Caught up in the AI rat race: Does technological peer pressure fuel AI washing or hushing?

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ABSTRACT

The SEC has cautioned public firms against artificial intelligence (AI) washing—overstating AI investments in corporate disclosures. Legal experts expect AI washing to increase as firms face intensified competitive pressures to deploy AI, but disclosure theory suggests competition may instead lead to AI hushing—understating AI investments in disclosures—due to proprietary cost concerns. My paper examines whether technological peer pressure (TPP) fuels AI washing or hushing. Using a word embedding machine learning model, I construct AI and investment dictionaries, and measure AI washing or hushing as the difference between a firm's decile rank in retrospective AI investment discussions (from annual reports or earnings calls) and its decile rank in actual AI investment among peer firms in a year. To mitigate endogeneity, I exploit a plausibly exogenous increase in peers' R&D intensity to capture a focal firm's TPP. I find that TPP induces AI washing, particularly among firms that opportunistically overstate AI investment, benefit more from capital market rewards, or gain strategic competition advantages from inflated disclosure. Overall, my findings shed light on how technological competition affects the *discordance* between corporate AI use disclosure and investment, highlighting a pressing regulatory concern given the SEC's mandate to ensure full, fair, and truthful disclosures for efficient capital allocation.

Keywords: technological peer pressure; technological competition; AI washing; AI hushing; disclosure of AI investment; actual AI investment; proprietary disclosure costs; AI-skilled employees; managers; AI-related patents.

Data Availability: Data are available from the public sources identified in the text.

1. Introduction

As a general-purpose technology, artificial intelligence (AI) has been heralded as the most transformative technology in business today, poised to revolutionize business models, improve business decision-making, drive product innovation, and reshape competitive landscapes (Agrawal et al. 2018; Babina et al. 2024). Firms that identify and venture into AI-driven opportunities at breakneck speed can secure first-mover competitive advantages over their peers (Brynjolfsson and McAfee 2017). Indeed, a hallmark of today's AI landscape is the unprecedented *technological peer pressure* (hereafter TPP) that firms face. McKinsey Global Institute projects that around 70% of firms will invest in some AI technologies by 2030, driven primarily by the imperative to remain technologically competitive. However, this fierce rat race for AI adoption may have led to the pressing issue of AI washing among public firms, as cautioned by former SEC Chair Gary Gensler, where companies over-hype their AI capabilities in public disclosures.[1] "In essence, they should say what they're doing, and do what they're saying," about firms' AI investments, Gensler stated.

Legal experts anticipate a rise in AI washing as companies grapple with mounting competitive pressures to deploy AI (Veronica et al. 2024). In response to TPP, laggard firms (those lagging in AI investment) may resort to AI washing to appear more technologically advanced and stand out. Meanwhile, frontrunner firms (those leading in AI investment) might do so to steer evolving AI industry standards towards their competencies, making it more difficult for swiftly advancing laggards to catch up; they may also aim to signal their AI efficiency gains to deter potential entrants. However, AI washing is not a panacea for achieving long-term competitive

[1] In a public speech on March 18, 2024, former SEC Chair Gary Gensler warned against corporate AI washing, emphasizing that public firms must accurately disclose their AI investment in business operations. Gensler also emphasizes that public companies must have a reasonable basis for their AI-related claims and disclose specific risks associated with their AI use. See https://www.sec.gov/newsroom/speeches-statements/sec-chair-gary-gensler-ai-washing.

advantages. There would be a "settling up" in the future once stakeholders realize that AI use disclosures were exaggerated, leading to reputation loss; and the SEC has recently initiated an "agency crackdown" on AI washing.[2] A countervailing line of research suggests that TPP instead might result in AI hushing, where firms disclose AI initiatives less than their actual investments. This may occur because TPP can suppress disclosure due to proprietary cost concerns (e.g., Cao et al. 2018; Glaeser and Landsman 2021), while competitive peer pressure spurs corporate AI investments (Bughin and Seong 2018). I seek to reconcile this conceptual tension by testing whether TPP is more likely to fuel AI washing or hushing. Probing this inquiry carries significant policy implications: TPP-induced distortions in AI use disclosures—whether through exaggeration or concealment—risk misallocating resources in capital markets. This poses a crucial concern for the SEC, mandated to ensure investors make informed decisions based on "full, fair, and truthful disclosure" (Gensler 2024). Addressing TPP-induced distortions in AI reporting is thus essential for safeguarding market efficiency and ensuring that capital flows to genuine innovative firms.

While competition is inherently multidimensional (Cao et al. 2018; Glaeser and Landsman 2021), I center on its technological dimension because technological advancement has long been recognized as the linchpin for U.S. economic growth (Solow 1956, 1957; Kogan et al. 2017), and because in today's knowledge-based economy, companies must continually accumulate technological capabilities, especially in AI. TPP increases corporate AI investments by creating a "survival of the fittest" environment where firms feel compelled to keep pace with their rivals' technological advancements. As firms observe their peers integrating AI into their operations, they face escalating pressures to follow suit, fearing the loss of competitive edge. Bughin and Seong (2018) note that "[t]he econometrics demonstrate that peer competitive pressure is the *largest*

[2] On March 18, 2024, the SEC took enforcement actions against two investment advisers, Delphia (USA) Inc. and Global Predictions Inc., for overstating their alleged use of AI in providing investment advice (Vanderford 2023).

influencer of the decision to adopt AI and make it work across all enterprise functions" (emphasis added). Weil (2023), in a survey of AI disclosures, similarly concludes that "[m]any companies recognized the *imperative* of evolving with rapid advancements in AI in order to remain competitive" (emphasis added). Given that TPP stimulates AI investment, I posit that TPP's impact on AI washing or hushing hinges on its differential impact on AI use disclosure. Regarding making voluntary AI use disclosure decisions, managers tradeoff equity valuation and strategic competition benefits against proprietary costs.

When TPP heats up, it can drive firms into three discordance equilibria, where AI use disclosure diverges from actual AI investment. First, if firms perceive that the valuation and strategic benefits of AI use disclosure outweigh proprietary costs, TPP may stimulate firms to overstate their AI investment, i.e., AI washing. This overstatement is facilitated by the complex, intangible, and rapidly evolving nature of AI, combined with its definitional ambiguity, which makes it costly for uninformed outsiders to verify actual AI investment level.[3] Such information asymmetry creates fertile ground for opportunistic managers to overstate AI investment, consistent with self-justification theory (Festinger 1962; Aronson 1995).[4] To reduce cognitive dissonance, managers may rationalize their AI washing as a strategic move—believing that overstating AI capabilities will help attract capital, which could eventually enable them to catch up and fulfill their previously exaggerated claims. Second, if valuation and strategic benefits outweigh

[3] GPT models epitomize the rapid evolution and complexity of AI technology. From GPT-1's 117 *million* parameters in 2018 to GPT-3's "staggering" 175 *billion* parameters in 2020, GPT model complexity increased exponentially, with a leap from simple word prediction to generating human-like text and code (emphasis added). Just three years later, in 2023, GPT-4 pushed boundaries even further (though its number of parameters was undisclosed), offering enhanced accuracy, smarter responses, and real-time internet search capabilities (Marr 2023). Compounding this technical complexity, AI's broad and nebulous definition across diverse technologies enables firms to strategically manipulate its meaning to capitalize on its popularity (Lutkevich 2024).

[4] Self-justification theory, rooted in Festinger's (1962) cognitive dissonance framework and further developed by Aronson (1969), suggests that individuals rationalize their beliefs and actions when faced with cognitive dissonance. In managerial decision-making, this can lead to an escalation of unethical behavior as managers rationalize questionable actions to maintain consistency with prior decisions (Lowell 2012).

proprietary costs but managerial concerns about protecting proprietary advantages remain salient, firms may increase disclosure but still below their increased AI investment. In this scenario, AI hushing results. Third, if proprietary disclosure costs outweigh valuation and strategic benefits, TPP will drive firms to disclose less AI use. Since TPP increases firms' AI investments but decreases AI use disclosure, AI hushing still results.

Following Cao et al. (2018), I measure TPP as the ratio of competitors' R&D stock (weighted by their proximity in the product market space) to a focal firm's own R&D stock, where R&D stock is defined as the accumulated value of R&D expenditures over the past five years. The idea is that a firm's perceived technological competition threats stem from its rivals' technological advancements, measured by these rivals' greater R&D investments (Bloom et al. 2013).

In the spirit of Baker et al. (2024),[5] I develop a novel measure to calibrate the degree of *discordance* between a firm's AI use disclosure and its actual investment, i.e., AI washing or AI hushing. I calculate this measure as the difference between a firm's two decile ranks among its peer firms in a year: (1) its rank of disclosed retrospective AI investment discussions and (2) its rank of actual AI investment. The core premise is that a firm's disclosed level of AI investment should reasonably align with its actual AI investment; therefore, a positive (negative) value of this measure indicates AI washing (hushing). To systematically construct AI- and investment-related dictionaries, I employ a word-embedding machine learning model (Li et al. 2021) that starts with unambiguous seed terms and expands to capture semantically similar terms. I measure AI use disclosure as the ratio of the weighted-frequency count of AI-related terms to total count of terms in the *retrospective investment* discussions from annual reports or earnings calls. I measure AI

[5] Baker et al. (2024) construct a firm-specific measure to identify diversity washing or hiding by comparing a firm's underlying diversity level with the relative amount of diversity, equity, and inclusion (DEI) discussion in its disclosures in a year. A firm engages in diversity washing (hiding) if its actual diversity level is less (more) than the relative amount of DEI discussion in its disclosures.

investment using the proportion of AI-skilled employees based on granular LinkedIn dataset of 23 million non-internship; this measure is grounded in the idea that firms' AI investments heavily depend on AI-skilled labor to develop, implement, and maintain; as such, more AI-skilled labor indicates greater AI investment level (Babina et al. 2024).

