Artificially Intelligent or Artificially Inflated? Determinants and Informativeness of Corporate AI Disclosures

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ABSTRACT

Artificial Intelligence (AI) is emerging as a General Purpose Technology (GPT) with the potential to transform industries, yet firms face both opportunities for genuine AI adoption and incentives to misrepresent AI capabilities. The intangible nature of AI investments and difficulty in verifying AI usage create conditions for 'AI washing'—where firms overstate AI engagement to attract investors and enhance valuations. Using textual analysis of corporate disclosures and firm-level AI employment data from 2016 to 2023, we document four key findings. First, AI disclosures are more prevalent among firms in AI-intensive industries, those with high innovation, and those facing greater investor scrutiny. Second, AI disclosures are positively associated with future operational efficiency and AI patent filings, but negatively correlated with dividend payouts, consistent with firms reinvesting AI-driven productivity gains rather than distributing excess cash. Third, firms that disclose AI without hiring AI-related employees—suspected AI washers—do not experience these outcomes and tend to be smaller, less innovative, and in non-AI-intensive industries. Finally, firms making real AI investments outperform AI washers in long-term abnormal returns, reinforcing the role of complementary human capital in unlocking AI's value. Our findings highlight that AI disclosures provide valuable market signals, but only when paired with real investments in AI-related human capital. As AI adoption accelerates, distinguishing between genuine AI integration and strategic misrepresentation will be critical for investors, regulators, and policymakers assessing firm value and the broader economic impact of AI.

1. Introduction

Artificial Intelligence (AI) is transforming industries by automating tasks, enhancing decision-making, and driving innovation. AI refers to machine-based systems that process information, recognize patterns, and make predictions, recommendations, or decisions to achieve human-defined objectives (OECD, 2019). Recent advances—particularly in machine learning, natural language processing, and generative AI—have dramatically expanded AI's capabilities, making it increasingly integral to business operations. AI is no longer confined to specialized technology firms; it is now used across industries, from finance and healthcare to retail and manufacturing, enhancing productivity, fostering innovation, and creating competitive advantages.

Given its transformative potential, AI is increasingly recognized as a General Purpose Technology (GPT)—a foundational technology with broad applicability, capable of driving complementary innovations across sectors and fundamentally reshaping the economy (Bresnahan and Trajtenberg, 1995). Lisa Cook, Member of the Federal Reserve Board of Governors, recently affirmed this view, stating on October 1, 2024, that "AI, and generative AI in particular, is likely to become a General Purpose Technology" (Cook, 2024). However, unlike traditional GPTs such as the steam engine or electricity, which primarily required investments in physical infrastructure, AI adoption depends heavily on intangible investments—human capital, organizational restructuring, and firm-specific data capabilities (Brynjolfsson, Rock, and Syverson, 2019; Bresnahan et al., 1996). These investments are difficult to quantify and often underreported in traditional financial metrics, creating uncertainty about the actual extent of firms' AI engagement.

Despite measurement challenges, investor enthusiasm for AI has surged, with firms that emphasize AI initiatives often experiencing valuation premiums (Babina et al., 2024).[1] This

[1] https://www.weforum.org/agenda/2024/03/ai-investment-opportunities-risks/

heightened demand for AI-related information has intensified pressure on companies to signal their AI capabilities, leading to a proliferation of AI-related disclosures in 10-K filings, earnings announcements, and conference calls. As discussed later, these topics include firms' use of machine learning, artificial intelligence, and, in the last year of our sample (year 2023), disclosures about generative AI. While some firms genuinely invest in AI-driven innovation, others may overstate or misrepresent their AI capabilities to attract investors and enhance market perception—a practice commonly referred to as AI washing. The incentives for AI washing are significant: firms can position themselves as technology leaders, gain access to capital, and boost share prices without making substantial investments in AI development.

This growing concern has not escaped regulatory scrutiny, particularly at the Securities and Exchange Commission (SEC), where fears of AI washing have intensified. The incentives for AI washing are substantial: firms that position themselves as AI leaders can attract investment, enhance their market perception, and capitalize on investor enthusiasm, even if their actual AI adoption is minimal. SEC Chair Gary Gensler has publicly cautioned that firms may be overstating their reliance on AI, prompting increased regulatory scrutiny of AI-related claims in mandatory filings (e.g., SEC, 2019). Specifically, the SEC has taken enforcement actions against firms suspected of AI washing, signaling its intent to curb misleading disclosures and ensure that AI-related statements reflect genuine technological adoption.

In this paper, we examine the determinants and informativeness of firms' AI-related disclosures, focusing on whether firms' public AI statements align with complementary investments in AI employment. Our study is guided by four central questions: (1) What types of firms are more likely to disclose AI activities? (2) Do these disclosures provide informative insights into firms' use of AI and their future efficiency, innovation, and dividend payout policy?

(3) How do firms that heavily disclose AI activities but have low in-house AI employment—whom we label as suspected AI "washers"—differ from non-washers regarding firm characteristics and informativeness? (4) What capital market outcomes are associated with AI disclosure, and do they differ for firms suspected of AI washing? By addressing these questions, we provide new insights into how firms communicate AI-related activities, the reliability of these disclosures, and their implications for investors and regulators.

Measuring AI disclosure, in general, and AI washing, specifically, is challenging due to the rapid evolution of AI technologies and the complexity of AI-related information. To address this, we employ textual analysis techniques to quantify AI-related disclosures in firms' 10-K filings, earnings announcements, and conference calls from 2016 to 2023. Specifically, we use a fine-tuned FinBERT natural language processing model to capture the quantity of AI-related disclosures, a more nuanced analysis than traditional bag-of-words approaches (Huang et al., 2023).

To assess whether AI disclosures align with actual investments, we complement our disclosure measures with firms' AI-related employment from Revelio, which serves as a proxy for firms' complementary AI investments (similar to Babina et al. 2024).[2] To identify potential AI washers, we draw from the greenwashing and diversity washing literature and classify firms as suspected AI washers if they fall into the highest tercile of AI disclosure but the lowest tercile of AI employment (Baker et al., 2024). This approach enables us to systematically identify firms that may be overstating their AI capabilities relative to their actual AI-related investments, shedding light on the credibility of corporate AI disclosures.

[2] It is possible firms use AI without investing in firm-specific AI labor if they outsource AI innovation to outside firms. However, our focus is on firm-specific AI labor investment for three reasons. First, Babina et al. (2024) demonstrate that firm-specific AI labor investment is effective. Second, the Federal Reserve specifically mentions that firm-specific and tailored investments are necessary. Finally, and more practically, we do not have firm-level data on AI outsourcing. Throughout, our tests focus on in house AI labor investment levels, and show that this is a credible signal that differentiates informative AI disclosure from uninformative AI disclosure.

We begin our analysis by descriptively examining the dynamics of AI disclosure and AI employment over time. Our sample starts in 2016 because prior research suggests this is when artificial intelligence began its current growth trajectory (Acemoglu et al., 2021).[3] We find that AI disclosures consistently grow across all major corporate communication channels over our sample period. We also find a parallel growth in AI employment, suggesting that, in many cases, firms' disclosures reflect genuine investments in AI technologies.

We then turn to the four key research questions outlined above. First, we examine the determinants of firms that disclose AI activities. We find that industry affiliation is the strongest predictor of AI disclosure, along with peer disclosure behavior—firms are significantly more likely to disclose AI if their industry peers do so as well. The impact of industry effects on AI disclosure is three times larger than that of the next most influential factors: firm-specific innovation levels (e.g., asset tangibility and R&D intensity) and external monitoring and demand for disclosure (e.g., analyst coverage).

We then separately examine the disclosure determinants for firms suspected of AI washing (i.e., those that disclose AI activity without significant firm-level human capital investment). Unlike firms that appear to genuinely invest in AI, suspected AI washers tend to be smaller firms that operate in industries where AI disclosure is less prevalent, have weaker innovation, and lower external oversight from analysts and institutional investors.

To better understand the relative importance of industry, firm-specific characteristics, and external monitoring for AI disclosure, we use a Shapley decomposition (Shapley, 1953). The results confirm that industry factors overwhelmingly drive AI disclosure, explaining 70 to 80 percent of the variation. However, for AI washers, firm-specific characteristics are the primary

[3] Acemoglu et al. (2021) refer to AI as tasks that can be simplified using computer algorithms, but acknowledge there is a broader definition of AI that subsequently includes generative AI.

drivers, accounting for about 60 percent of the variation. Additionally, we find that suspected AI washers tend to have lower litigation risk and weaker managerial ability, suggesting a reduced likelihood of external enforcement or internal discipline for misleading disclosures. However, these factors lose statistical significance in the full multivariate model, as their effects are outweighed by fundamental firm-level attributes such as size, growth opportunities, innovation intensity, and external monitoring. This pattern indicates that AI washing is more common among firms with limited resources and oversight, rather than being directly driven by weak governance or litigation exposure.

Next, we examine the association between AI disclosure and firm performance in the year following the disclosure, focusing on firm efficiency, AI patents, and dividend payout policy. We find that firms with higher AI disclosure experience greater efficiency gains and increased AI patent filings but reduce dividend payouts. These results suggest that, on average, firms' AI disclosures are indicative of actual efforts to integrate AI into operations, leading to productivity improvements and reinvestment in AI initiatives rather than cash distributions to shareholders. However, firms identified as suspected AI washers do not exhibit similar improvements in efficiency, patent activity, or dividend policies, indicating that their disclosures may not correspond to meaningful AI adoption.

We then analyze short- and long-term abnormal returns for three groups of firms: (i) firms with high AI disclosure and high AI employment, (ii) firms with high AI disclosure and low AI employment (suspected AI washers), and (iii) firms with low AI disclosure and low AI employment (comparison firms). In the short term, returns do not significantly differ among the three groups, suggesting that investors take a "wait and see" approach in evaluating AI disclosures. However, long-term performance tells a different story: firms that combine high AI disclosure with substantial AI employment significantly outperform both AI washers and comparison firms over 6-, 9-, and 12-month horizons. These findings, which are robust to bootstrapped standard errors and Fama-MacBeth regressions with Newey-West adjustments, provide further evidence that markets gradually recognize and reward genuine AI investments. In contrast, suspected AI washers do not outperform comparison firms and, in some cases, exhibit signs of underperformance, suggesting that investors may actually penalize firms suspected of overstating their AI capabilities.

The delayed market response to the quality of AI disclosures indicates that investors initially struggle to differentiate disclosures of substantive AI investments from superficial claims. However, over time, firm-specific investments in AI-related intangibles, particularly through AI employment, ultimately drive superior long-term performance. This pattern aligns with the Productivity J-Curve framework, which posits that GPTs like AI require substantial complementary investments that take time to materialize (Brynjolfsson, Rock, and Syverson, 2019). Early on, the market may not differentiate between firms genuinely investing in AI, those overstating their capabilities, and those lacking the resources to capitalize on AI opportunities, leading to similar short-term returns. However, as the true economic impact of AI adoption—or lack thereof—becomes evident, the market gradually adjusts valuations, rewarding genuine adopters while failing to sustain AI washers' inflated market positioning.

To ensure the robustness of our results, we conduct several validation tests. First, we test two alternative definitions of AI washing: (i) firms with high AI disclosures but zero AI employees, and (ii) firms that did not disclose AI in the first half of the sample, when incentives for misreporting were weaker. Across both definitions, suspected AI washers continue to exhibit lower efficiency, fewer AI patents, and higher dividend payouts, confirming that our findings are not driven by a specific definition of AI washing.

Second, we perform a falsification test using ESG scores to ensure that AI washing is distinct from general greenwashing behaviors. Our results do not hold in this specification, confirming that AI washing is a distinct phenomenon. Third, we consider whether our results differ for partitions of the sample other than suspected AI washers. We find that firms that are high on both disclosure and labor investment show improved efficiency, higher AI patent output, and lower dividends, while firms that are low on both demonstrate reduced efficiency, fewer AI patents, and higher dividend payments. Furhermore, we find no evidence of improvement for firms with high labor investment but low disclosure or firms that are middle in both. In other words, our results suggest that AI disclosure is informative about future outcomes when it is significant and also accompanied with significant labor investment.

Fourth, we examine alternative timing differences between disclosure and outcomes. In our main tests, current year AI disclosure is associated with next year's outcomes (i.e., efficiency, patents, and dividends), but not for suspected AI washers. These results extend to outcomes two- and three-years ahead as well, suggesting that our inability to find improved outcomes for AI washers is not due to those firms needing more time for their investments to pay off.

Finally, we perform a survival analysis to examine firms' transition away from suspected AI washing behavior. On average, firms remain in AI washing status for 2.5 years. Our hazard model reveals that firm size, operational concentration, analyst coverage, and institutional ownership are positively associated with AI washing exit. These findings suggest that resource availability, operational focus, and external monitoring play crucial roles in whether firms transition toward genuine AI adoption or abandon overstated AI claims.

We make several contributions to the literature. First, we extend the growing research on AI in capital markets by shifting the focus from how AI technologies complement or substitute human labor—particularly in financial analysis, auditing, and bank lending (e.g., Aghion et al., 2017; Babina et al., 2024; Coleman et al., 2022; Cao et al., 2023)—to how firms communicate their AI adoption through disclosures. While prior work has primarily examined the economic impact of AI implementation, we are among the first to systematically analyze firms' AI-related disclosures and their informativeness for investors. Our findings show that AI disclosure predicts future firm performance and stock prices, but *only* for firms with sufficient AI-related labor, underscoring the role of complementary human capital in realizing AI's benefits.

Second, we contribute to the cheap talk literature on misleading disclosure (i.e., "washing" behavior) by providing one of the first empirical examinations of AI washing. Understanding AI-related misrepresentation is critical given that the Federal Reserve has recognized AI as a GPT likely to transform economic activity, and the SEC has explicitly warned against AI washing, emphasizing that firms must not mislead investors about their use of AI technologies.[4] In March 2024, the SEC settled charges with two investment advisors over AI washing activities, underscoring the regulatory focus of this issue.[5] Our study is among the first to examine how market pressures influence disclosure behavior around emerging technologies, providing new insights into how firms manage investor expectations and regulatory scrutiny in the face of intangible and opaque AI investments.[6]

Our findings also contribute to the broader literature on misleading corporate disclosures, drawing parallels to greenwashing and diversity washing. Prior literature has shown that investors

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[4] https://www.wsj.com/articles/sec-head-warns-against-ai-washing-the-high-tech-version-of-greenwashing-6ff60da9

[5] https://www.bleepingcomputer.com/news/technology/investment-advisers-pay-400k-to-settle-ai-washing-charges/?trk=feed_main-feed-card_feed-article-content

[6] In a related context, Cheng, de Franco, Jiang, and Lin (2019) examine market reactions to firms' initial blockchain announcements during the cryptocurrency boom and find that investors react positively to disclosure even for firms suspected of washing (based on vague disclosure rather than actual investment). Our setting is broader than blockchain, considers actual investment levels, and we examine the determinants of the disclosure and other outcomes than market pricing. Our results differ in that we find investors appear to take a "wait and see" approach to AI disclosure, more broadly defined.

actively demand ESG-related initiatives (Baker et al., 2024) and has examined whether firms genuinely "walk the talk" on ESG commitments (Aswani et al., 2024; Dikolli et al., 2022). However, unlike ESG disclosures—where investor reactions often depend on psychological framing or social impact considerations—AI disclosures are more directly linked to financial outcomes through their impact on firm efficiency and product capabilities. Additionally, we show that washing behavior is not uniform across firms. Specifically, AI washing is not simply a subset of ESG washing, as firms suspected of ESG misrepresentation do not strongly correlate with those engaging in AI washing, suggesting that AI-related misstatements are driven by distinct incentives and market dynamics.

Third, we contribute to the labor and accounting literature by examining how firm-level AI-related employment intersects with corporate disclosure strategies. Bourveau, Chowdhury, Le, and Rouen (2023) highlight the importance of workforce characteristics in understanding firm strategies and investments using human capital disclosures in 10-K filings. Moreover, recent work on Generative AI's impact on labor markets highlights that, unlike prior waves of automation, AI affects white-collar jobs, complements high-skilled workers, and substitutes lower-skill roles (Berger, Cai, Qiu, Shen, 2024; Eisfeldt, et al., 2024).[7] We extend this research by focusing on AI-related human capital, aligning with the broader accounting and labor economics research using employee characteristics as proxies for underlying firm investments and strategic behavior (e.g., Abowd, Haltiwanger, Lane, 2004; Lustig, Syverson, and Van Nieuwerburgh, 2011). A key takeaway from our study is that AI-capable employees are a necessary condition to extract value from AI. By linking corporate disclosure, labor investment, and firm outcomes, we provide a richer perspective on how firms navigate AI adoption and how markets interpret these signals.

[7] In our textual analysis of firms' AI disclosure, we find that the phrase "Generative AI" starts to appear in Conference Calls in 2023. See Online Appendix Figure 1b for illustration.

2. Prior Literature and Hypothesis Development

2.1 Defining Artificial Intelligence and Its Economic Implications

AI is broadly defined as a machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions (OECD, 2019). AI encompasses several core methodologies, including machine learning, natural language processing, and computer vision (Agrawal et al., 2019). These techniques allow AI systems to process large-scale, high-dimensional data—such as text, speech, and images—to perform complex tasks like classification, prediction, and detection.

The commercialization of AI has accelerated over the past decade, driven by exponential increases in data availability, falling computation costs, and methodological advances in deep learning (Hodson, 2016). While AI adoption was initially concentrated in the technology sector, it has since expanded into finance, healthcare, manufacturing, and consumer services, with corporate executives widely reporting AI integration in decision-making and operations (see McKinsey Survey 2020).

AI is a GPT with widespread applications across industries, similar to past GPTs like the steam engine, electricity, and the internet (Bresnahan and Trajtenberg, 1995; Brynjolfsson, Rock, and Syverson, 2019). It has the potential to reshape economic activity by driving complementary innovations that enhance productivity and transform business models. Unlike traditional capital investments, AI has several distinct economic properties. First, AI enhances predictive capabilities, enabling firms to make data-driven decisions in areas such as fraud detection, credit risk assessment, and supply chain optimization. Second, AI is highly adaptable, allowing firms across industries to integrate it into product design, automation, and customer engagement. Third, AI is an intangible investment, relying on human expertise, computational power, and data infrastructure rather than physical assets like industrial robots (Mihet and Philippon, 2019). Finally, AI functions as an information good, particularly in machine learning, where models can be replicated and deployed across firms. However, AI's effectiveness often hinges on access to proprietary data, giving firms with superior datasets a competitive edge (Fedyk and Hodson, 2023; Jones and Tonetti, 2020). These attributes make AI both a transformative force as well as a strategic challenge for firms.

As AI adoption grows, firms face increasing pressure to signal AI capabilities to investors, given the technology's perceived potential to drive future growth, efficiency gains, and market valuation. However, AI investments are largely intangible and difficult to verify, creating an environment where firms may overstate or misrepresent their AI-related initiatives to capitalize on market enthusiasm—a phenomenon known as AI washing. Regulators, such as the SEC, have taken notice, warning firms against misleading AI disclosures and increasing scrutiny over AI-related claims in financial reporting. These concerns underscore the need to examine the informativeness and credibility of firms' AI disclosures, which we explore in the next section.

2.2 Hypothesis Development

The accounting literature on AI has primarily focused on its applications in specific domains, such as audit firms (e.g., Christ et al. 2020; Commerford et al. 2022; Libby and Witz 2024), financial analysts, and market participants (Allee, DeAngelis, Moon Jr., 2018), and research productivity (e.g., Bertomeu 2020; Bochkay et al. 2024). However, little research has examined firms' AI disclosures and how market participants interpret and respond to these disclosures.

