (2) includes disclosures with negative market reactions (i.e., *FB*<0). All other variables are defined as in Table 1 and Table 2. Column (3) includes all corporate disclosures in our baseline analysis in Table 2. *PosFB* equals *FB* if *FB*>0, and zero otherwise. *NegFB* equals *FB* when *FB*<0, and zero otherwise. Standard errors are clustered by firm. 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 Variable	Δ AI Job Postings			Dependent Variable	Δ Total GHG emission		
Subsample	Positive FB	Negative FB	Full	Subsample	Positive FB	Negative FB	Full
	(1)	(2)	(3)		(1)	(2)	(3)
FB	0.035**	0.090**		FB	-0.461	-1.111**	
	(2.51)	(2.57)			(-1.03)	(-2.40)	
PosFB			0.014	PosFB			0.135
			(1.17)				(0.36)
NegFB			0.068***	NegFB			-0.956**
			(2.68)				(-2.47)
F-stat			3.07	F-stat			2.73
P-value			0.080	P-value			0.099
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Industry × Year FE	Yes	Yes	Yes
Observations	23,587	22,495	47,322	Observations	53,753	52,242	106,409
R-squared	0.578	0.572	0.544	R-squared	0.620	0.615	0.592

Table 4: Cross-sectional tests based on investors' AI/green related expertise

This table presents the cross-sectional analyses of baseline regressions based on institutional investors' expertise in emerging technologies. We infer institutions' expertise from their portfolio holdings. Panel A examines AI-related investments and the expertise of institutions in AI technologies. We first classify AI industries as the top five 3-digit Cooperative Patent Classification (CPC) technology classes with the highest percentage of AI patents. AI patents are defined based on the AI prediction scores provided by the United States Patent and Trademark Office (USPTO) Artificial Intelligence Patent Dataset (AIPD). We define a patent to be an AI-related one if any of its eight AI prediction scores (corresponding to the eight AI components identified by AIPD, namely, machine learning, evolutionary computation, NLP, speech, vision, knowledge processing, AI hardware, and planning and control) is above 50%. We then identify a firm as AI-related (and assign an AI-score of one to it) if its major patent technology area in a year is one of the five AI industries. Otherwise, the firm is assigned a zero AI-score. We measure an institution's expertise in AI technologies in a given quarter as the weighted average AI-score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Then, we take average of the institution's quarterly AI expertise score across the four quarters prior to a disclosure event. For each AI-investment-related disclosure, the focal firm's average institutional AI expertise score, *InstitutionAIExpertise,* is calculated as the value-weighted average of the institutional AI expertise score across all institutional blockholders, with the weight being the number of the focal firm's outstanding shares held by the institution at the quarter end immediately prior to the disclosure event. Panel B examines green-related investments and the expertise of institutions in green technologies. We measure an institution's expertise in green technologies in a given quarter as the weighted average environmental score of all firms that it holds in the quarter, with the weight being the institution's dollar holdings in a firm relative to its total portfolio value. Next, we take average of the institution's quarterly green expertise score across the four quarters prior to a disclosure event. For each green-related corporate disclosure, the focal firm's average institutional green expertise score, *InstitutionGreenExpertise*, is then calculated as the value-weighted average of the institutional green expertise score across all its institutional blockholders (i.e., those holding 5% or more of the firm's outstanding shares). Each institutional blockholder'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 Variable	Δ AI Investment	Dependent Variable	Δ Total GHG emission
	(1)		(1)
FB × InstitutionAIExpertise	0.265***	FB × InstitutionGreenExpertise	-0.825**
	(3.32)		(-2.02)
FB	-0.005	FB	0.045
	(-0.27)		(0.22)
InstitutionAIExpertise	-0.028	InstitutionGreenExpertise	-0.113
	(-1.31)		(-1.19)
Controls	Yes	Controls	Yes
Firm FE	Yes	Firm FE	Yes
Industry × Year FE	Yes	Industry × Year FE	Yes
Observations	47,322	Observations	106,409
R-squared	0.544	R-squared	0.584

Table 5: Cross-sectional tests based on firms' exposure to technology competition

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

	Dependent Variable: Δ AI Job Postings		
Sample	High TPP	Low TPP	Full
	(1)	(2)	(3)
FB	0.075***	-0.006	-0.004
	(4.08)	(-0.29)	(-0.17)
FB × HighTPP			0.079***
			(2.76)
HighTPP			-0.014
			(-1.24)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	27,228	19,862	47,713
R-squared	0.595	0.567	0.544