I begin by validating my discordance measure through three empirical tests. First, I show that a hedge portfolio strategy—long in the lowest decile of discordance measure (AI hushing) and short in the highest decile of discordance measure (AI washing)—can yield significant abnormal returns over the subsequent one- to two-year horizon. This suggests that market participants initially overreact to AI disclosure-investment discordance, resulting in transient mispricing and exploitable arbitrage opportunities. Second, I find that securities class action lawsuits related to AI washing are disproportionately concentrated among firms with high value of discordance measure. Third, I observe that firm-years positioned at the extreme deciles of the discordance measure exhibit significantly greater analyst forecast dispersion and error compared to those at the middle deciles. Next, I assess the prevalence of AI disclosure-investment discordance by estimating a Poisson regression of AI use disclosure on actual AI investment. The effect is insignificant with low explanatory power, indicating that firms rarely disclose AI initiatives proportionally to their actual AI investments. This weak association also mitigates concern that my discordance measure is merely an artifact of a mechanical link between AI use disclosure and actual investment.

In the baseline analysis, I estimate an ordinary least squares (OLS) regression with the discordance between AI use disclosure and investment as the dependent variable and TPP as the key independent variable. I observe a significantly positive effect, indicating that firms facing stronger TPP are more likely to engage in AI washing. In terms of economic significance, a one-standard-deviation increase in TPP is associated with a 0.784 increase in the discordance between firm AI use disclosure and actual investment, representing 14.9% of one standard deviation of the discordance measure. To better understand the individual effects of TPP on AI use disclosure and AI investment, I separately regress AI use disclosure and AI investment on TPP. The results suggest that while TPP significantly stimulates both, the increase in disclosure is economically larger than the corresponding increase in investment, reinforcing main inference.

I estimate a panel vector autoregression (PVAR) model and conduct Granger causality Wald test. My results suggest that TPP causes AI washing, but not the other way around. Using the coefficient stability approach, I show that omitted variable bias is unlikely to overturn the main inference. To further mitigate endogeneity concern, I leverage state-wide R&D tax credits as a plausibly exogenous source of variation in TPP. These credits effectively incentivize R&D investment in peer firms located outside the focal firm's headquarters state but have no direct effect on the focal firm's R&D investment, resulting in a plausibly exogeneous increase in TPP (Bloom et al. 2013; Cao et al. 2018). I construct an instrumental variable *TaxCredit* capturing peer firms' exposure to these R&D tax credits and implement a two-stage least squares (2SLS) analysis. The first stage estimates the regression of *TPP* on *TaxCredit* and control variables to predict the exogenous component of TPP. The second stage uses the predicted *TPP* values to examine its impact on the discordance measure. The 2SLS results confirm that a plausibly exogenous increase in TPP induces higher degree of AI washing.

Finally, I perform cross-sectional variation analyses to understand the potential mechanisms. First, the effect of TPP on AI washing is stronger among firms using more boilerplate language in disclosures and those operating in less transparent information environments, consistent with managers opportunistically overstating AI investments. Second, the effect amplifies among firms with low cost of equity and high stock liquidity. These firms face less investor scrutiny and benefit more from market enthusiasm, creating stronger incentives to engage in AI washing under high TPP to more readily access capital. Third, the effect is stronger among firms with technological proximity to their peers and among those positioned as either frontrunners or laggards in AI investment, suggesting firms strategically exaggerate AI capabilities to gain competitive edge.

My contribution is three-fold. First, my research contributes to accounting literature on how technological competition shapes voluntary disclosure. Cao et al. (2018) suggest that technological competition reduces product disclosure containing "actionable information," but does not affect management earnings forecast containing limited proprietary information. Glaeser and Landsman (2021) show that technological competition reduces the patent application disclosure as it increases knowledge spillovers to peer firms and thus greater proprietary disclosure costs.[6] In contrast, when employee-employer matching benefits outweigh proprietary costs of disclosing specific job skill requirements, firms facing TPP increase such disclosure to find suitable "tech talent" (Cao et al. 2023). Importantly, prior studies examine how TPP affects tech-related disclosures *alone*. I extend this literature by examining how technological competition affects a technological version of washing or hushing, where I document a salient mismatch between firms' public disclosure of AI investments and their actual implementation.

Second, I develop and validate a firm-specific measure of *discordance* between AI use disclosure and actual investment to calibrate AI washing or hushing. By adding three innovations, my measure complements Barrios et al. (2025), who make important contributions by identifying firms in the top tercile of AI-related disclosure yet the bottom tercile of AI-skilled employment as

[6] Glaeser and Landsman (2021) also show that product market competition instead increases the disclosure of patent applications because such disclosure can pre-emptively deter product market rivals that do not have the related innovation capabilities."

AI washers. First, my measure extends their dichotomous classification (AI washer vs. non-AI washer) by distinguishing firms that understate their actual AI investment (i.e., AI hushing) from the remaining non-AI washers whose AI use disclosure and investment are aligned. This distinction matters because AI hushing *also* distorts resource allocation in capital markets but receives limited SEC attention. In contrast, AI use disclosure-investment concordance aligns well with the SEC's expectation. Second, I construct within-year decile rankings based on AI disclosure and investment relative to *peer* firms (not among all firms), accounting for cross-industry differences in AI exposure (Felten et al. 2021). Third, I narrow the scope of AI disclosure to *retrospective* AI *investment* discussions, i.e., AI *use* disclosure, capturing how firms portray their realized AI use in ways that misalign with their actual AI investment. This focus ensures that my measure can exclude firms that merely express intentions to invest in AI or discuss general AI trends without taking concrete action, i.e., AI wishing. Moreover, my inference also differs from that of Barrios et al. in that I identify TPP as a driver of AI washing, whereas they explore firm-specific determinants and market-based consequences of AI washing.

Third, my findings carry significant policy implications. I show how TPP can distort the AI use information flows in capital markets—not by suppressing disclosure, but by incentivizing firms to overstate their AI capabilities. This inflation of AI use disclosures has the potential to mislead investors, inflate investor expectations, and misallocate capital toward firms that may not possess the technological sophistication they claim. These results raise important concerns for regulators like the SEC, which is mandated to ensure that investors receive "full, fair, and truthful disclosure" (Gensler 2024). As the SEC advances efforts to codify AI disclosure requirements, my findings highlight the urgent need for comprehensive guidance promoting *accurate* AI investment reporting, particularly for firms under intense TPP.

2. Hypothesis Development

AI, an overarching term first coined by Stanford Professor John McCarthy in 1955, refers to "the science and engineering of making intelligent machines." As peer firms intensively invest in AI and integrate it into their business operations, TPP creates compelling incentives for firm managers to increase corporate AI investments. The rationale is that "[a] delay in investing in, adopting and integrating AI could lead to an erosion of market share" and "[a] lag in technological innovation could adversely impact their business, reputation, results of operations and financial condition" (Weil 2023). For example, Smartsheet Inc.'s 2023 10-K filing recognizes that its industry is marked by "rapid technological developments and innovations (such as the use of artificial intelligence and machine learning)," stressing the necessity to "keep pace with these rapid technological developments" to prevent potential harm to their competition capabilities.[7] Notably, TPP-driven AI investment imperatives also extend to frontrunner firms having integrated AI, as they seek to maintain their tech competition advantages. For instance, Nvidia Corporation, an AI leader in GPU technology, notes in its filings that "[t]he market for our products is intensely competitive and is characterized by rapid technological change and evolving industry standards." Consequently, the company commits to "continue to add AI-specific features to our GPU architecture to further extend our leadership position."[8] TPP creates a self-reinforcing cycle of AI investment across the competitive spectrum, propelling both newcomers and established leaders to continuously invest and enhance their AI capabilities.

Given that TPP drives firms to increase AI investment, its impact on the *discordance* between AI use disclosure and actual investment (i.e., AI washing or hushing) depends on its differential effect on voluntary AI use disclosure. AI washing occurs when TPP increases

[7] See https://www.sec.gov/Archives/edgar/data/1366561/000136656123000030/smar-20230131.htm.
[8] See https://www.sec.gov/Archives/edgar/data/1045810/000104581023000017/nvda-20230129.htm.

disclosure more than it increases investment, while AI hushing emerges when TPP increases investment more than it increases disclosure or reduces disclosure while increasing investment.

Managers weigh the costs and benefits when deciding how much to disclose about their firms' AI use. A firm's AI use disclosure often contains proprietary information "tying AI to its main products and services or to key business updates" (Ho et al. 2024, Part 3). Proprietary cost of disclosure theory suggests that when making disclosure decisions, managers consider rivals' reactions to the disclosed proprietary information, with proprietary costs as the friction preventing full disclosure (e.g., Darrough and Stoughton 1990; Feltham and Xie 1992). More intense technological competition would endogenize higher proprietary costs of disclosure that contains "actionable information in order to impose costs on the disclosing firm" (Cao et al. 2018). In the context of AI, such information can reveal the disclosing firm's proprietary AI strategies, enabling rivals to respond and intensify technological competition. For example, in 2021, Microsoft's disclosure of integrating OpenAI's GPT-3 with Azure's enterprise capabilities revealed the company's AI strategy: making large language models accessible to businesses.[9] This disclosure intensified technological competition in the AI field, having inspired Google to "accelerate its timeline for integrating text generation capabilities into its products" (Knight 2023). Google redoubled efforts on its flagship large language model, LaMDA (Language Model for Dialogue Applications), and launched Bard in 2023 as "an answer to ChatGPT."[10]

On the benefits side, firms can gain equity valuation benefits by emphasizing current AI use in their public disclosures. Corporate AI use disclosure contains value-relevant information, and managers tend to disclose such information to capital market participants to reduce adverse selection and cost of capital (Grossman 1981; Milgrom 1981; Milgrom and Roberts 1986). TPP

[9] See https://news.microsoft.com/source/features/ai/new-azure-openai-service/.
[10] See https://www.wired.com/story/meet-bard-googles-answer-to-chatgpt/.