Markets largely view AI as a transformative technology that firms can use to enhance firm performance through automation, process optimization, and innovation. For example, Deloitte's "State of Generative AI in the Enterprise Quarter Three Report" highlights that the most significant benefits of AI adoption include improved efficiency, productivity, and cost reduction, along with enhanced innovation and product development. [8] These findings align with research showing that AI can foster firm growth through automation (Aghion et al., 2017) and unlock previously unanticipated business opportunities (Agrawal et al., 2019). Studies have also shown that AI-related innovations positively correlate with firm efficiency, growth, and valuation (Alderucci et al., 2020; Damioli et al., 2021; Chen et al., 2019). Furthermore, firms that invest in AI-related human capital—such as hiring AI engineers and data scientists—tend to experience greater innovation and performance gains (Babina et al., 2024).

The combination of investor demand for AI exposure and the difficulty of verifying AI investments creates strong incentives for firms to emphasize AI in their disclosures. Regulators, including the SEC, have raised concerns that firms may misrepresent AI investments in an effort to attract capital. For example, the SEC issued a comment letter to Ideanomics, Inc., requesting greater transparency regarding the firm's claims about its "next-generation Artificial-Intelligent & Blockchain-Powered, Fintech" businesses (SEC, 2018).

The SEC's concerns mirror broader issues with voluntary corporate disclosures, where management forecasts and non-GAAP financial reporting have been scrutinized for their potential to mislead investors. Nonetheless, prior research suggests that, on average, voluntary disclosures provide useful information to market participants (e.g., Rogers and Stocken, 2005; Black et al., 2021). Moreover, firms tend to respond to investor demand for specific types of disclosures, tailoring their communication strategies accordingly (Chapman and Green, 2018; Johnson, 2024). Taken together, we predict that AI disclosures, on average, positively relate to firm performance. Stated formally: Stated formally:

[8] Deloitte Survey Hyperlink

H1: The level of firms' AI disclosure is positively related to future firm performance.

While AI disclosures may, on average, reflect real technological investments and firm-level innovation, some firms may overstate their AI capabilities to capitalize on market enthusiasm without making substantive AI-related investments. This phenomenon parallels misrepresentation in ESG disclosures, where firms exaggerate their commitment to diversity or environmental initiatives to enhance their public image. Prior research has documented diversity washing (Baker et al., 2024) and greenwashing among firms and investment advisors (Aswani et al., 2024; Dikolli et al., 2022; Kim and Yoon, 2022), finding that firms can receive higher ESG scores or investor attention despite lacking substantive underlying commitments. Similarly, SEC Chairperson Gary Gensler has recently warned firms about AI washing, emphasizing regulatory concerns over misleading AI disclosures.[9]

Following Babina et al. (2024) , we argue that genuine AI investment should manifest in firm-level AI employment, as AI-driven innovation requires specialized human capital to develop and integrate AI into business operations.[10] If firms heavily discuss AI information but fail to invest in AI-related employees, they are likely engaging in AI washing, and we expect them to experience weaker improvements in firm performance relative to firms making substantive AI investments. Stated formally:

H2: Suspected AI washers lower future firm performance relative to non-washers.

Whether market participants recognize AI washing or are misled by it remains an empirical question. AI innovations have the potential to increase efficiency, expand growth opportunities, and enhance firm value, and if AI disclosures accurately signal true capabilities, investors should

[9] https://www.wsj.com/articles/sec-head-warns-against-ai-washing-the-high-tech-version-of-greenwashing-6ff60da9

[10] One plausible concern with this assumption is the use of outsourcing. If a firm discloses high levels of information related to AI, but outsource all AI initiatives, our methodology would capture these firms as potential AI Washers. We argue that the inclusion of outsourcing firms in our AI washing classification biases against our results as potentially efficient AI outsourcers would be included in our AI washers classification.

respond positively. However, prior research suggests that investors often fail to fully discern misleading ESG disclosures, with firms that emphasize ESG narratives but lack substantive ESG investments still receiving increased investor attention (Baker et al., 2024).

The opacity and verifiability of underlying AI investments create similar challenges. Investors may struggle to assess whether AI disclosures reflect true technological advancements or whether firms are strategically embellishing their AI capabilities to appear more innovative. As a result, we do not predict a differential short-term market reaction to AI disclosures, as investors may initially respond to AI announcements without fully assessing their credibility. However, over time, as the real economic impact of AI adoption becomes evident, we expect firms that pair AI disclosures with substantive AI workforce investments to outperform their peers. Stated formally in null form:

H3a: There is no differential short-term market reaction to AI disclosures.
H3b: Firms with substantial investment in AI employees and AI disclosures significantly outperform other firms in the long-run.

3. Sample Selection and Variable Construction

Our study examines a sample period from 2016 to 2023, consistent with Acemoglu et al.'s (2022) finding that AI adoption across U.S. establishments significantly accelerated after 2016. Unlike typical accounting studies, we include utility and financial firms in our sample, as these industries are also exposed to the impacts and incentives associated with AI. We capture AI disclosures across multiple sources including earnings announcement press releases, conference calls, and annual 10-K filings.[11,12] To measure complementary investments in AI, in a similar spirit to Babina et al (2024), we employ textual analysis to classify individual-level AI employees from

[11] Professor Bill McDonald kindly provides the data source associated with 10-X filings on the Security and Exchange Commission's (SEC) EDGAR website. The "Stage One Parse" file cleans each fillings document of extraneous material. The document files are available at https://sraf.nd.edu/data/stage-one-10-x-parse-data/.
[12] Examining disclosure in the 10-K, conference call, and earnings announcements allows us to capture firm communications across different formal channels (Skinner 2024).

LinkedIn.[13] We use AI patent data provided by the United States Patent and Trademark Office (USPTO), analyst data from the I/B/E/S database, and mutual fund ownership data from CRSP mutual fund database. We obtain financial statement data from the COMPUSTAT annual database and stock return data from the CRSP daily files. After merging these datasets and applying our exclusion criteria, our final sample consists of 10,628 firm-year observations. Appendix 3 provides a table outlining our full sample selection procedures. This comprehensive dataset allows us to analyze AI disclosures, investments, and outcomes across a broad spectrum of U.S. public companies during a period of rapid AI adoption.

We fine-tune a FinBERT model to identify AI-related disclosures using approximately 1,600 manually labeled sentences from 10-K filings. Appendix 2b details the FinBERT tuning process, while Appendix 2c provides examples of AI-related sentences as classified by our model. Our approach examines key terms such as "machine learning," "data analytics," and "artificial intelligence" (among others). We also categorizes each sentence into one of five AI-related disclosure types: (i) general AI overview, (ii) specific AI applications, (iii) AI-related products, businesses, or patents, (iv) AI capability acquisition or development, and (v) forward-looking AI statements. Model testing indicates that our textual analysis process identifies AI-related disclosures with over 96% accuracy, ensuring a high degree of reliability in capturing AI-related corporate communication.

We then apply the fine-tuned model to the disclosure channels discussed previously to identify AI disclosures at scale.[14] We calculate AI disclosure scores (AI_CC, AI_10K, AI_EA) on

[13] See Appendix 2A for detailed construction steps on the identification of AI-related employees. We generally follow the process from Babina et al. (2024). Key words include: "artificial intelligence," "machine learning," "data science," "deep learning," "computer vision," "data mining," "big data," and "data analytics," and we also examine the employee's job classification/job title. 68 percent of firms have at least 1 AI-related employee.

[14] For 10-K fillings, these include item 1, "Business," item 1A, "Risk Factors," and item 7, "Management Discussion and Analysis of Financial Condition and Results of Operations."

a firm-year basis for each disclosure channel by counting sentences identified as AI-related and dividing by the total number of sentences in the respective disclosure channel.[15] This FinBERT-based approach leverages pre-training on financial texts, overcoming limitations of traditional dictionary methods and allowing for more accurate identification of AI-related content across various corporate communications (Huang et al., 2023).

We define a firm as a suspected AI washer if it discloses a high level of AI-related information (top tercile across any disclosure channel) but has low AI employment (in the bottom tercile of AI employees). We perform this ranking on an annual basis. This method allows us to capture firms that may be overstating their current AI capabilities.

Before examining detailed descriptive statistics, we present an overview of AI disclosure trends and AI employment patterns in our sample. Figure 1 illustrates the average AI disclosure ratios across firms from 2016 to 2023 for each disclosure channel. Figure 1 reveals a consistent upward trend in AI-related discussions across all three major disclosure channels, with conference calls exhibiting the largest proportion of AI related sentences. Notably, AI mentions in conference calls increased by more than 50% between 2016 and 2023, reflecting growing emphasis on AI-related strategies in firms' communications with investors.

Figure 2 visualizes the evolution of AI-related language in U.S. public firms' disclosures in our sample using TF-IDF trigrams.[16] The results indicate a clear progression in AI discourse over time. In the earlier years (2016-2017), firms' communications predominantly focused on "cloud-based" technologies and "data analytics." Over time, as the technology evolved, firms discussions shifted toward "machine learning" (2018-2020), followed by a shift toward explicit

[15] For quarterly channels such as earnings announcements and conference calls, we use the average of the four quarters in each fiscal year to calculate our disclosure scores.
[16] TF-IDF trigrams is a text analysis method measuring the relative importance of three-word phrases. TF (Term Frequency) counts phrase occurrences in a document, while IDF (Inverse Document Frequency) downweights common phrases across documents. This helps identify distinctive technical terminology in corporate communications.

references to "artificial intelligence" in recent years (2021-2023). Interestingly, firms identified as suspected AI washers consistently lagged behind non-AI washers by approximately one year in adopting these technological terms in their communications, that they tend to follow industry trends rather than lead in AI adoption. This delayed adoption of AI-related language may reflect firms responding to market pressures and investor expectations rather than genuine technological advancements.[17]

Figure 3 presents AI employment trends over time. Panel A presents the average number of AI employees per firm, which grew from approximately 5 in 2016 to over 12 by 2023, indicating a rising demand for AI-related talent. Panel B presents AI employees as a percentage of total employment, which increased from about 0.1% in 2016 to nearly 0.3% in 2023, suggesting a growing emphasis on AI-related roles relative to overall workforce composition. These employment trends indicate an increase in AI workforce *levels* and a growing importance of AI-related roles relative to overall employment. Moreover, the parallel upward trends in AI disclosure and AI employment suggest that, on average, firms' AI disclosures are indicative of actual AI investments, reinforcing the informativeness of AI-related corporate communications.

4. Empirical Results

4.1 Descriptive Statistics

Table 1 presents the summary statistics for our key variables. The mean values for AI disclosures in conference calls (*AI_CC*), 10-K filings (*AI_10K*), and earnings announcements (*AI_EA*) are 1.5%, 1.1%, and 1.1% of sentences, respectively. The standard deviations for these variables (2.6%, 2.0%, and 2.1%) suggest considerable variation in AI disclosure practices among

[17] We analyze each communication channel (10-K, Conference Calls, Earnings Announcements) separately in Figure 1 of the Online Appendix. The trends mirror those seen in aggregate disclosures. Conference calls disclosures, being less formal, see "generative AI" appear in 2023.

firms, particularly at the upper end of the distributions. The average number of AI employees (*AI_Employee*) is 13, with a high standard deviation of 25, indicating significant disparity in firms' AI workforce and, again, particularly at the upper end of the distribution. The average firm is 10 years old, is innovative (e.g., R&D expense is 6.6% of total assets), and has high levels of monitoring (e.g., an average of 7 analysts follow firms in our sample and average institutional ownership of 72%).[18]

Table 2 reports summary statistics examining the relationship between AI employment and disclosures. Specifically, we examine differences in AI employment across AI disclosure terciles, and vice versa. Panel A reports the average number of AI employees for firms in each disclosure tercile. In all employment terciles, we see that employment increases as disclosure increases. For firms with highest AI employment, we observe a significant increase in AI employees from 29.290 in the low disclosure group to 42.000 in the high disclosure group (t-stat = 8.245).

Panel B presents the average aggregated AI disclosure (AI_Dis_Agg) in each tercile group. Similar to the results in Panel A, across all disclosure terciles, we see that disclosure increases as employment increases. For firms in the highest tercile of AI disclosure, we observe a significant increase in AI disclosure from 0.072 in the low employment group to 0.110 in the high employment group (t-stat = 12.967).

Panel C presents correlations between AI disclosures in each respective disclosure channel and AI employment. We provide evidence that AI disclosure levels are strongly correlated across disclosure channels, with the highest correlation between 10-K filings and conference calls (0.727, $p<0.01$), followed by earnings announcements and conference calls (0.715, $p<0.01$). However, these disclosure measures show weaker correlations with actual AI employment, ranging from

[18] For our baseline sample, we include only firms with available data across all three disclosure channels. Consistent with prior research, these firms typically have higher institutional ownership.

0.224 to 0.336 (all $p<0.01$), suggesting potential disconnects or timing differences between firms' AI disclosures and their actual AI implementation.

4.2 The Determinants of AI Disclosure and AI Washing

To understand the determinants of AI disclosures (and suspected AI washing behavior), we estimate the following OLS regression model:

$$Y_{i,t} = \alpha_i + \beta_1 R\&D_{i,t} + \beta_2 Investment_{i,t} + \beta_3 Age_{i,t} + \beta_4 Size_{i,t} + \beta_5 Profitability_{i,t} + \beta_6 Tangibility_{i,t} + \beta_7 HHI\_Seg_{i,t} + \beta_8 MTB_{i,t} + \beta_9 Leverage + \beta_{10} N\_Analyst_{i,t} + \beta_{11} Insti\_Own_{i,t} + \beta_{12} AI\_DIS\_IND_{t,j} + Industry\ FE + Firm\ FE + \mu_{i,t} \quad (1)$$

where i indexes firm and t the year. The dependent variable, Y, is a set of AI disclosure and AI washing variables, including AI-related disclosure in earnings announcements, conference calls, and annual 10-K reports (*AI_EA, AI_CC, AI_10K*), and our measure of suspected AI washers (*AI_Washer*). We include variables related to firm characteristics including R&D expenses (R&D), investment ratio (*Investment*), firm age (*Age*), firm size (*Size*), performance *(Profitability),* asset tangibility (*Tangibility*), the concentration of operations *(HHI_Seg),* debt ratio *(Leverage),* and information environments such as analyst *following (N_Analyst)* and institutional ownership *(Insti_Own).* We also control for industry-wide AI disclosure.[19] Lastly, we include industry and year fixed effects to remove unobservable time- or industry-invariant factors that may lead to spurious associations between the independent variables and AI disclosures.[20] Standard errors are clustered by firm. All continuous variables are winsorized at the 1st and 99th percentiles.

Panel A of Table 3 shows our baseline multivariate results. All independent variables are standardized to facilitate comparisons across determinants. We first consider the determinants of firms AI disclosure across each communication channel (i.e., 10-K, conference call, and earnings

[19] We measure industry-wide AI disclosure (*AI_Dis_Ind*) as the count of firms making AI-related claims across all communication channels, aggregated by three-digit SIC code annually.
[20] We use the Fama-French 12 industry classification as our industry fixed effects.

announcement), presented in columns 1 through 3. Very clearly, the largest coefficients relate to industry fixed effects and the extent to which peer firms in the same industry disclose AI (*AI_Dis_Ind*). These results suggest that the primary determinant for whether a firm discloses AI related information is the industry in which they operate and the disclosure behavior of their peer firms. In terms of firm-level determinants, the next most significant variables relate to a firm's innovation activity. Specifically, Asset Tangibility is negatively associated with AI disclosure across all channels (i.e., 10-K, conference calls, and earnings announcements), suggesting that firms with intangible assets are more likely to disclose AI information. Similarly, R&D is positively associated with AI disclosures across all channels. After innovation, the next set of firm-level determinants that appear significant appear to relate to monitoring/demand for disclosure. Specifically, analyst following is positively associated with AI disclosure. Taken together, the results in Panel A of Table 3 suggest that AI disclosure appears to be found most often in AI-related industries, when a firm's peer firms are also disclosing AI information, when the firm is more innovative, and when the firm has greater external monitoring and/or faces greater external demand for AI disclosure.

Next, we separately examine the determinants of firms that are classified in our sample as suspected AI washers (i.e., top tercile of disclosure and bottom tercile of AI-related employment). These results are presented in Column 4. Perhaps not surprisingly, we find that the determinants of suspected AI washers are not aligned with the determinants of the disclosure in general. Specifically, suspected AI washers have *fewer* (not more) industry peers disclosing AI information, appear less innovative (i.e., a negative coefficient on R&D), and have weaker external monitoring and/or face relatively less demand for AI disclosure (i.e., a negative coefficient on institutional ownership). The suspected AI washers also appear to be smaller and have fewer growth opportunities than the rest of the firms in the sample. Taken together, the results suggest that suspected AI washing firms do not appear to fit the baseline expectation for why a firm would provide AI disclosure – as they do not concentrate in an AI-related industry, their peers do not disclose AI related information, and they are relatively less innovative, smaller, and face weaker outside scrutiny.

To better understand the relative importance of industry and firm level characteristics, we next perform an analysis to examine the relative influence that groups of determinants have on the R^2 of the determinants model. To do so, we classify the determinants into four categories: industry characteristics, firm characteristics, information/external monitoring, managerial characteristics, and litigation risk. We add the latter two categories to assess whether there are any manager-level variables that might related to the disclosure, and whether a firm's litigation risk might impact its likelihood of providing potentially misleading disclosure. Figure 4 presents a Shapley decomposition based on these categories. Figure 4 provides evidence that industry-level factors (Industry FE + Industry-wide AI disclosure) dominate the explanatory power of AI disclosure levels (accounting for approximately 60 to 70 percent of the R^2), followed by firm-specific factors. Interestingly, however, industry-level factors do not explain as much variation in the classification of suspected AI washers. Instead, firm-specific factors explain the most variation in the classification of suspected AI washers (accounting for over 60% of the R^2). Additionally, we find that information/external monitoring and litigation risk, while having negligible explanatory power in AI disclosure, explain much more of the variation in the classification of suspected AI washers.

Given the additional variables with incremental explanatory power of the classification of suspected AI washers relative to AI disclosure, we augment the multivariate determinants test of suspected AI washers using the categories from the Shapley decomposition. We present these results in Table 3, Panel B. Among firm level characteristics (Column 1) and consistent with the results from Panel A, R&D (-0.0233), size (-0.1039) and market-to-book ratio (-0.0123) are significantly negatively associated with the likelihood of being classified as a suspected AI washer. For external monitoring mechanisms (Column 2) and consistent with the results from Panel A, we find that analyst following (-0.0552) and institutional ownership (-0.0300) are negatively associated with the likelihood of being classified as a suspected AI washer.

For managerial characteristics (Column 3), we find that higher managerial ability (-0.0224) is negatively associated with the likelihood of being classified as a suspected AI washer while CEO stock ownership exhibits a positive association (0.0145). These results suggest that firms are less likely to be suspected of disclosure washing behavior when the manager is of higher ability, but more likely when the manager has a high concentration of wealth in the firm's stock. When examining litigation risk (Column 4), we find that elevated litigation risk is negative associated with the likelihood of being classified as a suspected AI washer (-0.0633). This suggests that firms are less likely to engage in washing behavior if they face higher litigation risk associated with making misleading claims.

However, when we combine all these categories into one model, the results generally revert back to those from Column 4 in Panel A. That is, whatever manager or litigation risk impacts there are on washing behavior appear to be dominated by a firm's size, innovation levels, external monitoring, and industry classification. Thus, we include the controls from Panel A in the remaining analyses.