Table 6: Cross-sectional tests based on the Paris Agreement

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

	Δ Total GHG emission		
Sample	Before (<=Year 2015)	After (>=Year 2016)	Full
	(1)	(2)	(3)
FB	-0.215*	-0.631***	-0.228*
	(-1.75)	(-2.58)	(-1.69)
FB × After			-0.550*
			(-1.90)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	45,987	60,368	106,409
R-squared	0.420	0.613	0.584

Table 7: More facets of the managerial learning

This table presents the analysis of more facets of the managerial learning by exploring the nature and timing of emerging corporate policies. Panel A presents the analysis of a firm's investment response to conventional-technology-related market feedback. Following Abis and Veldkamp (2022), we first compile a list of conventional-technology-related keywords. The sample of conventional-technology-related corporate disclosures are then defined as earnings conference calls or 8-K filings with at least one sentence that includes: (1) one or more conventional-technology-related keywords, (2) one or more forward-looking keywords, and (3) one or more investment related keywords in the same sentence. We exclude corporate disclosures that are AI-related. A firm's investment in conventional technologies is measured by its conventional-technology-related job postings. The dependent variable, Δ *Conventional Job Postings*, is defined as the difference between the natural logarithm of one plus the weighted sum of conventional-related job postings by a firm in the year after a conventional-investment-related corporate disclosure and the natural logarithm of one plus the weighted sum of conventional-related job postings by the firm in the year prior to the disclosure. Each job posting is weighted by the average conventional-technology-relevance score across all skills required for the job (following Abis and Veldkamp, 2022). Panels B examines the associations between AI/green investment changes and announcement returns when the related discussions in the disclosures only refer to the emerging technologies in a general way but are not about investment plans. The sample consists of earnings conference calls and 8-K filings with at least one sentence that includes both AI/green related keywords and forward-looking keywords, but without any investment-related keywords in the same sentence. In Panel B, the dependent variable is Δ *AI Job Postings* in Columns (1) and (2) and is Δ *Total GHG emission* in Columns (3) and (4). Panel C examines the associations between firms' past (i.e., pre-disclosure) AI/green investment changes and the market reactions to their AI/green-investment-related disclosures. In Panel C, 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 Panel C Columns (3) and (4), the dependent variable in *Past* Δ *Total GHG emission*, is the difference between the natural logarithm of one plus the firm's total GHG emissions in the year prior to the corporate disclosure and the natural logarithm of one plus its total GHG emissions in year before (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. *NonInvFB* is a firm's five-day cumulative abnormal return surrounding the date of a disclosure that mentions AI/green technologies but no investment plans. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Investment response to conventional-technology-related market feedback					
	Dependent Variable: Δ Conventional Job Postings				
	(1)	(2)	(3)	(4)	(5)
FB	0.012	0.010	0.006	0.010	0.010
	(1.02)	(0.81)	(0.53)	(0.92)	(0.83)
Firm Size		0.009***	0.009***	0.010***	-0.001
		(5.68)	(6.24)	(5.77)	(-0.29)
ROA		-0.023	-0.039	-0.002	0.013
		(-0.61)	(-1.06)	(-0.06)	(0.28)
R&D ratio		0.002	0.002	0.004***	-0.001
		(1.22)	(1.47)	(2.83)	(-0.40)
Cash Reserve		0.033***	0.027***	0.025**	0.018
		(3.26)	(2.93)	(2.09)	(0.70)
Δ Total Job Postings			0.044***	0.041***	0.042***
			(12.09)	(12.51)	(10.83)
Firm FE	No	No	No	No	Yes
Industry × Year FE	No	Yes	Yes	Yes	Yes
Observations	20,585	20,585	20,585	20,546	19,712
R-squared	0.000	0.007	0.063	0.132	0.250

Panel B: Feedback to non-investment-related disclosures				
Dependent Variables	Δ AI Job Postings		Δ Total GHG emission	
	(1)	(2)	(3)	(4)
NonInvFB	0.017	0.019	-0.178	0.301
	(0.51)	(0.64)	(-0.32)	(0.64)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
Observations	8,314	6,477	9,085	8,332
R-squared	0.385	0.727	0.006	0.669