intensifies such equity valuation benefits. For example, the U.S. capital markets have been "super-charged" by the *race* to leverage emerging AI technologies, leading to soaring stock prices for companies like Nvidia and Super Micro Computer. As Gensler stated, public company executives "might think that they will enhance their stock price by talking about their use of AI." Indeed, AI use disclosure exploits continued investor enthusiasm for AI-embracing companies that are often deemed as forward-thinking and well-positioned for future business success (LaCroix 2024; Brynjolfsson and McAfee 2017). Consistent with this, the SEC's former Enforcement Director Gurbir Grewal notes that "…as AI continues to develop, firms will rush to capitalize on investor interest by promoting their supposed use of AI" (Veronica et al. 2024). Many public firms, including those "not traditionally thought of as technology companies," now find it "advantageous, useful, or simply prudent to refer to AI in their periodic reports" (LaCroix 2024); according to Bloomberg Law's analysis, over 40% of S&P 500 companies mentioned current AI use in their most recent annual filings (Bultman 2024).[11]

In addition, TPP may amplify the strategic benefits of AI use disclosure. When TPP intensifies, disclosing AI initiatives signals to investors and customers that the company is at the forefront of technological innovation with prodigious growth potential. "Companies have always followed tech trends and tried to jump on the bandwagon," says Kjell Carlsson, head of an enterprise AI platform provider.[12] In response to competitive pressures of *appearing* tech advanced, laggard firms may strategically disclose more about their AI capabilities to position themselves as future leaders in technological innovation. For frontrunner firms, revealing R&D innovations strategically makes potential rivals aware of the disclosing firms' efficiency gains, serving as a

[11] Bloomberg Law conducted textual analysis on S&P 500 companies' SEC-filed 10-K reports from 2018 to 2023, tracking mentions of artificial intelligence and its relevant acronyms.
[12] See https://www.cio.com/article/3476097/under-pressure-to-show-progress-cios-must-beware-committing-ai-washing-themselves.html.

deterrent to potential market entrants (Hughes and Pae 2015). So, frontrunner firms, in response to TPP, may increase AI use disclosure to signal AI efficiency gains and deter potential rival entry. In addition, frontrunner firms may also increase disclosure to guide evolving AI industry standards toward their established competencies, reenforcing their AI leadership positions. For example, Tesla has been sued for overstating its Autopilot and Full Self-Driving capabilities.[13] Critics argue that Tesla did so to promote a camera-only autonomous driving and steer self-driving industry standards away from the costlier sensor suites (i.e., lasers and radars) used by its competitors like Waymo, despite safety concerns (Nedelea 2024).

Based on the above cost-benefit analysis, when technological competition heats up, it may tip the discordance equilibria and fuel AI washing or hushing in three scenarios. First, TPP may induce AI washing when firms believe that valuation and strategic benefits of AI disclosure exceed proprietary disclosure costs, leading them to inflate AI use disclosure. AI washing is facilitated by the intangible, complex, and rapidly evolving nature of AI technologies, compounded by AI's inherently nebulous definition that gives firms considerable latitude (Lutkevich 2024). These characteristics make it costly for uninformed outsiders to verify actual corporate AI investments, creating fertile ground for managers' opportunistic mindset. This mindset aligns with self-justification theory (Aronson 1969), positing that individuals *rationalize* inconsistent conducts and cognitions to reduce cognitive dissonance. When overstating corporate actual AI investments, managers justify to themselves that such overstated disclosures will help attract capital for AI investment and eventually fulfill their previous overstatement of AI use. In this scenario, I expect TPP to fuel AI washing.

[13] See https://securities.stanford.edu/filings-case.html?id=108095.

Second, TPP may make managers perceive equity valuation and strategic benefits as outweighing proprietary disclosure costs, leading them to disclose more about their AI use. However, the increased disclosure may still be less than the increased AI investment because managers remain concerned about protecting proprietary advantages or avoiding regulatory scrutiny. In this scenario, I expect TPP to induce AI hushing. Third, TPP may make managers perceive proprietary disclosure costs as exceeding equity valuation and strategic benefits, leading them to disclose less about their AI use. In this scenario, TPP leads to reduced disclosure of AI use but increased AI investment. I thus expect TPP to induce AI hushing.

Ex ante, it is unclear whether TPP will fuel AI hushing or washing. I state my hypothesis in the null form as follows:

H: Technological peer pressure does not affect the discordance between a firm's AI use disclosure and its actual AI investment.

3. Research Design

3.1. Sample

My initial sample comprises all firms with non-missing total assets in Compustat from 2011 to 2023. I begin my sample period in 2011 because firms' investment and deployment of emerging AI technologies have grown substantially starting in the 2010s (Babina et al. 2024). I exclude utility (SIC codes 4400–4999) and financial firms (SIC codes 6000–6999).[14] I then remove firm-years where both the firms' AI disclosure and actual AI investment levels are zero, as these firms are not engaged in AI activities and are thus irrelevant to the analysis of AI washing or hushing. Next, I require the firm-years to have cleaned texts (transcripts) of 10-Ks (earnings

[14] I delete utility firms because TPP operates differently in these heavily regulated industries. And I delete financial firms because these firms are subject to stringent regulations (e.g., Basel Accords, Dodd-Frank Act) and have unique financial structures and business models.

conference calls) from Notre Dame Software Repository for Accounting and Finance (StreetEvents) that has extracted textual information from raw SEC filings (XML files).[15] To focus on firms' disclosures of *current* AI use, I carefully limit my sample to those firms whose disclosures *must* contain the discussions of past or ongoing AI investments. This process reduces the sample by 11,767 (12,033) firm-years for 10-K's Business section (earnings calls' presentation section). Lastly, I augment my data with actual corporate AI investment information from LinkedIn's individual employment resumes, institutional ownership information from Thomson Reuters, acquisition information from Thomson Financial's SDC Platinum, stock price information from CRSP, analyst forecast information from I/B/E/S, and the text-based network industry classifications (TNIC) information from the Hoberg–Phillips Data Library.[16]

Table 1 reports my sample selection procedures for both the main and robustness samples. My final main (robustness) sample includes 26,333 (20,264) firm-year observations for 10-K Business section (conference call) analysis, covering 3,862 (2,970) unique firms with complete information on AI use disclosure at 10-K Business section (conference calls), AI investment based on employee resumes, TPP measure, and control variables.

<Insert Table 1 around here>

3.2. Key measurements

Technological peer pressure

Technological peer pressure (TPP) captures the intensity of technological competition threats a firm faces from its peer firms. Following Cao et al. (2018), I measure TPP by comparing the aggregate technological advancement of a firm's competitors across various product markets

[15] See https://sraf.nd.edu/sec-edgar-data/cleaned-10x-files/.
[16] "Text-based network industry classification" (TNIC) on product similarity data can be downloaded at the Hoberg–Phillips Data Library. See http://hobergphillips.tuck.dartmouth.edu/industryclass.htm.

to its own technological preparedness. To aggregate competition threats from the focal firm's peers, I calculate the closeness weight $\omega_{i,j}$ between each pair of focal firm i and peer j using the cosine similarity of their sales distributions across 4-digit SIC industries; firms with more overlapping product market industries and similar sales distributions are considered closer peers. The R&D stock for each firm-year is calculated using a perpetual inventory method (i.e., $G_{i,t} = R\&D_{i,t} + (1\text{-}15\%)\ R\&D_{i,t\text{-}1}$), where R&D expenditures from the previous five years are accumulated and adjusted by a 15% annual decay rate, reflecting the multi-year benefits of R&D investments and the gradual reduction in their value over time.

To capture aggregate technological advancement of a focal firm's competitors from various product markets, I multiply each peer firm's R&D stock $G_{j,t}$ by the closeness weight $\omega_{i,j}$ and sum the products across all peers, i.e., $\sum_{j \neq i} \omega_{i,j} \times G_{j,t}$. To capture the relative technological pressure on the focal firm, I divide this sum by focal firm i's own R&D stock $G_{i,t}$. Last, I calculate *TPP* for focal firm i in year t by taking the natural logarithm of $[1 + (\sum_{j \neq i} \omega_{i,j} \times G_{j,t}) / G_{i,t}]$. As reported in Table 2, the mean (median) of *TPP* measure in my sample is 5.201 (5.123), and TPP increased in recent years, reflecting the growing intensity of technological peer pressure in the AI era.

<Insert Table 2 around here>

Discordance between corporate AI use disclosure and AI investment

I measure the discordance between a firm's AI use disclosure and actual AI investment (*Discordance*) as the difference between two within-year decile ranks, calculated relative to its peer firms identified using TNIC.[17] The first decile rank is based on a sample firm's within-year

[17] To identify a focal firm's intransitive competitor network, I employ the text-based network industry classifications (TNIC) as developed by Hoberg and Phillips (2016). They analyze product descriptions in firms' 10-K filings to compute pairwise cosine similarity scores. Firms are classified as peers when their pairwise similarity score exceeds the threshold of 21.32%. After 2010, on average, a U.S. public firm has around 123 peer firms (mean) and 111 peer firms (median) per year.

AI use disclosure (*AI_disclose*), calculated as the ratio of the weighted-frequency count of AI-related terms to total count of terms from retrospective investment discussions at its Business (Item 1) section of 10-K filings. The Business section reflects a firm's *current* AI use, including how the firm *has* incorporated emerging AI technologies into its products or services, initiatives, R&D efforts, and relationships with customers or suppliers (Weil 2023).[18]

To ensure comprehensive coverage of AI-related terms at the Business section of 10-K filings, I employ a natural language processing approach using the *Word2vec* word embedding model, following Li et al. (2021). This model captures semantic context and identifies emerging AI-related terminology by learning vector representations of words based on their co-occurrence patterns. As AI technologies and their business applications rapidly evolve, so does the language used to describe them in corporate disclosures. The algorithm begins with an unambiguous set of AI-related seed terms (e.g., "machine learning", "neural network", "deep learning", "computer vision", "natural language processing").[19] It then trains a neural network to embed words in a semantic vector space. By computing cosine similarities between word vectors, the model identifies those terms semantically similar to the seed terms, capturing nuanced AI-related language. The final AI keyword dictionary captures a range of AI-related terms, from broader concepts like "predictive analytics" and "autonomous systems," to specific applications such as "autonomous vehicle navigation". To calculate *AI_disclose*, I use a *tf-idf* (i.e., term frequency-inverse document frequency) weighting scheme, which accounts for how often each term appears in a firm's disclosure and how distinctive that term is across all sample firms' disclosures.

