International Review of Financial Analysis 105 (2025) 104378

Contents lists available at ScienceDirect

International Review of Financial Analysis

journal homepage: www.elsevier.com/locate/irfa

Analyzing the market's reaction to AI narratives in corporate filings

Anup Basnet [a], Maxim Elias [b,*], Galla Salganik-Shoshan [c], Thomas Walker [d,f], Yunfei Zhao [e]

[a] DAN Department of Management & Organizational Studies, Western University, London, Canada
[b] TBS Business School, Toulouse, France
[c] Finance Division, Department of Business Administration, Guilford Glazer Faculty of Business and Management, Ben-Gurion University of the Negev, Beer Sheva, Israel
[d] Department of Finance, Concordia University, Montreal, Canada
[e] College of Business and Public Management, and Quantitative Finance Research Institute, Wenzhou-Kean University, Wenzhou, China
[f] Corvinus Institute for Advanced Studies (CIAS) at Corvinus University of Budapest, Hungary

ARTICLE INFO

JEL classification:
G10
G30
G40
O30

Keywords:
Narrative
Artificial intelligence
Corporate disclosure
Firm value
Textual analysis

ABSTRACT

The recent surge in artificial intelligence (AI) interest and investment, driven by advances in large language models, has led the market to reward adopters and penalize laggards. Yet, AI integration predates this "AI gold rush," with earlier adopters reaping significant benefits. Drawing on a 2005–2018 sample, a formative period before AI became mainstream, this paper examines how early AI adoption and its disclosure in corporate filings affect U.S. firms. Analyzing 10-K filings, we categorize AI-related mentions as actionable, speculative, or irrelevant. We establish causal links between these disclosures and firm value, with innovation and productivity as likely channels. Our findings indicate that markets distinguish between substantive AI initiatives and opportunistic signaling, swiftly pricing anticipated future gains. Actionable disclosures outlining clear implementation plans yield significant valuation benefits, particularly upon first introduction, whereas speculative or irrelevant disclosures have no impact. Moreover, firms with substantive AI disclosures subsequently increase innovation activities, evidenced by higher R&D spending and patent filings, which are a key step in a pathway to modest, lagged productivity gains and ultimately improved valuation. We further find that these innovation activities act as concurrent signals of strategic reorientation towards AI, reinforcing the market's swift positive valuation. We show that early adopters of actionable disclosures gain competitive advantages, while peers that either remain silent or offer only vague AI disclosures face market penalties. These findings highlight that the strategic communication of genuine technological initiatives can significantly impact a company's perceived value and competitive positioning in the market.

1. Introduction

It is widely accepted that artificial intelligence (AI) can improve efficiency and productivity, reduce friction across industries, and enable the delivery of personalized services (Aghion et al., 2019; Agrawal et al., 2018; Calvino & Fontanelli, 2023; Cao, 2023; Czarnitzki et al., 2023; Dirican, 2015; Marioni et al., 2024 and Varian, 2019). The recent launch of ChatGPT by OpenAI has been a powerful demonstration of AI's potential to disrupt a wide range of industries. ChatGPT is a multimodal language model that leverages deep learning techniques to generate human-like text and interpret images based on a given prompt or context. Following its public debut in December 2022, it achieved instant success, attracting over a million users in its first week. Since then, experts have acknowledged the potential of AI to accelerate automation in natural language processing tasks, revolutionizing areas such as customer service, content creation, language translation, research analytics, and education, among others. As a result, the implementation of AI-based technologies is increasingly viewed as an existential decision for businesses, with active adopters expected to gain a competitive edge over slower counterparts. The speed of adoption is widely regarded as the key differentiating factor between industry leaders and laggards.

Beyond the technological implications, how companies frame and disclose their AI adoption in corporate filings plays an important role in shaping market perceptions and firm valuations. Building on Shiller's (2017) seminal work on the economic importance of narratives, recent

* Corresponding author at: TBS Business School, 20 Boulevard Lascrosses, 31000 Toulouse, France.
E-mail addresses: abasnet3@uwo.ca (A. Basnet), m.elias@tbs-education.fr (M. Elias), salganik@bgu.ac.il (G. Salganik-Shoshan), thomas.walker@concordia.ca (T. Walker), yunzhao@wku.edu.cn (Y. Zhao).

https://doi.org/10.1016/j.irfa.2025.104378
Received 19 November 2024; Received in revised form 12 May 2025; Accepted 31 May 2025
Available online 2 June 2025

studies have examined the influence of corporate disclosures on financial markets and economic outcomes (Lang & Stice-Lawrence, 2015; Gentzkow et al., 2019; Kalamara et al., 2022; Loughran & McDonald, 2020; Nyman et al., 2021). Our research adds to this literature by studying the economic impact of a prominent recent narrative - the notion that AI offers sustained competitive advantage to early adopters while posing an existential threat to lagging firms.

We specifically analyze how the advent and dissemination of AI-related disclosures in corporate filings influenced investor perceptions and firm valuations before AI became mainstream. Our empirical approach prioritizes Tobin's Q as a forward-looking measure of firm value that captures investors' expectations of AI's future impact. While we acknowledge that the full effects on operational outcomes, such as accounting profitability or productivity, may take longer to emerge, our analysis systematically explores the channels through which AI adoption influences key intermediate performance dimensions, including innovation and labor productivity, which in turn affect the firm's market valuation. This choice reflects the economic reality that financial markets price the anticipated benefits of technological adoption long before measurable operational improvements materialize.

While one might expect that firms disclosing AI initiatives experience valuation gains, the voluntary and informal nature of these disclosures raises the risk of opportunistic or misleading statements. This calls for careful differentiation between informative, substantive disclosures and those containing misleading or irrelevant information. For instance, Jackson et al. (2019) caution against overestimating the effectiveness of mandatory non-financial disclosures in curbing irresponsible corporate behavior. Similarly, Davidson (2022) finds that disclosure fraud often stems from the pursuit of higher returns, arguing that equity incentives drive managers to make false disclosures to inflate stock prices. To address this, we assess the extent to which organizations are opportunistic in their timing and narrative framing by categorizing AI disclosures in corporate filings based on their informational value as *actionable*, *speculative*, and *irrelevant*. *Actionable* disclosures include concrete plans for AI implementation, *speculative* ones offer vague or no actionable details, and *irrelevant* mentions are not directly related to the firm's actual use of AI. We hypothesize that *actionable* disclosures, which signal genuine AI adoption, impact firm valuations positively, whereas *speculative* or *irrelevant* mentions have little to no impact.

To test this hypothesis, we analyze business descriptions in the 10-K filings of Russell 3000 companies between 2005 and 2018. We construct a glossary of AI-related keywords and manually classify their usage as actionable, speculative, or irrelevant based on the context in which companies use them. We then examine how the first introduction of AI disclosures affects firm value in the years immediately following the filings, focusing on changes in Tobin's Q to better isolate the causal effect of AI narratives. Our identification strategy leverages within-firm variation through panel fixed-effects models, complemented by a Local Projections Difference-in-Differences approach as a robustness check. This allows us to interpret our findings as causal rather than merely associational (Dube et al., 2023; Marioni et al., 2024). To rule out alternative explanations, we also conduct a pre-trend test, which confirms the robustness of our causal interpretation. We find that approximately 60 % of AI-related mentions are actionable, and these disclosures significantly increase firm market value. In contrast, firms that fail to introduce actionable AI keywords while their competitors do experience a relative decline in market value. This suggests that investors distinguish between credible information provided in corporate disclosures and opportunistic signaling, promptly pricing substantive AI initiatives into valuations. Our results also add to the literature on financial market efficiency (e.g., Cho, 2015; Cutillas Gomariz & Sánchez Ballesta, 2014; Goldstein & Yang, 2017; Goldstein & Yang, 2019; Zhang et al., 2015).

Beyond the ultimate impact on market valuation, and to illuminate the mechanisms through which AI disclosures influence firm value, we attempt to examine the sequential effects of these narratives. We first explore the relationship between AI disclosures and corporate innovation, using research and development (R&D) expenses and patent filings as proxies, and subsequently investigate the influence on labor productivity, considering innovation as a mediating factor. We find that firms disclosing AI-related keywords subsequently increase innovation activity, even after accounting for prior innovation levels. While these innovation responses can legitimately be viewed as an intermediate mechanism through which AI adoption ultimately influences firm value, our timing evidence also supports a complementary interpretation: the increase in R&D and patent activity functions as an immediate, concurrent signal of a firm's strategic reorientation towards AI. In this framework, credible and actionable AI narratives serve as an early signal of a firm's commitment to innovation, a signal that investors interpret in a forward-looking manner. Although improvements in accounting profitability or labor productivity may materialize only after prolonged periods of complementary investments (e.g., workforce training and organizational restructuring), market valuations, as captured by Tobin's Q, adjust immediately to anticipated future gains when disclosures signal a genuine commitment to AI implementation. Thus, while prior studies suggest a causal sequence from AI adoption through innovation and productivity to market valuation, our empirical evidence indicates that R&D spending and patent activity may also function as concurrent indicators of a firm's strategic reorientation, reinforcing the market's early positive reaction to AI disclosures.

The remainder of this paper is organized as follows: Section 2 reviews the relevant literature and presents our hypotheses; Section 3 describes the data and methodology; Section 4 discusses our analyses, main results, and robustness tests; and Section 5 concludes.

2. Literature review and hypothesis development

2.1. AI's economic and market impact

Artificial intelligence has the potential to revolutionize the economy, significantly impact employment, and transform how we invest, assess risks, and conduct financial market transactions. AI is widely regarded as a key driver of future economic growth, particularly through optimization of production and decision-making processes. However, there is an ongoing debate among economists surrounding the positive and negative effects associated with AI implementation (see, e.g., Autor, 2015; Berg et al., 2018; Aghion et al., 2019). For instance, Berg et al. (2018) emphasize the dual impact of advances in AI and robotics, arguing that while automation fosters growth, it also exacerbates inequalities. In their benchmark model, the authors show that while real wages eventually rise, they fall in the short run, and the recovery can take generations. In contrast, Acemoglu and Restrepo (2018) argue that automation can positively affect labor market equilibrium and national income. They suggest that automation increases capital accumulation, which results in heightened efficiency and productivity, while lowering the costs of production.

On the productivity front, Czarnitzki et al. (2023) analyze firm-level data across European industries and report that AI adoption generates substantial productivity gains, particularly in manufacturing and knowledge-intensive sectors. Their results suggest that AI complements existing capital and labor inputs, enabling firms to achieve higher output with equivalent resource allocations. In a similar vein, Calvino and Fontanelli (2023) examine French firms and identify AI as a critical "general-purpose technology", with productivity benefits that depend critically on complementary investments in digital infrastructure and workforce training. The authors argue that firms with pre-existing investments in complementary technologies capture disproportionately larger productivity premiums from AI adoption. Marioni et al. (2024) extend this line of inquiry by analyzing European firms' distance to the productivity frontier, demonstrating that AI innovation disproportionately benefits frontier firms, thereby potentially widening productivity gaps within industries. Early insights from Brynjolfsson and Hitt (2000) highlight the importance of complementary organizational factors in

realizing productivity gains from IT investments, a principle that extends to AI adoption as well. These studies collectively underscore AI's role as a catalyst for productivity transformation, albeit with distributional consequences across firms and sectors.

Beyond its role in driving productivity, AI also has the potential to transform the financial sector. Through machine learning, deep learning, systems management, and automation, AI offers opportunities to improve products and services. Its ability to reduce human errors, speed up processes, and improve decision-making can help revolutionize areas such as financial advisory and wealth management, risk assessment and management, fraud detection, portfolio optimization, credit evaluation, and cybersecurity (Cao, 2023; Heaton et al., 2017; Khandani et al., 2010; Salinas et al., 2020; Shanmuganathan, 2020; Zheng et al., 2019). These advancements have the potential to reshape the financial system, providing firms with a competitive edge through improved efficiency, accuracy, and service quality.