4.3 AI Disclosures, AI Washing, and Firm Performance

4.3.1 Firm Efficiency

To test our first hypothesis (H1) that AI disclosures are positively related to firm performance, we first examine whether AI disclosures correlate with future firm efficiency. We estimate the following OLS regression model:

$$Efficiency_{i,t+1} = \alpha_i + \beta_1 AI\_Variables + \beta_2 R\&D_{i,t} + \beta_3 Investment_{i,t} + \beta_4 AGE_{i,t} + \beta_5 Size + \beta_6 Profitability_{i,t} + \beta_7 Tangibility_{i,t} + \beta_8 HHI\_Seg_{i,t} + \beta_9 MTB_{i,t} + \beta_{10} Leverage_{i,t} + \beta_{11} N\_Analyst_{i,t} + \beta_{12} Insti\_Own_{i,t} + \beta_{13} AI\_Dis\_Ind + + Industry\ FE + Firm\ FE + \mu_{i,t} \qquad (2)$$

where i indexes firm and t the year. The dependent variable, *Efficiency*, measures operational efficiency using stochastic frontier analysis (SFA) (Aigner et al., 1977; Meeusen and Van den Broeck, 1977). SFA infers efficiency by assessing firms' resource use to generate revenue within each industry. As a parametric method, it allows direct statistical assessment of model parameters, accommodating random errors (Dopuch et al., 2003; Callen et al., 2005; Baik et al., 2013). Following Demerjian et al. (2012), inputs include cost of goods sold, net PP&E, net R&D, and employee count, with revenue as output. Firms can enhance efficiency through process optimization, automation, and enhanced decision-making, all of which can be facilitated by AI adoption. Given that our SFA model controls for industry-wide input-output relationships, our measure of efficiency captures firm-specific productivity advantages, making it well-suited to test whether AI disclosures signal real efficiency gains. All other variables are as previously defined.

Table 4 presents the results from estimating Equation 2. Columns (1)-(3) show that AI disclosures across all channels are positively and significantly associated with efficiency in the next year ($p < 0.01$). This indicates that firms disclosing more about their AI initiatives tend to be more efficient than other firms in their industry, consistent with H1. Moreover, the ratio of AI employees (column 4) is positively associated with efficiency (1.7757, $p < 0.01$), reinforcing the link between complimentary investments in AI workforce investments and firm performance. In contrast, firms classified as suspected AI washers (Column 5) do not exhibit significant improvements in efficiency, consistent with H2. This result supports the notion that firms with significant AI disclosures that are not substantiated by firm-specific complimentary investments may not have the current AI capabilities to improve their firm's performance, suggesting that their disclosures may be strategic rather than reflective of actual AI adoption.

4.3.2 Innovation Output

To further test H1, we examine the association between AI disclosures and AI innovation output, specifically AI patents. We estimate the following equation.

$$AI\_Patent_{i,t+1} = \alpha_i + \beta_1 AI\_Variables + \beta_2 R\&D_{i,t} + \beta_3 Investment_{i,t} + \beta_4 AGE_{i,t} + \beta_5 Size + \beta_6 Profitability_{i,t} + \beta_7 Tangibility_{i,t} + \beta_8 HHI\_Seg_{i,t} + \beta_9 MTB_{i,t} + \beta_{10} Leverage_{i,t} + \beta_{11} N\_Analyst_{i,t} + \beta_{12} Insti\_Own_{i,t} + \beta_{13} AI\_Dis\_Ind + + Industry\ FE + Firm\ FE + \mu_{i,t} \qquad (3)$$

where *AI_Patent* is the ratio of firms' AI-patent filings, as provided by the USPTO, over the total number of firms' patent filings in the period. We identify AI patents as patent filings with a greater than 50% likelihood of being classified in at least one following categories: AI Hardware, evolutionary computation, knowledge processing, machine learning, natural language processing, planning/control, speech, and vision (following Giczy et al., 2022).[21] Additionally, in this analysis, we remove firm-year observations that do not have any patent filings during the period to minimize the possibility that outsourcing decisions impact our inferences. All other variables are as previously defined.

Table 5 presents the results of estimating Equation 3. We find that AI disclosures across all channels are positively and significantly associated with AI patent ratios ($p < 0.01$). This robust relationship indicates that firms disclosing more about their AI initiatives are also more likely to incorporate AI in their innovations, suggesting a strong link between AI communication and AI innovation outputs. The ratio of AI employees is also positive and significantly associated with AI

[21] Appendix 4 provides detailed examples of patents classified as AI-related.

patent output, further supporting the connection between firm-specific complementary investments in AI employees and firm performance.

Firms suspected of AI washing (column 5) exhibit a negative and significant association with future AI patent ratios (-0.0371). This result implies that firms that heavily disclose AI information but do not have significant complementary investments in AI employees are less likely to produce tangible AI innovation outputs, highlighting the potential disconnect between AI disclosures and current AI capabilities for some firms.

4.3.3 Dividend Payout Policy

Building on our examination of AI disclosures' relation to firm efficiency and innovation, we now turn to firms' financial policies, specifically how AI disclosures relate to dividend payout decisions. This analysis provides insights into how firms weigh the potential trade-offs between technological advancement and immediate shareholder rewards. Specifically, we estimate the following equation.

$$Dividend_{i,t+1} = \alpha_i + \beta_1 AI\_Variables + \beta_2 R\&D_{i,t} + \beta_3 Investment_{i,t} + \beta_4 AGE_{i,t} + \beta_5 Size + \beta_6 Profitability_{i,t} + \beta_7 Tangibility_{i,t} + \beta_8 HHI\_Seg_{i,t} + \beta_9 MTB_{i,t} + \beta_{10} Leverage_{i,t} + \beta_{11} N\_Analyst_{i,t} + \beta_{12} Insti\_Own_{i,t} + \beta_{13} AI\_Dis\_Ind + + Industry\ FE + Firm\ FE + \mu_{i,t} \quad (4)$$

where *Dividend* is an indicator variable set to 1 if the firm pays a dividend in current period.

The results of estimating equation 4 are presented in Table 6. We find evidence that AI disclosures across all channels are negatively and significantly associated with dividend payouts. This result suggests that firms highlighting AI in their disclosures are less likely to pay dividends, possibly due to higher reinvestment needs for AI development or a focus on growth over income distribution. Similarly, the ratio of AI employees exhibits a significant negative relationship with dividend payouts, further supporting the notion that firms investing in AI-related human capital reallocate financial resources toward AI development rather than shareholder distributions.

However, interestingly, firms suspected of AI washing do not exhibit a consistent relationship with dividend policy, suggesting that these firms may be less constrained by AI investment needs and may still prioritize returning funds to shareholders rather than investing in AI capabilities.[22]

4.4 Capital Market Consequences

To address our third hypothesis (H3) regarding the capital market reactions to AI disclosures and potential AI washing, we examine short-term and long-term abnormal returns focused on quarterly conference calls. To reduce noise and improve identification, we compare the returns for three different groups: (1) Firms with low AI-related disclosure (bottom tercile of *AI_CC*) and low AI employment (bottom tercile of *AI_Employee*), (2) firms with high AI-related disclosure (top tercile of *AI_CC*) and low AI employment (bottom tercile of *AI_Employee* (i.e., suspected washers), and (3) firms with high AI-related disclosure (top tercile of *AI_CC*) and high AI employment (top tercile of *AI_Employee*). This analysis allows us to investigate whether investor reactions correlate with firms' AI disclosures and whether investors appear to discern between true AI claims and potentially exaggerated claims. Specifically, we estimate the following model:

$$RETURN_{i,q} = \alpha_i + \beta_1\ High\ Disclosure - Low\ Employees_{i,q} + \beta_2\ High\ Disclosure - High\ Employees_{i,q} + \beta_3\ Ln(MV)_{i,q} + \beta_4\ Lev_{i,q} + \beta_5\ BTM_{i.q} + Industry\ FE + Year\text{-}QTR\ FE + \mu_{i,t} \quad (5)$$

RETURN is a set of return variables including CAR_3day, BHAR_6m, BHAR_9m, and BHAR_12m, representing 3-day cumulative abnormal returns and 6-month, 9-month, and 12-month buy-and-hold abnormal returns, respectively. All abnormal returns are calculated after subtracting the returns for the firms' size and book-to-market matched portfolios following Daniel et al. (1997). *Ln(MV)* is the natural log of one plus the quarter-end market value of equity. *Lev* is

[22] Control variables show that firm age, size, profitability, and MTB are positively associated with dividend payouts, while investment rate exhibits a negative association. These results align with traditional dividend policy theories, suggesting that mature, profitable firms with lower investment needs are more likely to pay dividends.

the quarter-ending total liabilities divided by the quarter-ending stock-holders equity. *BTM* is the quarter-ending book value of equity divided by the quarter-ending market value of equity. In all analyses in Table 7, we use the low AI disclosure – low AI employment group as the comparison group.

In Panel A of Table 7, we estimate equation 5 using the full sample of firm-quarters in the groups mentioned previously. We do not find a significant difference in market reaction to AI disclosures in conference calls among any of the three groups. However, we do find evidence that the long-horizon buy-and-hold returns for firm-quarters that heavily discuss AI in conference calls and have elevated AI employment levels significantly outperform other firms, including firms with high disclosure and low employment (i.e., suspected AI washers).

In Table 7, Panel B, we estimate Equation 5 on the subset of firm-quarters with non-zero AI employment in case investors consider firms without *any* AI-related employees differently (i.e., perhaps they assume that the data is not correct and/or the firm is fully outsourcing its AI initiatives). The results from this sub-sample are consistent with the results in Panel A; we find that, while there is no significant difference in short-term returns, high AI disclosure and high AI employment firms significantly outperform other firms in the long run. Panel B also provides marginal evidence that high AI disclosure and low AI employment firms (i.e., suspected washers) underperform the reference group, potentially indicating long-term consequences of overstating current AI capabilities. Together, our results in Panels A and B provide strong evidence of the need for firm-specific investments in AI-related intangibles.

One potential concern with using panel data to regress long-term buy-and-hold returns on AI disclosures in quarterly conference calls is autocorrelation in the error term. We perform two additional analyses to reduce the probability that problems with the error term influence our results.

First, we bootstrap our standard errors with 1,000 iterations. We present the results of re-estimating Panels A and B with bootstrapped standard errors in Table 7 Panel C. We find consistent evidence that firms with high AI disclosure and high AI employment significantly outperform other firms.

Second, we estimate Fama-MacBeth regressions on a quarterly basis and allow for four lags when estimating the Newey-West adjusted standard errors to address autocorrelation in the error term. We present the results of the Fama-MacBeth regressions for the full sample, consistent with Panel A, and the sample of firm quarters with non-zero AI employment, consistent with Panel B, in Table 7, Panel D. We continue to find consistent evidence that firms with high AI disclosure and high AI employment exhibit significantly higher long-term abnormal returns relative to other firms, but that there is no significant difference in short-term abnormal returns.

Overall, we provide consistent evidence that firms with high AI disclosure and high AI employment significantly outperform other firms using long-horizon abnormal returns. On the other hand, we do not find evidence of differences in short-term abnormal returns among the firms included in our analyses, potentially indicating that market participants have a difficult time distinguishing between firms that disclose AI information in conference calls. However, we provide evidence that firms' investments in AI-related intangibles, specifically AI employees, are strongly associated with future abnormal returns.

4.5 Additional Analyses

4.5.1 Alternative AI Washer Measures

To assess the robustness of our analysis regarding firms suspected of AI washing, we employ two alternative specifications of our AI washing measure. First, we define suspected AI washers as firms with high AI disclosures but zero AI employees, providing a sharper contrast in actual AI implementation (*AI_Washer_Mvs0*). As previously mentioned, firms without any employees could be the most aggressively washing (unless they are fully outsourcing their AI initiatives, in which case it is an empirical question whether this is an effective way to realize AI benefits). Second, we collect disclosure information for the years prior to our sample (i.e., 2010 to 2015) and exclude firms with elevated levels of AI disclosure during this period under the assumption that firms were less likely to provide misleading disclosure when the expectation for disclosure was much weaker (*AI_Washer_pure*). A feature of this classification approach is that it does not rely on Revelio or employee data at all.

We present results of the first alternative, *AI_Washer_Mvs0*, in Panel A of Table 8 and the results of the second alternative, *AI_Washer_pure*, in Panel B. The results using these alternative measures are similar to our main findings with increased statistical significance in some specifications. Overall, our findings suggest that firms suspected of AI washing exhibit significantly lower efficiency, fewer AI patents, and an increased likelihood of paying a dividend, reinforcing our main conclusions about the real effects of AI washing.

4.5.2 ESG Falsification Test

To further validate our AI washing measure and inferences, we conduct a falsification test using ESG scores as the dependent variable. This test allows us to determine whether AI washing is systematically related to ESG washing or whether it represents a distinct strategic disclosure behavior. Table 9 presents the results. We find that none of our AI-related measures including AI disclosures (*AI_CC, AI_10K, AI_EA*), AI employment ratio, or AI washing status significantly predicts firms' ESG performance.[23] The coefficients are statistically insignificant across all specifications, with small economic magnitudes, indicating no meaningful relationship between AI disclosure practices and ESG outcomes.

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[23] ESG score is measured from the Refinitiv ESG database, which evaluates firms' environmental, social, and governance performance based on over 450 company-level ESG metrics.

These findings suggest that AI washing is not merely a subset of broader corporate "washing" behaviors (e.g., greenwashing or diversity washing). Instead, it appears to be a distinct phenomenon driven by the unique incentives surrounding AI adoption, rather than reflecting a general tendency for firms to engage in misleading disclosure across multiple domains. This difference is economically important because AI investments are directly tied to productivity and innovation outcomes, whereas ESG-related misrepresentation often involves more subjective or socially driven expectations rather than direct operational performance.

4.5.3 Robustness to alternative time periods and lagged dependent variables

In our main tests, we associate current year disclosure and labor investment to firm outcomes in the next year and find that suspected AI washers do not experience improvements while the rest of the sample does. One concern is that suspected AI washers are delayed adopters and/or are making investments that need more time to come to fruition. Therefore, in this section we consider whether our results differ if we consider outcomes two- and three-years ahead. Table 10 presents these results. The inferences remain consistent when extending the analysis to two and three years ahead (t+2 and t+3). Panel A shows that all AI disclosure measures (*AI_10K, AI_CC, AI_EA*) and AI employee ratio maintain significant positive associations with efficiency in both t+2 and t+3, with coefficients ranging from 0.64 to 0.78. Panel B demonstrates persistent positive relationships between AI disclosures and AI patent ratio output, with coefficients remaining significant and economically meaningful across both time horizons (ranging from 2.02 to 2.50). Panel C shows that firms with higher AI disclosures consistently pay lower dividends in both next two and three years. We find no such results for firms suspected of AI washing, suggesting that timing differences between investment and outcomes are unlikely to explain our results.

Also in our main tests, we regress disclosure on future outcomes without controlling for the level of current outcomes because we control for various fixed effects structures and because there can be econometric concerns with lagged dependent variables. Nevertheless, we assess the sensitivity of our findings to the inclusion of lagged dependent variables. As shown in Table 1 of the Online Appendix, our inferences are unchanged.

4.5.4 Partitions of the sample other than suspected AI washers

In our main tests, we compare the full sample to a partition of firms that are upper tercile in disclosure and lower tercile in AI employees, whom we refer to as suspected "AI washers." In this section, we consider the association between disclosure and future outcomes for other partitions of the sample, specifically for (1) "*AI_Good*" firms that are top tercile in both disclosure and AI employees, (2) "*AI_Silent*" firms that are bottom tercile on both disclosure and AI employees, (3) "*AI_Stealth*" firms that bottom tercile in disclosure but top tercile in AI employees, and (4) "*AI_Middle*" firms that are middle tercile in both disclosure and AI employees.

Panels A, B, and C of Table 11 present results examining the association between these various categories and firm efficiency, AI patent ratio, and dividend payout policy in the next period. Our results hold for *AI_Good* (high disclosure, high employee) firms. However, *AI_Silent* (low disclosure, low employee) firms show lower efficiency and fewer AI patents, and higher dividend payments, suggesting that firms without either fall behind their peers. Firms taking middle ground (*AI_Stealth* and *AI_Middle*) show no significant differences in these outcomes, suggesting that the benefits of AI materialize most effectively when firms fully commit to *both* investment and disclosure.

4.5.5 Hazard Model

To examine what factors influence firms' transition away from AI washing behavior, we employ a survival analysis approach where the original state is firms identified as suspected AI washers, and the transition state is when they exit this status. To do so, we extend our sample to 2010 to 2023 to allow sufficient time for firms to move from one state to the other. Panel A of Table 12 shows the lifecycle table of suspected AI washers, tracking their survival and exit patterns over time. On average, suspected AI washers continue to be identified by our models for 2.5 years. The survival probability declines from 0.3109 in year 1 to 0.0438 by year 14, suggesting that while many firms exit AI washing status early, some persist in this behavior for extended periods.

Panel B of Table 12 presents the hazard model results. Specifically, we employ the following model:

$$h(t) = \lambda p(\lambda t)^{(p-1)} exp(\beta_1 R\&D + \beta_2 Investment + \beta_3 Age + \beta_4 Size + \beta_5 Profitability + \beta_6 Tangibility + \beta_7 HHI\_Seg + \beta_8 MTB + \beta_9 Leverage + \beta_{10} N\_Analyst + \beta_{11} Insti\_Own + \beta_{11} AI\_Dis\_Ind + \delta Industry\ FE) + \varepsilon \quad (6)$$

where h(t) is the hazard rate at time t (probability of exiting AI washer status). $h_0(t) = \lambda p(\lambda t)^{(p-1)}$ is the baseline hazard function using a Weibull distribution.[24] Table 10 presents the results. First, we find evidence of "stickiness" in AI washing behavior: firm age and institutional ownership are negatively and significantly associated with the probability of exiting AI washing status. Specifically, a one-year increase in a firm's age reduces the likelihood of exiting AI washing by 24.6% (hazard ratio: 0.754). Firm characteristics also play a key role in the likelihood of exiting AI washing. Larger firms are 9.7% more likely to exit AI washing status, while firms with more concentrated operations are 61% more likely to exit. External monitoring, measured by analyst following, has a modest positive impact on the probability of exit (hazard ratio: 1.015). However, neither technological capacity (as measured by R&D intensity) nor investment rate shows a significant relationship with the exit of suspected AI washing.

[24] The model examines the probability of exiting AI washer status conditional on survival up to time t. A positive coefficient indicates an increased probability of exit, while a negative coefficient indicates a decreased probability of exit. γYear represents year fixed effects.

5. Conclusion

As Artificial Intelligence emerges as a transformative General Purpose Technology, firms face both opportunities for genuine innovation and incentives to engage in AI washing—where they claim AI capabilities without substantive backing. The increasing market enthusiasm for AI has heightened the demand for transparency, making it critical to distinguish between firms that truly invest in AI and those that merely signal AI adoption without meaningful investment.

Using textual analysis and firm-level AI employment data from 2016 to 2023, we uncover four main findings. First, AI disclosures are more prevalent among firms that operate in AI-intensive industries, firms with greater innovation, and those subject to higher external monitoring and investor demand for AI-related transparency. Second, AI disclosures are positively associated with future operational efficiency and AI patent filings, and negatively associated with dividend payout policies. This suggests that, on average, firms that disclose AI initiatives are actively integrating AI into their operations, reinvesting in innovation rather than distributing excess cash to shareholders. Third, not all AI disclosures are informative—firms that heavily discuss AI but invest little in AI-specific labor fail to experience efficiency gains, patent growth, or strategic reinvestment. These suspected AI washers tend to be smaller, operate in less AI-intensive industries, exhibit lower innovation, and face weaker external monitoring. Finally, firms that pair high AI disclosure with substantial AI employment significantly outperform AI washers in long-term buy-and-hold abnormal returns, reinforcing the idea that genuine AI investments—not just AI rhetoric—drive firm value.