[18] I do not examine Management Discussion and Analysis (MD&A) section of the 10-K because the MD&A section most likely contain managerial discussions on forward-looking AI investment plans.

[19] This predetermined list of AI-related seed terms is largely borrowed from prior literature (e.g., Cockburn et al. 2018; Abis and Veldkamp 2024; Golfman and Jin 2024) and the union of the AI-related keywords used in these papers. I also manually inspect each term to ensure that it unambiguously relates to describing firms' AI use. To ensure that multi-word phrases are treated as single terms, I use a phrase detection algorithm to concatenate frequent bigrams and trigrams with underscores (e.g., natural_language_processing) prior to model training.

To ensure that the AI disclosure in the Business section pertains to actual investment activities rather than general discussions of emerging technologies, I retain only sentences containing investment-related terms. I construct the investment keyword dictionary by applying a similar approach to that used for identifying AI-related language. Specifically, I apply the *Word2vec* model to expand an initial list of investment-related seed terms drawn from prior literature (e.g., Hoberg and Maksimovic 2015; Cao et al. 2024). The model learns vector representations of words based on their semantic context and identifies additional terms with high cosine similarity to the investment seeds. This process allows me to capture nuanced and evolving language related to corporate investment activities. Appendix B presents illustrative examples of corporate AI investment discussions extracted from annual reports and earnings calls.

The second decile rank is based on a sample firm's within-year actual AI investment, measured by the proportion of employees with AI-related skills. The idea is that AI technologies rely on human expertise for development, implementation, and maintenance. Therefore, the presence of AI-skilled employees indicates active investment and implementation of AI by a firm. Following Babina et al. (2024) and Jin et al. (2023), I leverage granular individual-level employment LinkedIn resumes to capture a firm's actual AI capabilities through the lens of its workforce composition. I apply the 67 keywords of AI-related core skills identified by Babina et al. (2024) to classify AI-skilled employees.[20] Specifically, I search for these keywords in job titles and skills listed on non-internship U.S. employee LinkedIn profiles. An employee is deemed AI-skilled if at least one of these keywords appears in her job position title or skills section. I then calculate *AI_invest* as the ratio of AI-skilled employees to the total number of employees with LinkedIn profiles for each firm-year. By using employment resume data rather than job postings,

[20] Babina et al. (2024) collect individual level employment resumes from Cognism, while Jin et al. (2023) collect such data from LinkedIn. Both of their descriptive statistics on the percentage of AI-skilled employees are similar.

AI_invest captures AI-skilled employees who are currently employed by a firm, not just positions the firm is attempting to fill.

A caveat of using LinkedIn data is that professional profiles are self-reported, raising concerns about AI skill information validity. Tucker et al. (2025) note that résumé-based measures of AI investment may reflect aspirational or exaggerated skill claims, as "resumes may be embellished, misrepresented, or even made up, especially when certain skills are perceived as desirable." These concerns are partially mitigated by three factors. First, given LinkedIn's prominence in tech recruitment and professional networking, employers routinely verify employees' skill claims through background checks and technical interviews (Chen 2024). Second, my analysis focuses on firm-level aggregates, which are less sensitive to individual-level reporting inconsistencies. Third, any exaggeration of individual AI skills would inflate the measured AI investment, introducing an upward bias in the investment component of the discordance measure. Since I find the positive effect of TPP on AI washing—where disclosure increases more than investment (see Section 4.1)—this potential bias would make it harder to uncover this effect.

As shown in Table 2, the mean (median) of *Discordance* is -0.933 (0) in my main sample for 10-K Business section analysis; the mean (median) of *Discordance_call* is 0.538 (0) in my robustness sample for earnings call analysis.

3.3. Validation tests of the discordance measure

I conduct three validation tests on my discordance measure. First, I draw upon the hedge-portfolio test used by Xie (2001) who analyze investor mispricing of abnormal accruals. If the market misprices the discordance measure, firms identified as AI washers (hushers) should be overvalued (undervalued) by the market. I test whether it reflects market mispricing related to the discrepancies. I construct a hedge portfolio of taking long positions in firms from the lowest

Discordance decile (i.e., those most likely engaging in AI hushing) and short positions in firms from the highest *Discordance* decile (i.e., those most likely engaging in AI washing). This hedge portfolio yields significantly positive annual size-adjusted abnormal returns over the subsequent one- and two-year horizons. Panel A of Table 3 suggests that the market initially overvalues firms engaging in AI washing and undervalues firms engaging in AI hushing, supporting the validity of my discordance measure in indicating mispricing arising from the mismatch between AI use disclosure and its investment.

<Insert Table 3 around here>

Second, I validate the effectiveness of my discordance measure in identifying AI washing firms. Inspired by Dechow et al. (2011)—who exploit SEC Accounting and Auditing Enforcement Releases to validate that firms with higher F-scores are more likely to engage in earnings misstatements—I analyze securities class action lawsuits related to alleged AI washing.[21] Specifically, I divide sample firms with positive *Discordance* into quintiles. If the discordance measure were ineffective, I would expect the lawsuit filings to be evenly distributed across the five quintiles. However, I observe a disproportionately large share of AI washing lawsuits concentrates on the highest quintile as shown in Panel B of Table 3. This pattern provides supporting evidence that the discordance measure can identify firms more likely to engage in AI washing.

Third, I examine analyst forecast properties to further validate my discordance measure. Prior research suggests that misleading firm disclosures increase analysts' difficulty in forecasting future firm performance, resulting in higher forecast dispersion and lower accuracy (Lang and Lundholm 1996; Hope 2003). Building on this insight, I expect that greater discordance between AI use disclosure and actual AI investment results in divergent analyst interpretations regarding

[21] Lawsuit filings related to AI washing are documented by the Stanford Law School Securities Class Action Clearinghouse: https://securities.stanford.edu/current-trends.html#collapse1.

firms' true AI capabilities and growth prospects. Consequently, these firms should exhibit higher forecast dispersion and error. I compare analyst forecast dispersion and error between firms in the extreme deciles of *Discordance* (i.e., AI-washing firms in the top decile and AI-hushing firms in the bottom decile) and firms in the middle deciles, where AI disclosures and investments are more aligned. Panel C of Table 3 shows that firms in the extreme deciles exhibit significantly higher forecast dispersion and greater forecast error than those in the middle deciles, further supporting the validity of my discordance measure.

To assess whether AI use disclosure-investment discordance is prevalent among my sample firms, I follow the spirit of Baker et al. (2024) and estimate a Poisson regression of a firm's AI use disclosure on its actual AI investment. As shown in Panel D of Table 3, the estimated coefficients are negligible and insignificant in both specifications—regardless of whether control variables from baseline model are included (Column 1) or excluded (Column 2). The low Pseudo R^2 values, particularly 0.02% in the no-controls specification (Column 2), indicate a weak association between firms' AI use disclosure and actual AI investment. These findings suggest that firms often do not disclose AI activities in proportion to their actual AI investment levels. Importantly, the lack of a strong relationship between AI use disclosure and actual investment also helps mitigate concern that my discordance measure is mechanically driven by a direct association between the two, thereby supporting its validity in capturing AI washing or hushing.

I calculate Pearson correlations of selected variables based on my main sample (N = 26,333). In untabulated results, I observe a significantly positive correlation (p-value < 0.01) between technological peer pressure (*TPP*) and the discordance between firm AI use disclosure and actual AI investment (*Discordance*). This positive association suggests that firms experiencing greater technological peer pressure are more likely to exhibit signs of AI washing.

3.4. Empirical models

To examine whether TPP fuels AI washing or hushing, I use ordinary least squares (OLS) regression to estimate the following empirical model (1):

$$Discordance_{i,t+1} = \alpha + \delta TPP_{i,t} + \Gamma X_{d,t} + \Gamma Z_{i,t} + \Gamma T_{i,t} + \tau_d \times \sigma_t + \varepsilon_{i,d,t} \quad (1)$$

where *i* indexes the firm, *d* indexes the 3-digit SIC industry, *t* indexes the year. In model (1), the dependent variable, $Discordance_{i,t+1}$, indicates the degree of mismatch between firm *i*'s AI use disclosure and its actual AI investment decile rankings relative to its peer firms in year *t*+1. $TPP_{i,t}$ indicates the technological competition threats firm *i* faces in year *t*. The lead-lag specification helps mitigate reverse causality concern, as firm AI disclosure and actual AI investment in year *t*+1 are arguably less likely to affect TPP in year *t*.

The baseline model includes $X_{d,t}$, $Z_{i,t}$, and $T_{i,t}$. $X_{d,t}$ represents time-variant peer firms' characteristics. *Peers_FinPCA* is the first principal component derived from five average financial characteristics of peers (i.e., sales, market-to-book, EBITDA/assets, PP&E/assets, and R&D/assets); *Peers_Tsimm* captures textual similarity in product descriptions between a focal firm and its peers. $Z_{i,t}$ includes time-variant firm attributes, including financial capacity, capital market incentives, analyst coverage, and growth potential that plausibly affect AI use disclosure or AI investment. $T_{i,t}$ represents a set of textual characteristics (i.e., total word count, sentiment, readability, and uncertainty) of the 10-K filing, accounting for a firm's general disclosure style that could otherwise confound the relation between TPP and the disclosure component of discordance. Appendix A provides detailed definitions of all variables used in this study.