Recent studies have also refined methodologies for measuring AI adoption and its productivity effects. Babina et al. (2023) leverage granular data from online job advertisements to track firm-level investments in AI-related roles, providing a novel proxy for AI adoption. The authors report that firms increasing AI hiring experience significant shifts in workforce composition, favoring high-skilled technical roles. Babina et al. (2024) further demonstrate that firms explicitly linking AI adoption to product innovation in their disclosures experience stronger market valuations, as investors perceive these narratives as signals of credible growth strategies. Their analysis of patent filings and R&D expenditures also shows that AI-driven product innovation correlates with sustained revenue growth, particularly in technology-intensive industries. Similarly, Webb (2020) shows that AI adoption, measured through job postings requiring AI skills, correlates with increased automation of routine tasks and leads to improved operational efficiency. These methodological innovations address longstanding challenges in operationalizing AI adoption metrics and provide robust empirical tools for assessing its economic impact.

Given AI's transformative impact across industries, financial markets are likely to reward firms embracing AI innovation. Thus, we expect firms adopting AI technologies to be viewed as better positioned to capitalize on future growth opportunities, resulting in increased investor confidence and higher valuations.

2.2. Narratives and financial outcomes

Shiller (2017) argues that latent content within narratives may drive economic fluctuations and consequently influence market volatility, returns, and risks. Narratives provide economic agents with information that must be processed into actionable knowledge. Such processing – often through textual analysis – is crucial for decision-making, as agents rely on it to form expectations and make rational choices. Nyman et al. (2021) further observe that actionable intelligence derived from narratives helps agents to make informed decisions. Using machine learning tools, the authors create a sentiment measure that demonstrates predictive power over economic variables, reinforcing the role of narratives in driving economic outcomes.

The role of textual analysis in empirical finance has further strengthened with advances in statistical techniques and computational power. Gentzkow et al. (2019) note how these developments enable deeper exploration of narratives in financial disclosures. Jegadeesh and Wu (2013) find that the tone of 10-K filings can trigger significant market reactions, both positive and negative. Similarly, Loughran and McDonald (2013) study the tone of S-1 IPO filings and show that uncertain language in S-1 forms reduces investors' ability to accurately assess information; as a result, the IPOs of companies using such language experience higher volatility and first-day returns. Hanna et al. (2020) investigate how Financial Times articles influence investor sentiment and trading volumes, reporting that investor behavior during bull periods is influenced by the tone and sentiment of the articles. Feldman et al. (2010) focus on tone changes in the Management Discussion and Analysis (MD&A) sections of SEC 10-K and 10-Q filings, constructing a lexicon of positive and negative words. They argue that the MD&A section contains valuable qualitative insights into management's expectations and outlook, which can affect market returns, and that its tone is highly correlated with market reactions.

Beyond tone, word choice in disclosures is also informative and can lead to distinct market responses. Cheng et al. (2019) document that firms using the term "blockchain" in an actionable context within 8-K filings experience positive market reactions, especially during periods of high Bitcoin returns. This contrasts with firms that mention only speculative plans to employ blockchain-related infrastructure or have related products but do not explicitly use the term in their disclosures. Similarly, Cohen et al. (2020) examine changes in the financial reports of publicly traded US firms, focusing on 10-K and 10-Q filings, and report that disclosure content serves as a reliable indicator of earnings, profitability, and even bankruptcy.

Our study builds on this literature by exploring the impact of AI-related narratives in corporate filings on firm performance. Specifically, we assess how the inclusion of AI keywords influences firm valuations, highlighting how the framing of such narratives shapes market perceptions and investor behavior.

2.3. Disclosure, narrative credibility, and the financial markets

In examining the relationship between AI adoption and stock valuation, it is crucial to consider how companies introduce this technology – not only through financial disclosures but also through other communication channels. While Rippington and Taffler (1995) emphasize the importance of financial reporting in conveying information related to a security's underlying value, relying solely on such disclosures may be insufficient. AI-related disclosures remain voluntary, as neither the 2023 International Financial Reporting Standards nor the EU Directive on non-financial information mandate their inclusion (Mazzotta et al., 2020). This voluntary nature raises concerns about the credibility of such disclosures and their potential impact on stock prices.

Jackson et al. (2019) further warn against overestimating the efficacy of mandatory non-financial disclosures in curbing irresponsible corporate behavior. In this context, the voluntary nature of AI-related disclosures invites speculation about their credibility and impact on stock prices. Disclosure fraud is often rooted in the quest for higher returns (Davidson, 2022). Liang et al. (2018), along with Kothari et al. (2009) show that credibility problems in financial reports affect reported earnings, book values and stock prices.

Given the limited research on the subject, we examine the authenticity of AI disclosures and their impact on firm valuation. We argue that only credible, actionable disclosures – those signaling genuine AI implementation – should have a positive impact on stock prices, while speculative or irrelevant mentions will have little to no impact on firm valuation.

2.4. AI and innovation

AI can also shape a company's innovation investments and outcomes. Using a decomposition framework, Fujii and Managi (2018) identify AI patents and the contributing factors, revealing that R&D activities across four distinct AI technology types substantially enhance intellectual property growth. Similarly, Parteka and Kordalska (2023) observe a notable increase in patent filings and scientific output due to AI advancements. Marioni et al. (2024) provide cross-country evidence that AI innovation accelerates productivity growth most effectively when firms operate near the technological frontier, suggesting that AI adoption interacts synergistically with existing innovation capabilities. In contrast, Pukthuanthong et al. (2025) warn that AI's gradual replacement of certain employee functions can result in a diminished managerial focus on workforce engagement. This, in turn, may dampen

innovation by lowering employee motivation.

Motivated by these studies, we further explore the link between AI-related disclosures and corporate innovation, viewing innovation metrics not necessarily as sequential mediators of value creation, but rather as concurrent signals of a firm's strategic reorientation towards AI. We hypothesize that firms strategically use AI disclosures to signal a commitment to innovation. As such, we expect that firms disclosing credible, actionable AI mentions will subsequently exhibit higher levels of innovation activity - measured through increased R&D spending and patent filings - compared to their non-disclosing peers or firms with speculative or irrelevant AI disclosures. This view aligns with research suggesting that innovation metrics may act as concurrent signals of a firm's strategic reorientation. Brynjolfsson and Hitt (2000) show that investments in information technology yield long-term performance improvements, even when short-term profitability remains subdued, suggesting that markets price in future benefits well in advance. Similarly, Shiller (2017) highlights how narrative-driven expectations play a central role in market valuations, while Gentzkow et al. (2019) find that textual signals in corporate disclosures are closely linked to forward-looking investor sentiment. Together, these studies imply that immediate market reactions to AI disclosures reflect investor confidence in a firm's potential for long-term gains, even if measurable improvements in productivity or profitability take longer to materialize.

3. Data and methodology

3.1. Data

To study the impact of AI narratives on firm performance, we collect 10-K annual filings for all U.S. companies in the Russell 3000 Index from 2005 to 2018. The filings are retrieved from the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) database.[1] Because we focus on the effect of voluntary AI-related disclosures, we examine Item 1 of the 10-K filings, which contains business descriptions. Companies often discuss their future use of technology and innovation in Item 1. We first identify whether companies mention any AI-related keywords and then classify their usage as *actionable*, *speculative*, and *irrelevant*. We supplement these data with financial, accounting, and patent data from CRSP, Compustat, and KPSS (2017, 2022). Our final sample includes 2615 firms.

Our analysis examines several firm outcomes. To capture innovation, we use R&D expenses (the ratio of research and development expenses to total assets) and patent counts (the natural logarithm of one plus the number of patent registrations). Labor productivity is measured by sales per employee. For market valuation, we use Tobin's Q – the ratio of a company's market value to its book value. Detailed variable definitions, including their specific measurement timing relative to AI disclosures, are provided in Appendix A1.

To identify AI mentions in corporate disclosures, we search for the following keywords: *adaptive algorithm, artificial intelligence, artificial neural network, automated decision-making, bot, chatbot, cognitive science, data science, deep learning, expert system, image recognition, machine intelligence, machine learning, natural language processing, natural language understanding, neural network, optical character recognition*, and *robotic process automation*. Although this list is not exhaustive, we attempted to capture all AI-related terms used in our sample 10-K disclosures, based on a consensus formed after the entire team independently assessed the relevance of each potential term.

We manually review the business descriptions of companies that mention these keywords and classify each usage based on context. A mention is classified as *actionable* if it provides a detailed action plan for utilizing the technology to meet the company's current and long-term objectives. If the mention lacks a clear or specific action plan, we classify it as *speculative*. Finally, mentions are labeled *irrelevant* if they do not directly refer to the company's core business or if the keyword is used only tangentially, with no clear reference to the industry, firm, or opportunities it presents.

Companies often use multiple keywords and may repeat some of them within the same filing. We classify each instance independently. If any mention within the disclosure is classified as actionable, we mark the AI disclosure narrative for that year as actionable. If there are no actionable mentions but at least one speculative mention, we classify the narrative for that year as speculative. If all mentions are irrelevant, the year's AI disclosure narrative is classified as irrelevant. In effect, we classify each firm-year narrative (as opposed to each individual keyword mention) by its highest category (actionable supersedes speculative, which supersedes irrelevant).

Even though our classifications are discrete, manual interpretation of business descriptions and the use of keywords can introduce subjectivity. To reduce personal perception biases, two team members classify each mention independently. In cases of disagreements, a third person reviews the business description and makes the final determination. Because the context in which keywords are used is pivotal for our classification, we classify manually rather than relying on textual analysis software.

Table 1 provides summary statistics of our classification and control variables. Panel A of Table 1 presents firm-year observations for each

Table 1
Summary statistics.

Panel A

Variable	Definition	Observations
Keyword	introduction of any AI keywords	250
Keyword Remove	removal of any AI keywords	114
Actionable	introduction of, and reclassification to, actionable AI keywords	202
Actionable New	genuinely new introduction of actionable AI keywords	182
Actionable Remove	removal or reclassification of actionable AI keywords	75
Speculative	introduction of speculative AI keywords	92
Speculative Remove	removal or reclassification of speculative AI keywords	37
Irrelevant	introduction of irrelevant AI keywords	79
Irrelevant Remove	removal or reclassification of irrelevant AI keywords	35
Speculative to Actionable	change from speculative to actionable keywords	12
Irrelevant to Actionable	change from irrelevant to actionable keywords	8
Actionable to No	change from actionable to no keywords	65
Actionable to Speculative	change from actionable to speculative keywords	10
Actionable to Irrelevant	change from actionable to irrelevant keywords	0

Panel B

Variable	Mean	Std. Dev.	Min	Max
Tobin's Q	2.03	1.79	0.63	12.77
Change in Tobin's Q	0.03	0.32	−0.68	1.67
R&D Expenses (Ratio)	0.06	0.14	0.00	0.94
Patents (ln)	0.46	1.09	0.00	7.66
Labor Productivity (Ratio)	0.56	0.95	0.00	6.98
Size (ln)	20.01	1.98	7.14	27.33
Sales Growth (Ratio)	0.20	0.66	−0.74	4.87
Leverage (Ratio)	0.20	0.23	0.00	1.05
Cash (Ratio)	0.14	0.18	0.00	0.94
Profitability (Ratio)	−1.47	9.48	−88.43	0.88
Observations	20,347			

In Panel A, we tabulate the frequency of keyword mentions by our sample firms in their 10-K filings during the period from 2005 to 2018. In Panel B, we present summary statistics for our dependent and control variables. All variable definitions appear in Appendix A1.