Overall, our findings highlight the informative nature of AI disclosures, but also the importance of AI-specific labor investments in translating AI adoption into long-term firm performance. As investors and regulators seek to evaluate AI-related claims, our results underscore the need for scrutiny in distinguishing substantive AI integration from overstated AI capabilities. Understanding the credibility of AI disclosures is increasingly vital as AI continues to shape firm strategy, market valuations, and regulatory oversight.

References

Abowd, J. M., J. Haltiwanger, and J. Lane. 2004. Integrated longitudinal employer-employee data for the United States. *The American Economic Review* 94 (2): 224-229.

Acemoglu, D., D. Autor, J. Hazell, and P. Restrepo. 2022. Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics* 40 (S1): 293-340.

Aghion, P., B. F. Jones, and C. I. Jones. 2017. Artificial intelligence and economic growth. *NBER Working paper*.

Agrawal, A., J. S. Gans, and A. Goldfarb. 2019. Artificial intelligence: The ambiguous labor market impact of automating prediction. *Journal of Economic Perspectives* 33 (2): 31-50.

Ahn, J., R. Hoitash, U. Hoitash, and E. Krause. 2023. The turnover, retention, and career advancement of female and racial minority auditors: Evidence from individual LinkedIn data. *SSRN Working paper.*

Aigner, D., C. K. Lovell, and P. Schmidt. 1977. Formulation and estimation of stochastic frontier production function models. *Journal of Econometrics* 6 (1): 21-37.

Alderucci, D., L. Branstetter, E. Hovy, A. Runge, and N. Zolas. 2020. Quantifying the impact of AI on productivity and labor demand: Evidence from U.S. census microdata. *Working paper.*

Allee, K.D., DeAngelis, M.D. and Moon Jr, J.R., 2018. Disclosure "scriptability". *Journal of Accounting Research*, 56(2), pp.363-430.

Aswani, J., A. Raghunandan, and S. Rajgopal. 2024. Are carbon emissions associated with stock returns? *Review of Finance* 28 (1): 75-106.

Babina, T., A. Fedyk, A. He, and J. Hodson. 2024. Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics* 151.

Baik, B., J. Chae, S. Choi, and D. B. Farber. 2013. Changes in operational efficiency and firm performance: A frontier analysis approach. *The Accounting Review* 30 (3): 996-1026.

Baker, A. C., D. F. Larker, C. G. McClure, D. Saraph, and E. M. Watts. 2024. Diversity washing. *Journal of Accounting Research.*

Barrios, J.M., 2022. Occupational licensing and accountant quality: Evidence from the 150-hour rule. *Journal of Accounting Research*, *60*(1), pp.3-43.

Berger, P.G., Cai, W., Qiu, L. and Shen, C.X., 2024. Employer and employee responses to generative AI: Early evidence. *SSRN Electronic Journal*.

Bertomeu, J. 2020. Machine learning improves accounting: Discussion, implementation and research opportunities. *Review of Accounting Studies* 25: 1135-1155.

Black, D. E., T. E. Christensen, J. T. Ciesielski, and B. C. Whipple. 2021. Non-GAAP earnings: A consistency and comparability crisis? *Contemporary Accounting Research* 38 (3): 1712-1747.

Bochkay, K., S. V. Brown, A. J. Leone, and J. W. Tucker. 2023. Textual analysis in accounting: What's next? *Contemporary Accounting Research* 40 (2): 765-805.

Bourveau, T., M. Chowdhury, A. Le, and E. Rouen. 2023. Human capital disclosures. *SSRN Working paper.*

Bresnahan, T. F., and M. Trajtenberg. 1995. General purpose technologies 'Engines of growth'? *Journal of Econometrics* 65 (1): 83-108.

Bresnahan, T., S. Greenstein, D. Brownstone, and K. Flamm. 1996. Technical progress and co-invention in computing and in the uses of computers. *Brookings Papers on Economic Activity: Microeconomic*s: 1-83.

Brynjolfsson, E., D. Rock, and C. Syverson. 2019. Artificial intelligence and the modern productivity paradox: A clash of expectations and statistics. *The Economics of Artificial Intelligence*. University of Chicago Press: 23-60.

Callen, J. L., M. Morel, and C. Fader. 2005. Productivity measurement and the relationship between plant performance and JIT intensity. *Contemporary Accounting Research* 22 (2): 271-309.

Cao, S., W. Jiang, B. Yang, and A. L. Zhang. 2023. How to talk when a machine is listening: Corporate disclosure in the age of AI. *The Review of Financial Studies* 36 (9): 3603-3642.

Chapman, K. L., and J. Green. 2018. Analysts' influence on managers' guidance. *The Accounting Review* 93 (1): 45-69.

Chen, M. A., Q. Wu, and B. Yang. 2019. How valuable is fintech innovation? *The Review of Financial Studies* 32 (5): 2062-2106.

Cheng, S.F., De Franco, G., Jiang, H. and Lin, P., 2019. Riding the blockchain mania: Public firms' speculative 8-K disclosures. *Management Science*, 65(12), pp.5901-5913.

Christ, M. H., S. Emett, S. Summers, and D. Wood. 2020. Prepare for takeoff: Improving audit efficiency and effectiveness with drone-enabled inventory audit procedures. *Review of Accounting Studies* 26: 1323-1343.

Coleman, B., K. Merkley, and J. Pecelli. 2022. Human versus machine: A comparison of robo-analyst and traditional research analyst investment recommendations. *The Accounting Review* 97 (5): 221-244.

Commerford, B. P., S. A. Dennis, J. A. Joe, and J. W. Ulla. 2022. Man versus machine: Complex estimates and auditor reliance on artificial intelligence. *Journal of Accounting Research* 60 (1): 171-201.

Cook, L. D. 2024. Artificial intelligence, big data, and the path ahead for productivity. *Federal Reserve Speech.*

Daniel, K., Grinblatt, M., Titman, S. and Wermers, R., 1997. Measuring mutual fund performance with characteristic-based benchmarks. *The Journal of Finance*, 52(3), pp.1035-1058.

Damioli, G., V. Van Roy, and D. Vertesy. 2021. The impact of artificial intelligence on labor productivity. *Eurasian Business Review* 11: 1-25.

Demerjian, P., B. Lev, and S. McVay. 2012. Quantifying managerial ability: A new measure and validity tests. *Management Science* 58 (7): 1229-1248.

Dikolli, S. S., M. M. Frank, Z. M. Guo, and L. J. Lynch. 2022. Walk the talk: ESG mutual fund voting on shareholder proposals. *Review of Accounting Studies* 27: 864-896.

Dopuch, N., M. Gupta, D. A. Simunic, and M. T. Stein. 2003. Production efficiency and the pricing of audit services. *Contemporary Accounting Research* 20 (1): 47-77.

Eisfeldt, A.L., Schubert, G., Zhang, M.B. and Taska, B., 2024. The labor impact of generative AI on firm values. *SSRN Electronic Journal.*

Fedyk, A., and J. Hodson. 2023. Trading on talent: Human capital and firm performance. *Review of Finance* 27 (5): 1659-1698.

Giczy, A. V., N. A. Pairolero, and A. A. Toole. 2022. Identifying artificial intelligence (AI) invention: A novel AI patent dataset. *The Journal of Technology Transfer* 47: 476-505.

Hodson, J. 2016. How to make your company machine learning ready. *Harvard Business Review*: 1-4.

Huang, A. H., H. Wang, and Y. Yang. 2023. FinBERT: A large language model for extracting information from financial text. *Contemporary Accounting Research* 40 (2): 806-841.

Jones, C. I., and C. Tonetti. 2020. Nonrivalry and the economics of data. *American Economic Review* 110 (9): 2819-2858.

Johnson, R. G. 2023. Analysts' influence on the decision-usefulness of managers' voluntary disclosures. *Working paper.*

Kim, S., and A. Yoon. 2022. Analyzing active fund managers' commitment to ESG: Evidence from the United Nations Principles for Responsible Investment. *Management Science* 69 (2): 741-758.

Lustig, H., C. Syverson, and S. Van Nieuwerburgh. 2011. Technological change and the growing inequality in managerial compensation. *Journal of Financial Economics* 99 (3): 601-627.

Libby, R., and P. D. Witz. 2024. Can artificial intelligence reduce the effect of independence conflicts on audit firm liability? *Contemporary Accounting Research* 41 (2): 1346-1375.

Lin, Y., M. Shen, R. Shi, and J. Zeng. 2024. The falling Roe and relocation of skilled women. *Working paper.*

McKinsey & Company. 2020. The state of AI in 2020: Survey. *McKinsey Digital/Quantum Black* (November).

Meeusen, W., and J. van Den Broeck. 1977. Efficiency estimation from Cobb-Douglas production functions with composed error. *International Economic Review* 18 (2): 435-444.

Mihet, R., and T. Philippon. 2019. The economics of big data and artificial intelligence. In *Disruptive Innovation in Business and Finance in the Digital World*: 29-43.

Peña-López, I. Artificial intelligence in society. OCED 2019

Rogers, J. L., and P. C. Stocken. 2005. Credibility of management forecasts. *The Accounting Review* 80 (4): 1233-1260.

Romer, P. M. 1990. Endogenous technological change. *Journal of Political Economy* 98 (5): 71-102.

SEC. 2018. Comment letter regarding Ideanomics, Inc.'s S-1 filed on August 24, 2019. Securities and Exchange Commission.

SEC. 2019. Comment letter regarding Progenics Pharmaceuticals, Inc.'s PREC14A filed on September 25, 2019. Securities and Exchange Commission.

Shapley, L. S. 1953. A value for n-person games. In *Contributions to the Theory of Games, Vol. II, Annals of Mathematics Studies*, Vol. 28: 307-317. Princeton University Press.

Skinner, A. N. 2024. Subject matter complexity and disclosure channel richness. *The Accounting Review* 99 (1): 393-425.

Yang, Y., Uy, M.C.S. and Huang, A., 2020. Finbert: A pretrained language model for financial communications. arXiv preprint arXiv:2006.08097.

Appendix 1. Variable Definitions

Variable	Definition	Note/Source
Age	Firm age	COMPUSTAT
AI_10K	The sum of sentences that are identified as pertaining to AI divided by the total number of sentences in items 1, 1a, and 7 of firms annual 10-k fillings.	Laughran and McDonald 10-K filings - Author Calculations
AI_CC	The sum of sentences that are identified as pertaining to AI divided by the total number of sentences in the conference call transcripts.	Capital IQ - Author Calculations
AI_Dis_Agg	The sum of AI_10K, AI_CC, and AI_EA.	Author Calculation
AI_DIS_Ind	The total AI disclosure score for each 3-digit SIC industry-year, calculated as the sum of firms' AI disclosures across all three communication channels (earnings announcements, conference call transcripts, and 10-K annual reports) within each industry-year group. This measure captures the overall intensity of AI-related discussions at the industry level.	Author Calculation
AI_EA	The sum of sentences that are identified as pertaining to AI divided by the total number of sentences in earnings announcements at quarterly level. To create an annual measure, we compute the mean of the quarterly ratios for each fiscal year.	WRDS SEC Filings - Author Calculations
AI_Employee (raw)	Total number of employees in AI-related roles at firm-fiscal year level. This includes titles such as “artificial intelligence”, “machine learning”, “data science”, “deep learning”, “computer vision”, “data mining”, “big data”, and “data analytics”. See Appendix 2a for details.	Revelio
AI_Employee (ratio)	The ratio of AI employees to total employees, where total employees is measured as the total number of employees reported in the Revelio dataset.	Revelio
AI_Patent	Ratio of firms’ AI-related patent filings divided by total number of patent filings. If the likelihood that the patent falls into one of the following categories exceeds 50%, we classify the patent as AI-related: AI Hardware, evolutionary computation, knowledge processing, machine learning, natural language processing, planning/control, speech, vision	USPTO Office
AI_Washer	Binary indicator for different corporate communication channels. We define a firm as an AI washer if it frequently mentions AI in its communications (top tercile) but has low actual AI employees (in the low tercile of AI employees) across years from 2016-2023 in our sample. This approach is applied to conference calls (AI_Washer_CC), earnings announcements (AI_Washer_EA), and 10-K filings (AI_Washer_10k). We then create a comprehensive AI washer indicator (AI_Washer) that flags a firm if it is identified as an AI washer in any of these three channels. This method allows	Author Calculation

	us to capture firms that may be overstating their AI involvement relative to their actual AI implementation across various corporate disclosure platforms.	
AI_Washer_Mvs0	An indicator variable that equals one for firms with high AI disclosure (top tercile of either 10-K disclosures, conference calls) and non-zero AI employee (AI_Employee), and 0 otherwise.	Author Calculation
AI_Washer_pure	An indicator variable that equals one if a firm is classified as an AI washer but was not in the high AI disclosure category during 2010-2015, and zero if the firm is classified as an AI washer but was in the high AI disclosure category during 2010-2015.	Author Calculation
AI_Good	An indicator variable that takes a value of 1 if a firm is in the top tercile of AI employee ratio and in the top tercile of at least one disclosure channel (AI_10K, AI_CC, or AI_EA), and 0 otherwise.	Author Calculation
AI_Silent	An indicator variable that takes a value of 1 if a firm is in the bottom tercile of AI employee ratio and in the bottom tercile of at least one disclosure channel (AI_10K, AI_CC, or AI_EA), and 0 otherwise.	Author Calculation
AI_Stealth	An indicator variable that takes a value of 1 if a firm is in the top tercile of AI employee ratio but in the bottom tercile of at least one disclosure channel (AI_10K, AI_CC, or AI_EA), and 0 otherwise.	Author Calculation
AI_Middle	An indicator variable that takes a value of 1 if a firm is in the middle tercile of both AI employee ratio and disclosure channels (AI_10K, AI_CC, or AI_EA), and 0 otherwise.	Author Calculation
BHAR (3m, 6m, 9m, 12m)	Buy-and-hold abnormal return calculated as the return from buying the stock on the earnings announcement date and holding for 3, 6, 9, or 12 month periods minus the return from holding the market index over the same period with daily returns multiplied by *Beta*.	CRSP Daily File
Board_Indep	Board independence is the ratio of the number of independent directors on the board to total board size.	BoardEx
$CAR_{[3day]}$	Cumulative abnormal return calculated as the firm's earnings announcement return minus the value-weighted index return over the same period multiplied by *Beta. Beta* is calculated as the regression coefficient when regressing daily firm returns on the market return over the fiscal year.	CRSP Daily file
CEO_Stock	CEO_STOCK_PCT is the value of CEO stock awards as a percentage of the firm's market value of equity.	Compustat Executive Compensation - Annual Compensation
Dividend	Indicator variable that takes a value of 1 if dividend paid in current period, otherwise 0	COMPUSTAT
Efficiency	Operational Efficiency using Stochastic Frontier Analysis Method (Aigner, Lovell, and Schmidt, 1977; Meeusen and van den Broeck, 1977) Input: Cost of Goods Sold; Net Property, Plant, and Equipment (PP&E); Net	COMPUSTAT

	R&D; Number of Employees Output: Revenue	
HHI_Seg	The Herfindahl-Hirschman Index (HHI) for firm diversification. The HHI is calculated by first dividing each segment's share of the firm's total sales. These shares are then squared and summed across all segments of the firm. The resulting HHI ranges from 0 to 1, with higher values indicating greater concentration and less diversification.	COMPUSTAT
High Disclosure - Few Employees	Indicator variable that takes a value of 1 if the firm is in the top tercile of AI_EA, and the bottom tercile of non-missing AI_Employee.	Author Calculations
High Disclosure - Many Employees	Indicator variable that takes a value of 1 if the firm is in the top tercile of AI_EA, and the top tercile of non-missing AI_Employee.	Author Calculations
Insti_Own	The number of shares owned by institutions divided by the total shares outstanding.	Thomson Reuters Institutional Holdings (13F)
Investment	Fixed investment ratio. Capital expenditure divided by lagged tangible assets.	COMPUSTAT
Leverage	Ratio of total debt divided by total assets.	COMPUSTAT
Low Disclosure - Few Employees	Indicator variable that takes a value of 1 if the firm is in the bottom tercile of AI_EA, and the bottom tercile of non-missing AI_EMPLOYEE.	Author Calculations
Managerial_Ability	Managerial ability.	Demerjian et al., 2012
MTB	Market value of equity divided by book value of equity.	COMPUSTAT
MutualFund	We construct mutual fund ownership using Thomson Reuters S12 holdings data merged with CRSP Mutual Fund Database via MFLINKS identifiers. Holdings are adjusted for stock splits using CRSP adjustment factors. We identify equity funds using Lipper and Strategic Insight objective codes. For each stock-quarter, we calculate the fraction of shares outstanding held by mutual funds. We exclude index funds, international funds, and hybrid funds to focus on actively managed domestic equity funds.	Thomson Reuters S12 holdings and CRSP Mutual Fund Database
N_Analyst	Number of Analysts providing EPS estimates for the firm.	I/B/E/S
Profitability	Operating income before depreciation and amortization divided by total assets at the current period.	COMPUSTAT
R&D	R&D expenditure divided by total assets.	COMPUSTAT
Tangibility	Ratio of net property, plant, and equipment divided by total assets at the current period.	COMPUSTAT
ESG	The combined ESG score.	Refinitiv ESG Database

Appendix 2. Key Variable Constructions
Appendix 2a. AI Employee Construction

We measure AI employees using the comprehensive employment data from Revelio Labs, which sources detailed employment records from professional networking sites (e.g., LinkedIn), job postings, and government records.[25] This data source offers several distinct advantages for identifying AI-related positions. First, unlike traditional employment databases that typically provide aggregate workforce statistics or limited samples, Revelio's data contains granular individual-level employment records with detailed job titles, positions, and standardized job classifications. This granularity enables precise identification of AI-related roles across organizational hierarchies and functional areas. Second, traditional databases often suffer from sparse coverage or selection bias toward specific industries or firm sizes, while Revelio provides extensive coverage across a broad cross-section of firms. This comprehensive coverage allows us to track employment patterns and AI talent deployment across firms of different sizes and industries over fiscal years. Third, the database's standardized job classification system helps address the challenge of inconsistent job titles across firms and over time, providing a more structured and reliable framework for identifying AI-related positions. Fourth, by sourcing from LinkedIn profiles, the data captures real-time changes in employment and job responsibilities, offering a more dynamic and current view of firms' AI talent composition compared to traditional annual reporting or survey-based measures.

In a similar spirit to Babina et al. (2024), we search for AI-related terms (such as "artificial intelligence," "machine learning," "data science," "deep learning," "computer vision," "data mining,", "big data", and "data analytics") in both raw job titles and standardized job

[25]Babina et al (2024) use the resume data from Cognisum.Inc, which is no longer accessible. Barrios (2022), and Ahn, Hoitash, Hoitash, and Krause (2023), Lin et al (2024), Baker et al. (2024), among others, have used Revelio data to study questions related to diversity, accountants, and auditors.

classifications. This dual approach helps mitigate potential measurement errors from job title variations or misclassifications. The raw title search captures the diverse ways firms designate AI roles, while the standardized classification provides a more structured identification framework.

We implement several filtering steps starting with the comprehensive Revelio individual position database (approximately 4 terabytes). After retaining only records with valid firm identifiers globally, the sample is 306,143,646 observations. After removing duplicates and merging with U.S firms with GVKEY or CIK, we obtain 152,623,519 observations. Restricting to our sample period beginning in 2016 yields 90,800,307 observations. Matching to Compustat firm-year shows 124,341 firm-year observations with non-missing total assets from 2016 onwards. Of these Compustat observations, 84,711 firm-years (68.1%) have at least one employee record in Revelio. This comprehensive coverage and detailed classification system allows us to construct a reliable measure of firms' AI human capital intensity, capturing technical and analytical AI roles.