To mitigate extreme outliers, I winsorize all the continuous variables used in baseline model at the 1^{st} and 99^{th} percentiles. Given that some unobservable industry characteristics (e.g., industry-specific technological trends, regulatory changes, and market conditions) could confound the baseline relation over time, I include industry-by-year fixed effect structure in model (1) to isolate the firm-specific main effect. Lastly, I cluster standard errors at the firm level to correct for potential heteroskedasticity.

In model (1), a significantly positive coefficient δ would suggest that TPP is associated with AI washing, where the increase in AI use disclosure exceeds the increase in actual AI investment. Conversely, a significantly negative coefficient δ would confirm the case of AI hushing, where the increase in AI use disclosure is smaller than the increase in actual AI investment, or where AI use disclosure decreases while actual AI investment increases.

To further investigate whether the positive or negative effect of TPP on discordance stems from disproportionate changes in AI use disclosure versus actual AI investment, I separately estimate OLS regressions of AI use disclosure and AI investment on TPP. A stronger effect on disclosure than investment would be consistent with AI washing, whereas a stronger effect on investment than disclosure—or a reduction in disclosure alongside increased investment—would support AI hushing. I use OLS regressions to estimate the following empirical models (2) and (3):

$$AI\_disclose_{i,t+1} = \alpha + \partial TPP_{i,t} + \mathit{\Gamma} X_{d,t} + \mathit{\Gamma} Z_{i,t} + \mathit{\Gamma} T_{i,t} + \tau_d \times \sigma_t + \varepsilon_{i,d,t} \quad (2)$$

$$AI\_invest_{i,t+1} = \alpha + \mu TPP_{i,t} + \mathit{\Gamma} X_{d,t} + \mathit{\Gamma} Z_{i,t} + \mathit{\Gamma} T_{i,t} + \tau_d \times \sigma_t + \varepsilon_{i,d,t} \quad (3)$$

Model (2) alters model (1) by replacing the dependent variable $Discordance_{i,t+1}$ with $AI\_disclose_{i,t+1}$, firm *i*'s disclosure level of current AI use at the Business section of 10-K filing in year *t*+1. Model (3) alters model (1) by replacing the dependent variable $Discordance_{i,t+1}$ with $AI\_invest_{i,t+1}$, firm *i*'s actual AI investment level in year *t*+1. In model (2), a significantly negative (positive) ∂ would suggest that TPP is associated with decreased (increased) disclosure level of firm current AI use. In model (3), a significantly positive μ would suggest that TPP is associated with increased actual firm AI investment level. When ∂ remains significantly negative and μ remains significantly positive, this case would suggest that TPP relates to AI hushing. When ∂ remains significantly positive and μ remains significantly positive, it would suggest that TPP is associated with increases in both firm AI use disclosure and actual AI investment levels. In this case, there are two possible scenarios. TPP could relate to AI hushing (washing) if the increased AI use disclosure effect is less (more) than the increased AI investment effect.

4. Empirical Results of Baseline Analyses

4.1. *Baseline results*

Column (1) at Table 4 reports the baseline regression results of estimating Equation (1), where the dependent variable is the discordance between AI use disclosure and actual AI investment. The coefficient on technological peer pressure (*TPP*) is positive and highly significant (coef = 0.261, t = 5.46), suggesting that firms facing stronger TPP exhibit greater discordance between what they disclose and what they invest in AI. This result indicates that, on average, TPP is associated with AI washing. The economic magnitude is also meaningful: a one-standard-deviation increase in TPP is associated with approximately a 0.784 (= 0.261 × 3.003) increase in the discordance between firm AI use disclosure and actual AI investment, which represents 14.9% (= 0.784 ÷ 5.249) of one standard deviation of the discordance measure.

<Insert Table 4 around here>

To understand whether the observed discordance increase is driven more by changes in AI use disclosure or AI investment, columns (2) and (3) separately regress AI use disclosure and AI investment on TPP. Column (2) shows that TPP is positively associated with AI use disclosure (coef = 0.050, t = 2.99), while Column (3) shows a similarly positive association with AI investment (coef = 0.032, t = 2.97). These results suggest that TPP relates to increases in both AI disclosure and investment, but the effect on AI disclosure is economically stronger, consistent with the notion that AI disclosure increases more than the increase in AI investment, i.e., AI washing.[22]

Turning to the control variables, my results reveal interesting patterns. Larger firms (*LnSize*) demonstrate less AI use disclosure-investment mismatch (Column 1) and are more likely to both disclose (Column 2) and invest (Column 3) in AI, consistent with larger organizations having more resources and robust governance structures that promote alignment between stated and actual AI initiatives. Firms with larger cash reserves (*Cash*) and higher market-to-book ratio (*MTB*) exhibit higher levels of AI investment (Column 3), which suggests that financial flexibility and strong growth prospects encourage firms to invest in AI. Interestingly, *Peer_Tsim*, which captures product market similarity to peer firms, is positively associated with *Discordance* (Column 1), but negatively associated with AI investment (Column 3). This pattern implies that firms facing intense product market similarity—those whose products closely resemble their peers'—may feel pressured to stand out by overstating AI capabilities. Rather than pursuing costly differentiation through genuine AI adoption, these firms overstate AI use to appear more innovative in crowded product spaces.

4.2. *Robustness checks of baseline finding*

I conduct four robustness checks to corroborate the baseline finding. First, the disclosure component of the discordance measure is derived from firms' 10-K Business sections. As a robustness check, I construct an alternative disclosure measure, *AI_disclose_call*, using the presentation sections of earnings call transcripts to capture manager-initiated voluntary disclosures, rather than analyst-elicited information (Duchin et al. 2024). Additionally, managers are often

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[22] A one-standard-deviation increase in TPP is associated with a 0.150 (= 0.050 × 3.003) increase in AI use disclosure and a 0.096 (= 0.032 × 3.003) increase in actual AI investment. Given that the standard deviations of *AI_disclose* and AI_*invest* are 0.112 and 0.199, respectively, these effects represent increases of 134.1% (= 0.150 ÷ 0.112) and 48.3% (= 0.096 ÷ 0.199) of one standard deviation in AI use disclosure and actual AI investment, respectively.

required to discuss retrospective investment projects as part of their fiduciary duty to investors during earnings calls (Cao et al. 2024). To isolate such discussions, I exclude sentences containing forward-looking phrases using Bozanic et al.'s (2018) dictionary and retain only those containing investment-related terms based on my investment dictionary. I calculate *AI_disclose_call* as the ratio of the weighted-frequency count of AI-related terms to total count of terms from retrospective investment discussions at earnings calls. I then average the ratio values of all earnings calls held by a firm in a year. I define *Discordance_call* as the difference between a firm's decile rank in *AI_disclose_call* and its decile rank in *AI_invest*, relative to TNIC-identified peers. I re-estimate baseline model (1) by replacing *Discordance* with *Discordance_call* and observe a significantly positive relation between *TPP* and *Discordance_call* in Panel A of Table 5.

<Insert Table 5 around here>

Second, the baseline finding is based on the discordance measure, whose investment component is derived from firms' employee resumes. The investment component measure focuses on internal AI capabilities, so it may understate AI investment for firms that heavily outsource their AI development. For robustness, I construct an alternative AI investment proxy, *AI_invest_patent*, using firms' AI-related patent grants. This measure captures AI innovation outputs, leveraging the insight that AI patents represent tangible, externally validated indicators of firms' technological engagement in AI. Following Chen et al. (2025), who identify AI-related patents using the USPTO's AI Patent Dataset—constructed via a machine learning model trained on patent texts, citations, and claims—I define *AI_invest_patent* as the ratio of AI-related patents granted to a firm to its total granted patents in a year. I then re-estimate model (1) using an alternative discordance measure, *Discordance_patent*, whose investment component is captured by *AI_invest_patent*. Panel B of Table 5 reports the result. I continue to observe a significantly positive association between *TPP* and *Discordance_patent*, indicating that TPP positively relates to AI washing when AI investment is measured using AI-related innovations.

Third, I construct an alternative dependent variable, *Discordance_SIC*, by identifying peer firms based on 4-digit SIC codes instead of the text-based network industry classification (TNIC). This robustness check ensures that my main findings are not sensitive to whether peer firms are identified using text-based industry similarity or standard 4-digit SIC codes. I re-estimate baseline model (1) by replacing *Discordance* with *Discordance_SIC* and continue to observe a significantly positive relation between *TPP* and *Discordance_SIC* in Panel C of Table 4.

Fourth, to address the concern that the COVID-19 pandemic may confound results due to disruptions in firm operations, investments, and disclosure practices, I re-estimate the baseline model after excluding firm-year observations from the 2020–2021 period. This robustness test helps ensure that the observed relation between TPP and AI washing is not driven by pandemic-specific anomalies. The results, reported in Panel D of Table 5, remain qualitatively unchanged, suggesting that the main inference holds outside the COVID-19 period.

4.3. *Reverse causality test*

To assess the causal direction between technological peer pressure and AI washing, I estimate panel vector autoregression (PVAR) model to detect potential bidirectional effects in main results following the method of Chen et al. (2022).[23] Panel A of Table 6 reports the PVAR results. As shown in column (1), the coefficient on TPP_{t-1} (0.328) is significantly positive even after controlling for $Discordance_{t-1}$. This finding is consistent with the baseline regression in Table

[23] I have chosen the lag order of 1 and *instlag* (the lag order of endogenous variables used as instruments) of 4. These are chosen both to minimize the modified Bayesian information criterion and the modified Quinn information criterion, following Abrigo and Love (2016), and to mitigate the model overfitting issues, following Arnerić and Situm (2022).

3, suggesting that technological peer pressure is positively associated with future AI washing. In contrast, the coefficient on *Discordance*$_{t-1}$ in column (2) is insignificant. These results suggest that technological peer pressure affects future AI washing, but not vice versa, helping to mitigate reverse causality concerns and to rule out the alternative explanation that AI washing induces technological peer pressure—for example, that firms overstating their AI capabilities may prompt rival firms to respond by increasing their own R&D investments, thereby raising peer pressure.