[1] We truncate our sample in 2018 to ensure that our findings (including our post-disclosure analyses) are not affected by the COVID-19 pandemic.

classification category. In total, our sample contains 1006 firm-year mentions of AI-related keywords, including repeat mentions, with 250 first-time keyword introductions (*Keyword*; reported in row 1). As noted, we keep only one classification per year even if firms mention multiple keywords in the same 10-K filing. Of the first-time keyword introductions, 202 are classified as actionable - 182 genuinely new introductions of actionable AI keywords (*Actionable New*) and 20 reclassifications from prior year's *Speculative* (12 *Speculative to Actionable*) or *Irrelevant* (8 *Irrelevant to Actionable*) mentions. Panel B of Table 1 provides descriptive statistics for the key variables. On average, sample firms have a Tobin's Q of 2.03, a market cap of $492 million, sales growth of 20 %, a long-term debt ratio of 0.20, a cash ratio of 0.14, and a net profit margin of −1.47.[2]

Fig. 1 illustrates the distribution of AI narrative mentions by industry and over time. To visualize the data more clearly, we use the Fama-French 12 industry classification instead of the Fama-French 48 classification used in other parts of our analyses. AI-related keywords are mentioned more frequently after 2015 and are mostly concentrated in the business equipment industry.

3.2. Methodology

Our empirical strategy is designed to capture the multifaceted impact of AI narratives. We first examine the relationship between AI narrative adoption and firm innovation activities, then explore effects on labor productivity - particularly as a downstream consequence of innovation (both discussed in Section 4.1) - and finally assess the impact of AI narratives on market valuation.

To test how firms' use of AI-related narratives affects their market valuations, we estimate the following regression model:

$$\Delta Valuation_i = \beta_0 + \beta_m \sum_{m=1}^{M} Keyword_{m,i,t} + \beta_n \sum_{n=M+1}^{N} Controls_{n,i,t} + \gamma_{firm} + \gamma_{year} + \varepsilon_{it} \quad (1)$$

In our baseline specification, we focus on the change in Tobin's Q from year t (the year of financial disclosures containing relevant keywords) to year $t+1$ as the dependent variable, to better isolate valuation changes attributable to new information.[3] We calculate Tobin's Q as the ratio of a company's market value to its book value. The primary explanatory variable is a dummy variable, *Keyword*, which equals one if a firm introduces at least one AI-related keyword in its 10-K SEC filing for the first time in fiscal year t. Depending on the model specification, we substitute *Keyword* with alternative dummy variables - *Actionable All* (noting that it may capture reclassifications of previously introduced keywords), *Speculative*, or *Irrelevant* - to examine the effect of distinct AI narratives on firm valuation. Extended specifications include indicators for the removal of AI narratives as well as for the direct introduction of genuinely new *Actionable* keywords in year t, provided no AI-related keywords appeared in prior filings (*Actionable New*). In other words, firms may disclose actionable narratives from the outset, or they may initially provide speculative or irrelevant AI disclosure and subsequently amend them to actionable. We differentiate between these two disclosure approaches. In total, we identify 182 changes from no prior mentions to actionable narratives (*Actionable New*), 12 changes from speculative to actionable narratives (*Speculative to Actionable*), and 8 changes from irrelevant to actionable narratives (*Irrelevant to Actionable*). Because of the limited number of observations for the latter two categories, we focus on "*Actionable New*" narratives in our empirical tests.

In line with previous studies, we include a set of firm-specific characteristics as control variables: firm size (*Size*), the sales growth rate (*Sales Growth*), the long-term debt ratio (*Leverage*), the cash ratio (*Cash*), and the net profit margin (*Profitability*). We winsorize the control variables at the 1st and 99th percentiles to mitigate the impact of outliers. Additionally, we include firm (γ_{firm}) and year (γ_{year}) fixed effects to account for possible unobservable factors. Firm fixed effects control for time-invariant firm characteristics (e.g., management quality, corporate culture, or inherent industry factors), effectively allowing each firm serve as its own control. Year fixed effects absorb macroeconomic shocks or market-wide trends. This fixed-effects specification allows us to isolate within-firm changes around AI disclosures, mitigating omitted variable bias and strengthening the causal interpretation of our results. The error term, ε_{it}, represents the random disturbance. For detailed variable definitions, refer to Appendix A1.

4. Analysis and results

In this section, we present the empirical results, structured to trace the sequential impact of AI adoption on firm outcomes. Before examining the ultimate impact of AI disclosure on firm valuation (which we address in Section 4.2), we first assess how AI adoption relates to innovation activity and subsequently to productivity, considering innovation as a potential mediating factor. This layered analysis offers one lens through which to explore the potential mechanisms linking AI adoption and firm value.

4.1. AI adoption, innovation activity, and productivity

We start by exploring if credible AI narratives correspond to actual changes in firm behavior or are merely rhetoric. Specifically, we examine whether firms that disclose AI initiatives follow through with increased innovation efforts and, subsequently, productivity improvements – channels through which value creation may materialize.

First, we focus on innovation activities and two key outcomes - R&D investment and patent output. An increase in R&D or patent activity following the disclosure would suggest that firms use AI-related keywords to signal their commitment to technology investment, which the market may then recognize through higher valuations. In this context, AI mentions may also serve as a proxy for broader innovation signaling, reinforcing investor perceptions of a firm's commitment to technological advancements. Because we classify the keyword mentions as *Actionable*, *Speculative* and *Irrelevant*, our research design allows us to identify credible signals and assess their impact on future firm investments in innovation. To examine this, we estimate the following model in Tables 2 and 3:

$$R\&D / Patent_{i,t+1} = \beta_0 + \beta_m \sum_{m=1}^{M} Keyword\ Treated_{m,i,t} + \beta_n \sum_{n=M+1}^{N} Controls_{n,i,t} + \gamma_{firm} + \gamma_{year} + \varepsilon_{it} \quad (2)$$

where the dependent variable is either R&D expenses or patents. We calculate R&D expenses as the ratio of research and development expenses to total assets, and patents as the natural logarithm of one plus the number of patent registrations in a given year. The primary explanatory variable is a dummy variable, *Keyword Treated*, that takes on a value of 1 for all years since a firm's first AI keyword disclosure (and zero before). Depending on the model specification, we substitute *Keyword Treated* with either *Actionable Treated*, *Speculative Treated*, or *Irrelevant Treated* to examine the effect of distinct AI narratives. All specifications include firm (γ_{firm}) and year (γ_{year}) fixed effects.

[2] Unlike ROA and ROE which are influenced by a company's capital structure and asset base, the net profit margin isolates operational profitability, independent of financing methods. Extremely low, even negative, net profit margins can arise when negative net income is paired with low sales, a scenario not uncommon in practice. Importantly, our findings remain robust when we use ROA instead.

[3] In unreported tests, we also verify that using the level of Tobin's Q at t + 1 yields qualitatively similar results.

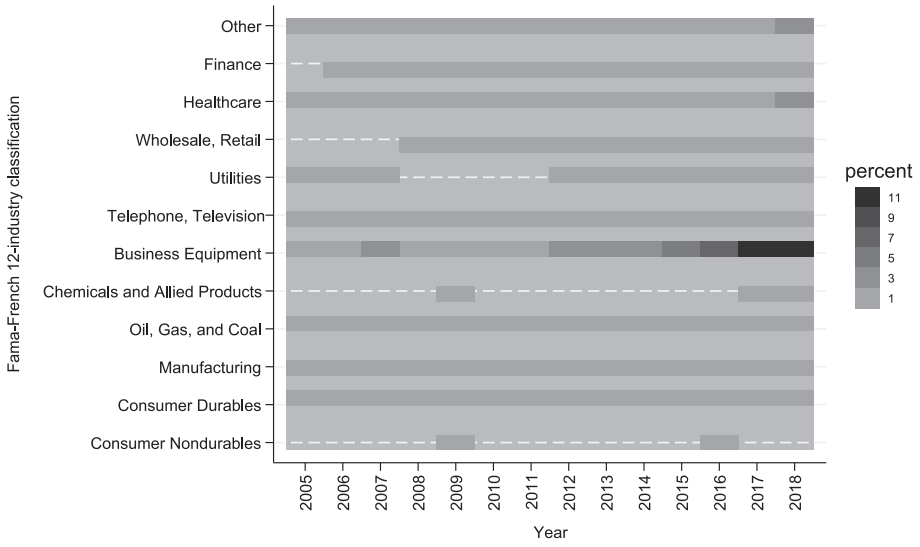


Fig. 1. Heat map of AI narratives by industry.
This figure shows the distribution of AI mentions by industry, based on the Fama-French 12 industry classification. Darker colors indicate years in which more firms use AI narratives.

Table 2
AI disclosure and R&D.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Keyword Treated	0.022***				0.016***			
	(0.001)				(0.002)			
Actionable Treated		0.034***				0.022**		
		(0.006)				(0.026)		
Speculative Treated			0.019				0.016*	
			(0.105)				(0.072)	
Irrelevant Treated				0.003				0.003
				(0.634)				(0.539)
Size	−0.009***	−0.009***	−0.008***	−0.008***	0.003	0.003	0.003	0.003
	(0.004)	(0.004)	(0.005)	(0.005)	(0.255)	(0.256)	(0.243)	(0.229)
Sales Growth	0.000	0.000	0.000	0.000	0.001	0.001	0.001	0.001
	(0.892)	(0.880)	(0.894)	(0.886)	(0.808)	(0.799)	(0.810)	(0.803)
Leverage	−0.043**	−0.042**	−0.042**	−0.042**	−0.045***	−0.045***	−0.045***	−0.045***
	(0.024)	(0.025)	(0.025)	(0.026)	(0.003)	(0.003)	(0.003)	(0.003)
Cash	0.015	0.015	0.014	0.014	0.013	0.014	0.013	0.013
	(0.386)	(0.380)	(0.414)	(0.413)	(0.367)	(0.366)	(0.391)	(0.389)
Profitability	−0.001***	−0.001***	−0.001***	−0.001***	−0.000*	−0.000*	−0.000*	−0.000*
	(0.010)	(0.010)	(0.009)	(0.009)	(0.091)	(0.090)	(0.090)	(0.089)
Lagged R&D Expenses					0.372***	0.372***	0.373***	0.373***
					(0.000)	(0.000)	(0.000)	(0.000)
Constant	0.301***	0.300***	0.300***	0.299***	0.026	0.025	0.025	0.024
	(0.000)	(0.000)	(0.000)	(0.000)	(0.619)	(0.626)	(0.629)	(0.649)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8283	8283	8283	8283	8283	8283	8283	8283
Adjusted R^2	0.717	0.717	0.717	0.717	0.752	0.752	0.752	0.752

We examine whether firms increase their research and development (R&D) expenditures after they mention AI-related keywords in their 10-K filings. The dependent variable is the ratio of R&D expenses to total assets measured one year after the SEC filing date. Keyword Treated is a dummy variable that takes a value of one for all years since the first mention of the keyword. We define Actionable Treated and Speculative Treated in a similar manner. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) *p*-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 2 reports regression results where the dependent variable is R&D expenses, measured one year after keyword mentions. This analysis examines whether firms ramp up R&D activities after introducing AI mentions in their filings. The results indicate a clear and prompt increase in innovation input among AI-narrative firms. The coefficient on *Keyword Treated*, reported in Column (1) is 0.022 ($p < 0.01$), implying that after firms introduce AI into disclosures, their R&D intensity (i.e., innovation inputs) increases significantly. This effect is economically meaningful and suggests a reallocation of resources towards innovation, potentially to develop or integrate AI technologies more effectively. Notably, firms whose AI narratives are actionable see an even larger rise in R&D, with the *Actionable Treated* coefficient of 0.034 ($p < 0.01$). By contrast, Columns (3) and (4) show no significant effect for *Speculative Treated* and *Irrelevant Treated*. In summary, firms that credibly commit to AI in public disclosure, outlining a detailed action plan for implementation, tend to back those words with greater R&D investment. Such follow-through, as we later show, may contribute to investors' re-evaluation of the firm's prospects, potentially contributing to an increase in firm value.