Appendix 2b. Fine-Tuning the FinBERT Model to Classify AI Disclosure

We employ the FinBERT model to identify AI-related corporate disclosures, which offers several distinct advantages in text vectorization and semantic understanding (Yang et al., 2020; Huang et al., 2022). First, while traditional bag-of-words or dictionary-based approaches treat words as independent units, FinBERT employs sophisticated contextual embeddings where each word is represented as a high-dimensional vector that captures its semantic relationship with the surrounding text. This vector representation allows FinBERT to understand that the same word can carry different meanings in different contexts. Second, FinBERT's pre-training on financial texts (corporate 10-K/Q filings, analyst reports, and earnings call transcripts) enables it to learn domain-specific semantic relationships and generate more accurate vector representations of financial terminology. For instance, in vectorizing phrases like "artificial intelligence investment" or "machine learning deployment," FinBERT captures not just the individual word meanings but also their collective implications in a financial context.

Third, FinBERT's transformer architecture enables it to generate contextual embeddings at multiple levels - words, phrases, and entire sentences. This hierarchical representation allows the model to capture both local semantic relationships (within phrases) and broader contextual information (across sentences). Fourth, through its self-attention mechanism, FinBERT can dynamically weigh the importance of different words and phrases in a sentence, creating context-aware vector representations that are particularly effective for identifying AI-related discussions in varied contexts. For example, when analyzing phrases like "investing in intelligence systems," FinBERT can distinguish between general business intelligence and artificial intelligence based on the broader document context.

To fine-tune the FinBERT model for classifying AI-related sentences, we start by collecting corporate disclosures from 10-K filings between 2016 and 2023. Specifically, we extracted sentences from Items 1, 1A, and 7 from firms' Form 10-K filings, as these sections often contain information about a firm's operations, risks, and strategies. Using the NLTK package in Python, we split the documents into individual sentences. Because not all sentences are useful for fine-tuning, we focus on sentences relevant to AI. We use keyword-based filtering to identify sentences containing terms like "machine learning," "data analytics," and "artificial intelligence." Using this process, we extract 640 sentences that contain these terms. To ensure diversity and balance in the dataset, we randomly select an additional 971 sentences, resulting in a total of 1,611 sentences for manual classification.

Each of the 1,611 sentences is manually reviewed and categorized into six categories. AI_Overview discusses general trends or developments in AI. AI_Use describes firms' use of AI without creating AI-related products. AI_Product/Business/Patentable refers to AI-related products, businesses, or patentable technologies developed by the firm. AI_Acquire/Build describes firms acquiring or building AI-related businesses instead of creating them in-house. AI_FLS refers to forward-looking statements about AI-related actions or plans. NON_AI refers to sentences that are unrelated to AI. These categories were not mutually exclusive; a sentence could belong to multiple categories, except for NON_AI, which was exclusive.[26] After classification, the sentences are distributed across the categories as follows: 7% are categorized as AI_Overview, 31% as AI_Use, 25% as AI_Product/Business/Patentable, 3% as AI_Acquire/Build, and 15% as AI_FLS. Overall, 40% of the sentences were AI-related, while 60% were classified as NON_AI. This balanced dataset provides a reasonable input source for fine-tuning the FinBERT model.

We split the human classified dataset into 80% for training, 10% for validation, and 10% for testing. Using the Transformers library from Python, we fine-tune the FinBERT model over 5 epochs, meaning the model passed through the entire training dataset five times. During the training process, raw model predictions are converted to probabilities using the sigmoid function, mapping the outputs to values between 0 and 1. A probability threshold of 0.5 is applied to classify sentences. Probabilities above 0.5 are assigned a label 1 and 0 otherwise. The fine-tuned model achieves a training accuracy of 96%, indicating that it could classify AI-related sentences effectively within the training set. This high accuracy demonstrates that the model successfully learned the patterns in the data.

After fine-tuning, the model can now classify AI-related sentences in corporate disclosures. In our context, we use this fine-tuned FinBERT model to classify sentences that are AI related by applying the model to earnings announcements, conference call transcripts, and Form 10-K annual

[26] See Appendix 2c for examples of sentences in each category.

filings.[27] We calculate AI disclosure scores (AI_CC, AI_10K, AI_EA) on a firm-year basis for each disclosure channel by counting sentences identified as AI-related and dividing by the total number of sentences in the respective disclosure channel.[28][29]

This domain-specific fine-tuning enhances the model's ability to generate precise vector representations of AI-related disclosures across different corporate communication channels. The resulting model can effectively identify and analyze AI-related content in 10-K reports, earnings announcements, and conference call transcripts, providing a more sophisticated and advanced measurement of firms' AI-related communications compared to traditional text analysis methods.

Appendix 2c. Examples of AI-related Sentences

AI_Overview

-Data driven marketing will also leverage the rapidly emerging field of cognitive computing, where computers are becoming intelligent often referred to as artificial intelligence.

-Additionally, several states and localities have enacted measures related to the use of artificial intelligence and machine learning in products and services.

-Every day, the innovations that our people create fuel the data economy, enabling advances in artificial intelligence and 5G applications that unleash opportunities from the data center to the intelligent edge and across the client and mobile user experience.

AI_USE

-We strive to co-innovate with customers by taking the proven concept of machine learning and applying it to their organizational needs.

-With the Accuray-exclusive Synchrony artificial intelligence (AI)-driven tumor tracking with dynamic delivery technology, the CyberKnife platform enables smaller treatment margins around the tumor, minimizing the amount of healthy tissue exposed to high-dose radiation.

AI_Product/Business/Patentable:

-General Ontrak, Inc., we, us or our is an artificial intelligence AI)-powered and telehealth-enabled, virtualized healthcare company, whose mission is to help improve the health and save the lives of as many people as possible.

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[27] For 10-K annual filings, we only extract sentences from item 1, "Business," item 1A, "Risk Factors," and item 7, "Management Discussion and Analysis of Financial Condition and Results of Operations."

[28] Because our AI-related sentences are not mutually exclusive, the AI score for each disclosure channel is calculated as one minus the percentage of sentences that are not AI-related, to avoid double counting.

[29] For AI_CC and AI_EA variables, we calculate firm-level AI scores by averaging the quarterly reports within each fiscal year.

-Our innovative artificial intelligence AI and data analytics solutions continue to gain worldwide awareness and recognition through comparative testing, product demonstrations, media exposure, and word of mouth.

AI_Acquire/Build

-Leveraging proprietary technology and machine learning expertise from our 2021 acquisition of VAY, we are enhancing value within the JRNY platform with these additional capabilities and growing our membership base, which has meaningfully improved the JRNY experience.

-On May 12, 2021, the Company established Future Big Data (Chengdu) Co., Ltd. in Chengdu, China.

AI_FLS

-We anticipate that ISG will benefit from the continued expansion of, and advances in, Artificial Intelligence AI).

-Leveraging proprietary technology and machine learning expertise from our acquisition of VAY, these new features are enhancing value within the JRNY platform, which we believe will continue to drive membership growth.

-It is our believe that Machine-Learning (ML) and Artificial intelligence (AI), lending and insurance underwriting platform would enable a superior loan product with improved economics that can be shared between consumers and lenders.

NON_AI

-The refining and re-refining industries are highly competitive with respect to both feedstock supply and refined/re-refined product markets.

-During the second quarter of 2020, we repaid the 45.0 million in outstanding borrowings, and for the remainder of 2020 and as of December 31, 2020 and 2019 there were no amounts outstanding under the Revolving Facility.

Appendix 3. Sample Selection Process

Selection Criteria	No.of Obs	Unique Firms
1. Raw Compustat data, fiscal years 2016-2023	102795	10519
Less: Duplicate observations, missing total assets/sales, or missing CIK		
2. Clean Compustat sample	57186	9961
Less: Missing annual 10-K filings		
3. Sample with annual 10-K filings	31037	6614
Less: Missing earnings announcements		
4. Sample with earnings announcements	20648	4749
Less: Missing conference call transcripts		
5. Sample with conference calls	16276	3667
Less: Missing employment data/CIK from Revelio		
6. Sample with employment data from Revelio	13885	3069
Less: Missing control variables (Analyst Following, Institutional Ownership, Segment Disclosure)		
7. Final baseline sample	10628	2536

Appendix 4.

Examples of AI patents

- Machine Learning:
  - Qualcomm - https://patents.google.com/patent/US8433665B2/en?oq=8433665
  - Toyota - https://patents.google.com/patent/US8688356B2/en?oq=8688356
- Evolutionary computation:
  - IBM - https://patents.google.com/patent/US9058564B2/en?oq=9058564
  - Adobe - https://patents.google.com/patent/US8014615B2/en?oq=8014615
- Natural language processing:
  - Facebook - https://patents.google.com/patent/US9830386B2/en?oq=9830386
  - Nokia - https://patents.google.com/patent/US9274646B2/en?oq=9274646
- Speech:
  - Apple Inc. - https://patents.google.com/patent/US9582608B2/en?oq=9582608
  - Amazon - https://patents.google.com/patent/US8996372B1/en?oq=8996372
- Vision:
  - Microsoft - https://patents.google.com/patent/US8483436B2/en?oq=8483436
  - Honeywell - https://patents.google.com/patent/US7925117B2/en?oq=7925117
- Knowledge Processing:
  - AT&T - https://patents.google.com/patent/US8892443B2/en?oq=8892443
  - Oracle - https://patents.google.com/patent/US9672080B2/en?oq=9672080
- Planning:
  - Google - https://patents.google.com/patent/US8655901B1/en?oq=8655901
  - Yahoo - https://patents.google.com/patent/US8754848B2/en?oq=8754848
- Hardware:
  - Salesforce - https://patents.google.com/patent/US9471666B2/en?oq=9471666
  - SanDisk - https://patents.google.com/patent/US8848430B2/en?oq=8848430

Figure 1 AI Disclosure Over Time

Figure 1 presents the ratio of AI-related sentences to total sentences across different communication channels (10-K filings, earnings announcements, and conference call transcripts) from 2016 to 2023. All variable definitions are in Appendix A.

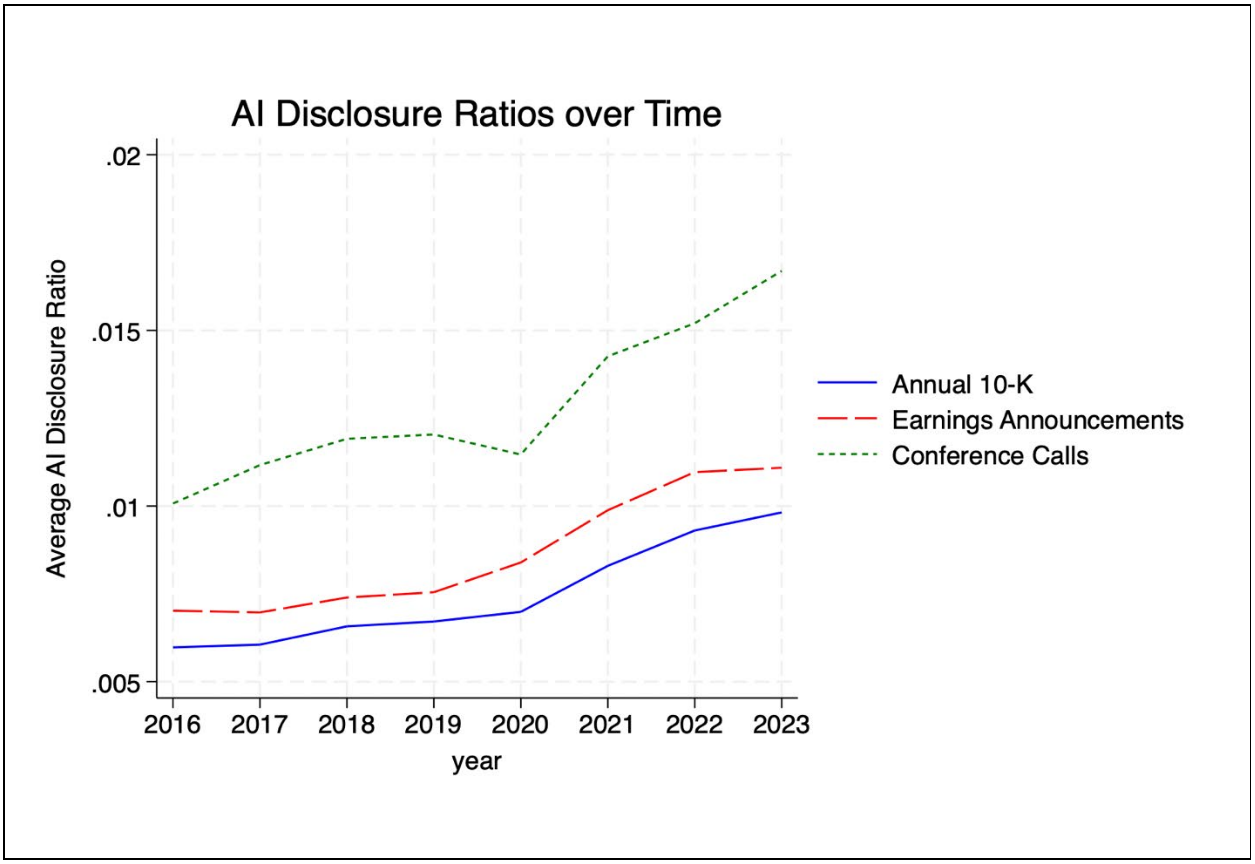


Figure 2.

This figure presents the top AI-related phrases mentioned in all reports (10-K, conference call and earnings announcements) from 2016-2023, comparing their term frequency-inverse document frequency (TF-IDF) scores between AI washers and non-AI washers.

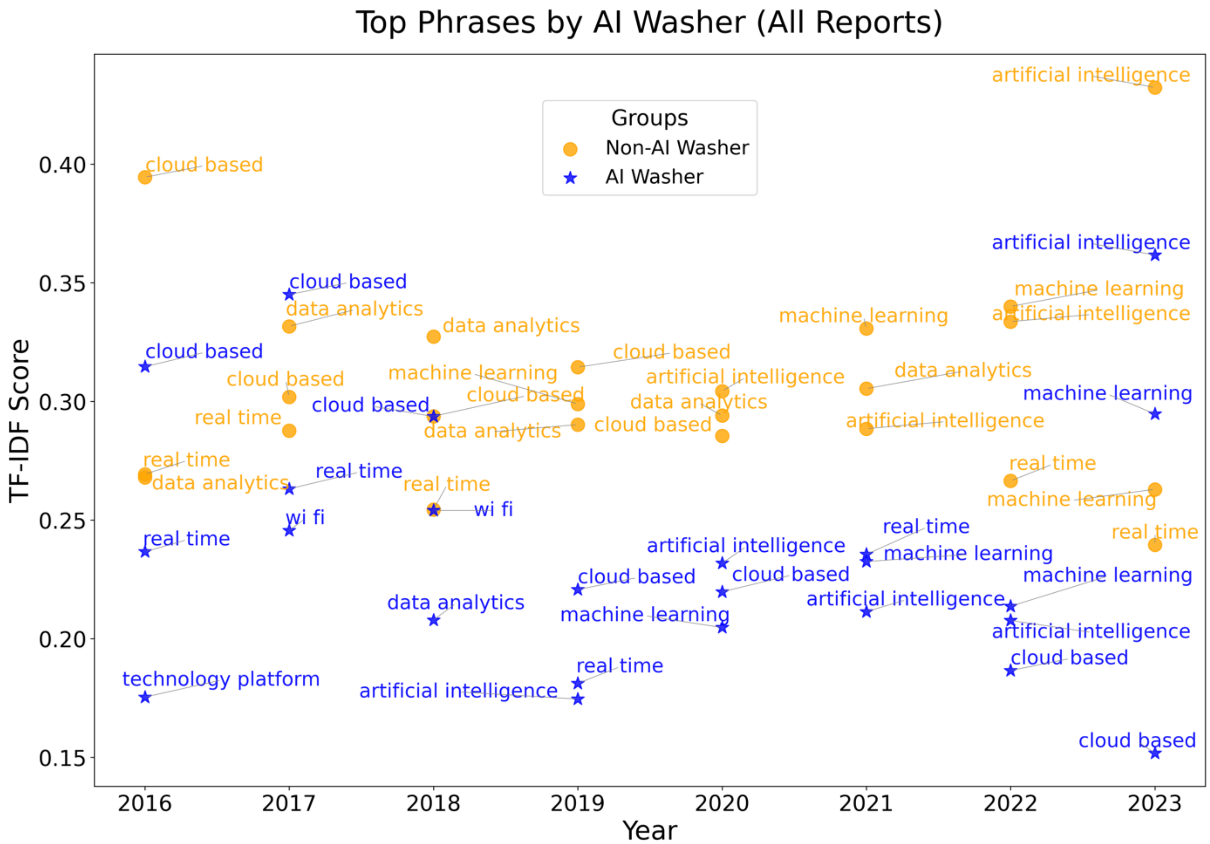
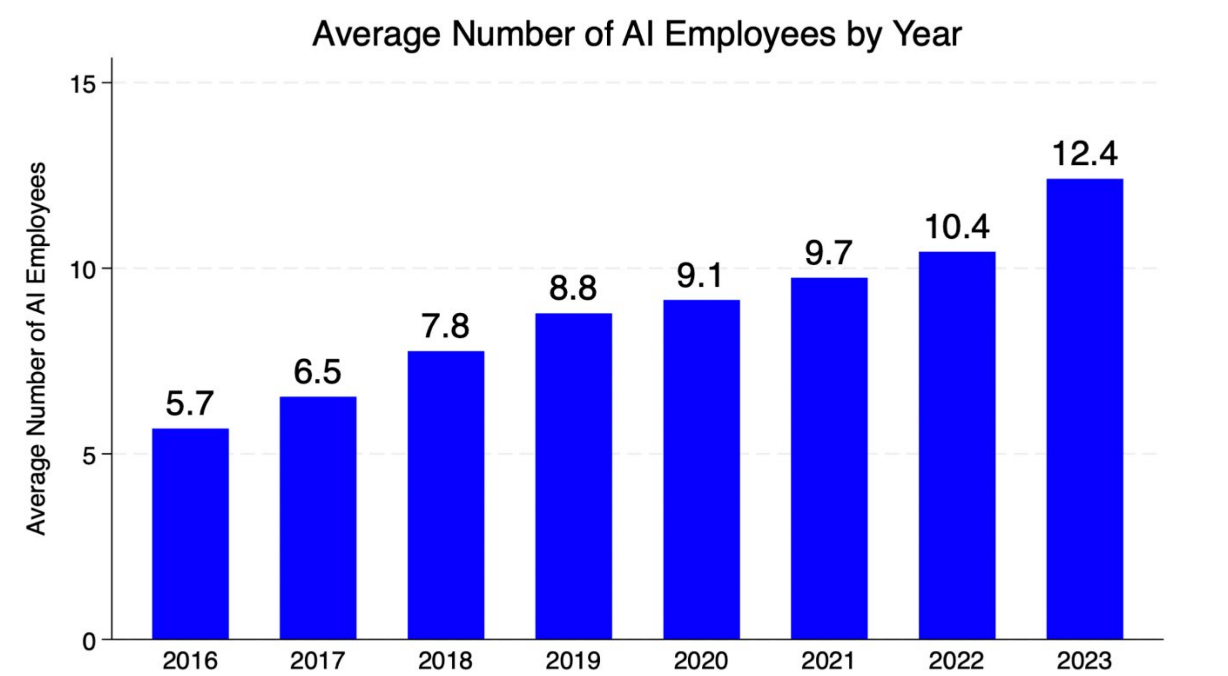


Figure 3 AI Employees

Panel 2a presents the average number of AI employees over the years. Panel 2b presents the ratio of AI employees over the total number of employees over the years. All variable definitions are in Appendix A.