<Insert Table 6 around here>

To further investigate the causality direction, I perform a Granger causality Wald test, which evaluates the null hypothesis that the excluded variable(s) do not Granger-cause the dependent variable. As shown in row (1) of Panel B, Table 6, the null hypothesis that technological peer pressure (*TPP*) does not Granger-cause AI washing (*Discordance*) is rejected. In contrast, row (2) indicates that the null hypothesis that AI washing (*Discordance*) does not Granger-cause technological peer pressure (*TPP*) cannot be rejected. These findings provide corroborating evidence that technological peer pressure leads to AI washing, but not the other way around.

4.4. *Omitted variable bias test*

Following Chen et al. (2021), I examine the robustness of baseline OLS results to potential omitted variable bias using the coefficient stability approach proposed by Oster (2019). This method evaluates the extent to which unobservable confounders would need to dominate observable covariates to nullify the positive effect of TPP on AI washing. The underlying logic is intuitive: if including observable covariates increases the model's explanatory power (measured by R-squared) while *modestly* attenuating the TPP effect, then unobservables with proportional selection to observables are unlikely to overturn the main inference.

I compare the estimated *TPP* coefficients and R-squared values from two regressions of the discordance measure on TPP: a restricted model with only industry-year fixed effects and a fully controlled model reported in Table 4 that adds observable covariates. I adopt conservative parametric assumptions based on Oster's recommendations: the maximum attainable R-squared is set to 1.3 times that of the full model, and the proportional selection parameter δ is set to 1. This assumes that unobserved factors influencing AI washing are no more important than the observed covariates already included. Under these assumptions, the bias-adjusted coefficient on *TPP* is computed as 0.209, slightly lower than the 0.261 estimated in the full model.[24] While there is some attenuation, the direction and magnitude of the effect remain consistent. The model's explanatory power also improves, with the R-squared increasing from 0.243 in the restricted model to 0.309 in the full model. Collectively, these results indicate that omitted variable bias is unlikely to alter the main inference that TPP positively affects AI washing.

5. Two-stage Least Squares Analysis

Endogeneity is a central concern in evaluating whether technological peer pressure fuels AI washing or hushing. For example, a firm's tech peer pressure, AI use disclosure, and actual AI investment may be simultaneously determined by common unobserved factors, such as managerial ability or a firm's innovation orientation, which could confound the causal inference of my baseline findings. To address this concern, I implement a two-stage least squares (2SLS) design that leverages state-level R&D tax credits, which provide financial incentives for affected firms to invest in qualified R&D activities (Bloom et al. 2013). Following Cao et al. (2023), I construct *TaxCredit* as the sum of R&D stocks of peer firms headquartered in states with R&D tax credits,

[24] The bias-adjusted coefficient on *TPP* is computed using Oster's (2019) formula as: $\beta^* = \beta_{full} - (\beta_{restricted} - \beta_{full}) \times [(R^2_{max} - R^2_{full}) / (R^2_{full} - R^2_{restricted})]$, where $\beta_{restricted} = 0.298$, $\beta_{full} = 0.261$, $R^2_{restricted} = 0.243$, $R^2_{full} = 0.309$, and $R^2_{max} = 1.3 \times R^2_{full} = 0.402$. Plugging in these values: $\beta^* = 0.261 - (0.298 - 0.261) \times [(0.402 - 0.309) / (0.309 - 0.243)] = 0.261 - 0.037 \times 1.409 \approx 0.209$.

weighted by their product market proximity to the focal firm. By focusing on peer firms domiciled outside of the focal firm's headquarters state, I ensure that the variation in peer firms' R&D activities is orthogonal to any inherent characteristics of the focal firm. This instrument provides a plausibly exogenous source of variation in TPP because state-level R&D tax credits create financial incentives for peer firms to increase R&D investments, but these incentives vary in ways unrelated to the focal firm's characteristics.

My instrument satisfies the relevance condition because it increases peer firms' R&D investments through tax incentives, thereby enhancing their technological capabilities and intensifying the TPP faced by the focal firm (Cao et al. 2023). The first-stage F-statistic of 36.25 exceeds the conventional threshold,[25] alleviating weak instrument concern. For the exclusion restriction to hold, my instrument should affect focal firm's AI disclosure-investment discordance *only* through the TPP channel. This restriction theoretically holds because state R&D tax credits enhance technological capabilities of peer firms domiciled in the granting states but exert minimal direct impact on focal firm operating outside of granting states.

Prior to the 2SLS estimation, I conduct the Wu–Hausman test and reject the null hypothesis that TPP is exogenous ($F = 45.38$, $p < 0.01$), supporting that TPP is an endogenous regressor. Since the model is exactly identified with one instrument (*TaxCredit*) for one endogenous regressor (*TPP*), the overidentifying restriction test isn't applicable in my scenario. In column (1) of Table 7, I re-estimate the baseline OLS regression using the reduced 2SLS sample. The coefficient on *TPP* continues to be statistically positive, consistent with my main inference.

In the first stage, I estimate the regression of *TPP* on concurrent *TaxCredit* and control variables from the baseline model to isolate the exogenous component of TPP. This step isolates

[25] The critical threshold for detecting weak instruments is 8.96 when there is a single instrument (Stock et al. 2002).

exogenous variation in TPP by ensuring that the variation is driven by peer firms' R&D activities induced by state-level R&D tax credits, rather than by focal firm endogenous attributes. As shown in column (2) of Table 7, *TaxCredit* is significantly positively associated with *TPP*, confirming the instrument's relevance. In the second stage, I use the predicted values of *TPP* from the first-stage regression to replace $TPP_{i,t}$ in Equation (1) examining its impact on the focal firm *i*'s discordance between AI use disclosure and actual AI investment (*Discordance*) in year *t*+1. The second-stage estimation results, reported in column (3) of Table 7, indicate that an exogenous increase in *TPP* leads to a significantly positive increase in *Discordance*. This pattern is consistent with the interpretation that TPP induces AI washing. Together, the 2SLS estimates mitigate endogeneity concerns arising from simultaneity or correlated omitted variables.

<Insert Table 7 around here>

6. Cross-sectional Variation Analyses

I explore the potential channels through which the impact of technological peer pressure on AI washing takes place. To answer "how", I examine whether the main effect varies with opportunistic overstatement of AI investment, capital market benefits, or strategic competition advantages from inflated disclosure. Examining heterogenous treatment effects also mitigates the concern that certain omitted firm characteristics potentially confound my main results, because such missing variables would also have to explain the cross-sectional variations in the treatment effects. To conduct cross-sectional variation analyses, I augment my baseline model (1) with each *Partition* variable and its interaction with *TPP* as follows:

$$Discordance_{i,t+1} = \alpha + \gamma TPP_{i,t} \times Partition + \mu TPP_{i,t} + \partial Partition + \Gamma X_{d,t} + \Gamma Z_{i,t} + \Gamma T_{i,t} + \tau_d \times \sigma_t + \varepsilon_{i,d,t} \quad (4)$$

where dependent variable *Discordance* captures the mismatch between a firm's AI use disclosure and actual AI investment as previously defined. *Partition* represents moderators defined below to indicate different types of firms whose characteristics shape AI washing.

6.1. *Opportunistic overstatement of AI investment*

I begin by testing whether the TPP effect is stronger among firms whose AI use disclosures rely heavily on boilerplate language, which allows managers to obscure verifiable claims. Following Lang and Stice-Lawrence (2015) and Dyer et al. (2017), I identify boilerplate phrases as frequently used tetragrams among all firm filings in a given fiscal year and compute the proportion of AI-investment-related sentences in the Business section containing such language. I define *Boilerplate* as an indicator variable that equals one if the proportion of AI-investment-related sentences containing at least one boilerplate phrase—relative to the total number of AI-investment-related sentences—in the Business section of a firm-year's 10-K filing is above the sample median, and zero otherwise. In Table 8, column (1) of Panel A shows that the coefficient on *TPP* × *Boilerplate* is significantly positive, suggesting that technological peer pressure leads to greater AI washing when firms use vague, non-committal disclosure language.

<Insert Table 8 around here>

Next, I assess whether the baseline effect amplifies among firms operating in less transparent information environments, where opportunistic disclosure is more difficult for external stakeholders to verify. To capture firms' information environments, I use the widely recognized measure of information asymmetry: bid-ask spreads. I calculate it as the mean of daily quoted bid-ask spreads measured over a year. I then define *LowInfoEnviron* as an indicator that equals to one if the average daily quoted bid-ask spread for a firm-year is above the sample median, and zero otherwise. As shown in column (2) of Panel A, the coefficient on *TPP* × *LowInfoEnviron* remains significantly positive, consistent with the notion that opaque information environments facilitate AI washing under technological peer pressure. Together, these results suggest that managers facing intense technological peer pressure are more likely to engage in AI washing when they can opportunistically do so with limited risk of detection—either by relying on generic, unverifiable disclosure language or by operating in opaque information environments.

6.2. *Capital market benefits*

To test whether capital market incentives amplify the effect of TPP on AI washing, I examine two firm-level conditions indicative of investor enthusiasm and financing advantages: low implied cost of equity and high stock liquidity. First, I assess whether firms with lower implied cost of equity exhibit stronger AI washing under TPP. When firms face intense TPP, those with favorable financing conditions may be more likely to engage in AI washing because they face less investor scrutiny and can more readily access capital to improve competitive positions and eventually fulfill their overstated AI use claims. I define *LowCOE* as an indicator for whether a firm-year's implied cost of equity falls below the sample median. I calculate the implied cost of equity based on the estimation method developed by Ohlson and Juettner-Nauroth (2005). As shown in column (1) of Panel B, the coefficient on *TPP* × *LowCOE* is significantly positive, indicating that the TPP effect on AI washing is stronger among firms that face lower equity financing costs. This result suggests that these firms exaggerate their AI initiatives when facing TPP to leverage their existing market credibility and easier access to capital.