Of course, an alternative explanation warrants consideration: firms

Table 3
AI disclosure and patent signaling.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Keyword Treated	0.150*				0.093*			
	(0.077)				(0.053)			
Actionable Treated		0.245***				0.133**		
		(0.009)				(0.019)		
Speculative Treated			0.009				0.036	
			(0.939)				(0.552)	
Irrelevant Treated				0.212				0.083
				(0.285)				(0.450)
Size	0.145***	0.144***	0.146***	0.144***	0.080***	0.080***	0.081***	0.080***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	−0.018	−0.018	−0.018	−0.017	−0.017	−0.017	−0.017	−0.017
	(0.131)	(0.133)	(0.129)	(0.139)	(0.127)	(0.128)	(0.125)	(0.129)
Leverage	−0.068	−0.062	−0.065	−0.068	−0.038	−0.035	−0.036	−0.037
	(0.522)	(0.555)	(0.542)	(0.522)	(0.566)	(0.599)	(0.584)	(0.573)
Cash	−0.120	−0.118	−0.121	−0.122	−0.004	−0.003	−0.005	−0.005
	(0.138)	(0.145)	(0.133)	(0.132)	(0.952)	(0.962)	(0.939)	(0.939)
Profitability	0.002***	0.002***	0.002***	0.002***	0.002**	0.002**	0.002**	0.002**
	(0.005)	(0.005)	(0.006)	(0.006)	(0.013)	(0.012)	(0.013)	(0.014)
Lagged Patents					0.489***	0.488***	0.490***	0.489***
					(0.000)	(0.000)	(0.000)	(0.000)
Constant	−1.532***	−1.540***	−1.552***	−1.522***	−0.924***	−0.930***	−0.935***	−0.924***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y
Observations	6944	6944	6944	6944	6944	6944	6944	6944
Adjusted R^2	0.836	0.836	0.836	0.836	0.875	0.875	0.875	0.875

We examine whether firms increase their patent registrations after they mention AI-related keywords in their 10-K filings. The dependent variable is the natural logarithm of the number of patents measured one year after the SEC filing date. Keyword Treated is a dummy variable that takes a value of one for all years since the first mention of the keyword. We define Actionable Treated and Speculative Treated in a similar manner. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

disclosing actionable AI keywords may be more innovative by nature – i.e., more active in R&D and patent generation – even without AI-related disclosures. If this is indeed the case, the relationship between AI mentions and subsequent innovation outcomes may simply reflect pre-existing innovation activity. AI mentions could then be a byproduct of such firms' broader innovation efforts rather than a direct signal of new innovation. However, even under this alternative explanation, AI-related disclosures would still serve to reinforce market perceptions and belief in these firms' ongoing commitment to technological leadership. Drawing on signaling theory, the disclosure of actionable AI narratives provides firms with a strategic tool to credibly communicate their intent to lead in technological innovation. To at least partially address potential endogeneity between innovation capacity and AI-related disclosures, we include one-year lagged R&D expenses as additional independent variables in the regressions reported in Columns (5) through (8) of Table 2. Although not a perfect control for endogeneity, this allows us to account for pre-existing innovation trends and better differentiate between active innovators leveraging AI (and being vocal about it) and peers potentially lagging in AI adoption. The results remain robust, supporting the idea that AI mentions, particularly actionable ones, play a significant role in signaling innovation and maintaining investor confidence. In other words, whether AI disclosures reflect pre-existing innovation tendencies or act as a new driver of growth, they contribute to maintaining investor confidence and signaling a firm's commitment to staying at the forefront of innovation.

In Table 3, we examine patent activity following AI disclosures as a measure of innovation output. The dependent variable is the natural logarithm of one plus the number of patents granted to the firm in the year after the disclosure. We restrict this analysis to firms that have at least some patenting activity in our sample period. Consistent with the R&D findings, AI narratives, particularly actionable ones, are associated with subsequent increases in patenting. The *Keyword Treated* and *Actionable Treated* variables in Columns (1) and (2) have statistically significant coefficients, indicating that patent registrations increase after firms mention AI-related keywords. This finding points to AI's role in improving the efficiency and output of the innovation process. In contrast, the coefficients for *Speculative Treated* and *Irrelevant Treated* are not significant, reinforcing that only substantive AI efforts translate into actual innovation gains. The inclusion of one-year lagged patenting activity in Columns (5) through (8) confirms the robustness of these results.

Collectively, these findings suggest that actionable AI disclosures in 10-Ks are not merely cheap talk but are often followed by tangible increases in innovation activities. This commitment to innovation, signaled by the narrative and substantiated by tangible innovation efforts, as demonstrated by higher R&D spending and patent output in the following years, forms the first critical step in the potential causal chain linking AI adoption to improved firm value. While we later examine the direct impact on market valuation, we interpret the observed increases in R&D and patents as concurrent signals of a firm's strategic reorientation. The market may react to the AI narrative itself as a forward-looking indicator of innovation and future benefits, well before R&D projects bear fruit or patents are granted, with these subsequent innovation activities serving to validate those initial expectations over time.

Next, having established that AI adoption is linked to increased innovation activity, a natural question follows: do these efforts translate into improved operational performance? Improved productivity is one frequently cited benefit of AI implementation and represents a crucial link between technological investment and, ultimately, firm valuation.

In Table 4, we thus examine a subset of firms for which longer-run data are available to assess potential productivity improvements. Using a subsample of firms with at least five years of post-disclosure data, and controlling for standard firm characteristics and fixed effects, we find modest gains in labor productivity (measured by sales per employee) emerging two to three years after an actionable AI disclosure, but only for firms supporting such disclosures with increased subsequent R&D spending. These firms indeed enjoy higher sales per employee relative to controls, statistically significant at the 10 % level in years 2,

Table 4
AI disclosure and productivity.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 year		2 year		3 year		4 year		5 year	
Keyword Treated	0.004		−0.086**		−0.089*		−0.086*		−0.032	
	(0.920)		(0.034)		(0.056)		(0.069)		(0.335)	
Keyword Treated x R&D	−0.076		0.277*		0.300*		0.326*		0.101	
	(0.631)		(0.058)		(0.080)		(0.075)		(0.406)	
Actionable Treated		−0.022		−0.050		−0.041		−0.041		−0.013
		(0.484)		(0.158)		(0.288)		(0.359)		(0.834)
Actionable Treated x R&D		0.056		0.273*		0.269*		0.286*		0.173
		(0.680)		(0.066)		(0.090)		(0.089)		(0.440)
R&D Expenses	−0.205	−0.212	−0.326*	−0.329*	−0.315	−0.318	−0.313	−0.315	−0.284	−0.288
	(0.242)	(0.232)	(0.089)	(0.090)	(0.124)	(0.125)	(0.149)	(0.151)	(0.201)	(0.201)
Size	0.003	0.003	0.007	0.007	0.006	0.006	0.003	0.003	0.007	0.007
	(0.741)	(0.720)	(0.508)	(0.519)	(0.567)	(0.577)	(0.794)	(0.779)	(0.549)	(0.520)
Sales Growth	0.019*	0.019*	0.008	0.008	0.024**	0.024**	0.029*	0.029*	0.018	0.018
	(0.063)	(0.063)	(0.325)	(0.330)	(0.021)	(0.021)	(0.067)	(0.066)	(0.169)	(0.168)
Leverage	0.087	0.088	0.144	0.143	0.166*	0.165*	0.185*	0.186*	0.233**	0.234**
	(0.282)	(0.279)	(0.105)	(0.107)	(0.066)	(0.068)	(0.073)	(0.072)	(0.036)	(0.036)
Cash	−0.037	−0.037	−0.045	−0.045	−0.069	−0.069	−0.099	−0.098	−0.031	−0.030
	(0.347)	(0.343)	(0.255)	(0.258)	(0.213)	(0.216)	(0.109)	(0.113)	(0.534)	(0.541)
Constant	0.316	0.312	0.260	0.262	0.291	0.292	0.358	0.351	0.265	0.256
	(0.103)	(0.110)	(0.241)	(0.236)	(0.183)	(0.180)	(0.139)	(0.145)	(0.248)	(0.260)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8037	8037	7790	7790	7397	7397	6450	6450	5586	5586
Adjusted R^2	0.608	0.608	0.612	0.612	0.626	0.625	0.630	0.629	0.637	0.637

We examine the effect of keyword mentions on firm productivity, calculated as the ratio of sales to employees 1, 2, 3, 4, or 5 years after the SEC filings. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

3, and 4 post-disclosure.[4] This indicates that innovation acts as an important conduit through which AI adoption can improve operational performance. Firms that not only announce AI initiatives but also invest in related innovation appear more likely to realize productivity gains, while those that do not follow through with such investment show no meaningful improvement in the timeframe we consider.

Taken together, the evidence on innovation and productivity suggests that while AI adoption may lead to eventual efficiency gains, these emerge gradually and are closely tied to sustained innovation efforts. These gains, though often delayed and mediated by innovation, represent the second key step in the broader pathway from AI adoption to improved firm value.

To complement our productivity analysis, we also examine the relationship between AI adoption and firm profitability, as reported in Appendix A3. As the measure of profitability, we use ROE, defined as net income divided by end of year total equity. We find no statistically significant association in the years immediately following AI disclosure. This null result likely reflects the long-run nature of AI investments contrasted with the short-term horizon of our analysis. In the near term, AI adoption often entails increased costs, such as R&D outlays and technology integration expenses, that can depress immediate accounting profits. Moreover, the financial returns from AI initiatives may be delayed or masked by the accounting treatment of intangible investments. As such, the absence of a detectable short-run profit effect should not be interpreted as evidence against the economic relevance of AI narratives; rather, it may underscore the importance of timing and the limitations of contemporaneous accounting metrics in capturing the full value of strategic technological investments. These findings remain robust when profitability is instead measured using ROA, defined as the ratio of net income to total assets.[5]

4.2. AI narratives and market valuation

Having established that actionable AI disclosures are associated with prompt increases in innovation activities and can, over a longer horizon and particularly when coupled with sustained R&D, lead to modest productivity improvements, we now turn to the ultimate impact of AI disclosures on subsequent firm valuation. This final step in our sequential analysis examines investors' reactions, which, as we hypothesize, may precede the full realization of operational outcomes.

A firm can use its disclosures to highlight future investments in technology or relevant use cases, either to inform or influence investors. Insofar as the market views AI adoption as a meaningful development, a firm's valuation should react positively following the disclosure of AI-related keywords, particularly when such keywords are introduced for the first time. Such disclosures can further be actionable, speculative, or irrelevant in nature. An actionable narrative informs investors about a specific action plan for implementing new technology, while speculative mentions involve vague plans, and irrelevant mentions are only tangential. We therefore expect a positive change in firm valuation following actionable narratives, but an insignificant or even negative reaction to speculative or irrelevant disclosures.[6] Apart from investors' expectations, a firm is more likely to invest in AI-related technology when it presents an actionable plan in its business description (Item 1 of the 10-K filings). Our focus on Item 1 is deliberate, as companies tend to present specific strategies in this section only if they intend to execute them. While actionable investments in AI may lead to improved operational efficiency over time (as suggested by our findings on innovation and productivity), investors often anticipate these future benefits, potentially translating AI disclosures into higher immediate firm valuations, particularly when these narratives signal a credible commitment to technological advancement.