Panel C: Past (Pre-disclosure) emerging-technology-related investment				
Dependent Variables	Past Δ AI Job Postings		Past Δ Total GHG emission	
	(1)	(2)	(3)	(4)
FB	-0.007	-0.019	-0.014	0.017
	(-0.49)	(-1.32)	(-0.29)	(0.62)
Controls	Yes	Yes	Yes	Yes
Firm FE	No	Yes	No	Yes
Industry × Year FE	No	Yes	No	Yes
Observations	47,445	46,583	87,083	86,874
R-squared	0.455	0.596	0.017	0.784

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

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

Panel A: AI investment				Panel B: Green investment			
Dependent Variable	Δ AI Job Postings			Dependent Variable	Δ Total GHG emission		
Subsample	Conference Call	8-K	Focused 8-K	Subsample	Conference Call	8-K	Focused 8-K
	(1)	(2)	(3)		(1)	(2)	(3)
FB	0.077***	0.048***	0.052**	FB	-0.434**	-0.507**	-0.594**
	(2.97)	(2.79)	(2.44)		(-2.17)	(-2.56)	(-2.15)
Controls	Yes	Yes	Yes	Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Industry × Year FE	Yes	Yes	Yes
Observations	19,600	34,978	10,434	Observations	58,605	89,575	40,608
R-squared	0.582	0.566	0.513	R-squared	0.623	0.596	0.630

Table 9: Investment response to the "emerging-policy-related" market feedback based on the emerging-technology-related components of a corporate disclosure

This table presents the analysis of a firm's investment response to the *emerging-policy-related* stock market reaction based on the "AI/green components" of a corporate disclosure. Panels A and B present results regarding AI-related and green-related investments, respectively. In Panel A, the dependent variable is Δ *AI Job Postings*. In Panel B, the dependent variable is Δ *Total GHG emission*. For each focal firm's AI/green-investment-related disclosure, we construct a counterfactual "market reaction" to the disclosure's non-AI/green-related components as the average market reaction to (up to five) matched firms' non-emerging-technology-investment-related disclosures with the closest textual similarity. *EmergingFB* is the difference between the focal firm's five-day cumulative abnormal return surrounding the disclosure date and the average "counterfactual" market reaction to matched firms' non-AI/green-investment-related disclosures. 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 Variable	Δ AI Job Postings		Dependent Variable	Δ Total GHG emission	
	(1)	(2)		(1)	(2)
EmergingFB	0.072***	0.065**	EmergingFB	-1.051***	-0.439**
	(2.71)	(2.40)		(-2.61)	(-2.02)
Controls	Yes	Yes	Controls	Yes	Yes
Firm FE	No	Yes	Firm FE	No	Yes
Industry × Year FE	No	Yes	Industry × Year FE	No	Yes
Observations	18,608	18,135	Observations	52,799	52,689
R-squared	0.444	0.586	R-squared	0.004	0.629

Table 10: Heterogeneous market feedback across emerging technology subcategories

This table presents the analysis of a firm's investment response to the market feedback on the disclosures of different emerging technology subcategories. In Panel A, we sort AI-related corporate disclosures into two subcategories, namely, robotic and non-robotic technologies. Robotic technologies are those involving the development/usage of robots or automation techniques. For each AI-related corporate disclosure, we measure its relatedness with robotic technologies by calculating the cosine similarity between a corporate disclosure vector and a robotic technology vector. Each element of the vectors corresponds to an AI-related keyword, which can be either robotic or non-robotic related. The value of an element in the corporate disclosure vector equals the number of times that a given keyword appears in the corporate disclosure. The value of an element in the robotic (non-robotic) technology vector equals one if the keyword is classified as robotic (non-robotic), and zero otherwise. We then classify the corporate disclosure into the robotic (non-robotic) category if its relatedness with the robotic (non-robotic) technologies is higher. In Panel B, following Sautner, van Lent, Vilkov, and Zhang (2022), we sort green-related corporate disclosures into three subcategories, namely, those discussing technological opportunities, regulatory interventions, and physical threats, respectively. For each green-related corporate disclosure, we first measure its relatedness with each of the three subcategories by calculating the cosine similarity between a corporate disclosure vector and a subcategory vector. Each element of the vectors corresponds to a green-related keyword, which can belong to each of the three subcategories. The value of an element in the corporate disclosure vector equals the number of times a given keyword appears in the corporate disclosure. The value of an element in the subcategory vector equals one if the keyword belongs to that subcategory, and zero otherwise. We then classify the corporate disclosure into a particular subcategory that it has the highest relatedness with. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment		
	Dependent Variable: Δ AI Job Postings	
Category	Robotic	Non-Robotic
	(1)	(2)
FB	0.057***	0.056**
	(3.02)	(2.26)
Controls	Yes	Yes
Firm FE	Yes	Yes
Industry × Year FE	Yes	Yes
Observations	28,691	16,650
R-squared	0.569	0.607