Second, I test whether stock liquidity moderates the main effect. High stock liquidity may reflect stronger investor demand for AI use disclosures, especially in today's "super-charged" U.S. capital markets where investor enthusiasm for AI-adopting firms remains strong. I define *HighLiquidity* as an indicator that equals one if the inverse Amihud illiquidity ratio for a firm-year—calculated as the annual average of the absolute daily return divided by daily dollar trading volume—is above the sample median, and zero otherwise. Column (2) of Panel B shows that the coefficient on *TPP* × *HighLiquidity* is also significantly positive, suggesting that firms with more liquid stocks are more likely to engage in AI washing when facing intense TPP. These findings complement the cost of equity results, reinforcing the notion that firms exploit investor optimism about AI technologies to attract capital market attention and funding when their stocks already enjoy high trading liquidity.

6.3. *Strategic competition advantages*

I further explore whether firms strategically overstate AI investments to gain a competitive edge, particularly when they face high technological proximity to peers or occupy extreme positions in the AI investment spectrum. First, I test whether the main effect is stronger when technological proximity is high—a condition that reflects intense, neck-and-neck innovation rivalry. Firms with high technological proximity share similar innovation profiles with their peers and may face heightened pressure to distinguish themselves. I define *TechProximity* as an indicator equal to one if a firm-year's technological proximity exceeds the sample median, and zero otherwise. I measure technological proximity as the average of pairwise uncentered correlations between focal firm and each peer firm based on the distribution of their patent applications across technology classes over the past two decades. As reported in column (1) of Panel C, the coefficient on *TPP* × *TechProximity* is significantly positive. This result supports the notion that firms strategically employ AI washing to stand out in crowded technological spaces and capture market attention by appearing more innovative than their similarly positioned rivals.

Next, I examine whether the main effect is stronger for firms at the diametric ends of the actual AI investment distribution, namely AI frontrunners and laggards. Frontrunners may strategically exaggerate their AI capabilities to reinforce their technological leadership, guide evolving AI industry standards toward their established competencies, or deter potential new entrants, while laggards may also do so to enhance perceptions and project greater competitiveness than they truly possess. I define *Frontrunner* and *Laggard* as indicators for firms in the top and bottom quintiles of AI investment, respectively. Columns (2) and (3) of Panel C show that the coefficients on *TPP* × *Frontrunner* and *TPP* × *Laggard* are both significantly positive. These results indicate both AI frontrunners and laggards strategically engage in AI washing when facing technological peer pressure—albeit likely for different competitive reasons. Overall, these findings provide evidence that strategic competitive advantage shapes the extent to which firms engage in AI washing under technological peer pressure.

7. Conclusion

I develop and validate a novel measure of discordance between a firm's AI use disclosure and actual AI investment and examine whether technological peer pressure (TPP) fuels AI washing or hushing. I construct this discordance measure as the difference between a firm's decile rankings of AI use disclosure and investment levels relative to peer firms in a year. I find that firms facing stronger TPP likely engage in AI washing. The two-stage least squares estimates confirm that an exogenous increase in TPP leads to a higher degree of AI washing. Results from a panel vector autoregression (PVAR) and Granger causality test mitigate reverse causality concern. The baseline effect is stronger among firms that opportunistically overstate AI investment, benefit more from capital market rewards, or gain strategic competition advantages from inflated AI use disclosure.

This study advances our understanding of how technological competition affects not only the AI disclosure but also its misalignment with actual AI investment. The findings also carry important policy implications. As firms face escalating pressure to demonstrate AI capabilities, they tend to inflate AI disclosures in ways that distort capital flows. These distortions could misallocate capital and undermine market efficiency. As the SEC moves toward regulating AI-related disclosures, my findings highlight the need for comprehensive guidance promoting accurate AI investment reporting—especially for firms operating under intense TPP.

Two limitations remain. First, I cannot directly observe firms' strategic intentions behind AI washing, such as attempts to deter potential entrants or steer evolving AI industry norms toward established competencies. Future research could explore these motives through field experiments, executive surveys, or qualitative case studies that enable direct observation of managerial decision making. Second, my discordance measure may underestimate the prevalence of both AI washing and hushing at investment distribution extremes. For top AI investment firms, the decile-based ranking approach compresses variation, so small but economically significant discrepancies between disclosure and investment may go undetected, potentially underestimating AI washing among AI investment leaders. Similarly, for bottom AI investment firms, my measure may not adequately detect subtle AI hushing because small absolute differences between disclosure and investment appear negligible when converted to decile rankings.

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Appendix A: Variable Definitions

Variable name	Definitions
Dependent variables	
$AI\_disclose_{i,t+1}$	The ratio of the weighted-frequency count of AI-related terms to total count of terms at the *retrospective investment* discussions of the Business (Item 1) section of 10-K filings filed by firm *i* at the end of year *t*+1. I exploit the word-embedding algorithm to self-construct the expanded list of AI-related keywords. (Source: Notre Dame Software Repository for Accounting and Finance)
$AI\_disclose\_call_{i,t+1}$	The ratio of the weighted-frequency count of AI-related terms to total count of terms at the *retrospective investment* discussions of the presentation section of earnings conference call transcripts. Then I average the ratio values of all earnings calls held by firm *i* during year *t*+1. I exploit the word-embedding algorithm to self-construct the expanded list of AI-related keywords. (Source: StreetEvents)
$AI\_invest_{i,t+1}$	The ratio of AI-skilled employees to the total number of employees with non-internship U.S. employee LinkedIn profiles for firm *i* at the end of year *t*+1. (Source: LinkedIn)
$AI\_invest\_patent_{i,t+1}$	The ratio of AI-related patents granted to a firm divided by total granted patents for firm *i* at the end of year *t*+1. (Source: USPTO)
$Discordance_{,t+1}$	The difference between two decile ranks of firm *i* among its peer firms (identified by TNIC) in year *t*+1: (1) firm *i*'s within-year 10-K business section of current AI use ($AI\_disclose_{i,t+1}$) rank and (2) its actual AI investment ($AI\_invest_{i,t+1}$) rank based on employee resumes. (Source: Notre Dame Software Repository for Accounting and Finance and LinkedIn)
$Discordance\_call_{i,t+1}$	The difference between two decile ranks of firm *i* among its peer firms (identified by TNIC) in year *t*+1: (1) firm *i*'s within-year earnings call presentation section of current AI use ($AI\_disclose\_call_{i,t+1}$) rank and (2) its actual AI investment ($AI\_invest_{i,t+1}$) rank based on employee resumes. (Source: StreetEvents and LinkedIn)
$Discordance\_patent_{i,t+1}$	The difference between two decile ranks of firm *i* among its peer firms (identified by TNIC) in year *t*+1: (1) firm i's within-year 10-K business section of current AI use ($AI\_disclose_{i,t+1}$) rank and (2) its actual AI investment level ($AI\_invest\_patent_{i,t+1}$) rank based on patent grants. (Source: Notre Dame Software Repository for Accounting and Finance and USPTO)
$Discordance\_SIC_{i,t+1}$	The difference between two decile ranks of firm *i* among its peer firms (identified by 4-digit SIC codes) in year *t*+1: (1) firm i's within-year 10-K business section of current AI use ($AI\_disclose_{i,t+1}$) rank and (2) its actual AI investment ($AI\_invest_{i,t+1}$) rank based on employee resumes. (Source: Notre Dame Software Repository for Accounting and Finance and LinkedIn)
Independent variables	
$TPP_{i,t}$	The natural logarithm of $(1 + \frac{\sum_{j \neq i} \omega_{i,j} G_{j,t}}{G_{i,t}})$. This proxy captures the competitive pressure firm *i* faces in year *t* from its peer firms *j* based on the aggregate technological advancements. $\omega_{i,j}$ reflects the similarity between firm i and each peer firm j, determined by how similar their sales distributions are across different 4-digit SIC industries. For each peer firm *j* (firm *i*), the R&D stock $G_{j,t}$ ($G_{i,t}$) represents the cumulative R&D investments over the past five years, adjusted for a 15% annual decay to reflect the diminishing value of past R&D expenditures. (Source: Compustat)