[4] This effect diminishes by year 5, with statistical significance moderating, likely due to the smaller subsample size.

[5] The results are not reported for the sake of brevity but can be provided upon request.

[6] In Appendix A2, we replace Tobin's Q with a firm's cumulative abnormal return (−1, +1) around the filing date to examine the effect of disclosures on investor reactions immediately around the event. We do not find any effect of AI keyword introductions on cumulative abnormal returns.

Table 5 reports the regression results for the introduction and removal of various types of AI narrative mentions and their effects on firm value. In this analysis, the dependent variable is the year-over-year change in Tobin's Q (ΔTobin's Q). We include all "*introduce*" dummy variables in Columns (1)–(5) and all "*remove*" dummy variables in Columns (6)–(10). As discussed in Section 3, if a firm introduces an AI-related term for the first time in its 10-K filing (i.e., it did not mention any AI-related keywords in the previous year but includes at least one this year), we assign a value of one to the *Keyword* dummy variable. If a firm stops mentioning an AI-related keyword in a given year (i.e., it mentioned a keyword in the previous year but does not mention it in the current year), we assign a value of one to the *Keyword Remove* dummy variable. The same classification is later applied for *actionable*, *speculative*, and *irrelevant* mentions, distinguishing between their introductions and removals.

In Column (1), the *Keyword* dummy is significantly positively related to firm value, with the introduction of any AI-related keyword increasing Tobin's Q by approximately 5.0 % ($p < 0.05$) on average. This finding aligns with the notion that the content of public disclosures matters to investors and lends support to our hypothesis that firms disclosing AI-related information experience a meaningful market impact.

Investors may perceive AI narratives differently based on the content and context of the information disclosed. Thus, in Columns (2) to (5), we distinguish between *Actionable*, *Speculative*, and *Irrelevant* first-time keyword mentions, respectively. Columns (2) and (3) shows a positive relationship between the *Actionable* dummy and Tobin's Q - whether defined as *Actionable All* (which in addition to first-time AI mention also includes reclassifications from prior non-actionable mentions) or *Actionable New* (which captures only genuinely new introductions) - suggesting that investors respond favorably to tangible, concrete plans for AI adoption and use. The *Actionable New* variable has a notably larger effect on Tobin's Q, with a coefficient of 0.055 (p-value <0.05), suggesting that much of the AI-related disclosure impact on firm value occurs when an actionable keyword is introduced for the first time, particularly if no AI technology was mentioned in the previous year's filing. Overall, actionable AI disclosures are associated with roughly a 4.7 % (5.5 %) year-over-year increase in Tobin's Q when considering the *Actionable All* (*Actionable New*) dummy. Comparing the magnitudes, the impact of an *Actionable* keyword introduction is essentially on par with the overall *Keyword* introduction effect (~5.0 %). This indicates that valuation gains from initial AI disclosures are driven largely by substantive, actionable narratives.[7] In sum, much of the AI narrative premium occurs when an AI initiative is announced for the first time, particularly when that announcement is actionable. It is worth emphasizing that all our regressions incorporate multiple controls, including firms' current profitability. Therefore, the positive and significant coefficients on the AI narrative introduction variables suggest that the market's reaction is not merely picking up the signal of strong fundamentals or profitability. Instead, investors appear to respond to the AI narrative itself - specifically, the forward-looking information it conveys about the firm's strategic direction - above and beyond any existing performance metrics.

To assess the robustness of these findings and strengthen the credibility of a causal link between AI disclosures and firm value, we follow Dube et al. (2023) and Marioni et al. (2024) and adopt an event-study difference-in-differences approach. Specifically, we employ an event-study style Local Projections DiD (LP-DiD) analysis, focusing on each firm's first AI disclosure as the treatment event and comparing its trajectory to that of control firms with no AI disclosures in the same period. This allows us to estimate the dynamic effects of the treatment while avoiding potential biases inherent in two-way fixed-effects models with staggered treatment timing.

For each firm's first AI disclosure year (t), we compare outcomes in the pre-treatment year ($t-1$) to post-treatment horizons $t+h$ (with $h = 1, 2$, and 3). Following Dube et al. (2023), control firms are restricted to those with no AI disclosures through $t+h$ (e.g., for $h = 3$, controls remain untreated until at least $t+4$) to reduce the risk of contamination from firms transitioning into treatment status during the event window.

The LP-DiD estimates, reported in Table 6, reveal a pattern consistent with our main findings. Firms introducing AI narratives experience significantly higher subsequent Tobin's Q than control firms that remain untreated. For example, three years after the initial AI disclosure, treated firms' Tobin's Q is, on average, 0.3 to 0.5 points higher than that of control firms (p-value <0.05), conditional on disclosure type. The LP-DiD estimates are derived from a necessarily smaller effective sample, reflecting the method's matching and event window requirements. This reduction in sample size can reduce statistical power and precision of the estimates, potentially explaining differences in the significance – and, to some extent, the magnitude – of certain coefficient estimates relative to our main results in Table 5. Despite these variations, which are not uncommon when comparing results from different estimation strategies with varying sample constraints, the overall consistency in the direction and pattern of the key effects reinforces the robustness of our main conclusions. As part of this analysis, we also test for parallel trends by estimating treatment effects in the pre-treatment period (*t-3* to *t-1*) using the same LP-DiD specification. As shown in Fig. 2, the estimated coefficients over this pre-treatment window are statistically indistinguishable from zero, indicating that firms eventually introducing AI-related disclosures followed similar trends to those of control firms prior to treatment. This supports the parallel trends assumption and reinforces the validity of our identification strategy. We further verify the robustness of these findings by restricting the control group to firms that never disclose AI-related information during the sample period. The results remain qualitatively unchanged as well, reinforcing the validity of our empirical design. Overall, this complementary analysis bolsters a causal interpretation of our results, supporting that the observed increase in firm value stems from AI disclosure rather than unobserved firm differences. While our main panel fixed-effects specification already controls for persistent firm attributes, the LP-DiD estimates serve as additional confirmation that the market reaction we document is indeed driven by the new information conveyed through AI disclosures, not pre-existing characteristics or broader industry trends.

Turning back to our main specification in Table 5, we find no significant effect for the *Speculative* or *Irrelevant* dummies (Columns 4 and 5). In other words, first-time mentions that are vague or tangential do not meaningfully affect firm valuation. Likewise, none of the "remove" indicators (*Keyword Remove*, *Actionable Remove*, *Speculative Remove*, and *Irrelevant Remove* in Columns 6–10) have a significant coefficient (all p-values >0.10), suggesting that ceasing to mention AI in public disclosures does not materially affect firm value.

We further differentiate between firms that initially provide *actionable* narratives but later remove AI mentions entirely (*Actionable to No*) and those that replace them with *speculative* or *irrelevant* narratives in subsequent 10-K filings. We identify 65 *Actionable to No* changes, 10 changes from *actionable* to *speculative* narratives (*Actionable to Speculative*), and no instances of changes from actionable to irrelevant narratives (*Actionable to Irrelevant*). Due to the limited number of observations in the latter two categories, we focus on *Actionable to No* narratives in Column (8) of Table 5. Once again, we find no significant relationship between the *Actionable to No* variable and Tobin's Q. This suggests that when firms remove actionable AI narratives, it may indicate that the technology has been implemented, reducing the need for further market updates and, therefore, limiting any additional valuation impact.

In conclusion, Tobin's Q increases markedly and significantly for

[7] In additional unreported analyses, we also examine the impact of continuous AI-related keyword mentions on firm valuation. Although continuous mentions produce statistically significant effects, their magnitude is considerably smaller than that of first-time introductions, highlighting the dominant role of initial disclosures in shaping investor perceptions.

Table 5
Introduction and removal of AI mentions and firm value.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Keyword	0.050**									
	(0.017)									
Actionable All		0.047**								
		(0.049)								
Actionable New			0.055**							
			(0.035)							
Speculative				0.021						
				(0.490)						
Irrelevant					0.047					
					(0.256)					
Keyword Remove						0.000				
						(0.993)				
Actionable Remove							0.016			
							(0.615)			
Actionable to No								−0.006		
								(0.865)		
Speculative Remove									−0.020	
									(0.669)	
Irrelevant Remove										0.025
										(0.665)
Size	−0.151***	−0.151***	−0.151***	−0.151***	−0.151***	−0.151***	−0.151***	−0.151***	−0.151***	−0.151***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***	−0.022***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.000	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001	0.001
	(0.989)	(0.976)	(0.976)	(0.975)	(0.979)	(0.974)	(0.975)	(0.974)	(0.973)	(0.973)
Cash	−0.034	−0.034	−0.034	−0.035	−0.035	−0.035	−0.035	−0.035	−0.035	−0.035
	(0.366)	(0.361)	(0.362)	(0.349)	(0.350)	(0.347)	(0.349)	(0.346)	(0.347)	(0.346)
Profitability	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.743)	(0.739)	(0.740)	(0.741)	(0.739)	(0.739)	(0.740)	(0.739)	(0.740)	(0.740)
Constant	3.064***	3.063***	3.063***	3.062***	3.063***	3.062***	3.062***	3.062***	3.061***	3.062***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20,167	20,167	20,167	20,167	20,167	20,167	20,167	20,167	20,167	20,167
Adjusted R^2	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167	0.167

We examine the effect of keyword mentions on changes in firm valuation. The dependent variable is the change in Tobin's Q calculated as $(Q_{t+1} - Q_t)/Q_t$. Keyword is a dummy variable that takes on a value of one if a firm mentions a keyword for the first time in a given year but did not mention any keywords in the previous year. Keyword Remove is a dummy variable that takes on a value of one if a firm mentioned a keyword in the previous year and removes the keyword in the current year. Similar classifications are applied for speculative and irrelevant mentions. Actionable All is a dummy variable which, in addition to first-time AI actionable mentions, also accounts for reclassifications from prior non-actionable mentions. Actionable New is a dummy variable which captures only genuinely new introductions of actionable AI mention. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

firms introducing actionable AI narratives, as opposed to speculative or irrelevant ones. While the effect persists when firms continue to provide relevant, actionable narratives or introduce new ones, its initial impact remains the strongest, emphasizing the outsized importance of first-time disclosures on firm valuation.

This brings us to a holistic view of the findings. The evidence suggests a sequence where an actionable AI disclosure triggers an immediate positive investor revaluation (higher market value). As discussed in Section 4.1, this swift market response is typically accompanied by, or shortly followed by, tangible innovation commitments (increased R&D and patenting). These innovation efforts, in turn, can contribute to longer-term, albeit modest, productivity gains. Thus, while the full operational benefits may take time to accrue, the market appears to react to the forward-looking signal of the AI narrative itself, with early innovation activities serving as concurrent validation of the firm's strategic commitment, rather than as direct, immediate drivers of the initial valuation jump.

4.3. Impact on competitors

Having established the direct impact of a firm's own AI narrative disclosures on its market valuation, we next broaden our analysis to consider how a firm's valuation is influenced by AI disclosure strategies of its competitors, emphasizing the role of competitive dynamics. As previous research suggests, firms that signal their intent to undertake transformative initiatives or significant projects through company disclosures are often rewarded by the market. As a result, firms often benchmark their strategic communications against industry peers, and falling behind can be detrimental. In our context, a company that neglects to disclose AI while its rivals do may be viewed as lagging. Conversely, a firm that embraces AI alongside its peers might avoid being penalized or even benefit from validating an industry trend. To test these ideas, we incorporate variables capturing both the firm's own disclosure status and that of its competitors, focusing particularly on how these interact. We define a competitor as any firm operating in the same Fama-French 48 industry.