Panel B: Green investment			
	Dependent Variable: Δ Total GHG emission		
Category	Opportunity	Regulatory	Physical
	(1)	(2)	(3)
FB	-0.707**	-0.835***	-0.084
	(-2.08)	(-2.84)	(-0.21)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Observations	40,953	46,655	25,427
R-squared	0.628	0.612	0.531

Table 11: Investment response to peer firms' emerging-technology-related market feedback

This table presents the pair-level analysis of a firm's investment response to each of its peers' emerging-technology-related market feedback. For each emerging-technology-related corporate disclosure of a firm, we analyze the AI/green investment response to its market feedback by each of the firm's same-industry peers (at the 4-digit SIC level). Panels A and B study AI-related and green-related investment, respectively. In Panel A, the dependent variable is Δ *AI Job Postings*. In Panel B, the dependent variable is Δ *Total GHG emission*. *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 FE* are indicators for each focal firm. *Pair FE* are indicators for each pair of a focal firm and its peer firm. *Industry* × *Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1. Standard errors are double clustered by focal firm and peer firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: AI investment

	Dependent Variable: Δ AI Job Postings		
	(1)	(2)	(3)
PeerFB	-0.002	-0.002	-0.002
	(-1.53)	(-1.42)	(-1.49)
FB		-0.003	-0.002
		(-0.60)	(-0.42)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Pair FE	No	No	Yes
Observations	1,902,799	1,902,107	1,902,024
R-squared	0.506	0.506	0.578

Panel B: Green investment

	Dependent Variable: Δ Total GHG emission		
	(1)	(2)	(3)
PeerFB	-0.235***	-0.229***	-0.225***
	(-6.40)	(-6.29)	(-6.33)
FB		-0.243	-0.384
		(-0.87)	(-1.59)
Controls	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes
Pair FE	No	No	Yes
Observations	1,345,675	1,344,697	1,344,472
R-squared	0.650	0.649	0.743

Table 12: Benefits of following the market feedback in terms of long-run performance

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

Panel A: AI investment

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

Panel B: Green investment						
Dependent Variables	$\text{ROA}_{t+1\rightarrow t+3}$			$\text{Return}_{t+1\rightarrow t+3}$		
Sample	Full	Negative CAR	Positive CAR	Full	Negative CAR	Positive CAR
	(1)	(2)	(3)	(4)	(5)	(6)
Follow	0.003**	0.016**	-0.002	0.053**	0.062**	0.008
	(2.39)	(2.51)	(-0.50)	(2.54)	(2.18)	(0.23)
Firm Size	-0.003	0.002	-0.006*	-0.040***	-0.043***	-0.023
	(-0.82)	(0.33)	(-1.89)	(-3.83)	(-5.56)	(-1.32)
R&D ratio	-0.007	-0.012*	0.004	0.017	0.030*	0.004
	(-1.51)	(-1.85)	(0.85)	(0.95)	(1.92)	(0.23)
Cash Reserve	0.010	-0.008	0.064**	-0.172***	-0.109***	-0.305**
	(0.63)	(-0.48)	(2.36)	(-2.64)	(-2.58)	(-2.25)
Sale Growth	0.000	-0.002	0.002	0.012*	0.017**	0.006
	(0.00)	(-0.74)	(0.92)	(1.74)	(2.12)	(0.57)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,020	17,071	8,448	26,020	17,071	8,448
R-squared	0.912	0.927	0.953	0.535	0.614	0.713