Panel 3a



Panel 3b

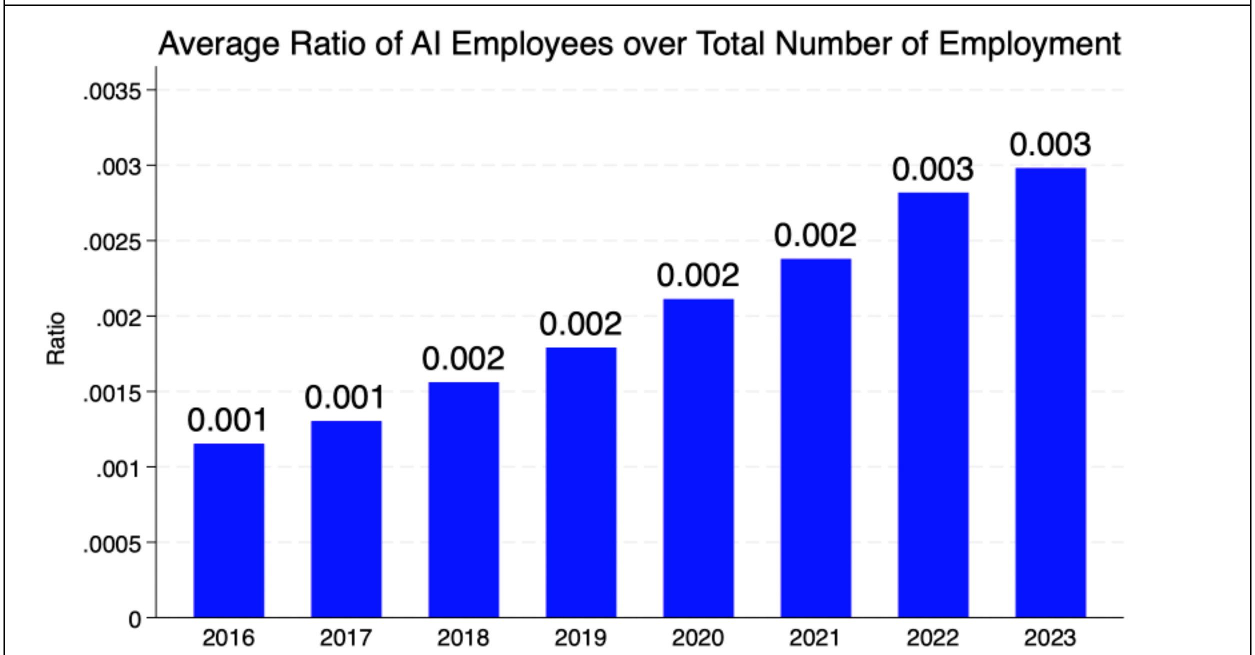


Figure 4

This figure presents Shapley value decomposition comparing the relative contribution (in percentage) of different factors to the R-squared values across four AI-related measures: 10-K disclosures (*AI_10K*), conference call transcripts (*AI_CC*), earnings announcements (*AI_EA*), and AI washing (*AI_Washer*). The analysis includes firm characteristics, information/monitoring environment, managerial factors, litigation risk, industry AI intensity, and fixed effects.

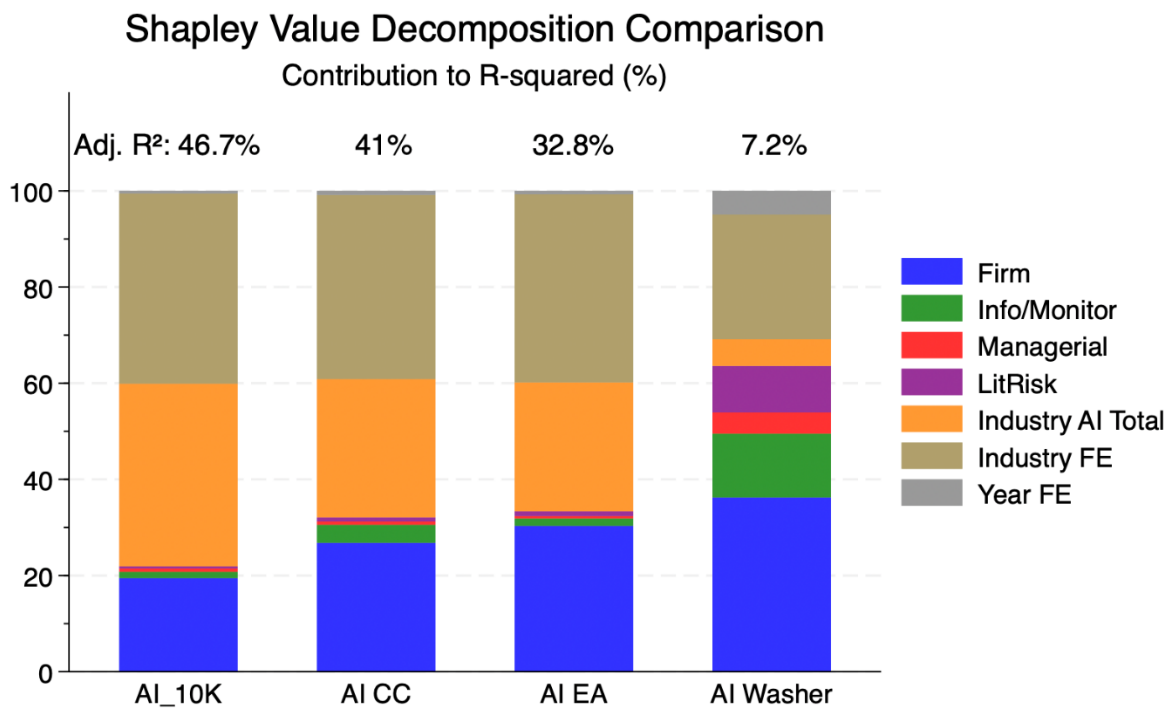


Table 1 Summary Statistics

This panel presents descriptive statistics for the variables used in the main analyses. Our final sample spans 2016-2023. Variable definitions are in Appendix A. All ratio variables are winsorized at the 1% and 99% levels.

Variable	N	Mean	SD	P25	Median	P75
AI_CC	10628	0.015	0.026	0	0.005	0.017
AI_10K	10628	0.011	0.02	0	0.003	0.013
AI_EA	10628	0.011	0.021	0	0	0.012
AI_Employee	10628	13.086	24.948	0	1	11
AI_Emploee(r)	10628	0.002	0.005	0	0	0.003
AI_Employee(log)	10628	1.343	1.547	0	0.693	2.485
AI_Washer	10628	0.144	0.351	0	0	0
AI_Washer_pure	1532	0.425	0.494	0	0	1
AI_Washer_Mvs0	7198	0.21	0.407	0	0	0
R&D	10628	0.066	0.13	0	0.007	0.078
Size	10628	7.196	1.956	5.906	7.223	8.521
HHI_Seg	10628	0.538	0.286	0.324	0.449	0.794
Tangibility	10628	0.455	0.442	0.133	0.303	0.66
Leverage	10628	0.311	0.29	0.106	0.279	0.435
Age	10628	9.817	3.006	8	10	12
Investment	10628	0.286	0.428	0.103	0.18	0.314
CFO	10628	0.021	0.244	0.01	0.071	0.123
Profitability	10628	0.025	0.278	0.012	0.089	0.143
MTB	10628	2.541	2.359	1.238	1.739	2.888
Restatement	10628	0.033	0.178	0	0	0
Volatility	10628	0.032	0.018	0.019	0.028	0.04
N_Analyst	10628	7.399	7.556	2	5	11
MutualFund	10403	0.105	0.078	0.041	0.094	0.155
Insti_Own	10628	0.72	0.273	0.566	0.801	0.922
Board_Indep	8481	0.808	0.102	0.75	0.857	0.875
AI_Dis_Ind	10628	5.07	10.717	0.073	0.406	2.826
Managerial_Ability	9269	-0.008	0.146	-0.098	-0.038	0.041
CEO_Stock	6160	0.001	0.002	0	0.001	0.001
LitRisk	9430	0.058	0.053	0.023	0.041	0.074
Efficiency	10626	0.694	0.132	0.665	0.703	0.758
AI_Patent(r)	4314	0.288	0.359	0	0.1	0.503
Dividend	10628	0.396	0.489	0	0	1

Table 2 Firm AI Disclosures and AI Employment

This table presents the relationship between AI employment and AI disclosures. Panel A reports average AI employee counts across the high and low tercile groups. Panel B shows average AI disclosure (AI_Dis_Agg) scores across the high and low tercile groups. In both panels, 'Difference' represents the mean difference between high and low groups, with corresponding t-statistics. Panel C presents pairwise correlations between AI-related measures, including 10-K filings (AI_10k), conference calls (AI_CC), earnings announcements (AI_EA), and AI employment. Variable definitions are in Appendix A. All ratio variables are winsorized at the 1% and 99% levels.

Panel A. Average AI Employee by Disclosure Tercile

		AI_Dis_Agg				
		Low	Middle	High	Difference (High-Low)	t-stat
AI_Employee	Low	0.018	0.035	0.026	0.008	1.138
	Middle	2.937	3.382	3.627	0.690	4.555
	High	29.290	35.956	42.000	12.710	8.245

Panel B. Average AI Disclosure by Employment Tercile

		AI_Dis_Agg		
		Low	Middle	High
AI_Employee	Low	0.001	0.012	0.072
	Middle	0.002	0.015	0.084
	High	0.002	0.015	0.110
	Difference (High-Low)	0.001	0.002	0.039
	t-stat	8.142	7.170	12.967

Panel C. AI-related Measures Pairwise Correlation Table

Variables	(1)	(2)	(3)	(4)
(1) AI_10k	1.000			
(2) AI_CC	0.727***	1.000		
(3) AI_EA	0.666***	0.715***	1.000	
(4) AI_Employee(raw)	0.314***	0.336***	0.224***	1.000

**** p<0.01, ** p<0.05, * p<0.1*

Table 3 Determinants of Disclosure and Suspected AI Washing

This table reports the results of regressions of the set of AI disclosure and AI_Washer on firm characteristics, including R&D, investment rate, age of the firm, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, industry fixed effect and year fixed effect. Variables employed in this table are standardized. All variables are defined in Appendix A. All ratio variables are winsorized at the 1% and 99% levels. Coefficients on the year indicators are not tabulated for brevity. Robust standard errors (in parentheses) are adjusted for firm clustering. ***, **, and * denoted significance at the 1%, 5%, and 10% levels (two-tailed).

Panel A. Basic Controls

	(1)	(2)	(3)	(4)
VARIABLES	AI_10K	AI_CC	AI_EA	AI_Washer
R&D	0.0012***	0.0028***	0.0021***	-0.0219***
	(0.0004)	(0.0006)	(0.0005)	(0.0079)
Investment	0.0003	0.0007**	0.0007***	-0.0032
	(0.0002)	(0.0003)	(0.0002)	(0.0043)
Age	0.0007*	-0.0008*	-0.0007*	-0.0024
	(0.0003)	(0.0005)	(0.0004)	(0.0063)
Size	-0.0004	-0.0012*	-0.0022***	-0.0961***
	(0.0005)	(0.0006)	(0.0005)	(0.0093)
Profitability	-0.0000	0.0007	-0.0001	-0.0063
	(0.0003)	(0.0005)	(0.0005)	(0.0075)
Tangibility	-0.0022***	-0.0019***	-0.0019***	-0.0173**
	(0.0003)	(0.0004)	(0.0003)	(0.0069)
HHI_Seg	-0.0005	-0.0012***	-0.0004	-0.0018
	(0.0003)	(0.0004)	(0.0003)	(0.0058)
MTB	0.0004	0.0008*	0.0007*	-0.0112**
	(0.0003)	(0.0005)	(0.0004)	(0.0052)
Leverage	-0.0004*	-0.0010***	-0.0006**	-0.0073
	(0.0002)	(0.0003)	(0.0003)	(0.0046)
N_Analyst	0.0018***	0.0038***	0.0024***	-0.0018
	(0.0005)	(0.0006)	(0.0005)	(0.0067)
Insti_Own	-0.0001	0.0002	-0.0008**	-0.0179***
	(0.0003)	(0.0004)	(0.0004)	(0.0059)
AI_Dis_Ind	0.0065***	0.0077***	0.0044***	-0.0721***
	(0.0007)	(0.0010)	(0.0008)	(0.0108)
indd = 2, Consumer Durables	0.0055***	0.0035	0.0048***	0.0943**
	(0.0013)	(0.0022)	(0.0015)	(0.0378)
indd = 3, Manufacturing	0.0040***	0.0010	0.0038***	0.1194***
	(0.0008)	(0.0011)	(0.0009)	(0.0276)
indd = 4, Oil, Gas, and Coal	0.0035***	0.0004	0.0034***	0.0219
	(0.0008)	(0.0012)	(0.0010)	(0.0265)
indd = 5, Chemicals	-0.0000	-0.0031***	0.0007	0.0411
	(0.0006)	(0.0011)	(0.0009)	(0.0305)
indd = 6, Business Equipment	0.0143***	0.0166***	0.0155***	0.2869***
	(0.0014)	(0.0021)	(0.0017)	(0.0341)
indd = 7, Telephone and TV	0.0079***	0.0088***	0.0111***	0.2611***
	(0.0015)	(0.0020)	(0.0022)	(0.0601)
indd = 8, Utilities	0.0033***	0.0036**	0.0067***	0.0564**
	(0.0010)	(0.0015)	(0.0013)	(0.0274)
indd = 9, Retail	0.0023***	0.0029***	0.0028***	0.0714***
	(0.0006)	(0.0010)	(0.0010)	(0.0257)
indd = 10, Healthcare	-0.0032***	-0.0057***	-0.0049***	0.0409
	(0.0007)	(0.0012)	(0.0010)	(0.0266)
indd = 11, Finance	0.0053***	0.0081***	0.0071***	0.0379
	(0.0012)	(0.0019)	(0.0019)	(0.0255)
indd = 12, Other	0.0054***	0.0049***	0.0047***	0.0292
	(0.0009)	(0.0015)	(0.0010)	(0.0243)
Constant	0.0059***	0.0106***	0.0058***	0.0334*
	(0.0005)	(0.0009)	(0.0007)	(0.0202)

Observations	10,628	10,628	10,628	10,628
Adjusted R-squared	0.3949	0.3839	0.3348	0.1431
Year FE	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm

Panel B. Additional Controls

	(1)	(2)	(3)	(4)	(5)
VARIABLES	AI_Washer	AI_Washer	AI_Washer	AI_Washer	AI_Washer
Firm Characteristics					
R&D	-0.0233***				-0.0249
	(0.0080)				(0.0203)
Investment	-0.0031				-0.0082
	(0.0044)				(0.0116)
Age	-0.0029				-0.0114
	(0.0064)				(0.0146)
Size	-0.1039***				-0.1010***
	(0.0076)				(0.0273)
Profitability	-0.0032				0.0040
	(0.0138)				(0.0276)
Tangibility	-0.0154**				-0.0119
	(0.0068)				(0.0097)
HHI_Seg	-0.0028				-0.0050
	(0.0058)				(0.0096)
MTB	-0.0123**				-0.0209***
	(0.0052)				(0.0078)
Leverage	-0.0076				0.0053
	(0.0048)				(0.0071)
CFO	-0.0069				-0.0124
	(0.0137)				(0.0263)
Restatement	-0.0024				-0.0003
	(0.0031)				(0.0038)
Volatility	0.0030				-0.0280***
	(0.0064)				(0.0106)
Info/Monitor					
N_Analyst		-0.0552***			-0.0075
		(0.0053)			(0.0097)
MutualFund		0.0058			0.0060
		(0.0064)			(0.0095)
Insti_Own		-0.0300***			-0.0092
		(0.0078)			(0.0124)
Board_Indep		-0.0001			-0.0001
		(0.0047)			(0.0060)
Managerial Characteristics					
Managerial_Ability			-0.0224***		-0.0034
			(0.0049)		(0.0062)
CEO_Stcok			0.0145**		0.0030
			(0.0064)		(0.0082)
Litigation Risk					
LitRisk				-0.0633***	0.0218**
				(0.0048)	(0.0102)
Constant	0.0709***	0.0674***	0.0654***	0.0521***	0.0814***
	(0.0197)	(0.0193)	(0.0241)	(0.0191)	(0.0259)
Observations	10,649	8,337	5,445	9,448	4,642
Adjusted R-squared	0.1409	0.0889	0.0389	0.0936	0.0718
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Table 4. Efficiency and AI Disclosure, AI Employees, and AI Washing

This table reports regression results examining the relationship between firm efficiency and three key variables—AI disclosures (AI_CC, AI_10K, and AI_EA), AI employees, and AI washing—for the subsequent period. We control for firm characteristics including R&D, investment rate, age of the firm, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, industry fixed effect and year fixed effect. All variables are defined in Appendix A. All ratio variables are winsorized at the 1% and 99% levels. Coefficients on the year and industry indicators are not tabulated for brevity. Robust standard errors (in parentheses) are adjusted for firm clustering. ***, **, and * denoted significance at the 1%, 5%, and 10% levels (two-tailed).

VARIABLES	(1) Efficiency(t+1)	(2) Efficiency(t+1)	(3) Efficiency(t+1)	(4) Efficiency(t+1)	(5) Efficiency(t+1)
AI_10K	0.6114***				
	(0.1522)				
AI_CC		0.6179***			
		(0.0821)			
AI_EA			0.6906***		
			(0.1018)		
AI_Employee(ratio)				1.7757***	
				(0.5242)	
AI_Washer					0.0039
					(0.0054)
R&D	-0.3177***	-0.3245***	-0.3226***	-0.3166***	-0.3113***
	(0.0456)	(0.0455)	(0.0455)	(0.0455)	(0.0456)
Investment	-0.0048	-0.0055	-0.0054	-0.0052	-0.0043
	(0.0060)	(0.0059)	(0.0060)	(0.0060)	(0.0060)
Age	-0.0005	-0.0002	-0.0003	-0.0001	-0.0004
	(0.0010)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Size	-0.0146***	-0.0143***	-0.0140***	-0.0149***	-0.0147***
	(0.0018)	(0.0018)	(0.0018)	(0.0018)	(0.0018)
Profitability	0.0859***	0.0850***	0.0871***	0.0881***	0.0863***
	(0.0228)	(0.0228)	(0.0229)	(0.0231)	(0.0228)
Tangibility	0.0012	0.0008	0.0011	-0.0008	-0.0018
	(0.0054)	(0.0054)	(0.0054)	(0.0054)	(0.0054)
HHI_Seg	-0.0463***	-0.0453***	-0.0466***	-0.0478***	-0.0475***
	(0.0105)	(0.0104)	(0.0104)	(0.0105)	(0.0105)
MTB	0.0043***	0.0043***	0.0042***	0.0043***	0.0044***
	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Leverage	0.0414***	0.0426***	0.0420***	0.0414***	0.0406***
	(0.0127)	(0.0127)	(0.0127)	(0.0128)	(0.0128)
N_Analyst	0.0024***	0.0022***	0.0023***	0.0025***	0.0025***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Insti_Own	0.0118	0.0106	0.0134	0.0096	0.0118
	(0.0089)	(0.0089)	(0.0089)	(0.0089)	(0.0090)
AI_Dis_Ind	0.0026***	0.0025***	0.0027***	0.0028***	0.0030***
	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Constant	0.7852***	0.7802***	0.7781***	0.7840***	0.7858***
	(0.0184)	(0.0181)	(0.0181)	(0.0183)	(0.0185)
Observations	8,558	8,558	8,558	8,558	8,558
Adjusted R-squared	0.2536	0.2572	0.2559	0.2515	0.2485
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Table 5 AI Patent and AI Disclosure, AI Employees, and AI Washing

This table reports regression results examining the relationship between AI patents and three key variables—AI disclosures (AI_CC, AI_10K, and AI_EA), AI employee ratio, and AI washing—for the subsequent period. We control for R&D, investment rate, age of the firm, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, industry fixed effect and year fixed effect. All variables are defined in Appendix A. All ratio variables are winsorized at the 1% and 99% levels. Coefficients on the year and industry indicators are not tabulated for brevity. Robust standard errors (in parentheses) are adjusted for firm clustering. ***, **, and * denoted significance at the 1%, 5%, and 10% levels (two-tailed).