In Table 7, we estimate several models similar to those in Eq. (1), all examining how the firm and competitor AI disclosure patterns jointly affect firm valuation. However, while our previous analysis focused on within-firm changes following initial AI disclosures, here we implement a level-based difference-in-differences approach that allows us to assess the relative positioning of firms within their competitive landscape. In particular, this specification uses Tobin's Q at t + 1 as the dependent variable rather than year-over-year changes, allowing us to capture sustained valuation differences between firms with different AI narrative strategies over time. Our key explanatory variables include *Keyword Treated*, *Actionable Treated*, and *Speculative Treated* - dummy variables that take a value of 1 for all years since a firm's first mention of any,

Table 6
AI disclosure and firm value: LP-DiD analysis.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	h = 1	h = 2	h = 3	h = 1	h = 2	h = 3	h = 1	h = 2	h = 3
Keyword (post x treated)	0.158	0.202	0.331*						
	(0.176)	(0.170)	(0.067)						
Actionable All (post x treated)				0.367**	0.390**	0.467**			
				(0.011)	(0.026)	(0.041)			
Actionable New (post x treated)							0.409**	0.381*	0.421*
							(0.013)	(0.054)	(0.098)
Size	−0.051***	−0.055***	−0.053***	−0.051***	−0.058***	−0.058***	−0.051***	−0.057***	−0.056***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	−0.163***	−0.171***	−0.160***	−0.165***	−0.164***	−0.153***	−0.165***	−0.164***	−0.154***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Leverage	0.146**	0.041	0.007	0.148**	0.044	0.028	0.145**	0.037	0.019
	(0.022)	(0.624)	(0.946)	(0.019)	(0.593)	(0.784)	(0.022)	(0.650)	(0.855)
Cash	−0.523***	−0.718***	−0.801***	−0.540***	−0.712***	−0.824***	−0.539***	−0.711***	−0.823***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Profitability	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.369)	(0.435)	(0.649)	(0.367)	(0.445)	(0.650)	(0.368)	(0.447)	(0.652)
Constant	0.303***	0.379***	0.417***	0.309***	0.403***	0.450***	0.307***	0.400***	0.444***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	16,716	15,651	14,551	17,188	16,192	15,138	17,228	16,240	15,194
Adjusted R^2	0.057	0.040	0.036	0.057	0.039	0.037	0.057	0.039	0.036

We implement an event-study style Local Projections DiD (LP-DiD) model. The dependent variable is the change in Tobin's Q, calculated as ($Q_{t+h} - Q_{t-1}$), where the value of h is provided in the column header. Firm characteristics used as controls are measured at t-1. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

actionable, and speculative AI-related keyword in its 10-K filings, respectively. This typical difference-in-differences specification effectively captures how the persistent adoption of AI narratives shapes relative firm valuations, not just the immediate market reaction to initial disclosures. We also include corresponding competitor variables: *Competitor Keyword Treated*, *Competitor Actionable Treated*, and *Competitor Speculative Treated*, which similarly take the value of 1 for all years since the first AI-related mentions by firms in the same Fama-French 48 industry. These variables allow us to investigate how a firm's valuation responds to the AI disclosure strategies adopted by its competitors over time. In addition, we control for standard firm characteristics as well as firm and year fixed effects.

The findings in Table 7 confirm that AI narratives have a significant relative component in determining valuation levels, and the nature of AI disclosures also matters. Firms adopting AI narratives (*Keyword Treated*) while operating in industries where competitors also discuss AI (*Competitor Keyword Treated*) maintain higher valuation levels, with this effect particularly pronounced when firms adopt actionable AI disclosures (*Actionable Treated*) in response to competitors' actionable AI narratives (*Competitor Actionable Treated*), as reflected in Column (2). The interaction of *Actionable Treated* and *Competitor Actionable Treated* is significantly positive at the 5 % level. This suggests that the market rewards substantive, actionable AI commitments most generously when they align with similar commitments from industry peers. The persistence of these valuation premiums beyond the initial public disclosure period also emphasizes the importance of keeping pace with industry norms in technological narratives.

In contrast, firms that only offer speculative AI mentions (*Speculative Treated*) when competitors make actionable AI disclosures (*Competitor Actionable Treated*) are penalized by the market, as reflected by a lower Tobin's Q the following year. This indicates that half-hearted or vague AI narratives are less effective at closing the valuation gap when competitors in the same industry are making concrete AI commitments. The market appears to distinguish between substantive and speculative AI narratives, rewarding the former more generously in competitive contexts.

Together, our competitive analysis indicates that the market's valuation of firms in relation to AI narratives is strongly context-dependent. Firms that credibly embrace AI alongside their peers enjoy higher valuation levels, while those that neglect or under-report AI initiatives while competitors advance face persistent valuation discounts. This highlights the importance of not only what a firm discloses about its AI initiatives, but also how those disclosures position the firm relative to its peers. It may also explain why some firms act opportunistically in their timing and narrative framing of AI-related disclosures.

4.4. Robustness tests

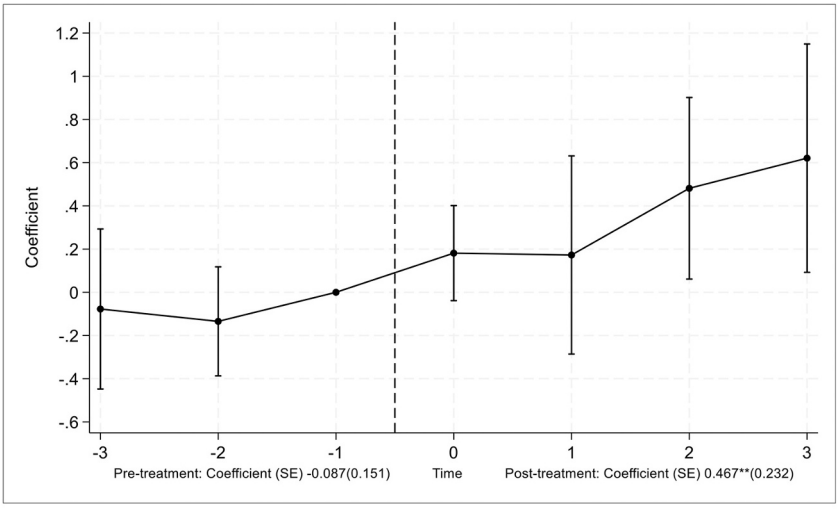
To further validate our main findings regarding the impact of AI narrative disclosures on firm valuation, we conduct a series of robustness tests. First, we employ entropy balancing to account for fundamental differences between firms that use AI narratives and those that do not. Second, we split our sample into high-tech and non-high-tech firms to identify possible discrepancies across different sectors. Third, we adjust for the public popularity of AI-related keywords, which may influence firms to speculatively include such terms in their corporate disclosures.

To account for observable differences between firms that use AI narratives and firms that do not, we resort to the entropy balancing technique developed by Hainmueller (2012). Specifically, we balance the means of all control variables used in Eq. (1). Table 8 presents regression results after entropy balancing. The findings remain qualitatively similar to those in Table 5: actionable AI disclosures continue to show a positive and significant association with firm value, while the dummies for speculative and irrelevant disclosures remain insignificant.

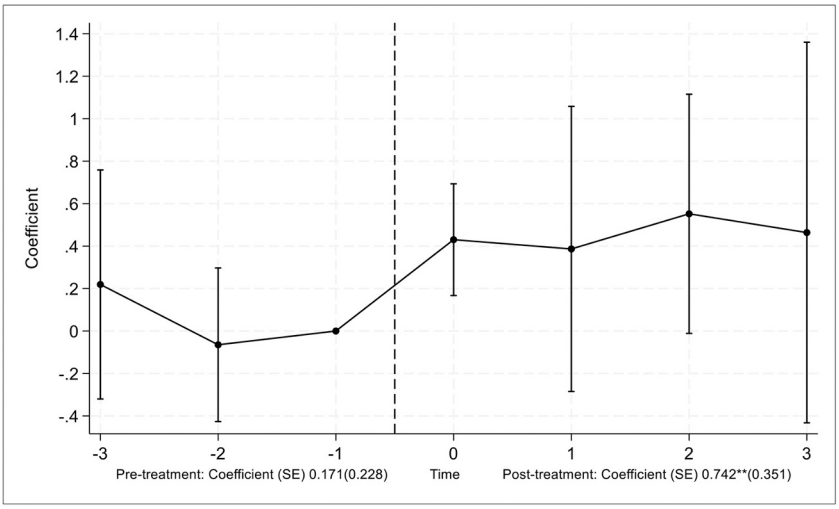
Second, to explore whether the impact of AI-related disclosures on firm valuation varies across sectors, we divide our sample into two groups, high-tech firms and non-high-tech firms, following the approach of Loughran and Ritter (2004). In Table 9, we present regression estimates for high-tech firms in Columns (1) to (3) and for non-high-tech firms in Columns (4) to (6). For both groups, the results are consistent with Table 5, reinforcing our main findings.

Third, we test whether our hypothesis holds in periods when firms are more likely to use AI-related narratives due to the increasing popularity or trendiness of specific terms. To capture this temporal variation in public interest, we use Google Trends, which tracks the

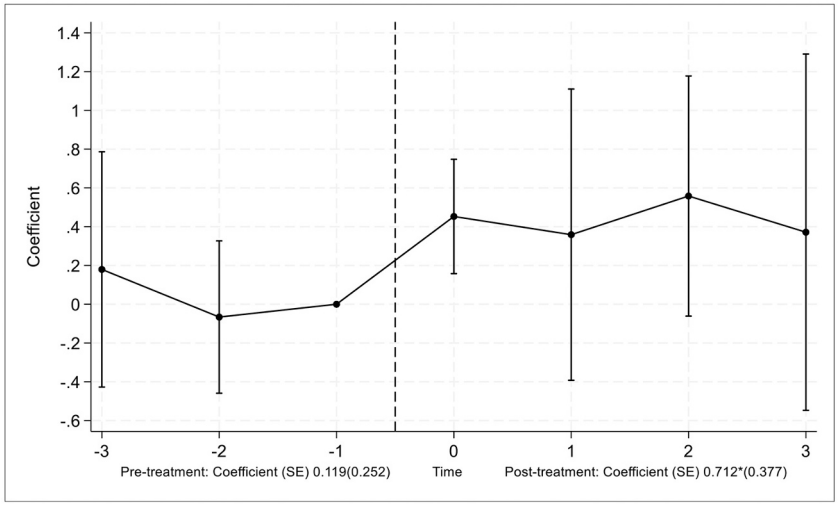
Panel A. Keyword



Panel B. Actionable All



Panel C. Actionable New



(caption on next page)

Fig. 2. Event-study LP-DiD effects on Tobin's Q around AI disclosures.
The figure reports event-time coefficient estimates from a local-projections difference-in-differences regression. The horizontal axis shows event time h in years relative to the treatment year ($t = 0$, vertical dashed line). The year immediately before treatment ($h = -1$) is the reference period and is normalized to zero. Each point represents the estimated difference in Tobin's Q between treated firms and a matched set of control firms that make no AI-related disclosure until at least $t + 4$. Control variables match those used in Table 6. Vertical bars give 95 % confidence intervals based on heteroskedasticity-robust standard errors clustered by firm. Pooled pre- and post-treatment estimate averages appear to the left and right of the "Time" label on the x-axis, respectively. Panel A (*Keyword*) defines $t = 0$ as the first year a firm mentions any AI-related keyword in its 10-K after having mentioned none the previous year; Panel B (*Actionable All*) dates $t = 0$ to the first actionable AI disclosure, including cases where earlier non-actionable mentions are reclassified as actionable; Panel C (*Actionable New*) restricts $t = 0$ to genuinely new actionable AI disclosures, excluding any reclassifications from prior years. Coefficients for $h = -3$ and $h = -2$ are close to zero, supporting parallel trends, while post-treatment estimates are positive, indicating a persistent uplift in market valuation following disclosure.