Table 13: Alternative measures of emerging-technology investments

This table presents robustness tests of the baseline analysis using alternative measures of emerging-technology investments. In Columns (1) to (3), the dependent variable, Δ *AI Patents*, is the difference between the natural logarithm of one plus the number of AI patents generated during the N-year period (N=1, 2, 3) after an AI-investment-related corporate disclosure, and that generated during the one-year period prior to the disclosure. AI patents are defined based on the AI prediction scores provided by the United States Patent and Trademark Office (USPTO) Artificial Intelligence Patent Dataset (AIPD). We define a patent to be an AI-related one if any of its eight AI prediction scores (corresponding to the eight AI components identified by AIPD, namely, machine learning, evolutionary computation, NLP, speech, vision, knowledge processing, AI hardware, and planning and control) is above 50%. In Columns (4) to (6), the dependent variable, Δ *Green Patents*, is the difference between the natural logarithm of one plus the number of green patents generated during the N-year period (N=1, 2, 3) after a green-investment-related corporate disclosure, and that generated during the one-year period prior to the disclosure. Green patents are defined based on the list of IPC/CPC codes from the Organization for Economic Co-operation and Development (OECD). In Column (7), the dependent variable is Δ *Green Job Postings*, measured as the difference between the natural logarithm of one plus the weighted sum of green-related job postings by a firm in the year after a green-investment-related corporate disclosure and the natural logarithm of one plus the weighted sum of green-related job postings by the firm in the year prior to the disclosure. Each job posting is weighted by the average green-relevance score across all skills required for the job. The green-relevance score of each skill in the job postings is one if it belongs to the Environment skill cluster family provided by the Burning Glass database, and zero otherwise. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure date. All other variables are defined as in Table 1 and Table 2. Standard errors are clustered by firm. T-statistics are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Dependent Variable:	Δ AI Patents			Δ Green Patents			Δ Green Job Postings
	1-year	2-year	3-year	1-year	2-year	3-year	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
FB	0.044**	0.053**	0.041*	0.007***	0.009***	0.005	0.046**
	(2.13)	(2.15)	(1.69)	(2.88)	(2.72)	(1.42)	(1.98)
Firm Size	-0.010	-0.001	-0.003	-0.000	0.003	0.005*	0.035***
	(-0.69)	(-0.06)	(-0.20)	(-0.34)	(1.59)	(1.69)	(3.29)
ROA	0.090	0.090	0.296*	-0.017	-0.030	-0.040	-0.192*
	(0.56)	(0.48)	(1.65)	(-1.30)	(-1.42)	(-1.47)	(-1.70)
R&D ratio	-0.023**	-0.028*	-0.006	-0.001**	-0.000	-0.000	0.005
	(-1.97)	(-1.86)	(-0.67)	(-2.48)	(-0.47)	(-0.18)	(0.68)
Cash Reserve	-0.059	-0.056	0.043	-0.002	-0.010	-0.016	0.085*
	(-1.01)	(-0.76)	(0.62)	(-0.39)	(-0.99)	(-1.20)	(1.71)
Sales Growth	0.009	0.014	0.008	-0.001	-0.001	0.000	
	(1.29)	(1.46)	(1.32)	(-0.78)	(-0.31)	(0.05)	
Δ Total Job Postings							0.161***
							(21.34)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry × Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,686	37,376	27,834	159,069	137,782	123,012	95,992
R-squared	0.522	0.503	0.666	0.146	0.239	0.475	0.281

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

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

Appendix Table A2: Emerging-technology investment response to non-emerging-technology-related market feedback

This table presents the analysis of a firm's emerging technology investment response to the non-emerging-policy-related stock market reaction based on the matched non-emerging-technology-related corporate disclosures constructed in Table 5. Panels A and B present results regarding AI-related and green-related investments, respectively. In Panel A, the dependent variable is Δ *AI Job Postings*. In Panel B, the dependent variable is Δ *Total GHG emission*. Corporate disclosures in this table are the non-emerging-technology-investment-related disclosures that are matched to the AI/green-investment-related disclosures by the same firm with the closest textual similarity. *FB* is the firm's five-day cumulative abnormal return surrounding the disclosure (i.e., [-2, 2] with disclosure date as day 0). *Firm FE* are indicators for each firm. *Industry × Year FE* are indicators for each pair of industry (at the 2-digit SIC level) and year. All other variables are defined as in Table 1 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 Variable	Δ AI Job Postings		Dependent Variable	Δ Total GHG emission	
	(1)	(2)		(1)	(2)
FB	0.017	-0.002	FB	-0.195	0.264
	(0.76)	(-0.07)		(-0.36)	(0.65)
Controls	Yes	Yes	Controls	Yes	Yes
Firm FE	No	Yes	Firm FE	No	Yes
Industry × Year FE	No	Yes	Industry × Year FE	No	Yes
Observations	11,982	11,806	Observations	8,702	8,331
R-squared	0.394	0.602	R-squared	0.007	0.672

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

Panel A: Focused 8-K filings

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

Item 8.01. Other Events.

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

Item 9.01. Financial Statements and Exhibits.

EXHIBITS*

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

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

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

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

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

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

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

<u>Panel B: Earnings conference calls</u>

AI-investment-related disclosures:

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

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

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

Green-investment-related disclosures:

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

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

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