	(1)	(2)	(3)	(4)	(5)
VARIABLES	AI_Patent (t+1)	AI_Patent (t+1)	AI_Patent (t+1)	AI_Patent (t+1)	AI_Patent (t+1)
AI_10K	2.4114***				
	(0.7671)				
AI_CC		1.9372***			
		(0.2924)			
AI_EA			2.0831***		
			(0.3548)		
AI_Employee(ratio)				12.6680***	
				(1.9596)	
AI_Washer					-0.0371**
					(0.0186)
R&D	0.0242	-0.0066	0.0073	-0.0076	0.0134
	(0.0652)	(0.0652)	(0.0653)	(0.0649)	(0.0684)
Investment	0.0188	0.0190	0.0195	0.0168	0.0214
	(0.0135)	(0.0138)	(0.0136)	(0.0138)	(0.0137)
Age	-0.0040	-0.0024	-0.0019	-0.0004	-0.0031
	(0.0029)	(0.0029)	(0.0029)	(0.0028)	(0.0029)
Size	0.0051	0.0061	0.0063	0.0050	-0.0002
	(0.0075)	(0.0073)	(0.0074)	(0.0076)	(0.0076)
Profitability	0.0203	0.0133	0.0219	0.0243	0.0202
	(0.0352)	(0.0354)	(0.0355)	(0.0367)	(0.0368)
Tangibility	-0.0845***	-0.0882***	-0.0906***	-0.0939***	-0.1105***
	(0.0271)	(0.0270)	(0.0272)	(0.0262)	(0.0277)
HHI_Seg	-0.0001	-0.0080	-0.0129	-0.0200	-0.0185
	(0.0301)	(0.0299)	(0.0301)	(0.0302)	(0.0307)
MTB	0.0056**	0.0053**	0.0051**	0.0059***	0.0054**
	(0.0022)	(0.0022)	(0.0022)	(0.0022)	(0.0023)
Leverage	-0.0050	0.0066	0.0035	0.0034	-0.0050
	(0.0262)	(0.0270)	(0.0268)	(0.0259)	(0.0273)
N_Analyst	0.0013	0.0005	0.0012	0.0017	0.0021
	(0.0014)	(0.0014)	(0.0014)	(0.0014)	(0.0014)
Insti_Own	-0.0072	-0.0103	0.0006	-0.0307	-0.0125
	(0.0274)	(0.0270)	(0.0277)	(0.0270)	(0.0281)
AI_Dis_Ind	0.0157***	0.0159***	0.0168***	0.0161***	0.0175***
	(0.0011)	(0.0010)	(0.0009)	(0.0009)	(0.0009)
Constant	0.1412*	0.1232*	0.1136	0.1079	0.2005**
	(0.0767)	(0.0746)	(0.0756)	(0.0746)	(0.0795)
Observations	3,571	3,571	3,571	3,571	3,571
Adjusted R-squared	0.5205	0.5201	0.5168	0.5303	0.5057
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Table 6 Dividend Payout Policy and AI Disclosure, AI Employees, and AI Washing

This table reports regression results examining the relationship between dividend payout policy and three key variables—AI disclosures (AI_CC, AI_10K, and AI_EA), AI employees, and AI washing—for the subsequent period. We control for R&D, investment rate, age of the firm, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, industry fixed effect and year fixed effect. All variables are defined in Appendix A. All ratio variables are winsorized at the 1% and 99% levels. Coefficients on the year and industry indicators are not tabulated for brevity. Robust standard errors (in parentheses) are adjusted for firm clustering. ***, **, and * denoted significance at the 1%, 5%, and 10% levels (two-tailed).

VARIABLES	(1) Dividend (t+1)	(2) Dividend (t+1)	(3) Dividend (t+1)	(4) Dividend (t+1)	(5) Dividend (t+1)
AI_10K	-1.7562***				
	(0.4480)				
AI_CC		-1.8471***			
		(0.3316)			
AI_EA			-2.0155***		
			(0.4167)		
AI_Employee(ratio)				-7.1399***	
				(1.4510)	
AI_Washer					0.0166
					(0.0232)
R&D	0.0197	0.0407	0.0347	0.0241	0.0060
	(0.0660)	(0.0654)	(0.0645)	(0.0662)	(0.0666)
Investment	-0.0205**	-0.0182*	-0.0187*	-0.0187*	-0.0216**
	(0.0104)	(0.0103)	(0.0102)	(0.0103)	(0.0104)
Age	0.0212***	0.0204***	0.0205***	0.0195***	0.0208***
	(0.0028)	(0.0028)	(0.0028)	(0.0028)	(0.0028)
Size	0.1025***	0.1016***	0.1007***	0.1034***	0.1040***
	(0.0076)	(0.0075)	(0.0076)	(0.0075)	(0.0077)
Profitability	0.1300***	0.1332***	0.1268***	0.1237***	0.1293***
	(0.0398)	(0.0397)	(0.0394)	(0.0393)	(0.0401)
Tangibility	0.0313	0.0321	0.0314	0.0357	0.0414
	(0.0289)	(0.0287)	(0.0288)	(0.0288)	(0.0289)
HHI_Seg	-0.0472	-0.0501	-0.0462	-0.0427	-0.0437
	(0.0308)	(0.0307)	(0.0307)	(0.0308)	(0.0308)
MTB	0.0108***	0.0111***	0.0112***	0.0111***	0.0107***
	(0.0036)	(0.0036)	(0.0036)	(0.0036)	(0.0036)
Leverage	-0.0525	-0.0559	-0.0542	-0.0536	-0.0498
	(0.0375)	(0.0373)	(0.0373)	(0.0376)	(0.0377)
N_Analyst	-0.0039**	-0.0033*	-0.0037**	-0.0042**	-0.0043**
	(0.0018)	(0.0018)	(0.0017)	(0.0018)	(0.0018)
Insti_Own	-0.1570***	-0.1535***	-0.1617***	-0.1483***	-0.1551***
	(0.0362)	(0.0361)	(0.0358)	(0.0362)	(0.0364)
AI_Dis_Ind	-0.0028**	-0.0026**	-0.0030**	-0.0031**	-0.0038***
	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0013)
Constant	-0.2621***	-0.2474***	-0.2406***	-0.2544***	-0.2787***
	(0.0760)	(0.0758)	(0.0760)	(0.0758)	(0.0770)
Observations	8,681	8,681	8,681	8,681	8,681
Adjusted R-squared	0.3521	0.3547	0.3537	0.3527	0.3491
Year FE	Yes	Yes	Yes	Yes	Yes

Table 7 Abnormal Returns

This table reports the results of regressions examining the impact of AI disclosures in conference calls and AI employment on firms' stock returns over various time horizons on a quarterly basis. The dependent variables are CAR_3day, BHAR_6m, BHAR_9m, and BHAR_12m, representing 3-day cumulative abnormal returns and 6-month, 9-month, and 12-month buy-and-hold abnormal returns, respectively. All abnormal returns are calculated after subtracting the returns for the firms' size and book-to-market matched portfolios following Daniel et al. (1997). *High Disclosure – Few Employees* is an indicator set to one for firms with high AI-related disclosure (top tercile of AI_CC) and low AI employment (bottom tercile of AI_Employee (i.e., suspected washers) and *High Disclosure – Many Employees* is an indicator set to one for firms with high AI-related disclosure (top tercile of AI_CC) and high AI employment (top tercile of AI_Employee). The reference group includes firms with low AI-related disclosure (bottom tercile of AI_CC) and low AI employment (bottom tercile of AI_Employee). Models include controls for size, book-to-market, and leverage. All variables are defined in Appendix A.

Panel A: Full Sample

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CAR_3day	BHAR_3m	BHAR_6m	BHAR_9m	BHAR_12m
High Disclosure – Few Employees	-0.0004	-0.0000	-0.0023	-0.0010	-0.0029
	(0.0006)	(0.0023)	(0.0030)	(0.0045)	(0.0056)
High Disclosure – Many Employees	0.0003	0.0031*	0.0061***	0.0077**	0.0106**
	(0.0005)	(0.0016)	(0.0023)	(0.0035)	(0.0044)
Observations	18,465	18,162	17,769	17,287	16,473
Adjusted R-squared	0.0750	0.4433	0.6029	0.6386	0.6706
Controls	Yes	Yes	Yes	Yes	Yes
Industry and Year-QTR FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel B: Non-Zero AI Employment

	(1)	(2)	(3)	(4)	(5)
VARIABLES	CAR_3day	BHAR_3m	BHAR_6m	BHAR_9m	BHAR_12m
High Disclosure – Few Employees	-0.0011	-0.0025	-0.0054	-0.0089*	-0.0111*
	(0.0007)	(0.0026)	(0.0037)	(0.0051)	(0.0066)
High Disclosure – Many Employees	-0.0005	0.0048**	0.0084***	0.0131***	0.0149**
	(0.0007)	(0.0022)	(0.0031)	(0.0049)	(0.0062)
Observations	8,741	8,566	8,352	8,103	7,704
Adjusted R-squared	0.0805	0.4419	0.5686	0.6236	0.6535
Controls	Yes	Yes	Yes	Yes	Yes
Industry and Year-QTR FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel C: Bootstrapped Standard Errors

VARIABLES	(1) CAR_3day	(2) BHAR_3m	(3) BHAR_6m	(4) BHAR_9m	(5) BHAR_12m	(6) CAR_3day	(7) BHAR_3m	(8) BHAR_6m	(9) BHAR_9m	(10) BHAR_12m
High Disclosure – Few Employees - Full	-0.0004	-0.0000	-0.0023	-0.0010	-0.0029					
	(0.0006)	(0.0036)	(0.0036)	(0.0045)	(0.0054)					
High Disclosure – Many Employees - Full	0.0003	0.0031**	0.0061**	0.0077***	0.0106***					
	(0.0005)	(0.0016)	(0.0027)	(0.0027)	(0.0039)					
High Disclosure – Few Employees – Non-Zero						-0.0011	-0.0025	-0.0054	-0.0089	-0.0111
						(0.0008)	(0.0027)	(0.0063)	(0.0067)	(0.0068)
High Disclosure – Many Employees – Non-Zero						-0.0005	0.0048**	0.0084	0.0131*	0.0149*
						(0.0007)	(0.0023)	(0.0055)	(0.0075)	(0.0086)
Observations	18,465	18,162	17,769	17,287	16,473	8,741	8,566	8,352	8,103	7,704
Adjusted R-squared	0.0747	0.4430	0.6027	0.6383	0.6703	0.0798	0.4410	0.5662	0.6218	0.6515
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year-Qtr FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Bootstrapped standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Panel D: Fama-MacBeth

VARIABLES	(1) CAR_3day	(2) BHAR_3m	(3) BHAR_6m	(4) BHAR_9m	(5) BHAR_12m	(6) CAR_3day	(7) BHAR_3m	(8) BHAR_6m	(9) BHAR_9m	(10) BHAR_12m
High Disclosure – Few Employees - Full	-0.0006	-0.0013	0.0011	0.0060	0.0041					
	(0.0009)	(0.0033)	(0.0037)	(0.0067)	(0.0068)					
High Disclosure – Many Employees - Full	0.0002	0.0045	0.0090**	0.0162*	0.0165*					
	(0.0007)	(0.0032)	(0.0038)	(0.0085)	(0.0088)					
High Disclosure – Few Employees – Non-Zero						-0.0014	0.0088	0.0016	0.0079	-0.0029
						(0.0014)	(0.0091)	(0.0034)	(0.0117)	(0.0051)
High Disclosure – Many Employees – Non-Zero						0.0004	0.0075**	0.0163*	0.0267*	0.0187**
						(0.0007)	(0.0035)	(0.0086)	(0.0153)	(0.0085)
Observations	18,465	18,162	17,769	17,287	16,473	8,741	8,566	8,352	8,103	7,704
Number of Estimations	32	32	31	30	29	32	32	31	30	29
Adjusted R-squared	0.0171	0.0721	0.1460	0.1710	0.1741	0.0229	0.0870	0.1619	0.1934	0.1663
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Newey-West Standard errors with 4 lags in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Alternative AI Washing Definitions

This table presents robustness tests examining the relationship between AI washing and firm outcomes (efficiency, AI patent ratio, and investment rate). Panel A employs AI_Washer_Mvs0, which defines firms with high AI disclosures but zero AI employees, as opposed to the lowest tercile of AI employees, as suspected AI washers. Panel B uses AI_Washer_pure, which excludes early AI disclosers (2010-2015) from the original AI washer classification. All specifications control for R&D intensity, investment rate, firm age, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, and year and industry fixed effects. All ratio variables are winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A: Alternative AI Washer Many vs 0

	(1)	(2)	(3)
VARIABLES	Efficiency(t+1)	AI_Patent (t+1)	Dividend (t+1)
AI_Washer_Mvs0	-0.0129**	-0.1008***	0.0576**
	(0.0060)	(0.0217)	(0.0274)
Observations	5,744	2,831	5,830
Adjusted R-squared	0.2431	0.5041	0.3770
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Cluster	Firm	Firm	Firm

Panel B: Alternative AI Washer_pure

	(1)	(2)	(3)
VARIABLES	Efficiency(t+1)	AI_Patent (t+1)	Dividend (t+1)
AI_Washer_pure	-0.0276**	-0.0987**	-0.0835
	(0.0126)	(0.0389)	(0.0510)
Observations	1,195	549	1,224
Adjusted R-squared	0.2893	0.2725	0.2855
Controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Cluster	Firm	Firm	Firm

Table 9 ESG Falsification Test

This table examines the relationship between AI-related measures and ESG scores obtained from the Refinitiv database. The dependent variable is ESG score. The key independent variables are AI conference call disclosures (AI_CC), AI disclosures in 10-K filings (AI_10K), AI disclosures in earnings announcements (AI_EA), AI employee ratio (AI_Employee(ratio)), and AI washer status (AI_Washer). All specifications control for R&D intensity, investment rate, firm age, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, and year and industry fixed effects. All ratio variables are winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ESG	ESG	ESG	ESG	ESG
AI_10K	0.3185				
	(0.2706)				
AI_CC		0.0529			
		(0.1911)			
AI_EA			-0.0456		
			(0.2265)		
AI_Employee(ratio)				-1.0044	
				(0.6786)	
AI_Washer					0.0139
					(0.0098)
Observations	8,296	7,512	7,063	7,261	7,295
Adjusted R-squared	0.4080	0.3966	0.4059	0.4102	0.4102
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Table 10. Robustness Tests

This table presents regression results examining the long-term relationship between firm performance measures (efficiency in Panel A, AI patent ratio in Panel B, and dividend payout in Panel C) and AI-related variables (AI disclosures in conference calls, 10-K filings, and earnings announcements, AI employee ratio, and AI washing behavior) for two- and three-year ahead periods. All specifications control for R&D intensity, investment rate, firm age, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, and year and industry fixed effects. All ratio variables are winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Efficiency									
	T+2	T+2	T+2	T+2	T+2	T+3	T+3	T+3	T+3	T+3
AI_10K	0.6386***					0.5676***				
	(0.1625)					(0.1826)				
AI_CC		0.6460***					0.6676***			
		(0.0916)					(0.0899)			
AI_EA			0.6970***					0.7766***		
			(0.1124)					(0.1235)		
AI_EMPLOYEE(ratio)				2.0717***					2.1076***	
				(0.5905)					(0.6245)	
AI_Washer					0.0009					0.0017
					(0.0061)					(0.0062)
Observations	6,672	6,672	6,672	6,672	6,672	5,166	5,166	5,166	5,166	5,166
Adjusted R-squared	0.2514	0.2553	0.2534	0.2499	0.2460	0.2361	0.2414	0.2404	0.2351	0.2314
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Panel B

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	AI_Patent									
VARIABLES	T+2	T+2	T+2	T+2	T+2	T+3	T+3	T+3	T+3	T+3
AI_10K	2.4988***					2.1255**				
	(0.7932)					(0.8361)				
AI_CC		2.1788***					2.0863***			
		(0.3408)					(0.3748)			
AI_EA			2.1030***					2.1497***		
			(0.4078)					(0.4549)		
AI_EMPLOYEE(ratio)				12.8722***					12.5490***	
				(2.2474)					(2.5685)	
AI_Washer					-0.0350*					-0.0471**
					(0.0203)					(0.0223)

Observations	2,841	2,841	2,841	2,841	2,841	2,253	2,253	2,253	2,253	2,253
Adjusted R-squared	0.5279	0.5305	0.5241	0.5374	0.5135	0.5355	0.5397	0.5356	0.5457	0.5256
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Panel C

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
					Dividend					
VARIABLES	T+2	T+2	T+2	T+2	T+2	T+3	T+3	T+3	T+3	T+3
AI_10K	-1.7926***					-1.4828***				
	(0.5046)					(0.5135)				
AI_CC		-2.0628***					-2.1236***			
		(0.3793)					(0.4151)			
AI_EA			-2.3247***					-2.7883***		
			(0.4736)					(0.5259)		
AI_EMPLOYEE(ratio)				-8.5676***					-9.1579***	
				(1.7511)					(1.9994)	
AI_Washer					0.0168					0.0294
					(0.0258)					(0.0280)
Observations	6,768	6,768	6,768	6,768	6,768	5,249	5,249	5,249	5,249	5,249
Adjusted R-squared	0.3468	0.3503	0.3496	0.3484	0.3440	0.3397	0.3441	0.3452	0.3422	0.3380
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm

Table 11. Alternative Partitions of AI Disclosure and AI Employee

This table examines how different AI strategies affect firm performance. We classify firms into categories based on their AI disclosure and employee ratios using terciles of the sample: AI_Good (top tercile in both), AI_Silent (bottom tercile in both), AI_Stealth (top tercile in AI employees, bottom tercile in disclosure), AI Washer (top tercile in disclosure, bottom tercile in AI employee), and AI_Middle (middle tercile in both). Panel A reports results for efficiency, Panel B for AI patent ratio, and Panel C for dividend payout. All specifications control for R&D intensity, investment rate, firm age, firm size, profitability, tangibility, concentration of operation, Market-to-book ratio, leverage ratio, analyst following, institutional ownership, industry level AI disclosure, and year and industry fixed effects. All ratio variables are winsorized at the 1% and 99% levels. Standard errors reported in parentheses are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Panel A AI and Efficiency

VARIABLES	(1) Efficiency(t+1)	(2) Efficiency(t+1)	(3) Efficiency(t+1)	(4) Efficiency(t+1)	(5) Efficiency(t+1)
AI_Good	0.0201***				
	(0.0043)				
AI_Middle		-0.0071			
		(0.0053)			
AI_Stealh			0.0053		
			(0.0044)		
AI_Washer				0.0039	
				(0.0054)	
AI_Silent					-0.0229***
					(0.0046)
Constant	0.7904***	0.7865***	0.7885***	0.7841***	0.8108***
	(0.0165)	(0.0163)	(0.0165)	(0.0165)	(0.0179)
Observations	8,558	8,558	8,558	8,558	8,558
Adj. R^2	0.2513	0.2487	0.2486	0.2485	0.2536
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Panel B AI and AI_Patent

VARIABLES	(1) AI_Patent (t+1)	(2) AI_Patent (t+1)	(3) AI_Patent (t+1)	(4) AI_Patent (t+1)	(5) AI_Patent (t+1)
AI_Good	0.1375***				
	(0.0207)				
AI_Middle		-0.0237			
		(0.0175)			
AI_Stealh			0.0086		
			(0.0180)		
AI_Washer				-0.0371**	
				(0.0186)	
AI_Silent					-0.1391***
					(0.0164)
Observations	3,571	3,571	3,571	3,571	3,571
Adj. R^2	0.5248	0.5049	0.5046	0.5057	0.5253
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Panel C AI and Dividend Payout Policy