Table 7
Analysis of competitors.

	(1)	(2)	(3)
Competitor Keyword Treated	−0.032		
	(0.447)		
Keyword Treated	0.022		
	(0.830)		
Competitor Keyword Treated x Keyword Treated	0.159		
	(0.464)		
Competitor Actionable Treated		−0.049	−0.033
		(0.279)	(0.476)
Actionable Treated		0.037	
		(0.817)	
Competitor Actionable Treated x Actionable Treated		0.571**	
		(0.039)	
Speculative Treated			0.009
			(0.939)
Competitor Actionable Treated x Speculative Treated			−0.335*
			(0.062)
Size	0.166***	0.165***	0.167***
	(0.000)	(0.000)	(0.000)
Sales Growth	0.018	0.017	0.018
	(0.483)	(0.485)	(0.477)
Leverage	0.533***	0.524***	0.540***
	(0.000)	(0.000)	(0.000)
Cash	0.816***	0.814***	0.814***
	(0.000)	(0.000)	(0.000)
Profitability	−0.008**	−0.008**	−0.008**
	(0.017)	(0.018)	(0.017)
Constant	−1.528***	−1.503***	−1.541***
	(0.004)	(0.004)	(0.003)
Firm fixed effects	Y	Y	Y
Year fixed effects	Y	Y	Y
Observations	20,167	20,167	20,167
Adjusted R^2	0.678	0.679	0.678

We examine how a firm's value changes when the firm and its competitors mention keywords differently. The dependent variable is firm value measured as Tobin's Q one year after the SEC filing date. Keyword Treated is a dummy variable that takes a value of one for all years since the first mention of the keyword. We define Actionable Treated and Speculative Treated in a similar manner. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

frequency of search queries for specific terms over time as a proxy. A higher number of Google searches for AI-related keywords indicate a greater level of public interest in AI.

We collect monthly Google trend data for our sample keywords and average them to calculate yearly trends for each keyword. We then take the average across all keywords to calculate a yearly AI-related Google search index. We divide our sample period into two subperiods: one with below-median AI search frequency and another with above-median search interest. Table 10 presents regression results for the two subsamples, following the same model specification as in our main analysis. The results are qualitatively similar to those in Table 5, yet reveal important nuances in how market reactions to AI disclosures vary with public interest levels. When public interest in AI is above the median level (columns 1–3), the introduction of AI keywords is associated with positive but modest valuation effects. The valuation effects are, however, more pronounced during periods of lower public interest in AI. Specifically, the coefficient estimates for *Keyword*, *Actionable All*, and *Actionable New* are notably larger and statistically significant in the subperiod with below-median AI popularity (columns 4–6). This suggests that AI disclosures have a stronger positive impact on firm valuation when public interest in AI, as measured by search trends, is lower. By contrast, when AI interest is high, the market appears to apply greater scrutiny to AI disclosures. This may indicate that during "AI hype" periods, investors become more selective, rewarding substantive AI implementations rather than merely reacting to the presence of trendy terminology. These findings refine our understanding of how contextual factors influence the relationship between AI disclosures and firm valuation, demonstrating that the timing of AI narrative adoption relative to broader public interest cycles is also a critical consideration for companies contemplating their disclosure strategies.

5. Conclusion

Inspired by Shiller's (2017) work on the importance of studying the spread and impact of narratives in economics, we examine how firms' use of AI-related narratives in corporate disclosures affects firm valuation. Given the growing consensus that AI-based technologies will significantly impact both individual businesses and the broader economy, we focus on AI-related narratives in the annual 10-K filings of Russell 3000 companies from 2005 to 2018. We manually classify AI-related keywords as *actionable*, *speculative*, and *irrelevant* based on the context of their usage and examine how their introduction or removal affects firm value, as measured by Tobin's Q. Our study not only assesses the ultimate impact on market valuation but also looks into the sequential pathways - from innovation to productivity - through which these effects may materialize. Our primary focus on market-based outcomes reflects the forward-looking nature of narrative impacts, where investors often price in expected benefits of AI initiatives even if tangible operational gains are not yet realized. In fact, our sample firms often incur substantial AI-related R&D costs, which can temporarily depress earnings.

We find that financial markets distinguish between "AI hype" and genuine AI-driven strategies in corporate narratives. Firms announcing credible AI initiatives in their business descriptions enjoy significant valuation premiums compared to their counterparts offering only vague mentions or no mention at all. The market rewards firms that signal a commitment to AI-driven innovation, as reflected in higher Tobin's Q. Conversely, firms that remain silent on AI, or use only buzzwords without substance while their peers position themselves as AI adopters, tend to be penalized, experiencing relative declines in valuation. These findings underscore the importance of narrative credibility - investors are not blindly swayed by the mere presence of AI-related language but rather respond to the informativeness and strategic implications of that language.

We also explore what happens following the initial public disclosures, tracing a sequence of effects. Firms that adopt substantive, actionable AI narratives tend to follow up with real actions. First, we

Table 8
Entropy balancing.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Keyword	0.043**									
	(0.049)									
Actionable All		0.049**								
		(0.046)								
Actionable New			0.057**							
			(0.031)							
Speculative				0.012						
				(0.693)						
Irrelevant					0.051					
					(0.233)					
Keyword Remove						−0.003				
						(0.921)				
Actionable Remove							0.012			
							(0.692)			
Actionable to No								−0.011		
								(0.731)		
Speculative Remove									−0.042	
									(0.352)	
Irrelevant Remove										0.009
										(0.865)
Size	−0.180***	−0.177***	−0.173***	−0.186***	−0.202***	−0.173***	−0.168***	−0.164***	−0.178***	−0.212***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	−0.027**	−0.020*	−0.021*	−0.054***	−0.022	−0.034***	−0.026**	−0.024**	−0.065***	−0.050**
	(0.014)	(0.059)	(0.052)	(0.000)	(0.225)	(0.001)	(0.016)	(0.028)	(0.000)	(0.046)
Leverage	−0.028	−0.014	−0.016	−0.009	0.083	0.006	0.056	0.060	−0.020	−0.035
	(0.532)	(0.770)	(0.737)	(0.900)	(0.408)	(0.925)	(0.361)	(0.361)	(0.846)	(0.805)
Cash	−0.090*	−0.093*	−0.092	−0.087	0.016	−0.086	−0.168**	−0.196**	−0.002	0.129
	(0.065)	(0.087)	(0.102)	(0.129)	(0.876)	(0.166)	(0.029)	(0.013)	(0.972)	(0.237)
Profitability	−0.001	−0.002*	−0.002**	−0.001	−0.001	−0.003***	−0.005***	−0.005***	−0.001	−0.005***
	(0.500)	(0.054)	(0.044)	(0.222)	(0.799)	(0.000)	(0.000)	(0.000)	(0.103)	(0.003)
Constant	3.732***	3.681***	3.582***	3.868***	4.124***	3.524***	3.454***	3.368***	3.664***	4.346***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	20,167	20,167	20,167	20,167	20,167	20,167	20,167	20,167	20,167	20,167
Adjusted R^2	0.209	0.206	0.204	0.225	0.220	0.216	0.216	0.215	0.232	0.241

We re-estimate Table 5 after employing the entropy balancing technique. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 9
High-tech versus non-high-tech firms.

	(1)	(2)	(3)	(4)	(5)	(6)
	High-tech			Non-high-tech		
Keyword	0.049			0.051*		
	(0.162)			(0.052)		
Actionable All		0.082*			0.034	
		(0.057)			(0.251)	
Actionable New			0.089*			0.043
			(0.059)			(0.170)
Size	−0.180***	−0.180***	−0.180***	−0.145***	−0.145***	−0.145***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	−0.044**	−0.044**	−0.044**	−0.020***	−0.020***	−0.020***
	(0.030)	(0.029)	(0.028)	(0.001)	(0.001)	(0.001)
Leverage	0.001	0.004	0.004	−0.001	−0.001	−0.001
	(0.985)	(0.963)	(0.960)	(0.969)	(0.981)	(0.979)
Cash	−0.092	−0.091	−0.092	−0.022	−0.023	−0.022
	(0.157)	(0.158)	(0.155)	(0.618)	(0.608)	(0.611)
Profitability	−0.003*	−0.003*	−0.003*	0.000	0.000	0.000
	(0.079)	(0.080)	(0.080)	(0.694)	(0.699)	(0.699)
Constant	3.626***	3.624***	3.621***	2.940***	2.939***	2.939***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	2763	2763	2763	17,404	17,404	17,404
Adjusted R^2	0.218	0.218	0.218	0.159	0.159	0.159

We divide our sample firms into high-tech (columns 1 to 3) and non-high-tech firms (columns 4 to 6) based on a firm's 3-digit SIC code and examine the effect of keyword mentions on firm value in each subsample by re-estimating Eq. (1). The dependent variable is the change in Tobin's Q calculated as $(Q_{t+1} - Q_t)/Q_t$ one year after the SEC filing date. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Table 10
Firm value and Google trends.

	(1)	(2)	(3)	(4)	(5)	(6)
	High AI popularity			Low AI popularity		
Keyword	0.035			0.073*		
	(0.189)			(0.090)		
Actionable All		0.040			0.114**	
		(0.179)			(0.022)	
Actionable New			0.048			0.139***
			(0.137)			(0.009)
Size	−0.142***	−0.142***	−0.142***	−0.206***	−0.206***	−0.206***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Sales Growth	−0.021**	−0.021**	−0.021**	−0.028***	−0.028***	−0.028***
	(0.034)	(0.034)	(0.034)	(0.001)	(0.001)	(0.001)
Leverage	0.019	0.019	0.019	−0.003	−0.003	−0.003
	(0.672)	(0.664)	(0.664)	(0.946)	(0.946)	(0.943)
Cash	−0.073	−0.073	−0.073	0.058	0.059	0.060
	(0.217)	(0.217)	(0.217)	(0.332)	(0.323)	(0.317)
Profitability	−0.001	−0.001	−0.001	0.001	0.001	0.001
	(0.254)	(0.252)	(0.251)	(0.565)	(0.564)	(0.564)
Constant	2.886***	2.886***	2.886***	4.142***	4.147***	4.148***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Firm fixed effects	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y
Observations	9688	9688	9688	10,210	10,210	10,210
Adjusted R^2	0.170	0.170	0.170	0.140	0.140	0.140

We examine the effect of keyword mentions on firm value after considering the popularity of AI search words on Google during our sample period. Specifically, we use Google Trends to identify the popularity of our keywords. The dependent variable is the change in Tobin's Q calculated as $(Q_{t+1} - Q_t)/Q_t$ one year after the SEC filing date. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

document increases in R&D spending and patent filings in the years after an actionable AI disclosure is introduced. This suggests that many firms "put their money where their mouth is" by committing resources to AI projects that validate their initial statements. Second, we find that these innovation efforts can subsequently contribute to modest gains in labor productivity, particularly for firms that sustain R&D investments, though these productivity improvements emerge more gradually. Such follow-through likely reinforces investor confidence and helps sustain the valuation premium over time. It also provides an encouraging sign that AI adoption narratives often reflect genuine innovation activity, not just cheap talk.

Importantly, the timing of these effects offers interesting insights. The positive market revaluation occurs swiftly, in the year immediately following an AI disclosure. This market reaction is concurrent with the initial surge in innovation activities but precedes the realization of significant labor productivity gains and any observable short-term improvements in accounting profitability (which, if anything, may be initially depressed by increased R&D). This temporal pattern supports a nuanced interpretation: while the sequence of AI adoption leading to innovation, then to productivity improvements, and ultimately to improved value is a plausible long-term mechanism, the market's immediate reaction appears to be driven by the forward-looking information content of the AI narrative itself and the concurrent signal of strategic reorientation provided by the prompt increase in innovation. Investors anticipate future benefits long before they appear on the balance sheet or in operational metrics. While profitability gains may eventually materialize as these AI investments mature, that outcome lies beyond our sample period; a comprehensive examination of long-run profit effects is a subject we leave for future research. For now, our evidence highlights that narratives - specifically, credible and concrete ones - have real and immediate financial effects. In a broader sense, this aligns with Shiller's (2017) idea of "narrative economics": the stories companies tell can move markets. As AI continues to evolve and diffuse, understanding how and when such narratives translate into value will remain an important focus for both managers and investors.

Our findings also carry broader implications for investors, corporations, and policymakers. Firms discussing new technologies in their disclosures should outline concrete action plans rather than vague or speculative statements to ensure investors are meaningfully informed. Disclosures that lack specific implementation strategies offer little benefit and may undermine credibility. This further raises an important consideration for policymakers: the potential need to regulate corporate disclosures to promote transparency and ensure companies present clear, actionable strategies for technological innovation. Such measures could help minimize the misuse of trendy narratives as superficial buzzwords.

Declaration of competing interest

The authors declare no conflict of interest.

Acknowledgements

We appreciate the financial assistance provided through the Social Sciences and Humanities Research Council (SSHRC) and the L. Jacques Ménard BMO Centre for Capital Markets at Concordia University. In addition, we are grateful for the editorial assistance provided by Victoria Kelly and Gabrielle Machnik-Kekesi.

The information, views, and opinions expressed in this document are the sole responsibility of the authors. The authors are listed in alphabetical order; each author contributed equally to the project.

Appendix A. Appendix

Appendix A1
Variable definitions.

Variable	Definitions
Tobin's Q	Ratio of the market value of a company to its book value. We calculate the market value of a company by adding the market value of equity (the price of the common stock times the total number of shares outstanding) and total assets and subtracting the book value of equity [Source: CRSP, Compustat]
Change in Tobin's Q	Change in Tobin's Q from the previous year calculated as $(Q_{t+1} - Q_t)/Q_t$
R&D Expenses	Ratio of research and development expenses to total assets [Source: Compustat]
Patents	Natural logarithm of one plus the number of patents registrations in a given year [Source: KPSS 2017, 2022]
Labor Productivity	Ratio of total sales to the total number of employees in a firm [Source: Compustat]
Keyword	Dummy variable that takes on a value of one if a firm mentions an AI-related keyword in Item 1 of its 10-K filing for the first time in a given year but did not mention any keywords in the previous year. The keyword can be any word from the following list: adaptive algorithm, artificial intelligence, artificial neural network, automated decision-making, bot, chatbot, cognitive science, data science, deep learning, expert system, image recognition, machine intelligence, machine learning, natural language processing, natural language understanding, neural network, optical character recognition, and robotic process automation.
Actionable All	Dummy variable that takes on a value of one if the narrative in a year is classified as actionable and the narrative in the previous year was not classified as actionable. We classify a narrative as actionable if the keyword mention lays out a detailed action plan of utilizing said technology/innovation to better fulfil the current and long-term goals of the company.
Actionable New	Dummy variable that takes on a value of one if a firm did not mention any AI-related keyword in the previous year and the narrative in the current year is classified as actionable
Speculative	Dummy variable that takes on a value of one if the narrative in a year is classified as speculative and the narrative in the previous year was not classified as speculative. Companies often use multiple keywords, and may repeat some of them, in the same filing. If there are no actionable mentions but at least one speculative mention, we classify the narrative for that year as speculative. We classify a narrative as speculative if the keyword mention contains no (or a vague) action plan pertaining to the use of the technology/innovation
Irrelevant	Dummy variable that takes on a value of one if the narrative in a year is classified as irrelevant and the narrative in the previous year was not classified as irrelevant. Companies often use multiple keywords, and may repeat some of them, in the same filing. If all mentions are irrelevant, the year's AI disclosure narrative is classified as irrelevant. We classify a narrative as irrelevant if the keyword mention does not directly refer to the role played by the technology/innovation in the company's core business and the keyword is used only tangentially, with no clear reference to the industry, institution, or the opportunity they present
Keyword Remove	Dummy variable that takes on a value of one if a firm mentioned an AI-related keyword in the previous year but did not mention any AI-related keyword in the current year
Actionable Remove	Dummy variable that takes on a value of one if the narrative in the previous year was classified as actionable and the narrative in the current year is not classified as actionable
Actionable to No	Dummy variable that takes on a value of one if the narrative in the previous year was classified as actionable and the firm does not mention any AI-related keywords this year
Speculative Remove	Dummy variable that takes on a value of one if the narrative in the previous year was classified as speculative and the narrative in the current year is not classified as speculative
Irrelevant Remove	Dummy variable that takes on a value of one if the narrative in the previous year was classified as irrelevant and the narrative in the current year is not classified as irrelevant
Keyword Treated	A dummy variable that takes a value of one for all years since the first mention of the keyword.
Actionable Treated	A dummy variable that takes a value of one for all years since the first mention of the actionable keyword.
Speculative Treated	A dummy variable that takes a value of one for all years since the first mention of the speculative keyword.
Irrelevant Treated	A dummy variable that takes a value of one for all years since the first mention of the irrelevant keyword.
Competitor Keyword Treated	Dummy variable that takes on a value of one for all years since competitor/s to a firm mention of the keyword. We define a competitor as a firm operating in the same Fama-French 48 industry
Competitor Actionable Treated	Dummy variable that takes on a value of one for all years since competitor/s to a firm mention of the actionable keyword.
Other variables	
Size	Natural logarithm of the market value of equity calculated by multiplying the number of outstanding shares and the share price [Source: CRSP, Compustat]
Sales Growth	Ratio of $(Sales_{t-1}\text{-}Sales_{t-2})/Sales_{t-2}$ [Source: Compustat]
Leverage	Ratio of total long-term debt to total assets [Source: Compustat]
Cash	Ratio of cash to total assets [Source: Compustat]
Profitability	Ratio of net income to sales [Source: Compustat]

Appendix A2
Cumulative abnormal returns around the 10-K SEC filing date.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Keyword	0.003									
	(0.649)									
Actionable All		−0.003								
		(0.708)								
Actionable New			0.005							
			(0.588)							
Speculative				0.003						
				(0.825)						
Irrelevant					0.003					
					(0.765)					
Keyword Remove						0.005				

(continued on next page)

Appendix A2 (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
						(0.689)				
Actionable Remove							0.012			
							(0.298)			
Actionable to No								0.010		
								(0.469)		
Speculative Remove									−0.016	
									(0.470)	
Irrelevant Remove										−0.025
										(0.448)
Size	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000	−0.000
	(0.978)	(0.982)	(0.978)	(0.979)	(0.977)	(0.974)	(0.966)	(0.972)	(0.985)	(0.985)
Sales Growth	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003	−0.003
	(0.314)	(0.314)	(0.314)	(0.314)	(0.314)	(0.314)	(0.314)	(0.313)	(0.312)	(0.313)
Leverage	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003	0.003
	(0.749)	(0.749)	(0.741)	(0.747)	(0.751)	(0.744)	(0.748)	(0.749)	(0.746)	(0.755)
Cash	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015	0.015
	(0.355)	(0.368)	(0.354)	(0.360)	(0.360)	(0.360)	(0.359)	(0.360)	(0.362)	(0.362)
Profitability	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
	(0.179)	(0.179)	(0.180)	(0.179)	(0.180)	(0.180)	(0.179)	(0.179)	(0.178)	(0.180)
R&D Expenses	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021	0.021
	(0.646)	(0.644)	(0.648)	(0.645)	(0.645)	(0.648)	(0.646)	(0.646)	(0.642)	(0.641)
Earnings Surprise	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**	0.002**
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.043)
Constant	0.003	0.003	0.003	0.003	0.003	0.003	0.004	0.003	0.002	0.002
	(0.964)	(0.967)	(0.964)	(0.965)	(0.963)	(0.960)	(0.953)	(0.958)	(0.970)	(0.970)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	10,642	10,642	10,642	10,642	10,642	10,642	10,642	10,642	10,642	10,642
Adjusted R^2	0.011	0.011	0.011	0.011	0.011	0.011	0.012	0.011	0.011	0.012

We examine the effect of AI-related keyword mentions in a firm's 10-K filing on a firm's stock price around the corporate disclosure. To measure the market reaction, we calculate the cumulative abnormal return −3 to +3 days around the event with −350 to −100 days as the estimation period and the Fama-French 3-factor model as the return generating process. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Appendix A3

AI disclosure and profitability.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	1 year		2 year		3 year		4 year		5 year	
Keyword Treated	0.069		0.096		−0.005		−0.096		−0.142	
	(0.452)		(0.278)		(0.949)		(0.278)		(0.110)	
Actionable Treated		0.105		0.138		0.052		−0.075		−0.282**
		(0.303)		(0.266)		(0.604)		(0.580)		(0.037)
Size	0.032	0.032	0.013	0.013	−0.015	−0.016	−0.025	−0.025	0.054	0.055
	(0.263)	(0.261)	(0.644)	(0.646)	(0.616)	(0.609)	(0.378)	(0.375)	(0.117)	(0.112)
Sales Growth	−0.037	−0.036	−0.023	−0.022	−0.034	−0.034	−0.001	−0.001	0.043	0.042
	(0.255)	(0.258)	(0.518)	(0.522)	(0.282)	(0.283)	(0.976)	(0.973)	(0.282)	(0.287)
Leverage	0.891***	0.892***	0.526**	0.527**	0.340*	0.340*	0.159	0.158	0.269	0.271
	(0.000)	(0.000)	(0.013)	(0.013)	(0.096)	(0.096)	(0.449)	(0.453)	(0.156)	(0.153)
Cash	−0.057	−0.056	0.236	0.237	−0.005	−0.003	−0.155	−0.153	−0.110	−0.111
	(0.747)	(0.749)	(0.182)	(0.180)	(0.974)	(0.984)	(0.317)	(0.323)	(0.518)	(0.512)
R&D Expenses	0.011	0.008	0.239	0.235	0.561	0.557	−0.116	−0.116	0.400	0.408
	(0.974)	(0.981)	(0.489)	(0.497)	(0.106)	(0.109)	(0.701)	(0.700)	(0.227)	(0.218)
Constant	−0.924	−0.927	−0.588	−0.590	0.049	0.051	0.399	0.401	−1.245*	−1.247*
	(0.117)	(0.115)	(0.308)	(0.306)	(0.939)	(0.936)	(0.490)	(0.488)	(0.077)	(0.077)
Firm fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Year fixed effects	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	8145	8145	7925	7925	7634	7634	7227	7227	6295	6295
Adjusted R^2	0.154	0.154	0.137	0.137	0.131	0.131	0.119	0.119	0.121	0.121

We examine the effect of AI keyword mentions on firm profitability. As the measure of profitability, we use ROE, defined as a firm's net income divided by its end-of-year total equity 1, 2, 3, 4, or 5 years after the corresponding SEC filings containing AI mentions. All variables are defined in Appendix A1. For each variable, we report the regression coefficient and the corresponding heteroskedasticity-adjusted (clustered at the firm level) p-value in brackets below the coefficient. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % level, respectively.

Data availability

Data will be made available on request.

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