	(1)	(2)	(3)	(4)	(5)

VARIABLES	Dividend (t+1)	Dividend (t+1)	Dividend (t+1)	Dividend (t+1)	Dividend (t+1)
AI_Good	-0.0820***				
	(0.0225)				
AI_Middle		-0.0211			
		(0.0227)			
AI_Stealh			0.0303		
			(0.0240)		
AI_Washer				0.0166	
				(0.0232)	
AI_Silent					0.0538***
					(0.0188)
Observations	8,681	8,681	8,681	8,681	8,681
Adj. R^2	0.3524	0.3492	0.3494	0.3491	0.3511
Controls	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Table 12 Hazard Survival Model

Panel A presents the lifecycle table for AI washers from 2010 to 2023. Time (Year) represents the duration a firm maintains its AI washing status. AI_Washer at Risk indicates the number of firms that remain as AI washers at the beginning of each year. AI_Washer (Exit) shows the number of firms that exit AI washer status during that year. Censored represents the number of firms that drop out of the sample due to delisting, merger, or reaching the end of the sample period. Survival Rate indicates the Kaplan-Meier estimate of the probability of remaining an AI washer. The 95% confidence intervals and standard errors for the survival rates are reported in the last three columns. Panel B reports Cox proportional hazard model estimates for the probability of firms exiting AI washing status. The model includes firm-level controls, year and industry fixed effects, with firm-clustered standard errors reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A. AI Washer Lifecycle

Time	AI_Washer at Risk	AI_Washer (Exit)	Censored	Survival Rate	std. error	95% Confidence Interval	
1	902	351	87	0.6109	0.0162	0.5782	0.6418
2	464	109	46	0.4674	0.0173	0.4331	0.5008
3	309	65	18	0.3691	0.0174	0.3349	0.4032
4	226	39	22	0.3054	0.0171	0.2721	0.3392
5	165	34	14	0.2424	0.0167	0.2105	0.2757
6	117	22	14	0.1969	0.0161	0.1663	0.2294
7	81	21	12	0.1458	0.0153	0.1173	0.1772
8	48	9	6	0.1185	0.0149	0.0912	0.1495
9	33	7	3	0.0933	0.0145	0.0675	0.1241
10	23	6	4	0.069	0.0137	0.0454	0.0991
11	13	2	3	0.0584	0.0135	0.0357	0.0887
12	8	2	4	0.0438	0.0135	0.0225	0.0758
13	2	0	1	0.0438	0.0135	0.0225	0.0758
14	1	0	1	0.0438	0.0135	0.0225	0.0758

Panel B. Survival Analysis

	(1)
VARIABLES	Prob(ExitAI_Washer)
R&D	0.756
	(0.354)
Investment	0.975
	(0.0791)
Age	0.754***
	(0.0121)
Size	1.097**
	(0.0402)
Profitability	0.990
	(0.161)
Tangibility	1.040
	(0.122)
HHI_Seg	1.608***
	(0.245)
MTB	1.013
	(0.0165)
Leverage	1.080
	(0.161)
N_Analyst	1.015*
	(0.00893)
Insti_Own	0.408***
	(0.0664)
AI_Dis_Ind	0.997
	(0.00613)
Constant	0.684
	(0.226)
Observations	1,194
Industry FE	Yes

Online Appendix

Figure 1

This figure presents the top AI-related phrases mentioned in 10-K (1a), conference call (1b), and earnings announcements (1c) from 2016-2023, comparing their term frequency-inverse document frequency (TF-IDF) scores between AI washers and non-AI washers.

Figure 1a

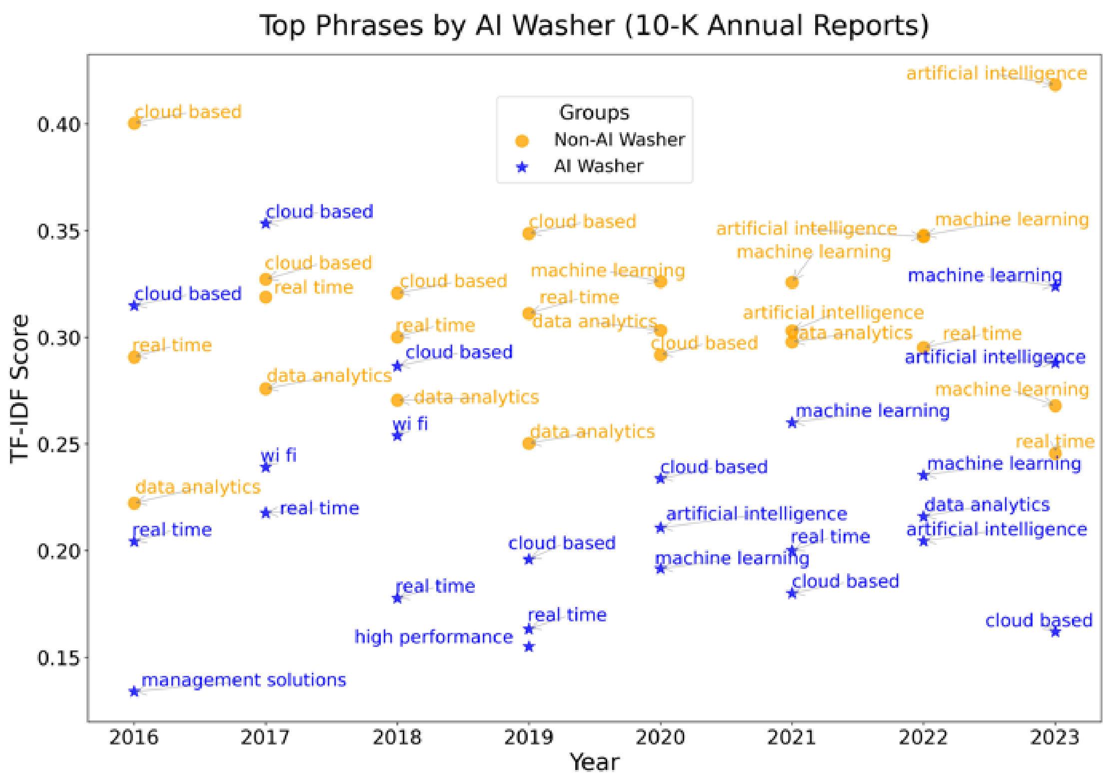


Figure 1b

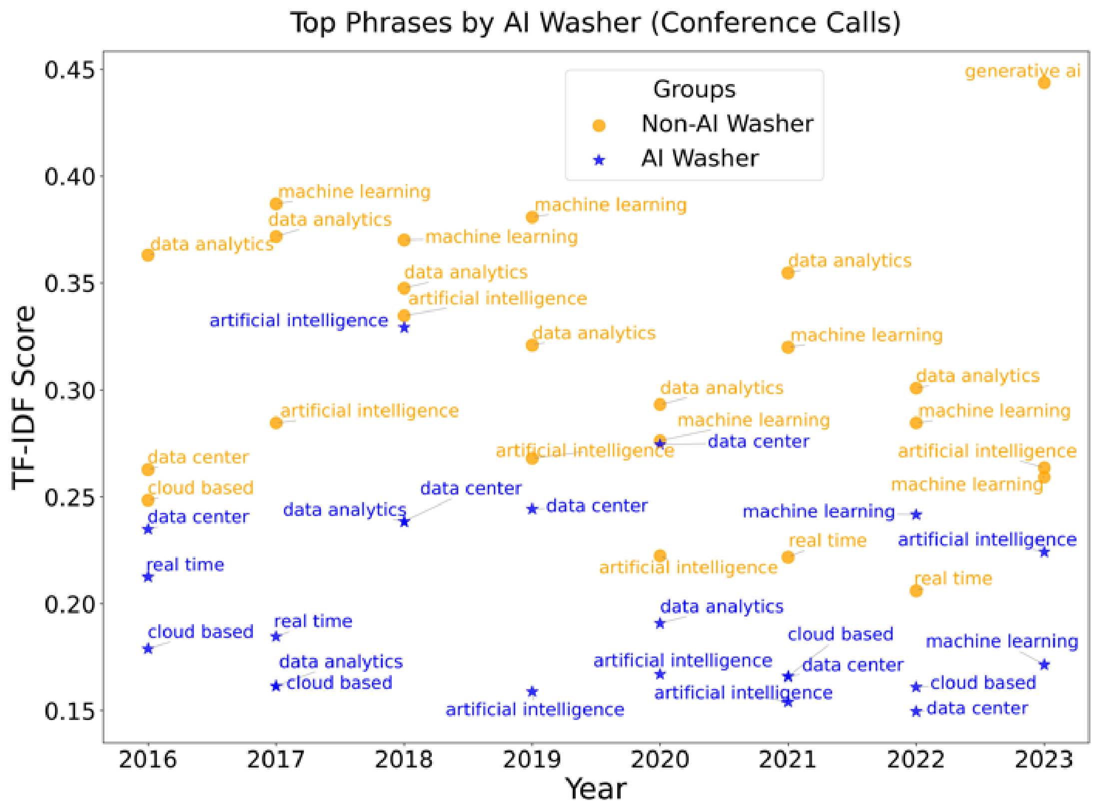
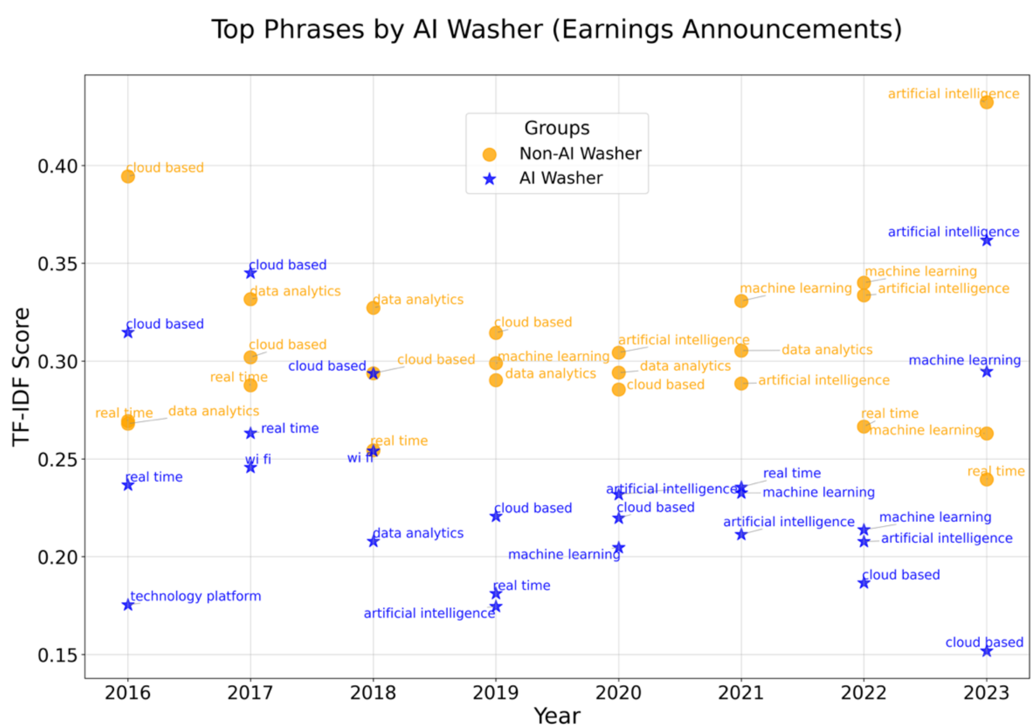


Figure 1c



OA Table 1. Dynamic Regressions with Lagged Dependent Variables

Panel A. AI measures and Efficiency (t+1)

VARIABLES	(1) Efficiency(t+1)	(2) Efficiency(t+1)	(3) Efficiency(t+1)	(4) Efficiency(t+1)	(5) Efficiency(t+1)
Efficiency	0.7905***	0.7889***	0.7898***	0.7917***	0.7922***
	(0.0198)	(0.0199)	(0.0198)	(0.0198)	(0.0197)
AI_10K	0.1377***				
	(0.0416)				
AI_CC		0.1718***			
		(0.0331)			
AI_EA			0.1530***		
			(0.0374)		
AI_EMPLOYEE(ratio)				0.1680	
				(0.2677)	
AI_Washer					-0.0002
					(0.0024)
R&D	-0.1303***	-0.1328***	-0.1315***	-0.1291***	-0.1286***
	(0.0212)	(0.0214)	(0.0213)	(0.0213)	(0.0211)
Investment	-0.0015	-0.0017	-0.0016	-0.0014	-0.0014
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Age	0.0018***	0.0018***	0.0018***	0.0018***	0.0018***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Size	-0.0021***	-0.0020**	-0.0020**	-0.0021***	-0.0021***
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Profitability	-0.0461***	-0.0461***	-0.0457***	-0.0460***	-0.0463***
	(0.0096)	(0.0096)	(0.0096)	(0.0096)	(0.0096)
Tangibility	0.0020	0.0021	0.0020	0.0014	0.0013
	(0.0027)	(0.0027)	(0.0027)	(0.0027)	(0.0027)
HHI_Seg	0.0061	0.0063	0.0060	0.0059	0.0059
	(0.0047)	(0.0047)	(0.0047)	(0.0047)	(0.0047)
MTB	0.0014*	0.0014	0.0014	0.0014*	0.0014*
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Leverage	0.0130**	0.0134**	0.0132**	0.0128**	0.0127*
	(0.0065)	(0.0066)	(0.0065)	(0.0065)	(0.0065)
N_Analyst	0.0006***	0.0005***	0.0006***	0.0006***	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Insti_Own	0.0073*	0.0070*	0.0076*	0.0070*	0.0072*
	(0.0040)	(0.0040)	(0.0040)	(0.0040)	(0.0040)
AI_Dis_Ind	0.0005***	0.0005***	0.0006***	0.0006***	0.0006***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)

Constant	0.1299***	0.1297***	0.1290***	0.1292***	0.1292***
	(0.0165)	(0.0165)	(0.0164)	(0.0165)	(0.0166)
Observations	8,558	8,558	8,558	8,558	8,558
Adjusted R-squared	0.6788	0.6792	0.6789	0.6785	0.6785
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Panel B.

	(1)	(2)	(3)	(4)	(5)
VARIABLES	AI_Patent(t+1)	AI_Patent(t+1)	AI_Patent(t+1)	AI_Patent(t+1)	AI_Patent(t+1)
AI_Patent	0.6539***	0.6535***	0.6570***	0.6463***	0.6658***
	(0.0301)	(0.0296)	(0.0296)	(0.0309)	(0.0290)
AI_10K	0.8094***				
	(0.2961)				
AI_CC		0.7141***			
		(0.1415)			
AI_EA			0.6912***		
			(0.1747)		
AI_EMPLOYEE(ratio)				4.7291***	
				(1.0524)	
AI_Washer					-0.0045
					(0.0101)
	(0.0309)	(0.0309)	(0.0309)	(0.0308)	(0.0313)
Investment	0.0080	0.0082	0.0083	0.0068	0.0092
	(0.0098)	(0.0099)	(0.0098)	(0.0099)	(0.0098)
Age	-0.0016	-0.0010	-0.0008	-0.0002	-0.0012
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Size	0.0018	0.0023	0.0020	0.0017	0.0003
	(0.0033)	(0.0033)	(0.0033)	(0.0034)	(0.0033)
Profitability	0.0045	0.0012	0.0050	0.0022	0.0042
	(0.0172)	(0.0174)	(0.0172)	(0.0178)	(0.0173)
Tangibility	-0.0340***	-0.0347***	-0.0357***	-0.0373***	-0.0418***
	(0.0120)	(0.0121)	(0.0120)	(0.0119)	(0.0121)
HHI_Seg	-0.0029	-0.0058	-0.0076	-0.0111	-0.0091
	(0.0164)	(0.0162)	(0.0162)	(0.0163)	(0.0162)
MTB	0.0020*	0.0019	0.0018	0.0022*	0.0018
	(0.0011)	(0.0012)	(0.0011)	(0.0012)	(0.0012)
Leverage	-0.0025	0.0018	0.0006	-0.0000	-0.0023
	(0.0125)	(0.0129)	(0.0128)	(0.0127)	(0.0128)
N_Analyst	0.0003	0.0000	0.0003	0.0006	0.0006

	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Insti_Own	0.0046	0.0034	0.0078	-0.0033	0.0041
	(0.0138)	(0.0137)	(0.0139)	(0.0139)	(0.0140)
AI_Dis_Ind	0.0054***	0.0055***	0.0058***	0.0057***	0.0059***
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Constant	0.0397	0.0321	0.0297	0.0264	0.0540
	(0.0353)	(0.0350)	(0.0351)	(0.0347)	(0.0365)
Observations	3,133	3,133	3,133	3,133	3,133
Adjusted R-squared	0.7538	0.7541	0.7533	0.7554	0.7519
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm

Panel C

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Dividend(t+1)	Dividend(t+1)	Dividend(t+1)	Dividend(t+1)	Dividend(t+1)
Dividend	0.9059***	0.9052***	0.9057***	0.9058***	0.9065***
	(0.0072)	(0.0072)	(0.0072)	(0.0072)	(0.0071)
AI_10K	-0.2536***				
	(0.0949)				
AI_CC		-0.3183***			
		(0.0799)			
AI_EA			-0.2495***		
			(0.0759)		
AI_EMPLOYEE(ratio)				-0.9635***	
				(0.3536)	
AI_Washer					0.0032
					(0.0050)
R&D	0.0229	0.0270*	0.0244*	0.0234*	0.0211
	(0.0141)	(0.0143)	(0.0142)	(0.0142)	(0.0141)
Investment	0.0007	0.0011	0.0009	0.0009	0.0005
	(0.0038)	(0.0038)	(0.0038)	(0.0038)	(0.0038)
Age	0.0023***	0.0022***	0.0022***	0.0021***	0.0022***
	(0.0008)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Size	0.0103***	0.0102***	0.0101***	0.0105***	0.0105***
	(0.0019)	(0.0019)	(0.0019)	(0.0019)	(0.0019)
Profitability	0.0306***	0.0313***	0.0302***	0.0297***	0.0304***
	(0.0097)	(0.0098)	(0.0097)	(0.0097)	(0.0097)
Tangibility	-0.0012	-0.0013	-0.0010	-0.0005	0.0002
	(0.0062)	(0.0062)	(0.0062)	(0.0062)	(0.0062)
HHI_Seg	0.0069	0.0063	0.0071	0.0076	0.0075
	(0.0066)	(0.0066)	(0.0066)	(0.0066)	(0.0066)

MTB	0.0017**	0.0018**	0.0018**	0.0018**	0.0017**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)
Leverage	-0.0151**	-0.0157**	-0.0152**	-0.0152**	-0.0146**
	(0.0064)	(0.0065)	(0.0064)	(0.0064)	(0.0064)
N_Analyst	-0.0003	-0.0002	-0.0003	-0.0003	-0.0003
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Insti_Own	-0.0178**	-0.0174**	-0.0184**	-0.0166**	-0.0174**
	(0.0080)	(0.0080)	(0.0080)	(0.0080)	(0.0080)
AI_Dis_Ind	-0.0001	-0.0001	-0.0002	-0.0002	-0.0003
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Constant	-0.0461***	-0.0435***	-0.0436***	-0.0451***	-0.0487***
	(0.0150)	(0.0150)	(0.0150)	(0.0150)	(0.0153)
Observations	8,681	8,681	8,681	8,681	8,681
Adjusted R-squared	0.8834	0.8835	0.8834	0.8834	0.8834
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes
Cluster	Firm	Firm	Firm	Firm	Firm