Peers_LnSales$_{i,t}$	The average value of firm *i*'s each peer firm *j*'s natural logarithm of total sales in year *t*. (Source: Compustat)
Peers_MTB$_{i,t}$	The average value of firm *i*'s each peer firm *j*'s ratio of market capitalization to the book value of equity of in year *t*. (Source: Compustat)
Peers_EBITDA$_{i,t}$	The average value of firm *i*'s each peer firm *j*'s earnings before interest, taxes, depreciation, and amortization scaled by total assets in year *t*. (Source: Compustat)
Peers_PPE$_{i,t}$	The average value of firm *i*'s each peer firm *j*'s property, plant, and equipment scaled by total assets in year *t*. (Source: Compustat)
Peers_R&D$_{i,t}$	The average value of firm *i*'s each peer firm *j*'s total R&D expenditures scaled by total assets in year *t*. (Source: Compustat)
Peers_ FinPCA$_{,t}$	The first principal component from a principal component analysis (PCA) based on five peer financial characteristics for firm *i* in year *t*: *Peers_LnSales*, *Peers_MTB*, *Peers_EBITDA*, *Peers_PPE*, and *Peers_R&D*. (Source: Compustat)
Peers_Tsim$_{i,t}$	The sum of each peer firm *j*'s net similarity index relative to that of firm *i* in year *t*. The net similarity index is the raw product cosine similarity value between peer firm *j* and focal firm *i* less the minimum similarity threshold 0.2132 (Source: Hoberg and Phillips (2016)).
Size$_{i,t}$	Total assets of firm *i* at the end of year *t*. (Source: Compustat)
LnSize$_{i,t}$	Natural logarithm of total assets of firm *i* at the end of year *t*. (Source: Compustat)
Lev$_{i,t}$	Total liabilities divided by total assets of firm *i* at the end of year *t*. (Source: Compustat)
MTB$_{i,t}$	The ratio of market capitalization to the book value of equity of firm *i* at the end of year *t*. (Source: Compustat)
Cash$_{i,t}$	Cash and short-term investments divided by total assets of firm *i* at the end of year *t*. (Source: Compustat)
PPE$_{i,t}$	Property, plant, and equipment divided by total assets of firm *i* at the end of year *t*. (Source: Compustat)
ROA$_{i,t}$	Earnings before extraordinary items divided by total assets. (Source: Compustat)
Loss$_{i,t}$	An indicator that equals one if the earnings before extraordinary items of firm *i* during year *t* is lower than zero. (Source: Compustat)
ROAVol$_{i,t}$	The standard deviation of earnings scaled by assets over the previous five years. (Source: Compustat)
CAPEX$_{i,t}$	Capital expenditures divided by total assets. (Source: Compustat)
Analysts$_{i,t}$	The number of analysts following firm *i* at the end of year *t*. (Source: I/B/E/S)
LnAnalysts$_{i,t}$	Natural logarithm of one plus the number of analysts following of firm *i* at the end of year *t*. (Source: I/B/E/S)
WWIndex$_{i,t}$	The Whited–Wu (WW) (2006) index is defined as $(-0.091 \times \text{CF}) - (0.062 \times \text{DIVPOS}) + (0.021 \times \text{TLTD}) - (0.044 \times \text{LNTA}) + (0.102 \times \text{ISG}) - (0.035 \times \text{SG})$, where CF is a ratio of cash flow divided by total assets; DIVPOS is an indicator that equals to 1 if the firm pays a dividend, and 0 otherwise; TLTD = long-term debt to total assets; LNTA = logarithm of total assets; ISG = 2-digit SIC industry sales growth; and SG = firm sales growth. Higher values of the WW index imply greater levels of financial constraint. (Source: Compustat)
MA$_{i,t}$	An indicator variable that equals 1 if firm *i* makes acquisitions during fiscal year *t*+1 and the transaction value is available and 0 otherwise. Source: Thomson Financials' SDC Platinum.
GunningFog$_{i,t}$	The Gunning Fog index at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
LnWordCount$_{i,t}$	The natural logarithm of the total number of words at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)

Sentiment$_{i,t}$	The Loughran-McDonald dictionary's positive word count minus negative word count, scaled by the total word count at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
Uncertainty$_{i,t}$	The proportion of words reflecting uncertainty, calculated using the Loughran-McDonald dictionary's uncertainty word count, scaled by the total word count at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
LnComplexity$_{i,t}$	The natural logarithm of the total number of complex words at the 10-K filing of firm *i* in year *t*. (Source: SEC Analytics Suite)
Instrumental variable	
TaxCredit$_{i,t\text{-}1}$	$\sum_{j\neq i}\omega_{i,j}\times I_{TaxCredit}(S_{j,t})\times I(S_{j,t}\neq S_{i,t})$, where $\omega_{i,j}$ is the closeness weight between firm *i* and peer firm *j*, based on their product market proximity; $I_{TaxCredit}(S_{j,t})$ is an indicator variable that equals 1 if state $S_{j,t}$ has introduced R&D tax credits by the end of year *t*, and 0 otherwise; $I(S_{j,t}\neq S_{i,t})$ ensures that only peer firms *j* headquartered in different states from the focal firm *i* are included. (Source: Bloom et al. (2013))
Partition variables	
Boilerplate$_{i,t}$	An indicator variable for whether the proportion of AI investment discussion sentences that contain at least one of boilerplate phrases relative to the total number of AI-related sentences at the Business section of 10-K reports. I follow the approach of Lang and Stice-Lawrence (2015) and Dyer et al. (2017) to identify the boilerplate phrases as four-word sequences (i.e., tetragrams) that appear in a high proportion—at least 75%—of all firm 10-K filings each year. (Source: Notre Dame Software Repository for Accounting and Finance, Lang and Stice-Lawrence (2015), and Dyer et al. (2017)).
LowInfoEnviron$_{i,t}$	An indicator variable for whether the bid-ask spread for firm *i* in year *t* is above its sample median. I calculate the bid-ask spread as the average daily quoted bid-ask spread measured over the current year t. (Source: CRSP)
LowCOE$_{i,t}$	An indicator variable that equals 1 if the implied cost of equity of firm *i* is below its sample median in year *t*, and 0 otherwise. To determine the implied cost of equity, I use the estimation method developed by Ohlson and Juettner-Nauroth (2005). (Source: I/B/E/S, CRSP, and Ohlson and Juettner-Nauroth (2005))
HighLiquidity$_{i,t}$	An indicator variable for whether firm *i*'s mean of daily dollar trading volume divided by absolute return (i.e., the inverse of the Amihud illiquidity ratio) in year *t* is above the sample median. (Source: CRSP)
TechProximity$_{i,t}$	An indicator variable for whether firm *i*'s technological proximity (i.e., the pairwise uncentered correlation between firm *i* and its peers, based on patent applications across technology classes over the past two decades) in year *t* exceeds its sample median. (Source: USPTO)
Frontrunner$_{i,t}$	An indicator variable that equals 1 if *AI_invest* value of firm *i* belongs to the top quintile of actual AI investment level in year *t*, and 0 otherwise. (Source: LinkedIn)
Laggard$_{i,t}$	An indicator variable that equals 1 if *AI_invest* value of firm *i* belongs to the bottom quintile of actual AI investment level in year *t*, and 0 otherwise. (Source: LinkedIn)

Appendix B: Examples of Corporate AI Investment Discussions

Cavitation Technologies Incorporation 2023 Annual Report:
The Company continues to enhance its Nano Reactor® system and related processing solutions with AI-enabled diagnostics to improve reliability and efficiency for industrial clients.

ShiftPixy Incorporation 2020 Annual Report:
The Company's business model includes the development of a technology platform and mobile application that utilizes artificial intelligence and machine learning algorithms to match workers with open shifts in real-time, streamline scheduling, and enhance workforce management for clients.

Stitch Fix Incorporation 2019 Annual Report:
Our data science capabilities are core to our business model and support nearly every aspect of our client experience, including inventory management, demand forecasting, algorithmic buying, personalized styling, and trend and fashion forecasting. [...] We use a combination of human judgment and advanced algorithms, including machine learning, to make client recommendations and improve personalization.

DISH DBS Corporation 2019 Annual Report:
We continue to invest in the innovation of our services, customer support systems and technology infrastructure. We utilize advanced technologies, including automation and machine learning, in our operations to optimize signal transmission and network performance, improve customer service experiences, and reduce operating costs.

Q2 2021 Fortive Corporation Earnings Conference Call:
In the second quarter, we continued our investment in digital solutions, including AI and machine learning capabilities, to enhance predictive maintenance offerings and deepen customer engagement. These investments support our long-term strategy of integrating data and analytics across our solutions portfolio.

Q2 2020 Cognex Corporation Earnings Conference Call:
We continue to expand our investment in advanced vision technologies, including the use of artificial intelligence and deep learning to improve defect detection and inspection accuracy in complex manufacturing environments.

Q3 2021 Agilent Technologies Incorporation Earnings Conference Call:
For example, in our CrossLab Group, we've been using AI and machine learning to improve instrument diagnostics and predictive maintenance, reducing downtime and improving the customer experience.

Q1 2020 Bruker Corporation Earnings Conference Call:
We are seeing increasing interest in our MALDI Biotyper and FluoroSpot systems, and we are developing AI-based tools to support more automated and accurate analysis of mass spec and other bioanalytical data.

Table 1 Sample Selection

The table lists the sample-selection procedures. My main sample includes 26,333 firm-year observations in 2011–2023 for 10-K Business section analysis, covering 3,862 unique U.S. public firms. Panel A lists its sample-selection procedures. My robustness sample includes 20,264 firm-year observations in 2011–2023 for conference call analysis, covering 2,970 unique U.S. public firms.

Panel A: 10-K Business section main sample

U.S. Firm-years with non-missing total assets in Compustat for 2011–2023	166,719
Less:	
Firm-years in the financial (SIC codes 6000–6999) and utility sectors (SIC codes 4400–4999)	(85,309)
Firm-years without available data for calculating *TPP*	(32,154)
Firm-years without clean texts of 10-Ks from Notre Dame Software Repository for Accounting and Finance	(8,216)
Firm-years without the discussions of current AI investments at the Business section and without the actual AI investments	(11,767)
Firm-years without data for calculating the control variables in my main model	(2,940)
My main sample in firm-years	26,333

Panel B: Earnings call robustness sample

U.S. Firm-years with non-missing total assets in Compustat for 2011–2023	166,719
Less:	
Firm-years in the financial (SIC codes 6000–6999) and utility sectors (SIC codes 4400–4999)	(85,309)
Firm-years without available data for calculating *TPP*	(32,154)
Firm-years without clean transcripts of conference calls from StreetEvents	(15,161)
Firm-years without the discussions of current AI investments at the earnings calls' presentation section and without the actual AI investments	(12,033)
Firm-years without data for calculating the control variables in my main model	(1,798)
My robustness sample in firm-years	20,264

Table 2 Descriptive Statistics

This table presents the descriptive statistics for the main sample used in the empirical tests. The table reports the summary statistics of the dependent variables, key explanatory variable, and control variables used in the baseline model specification.

Variables	N	Mean	Std. Dev.	25%	Median	75%
Dependent variables:						
Discordance	26,333	-0.933	5.249	-6	0	2
Discordance_call	20,264	0.538	5.079	-3	0	5
Discordance_patent	26,333	-1.657	5.022	-6	-2	1
Discordance_SIC	23,787	-1.546	5.180	-6	0	0
AI_disclose	26,333	0.052	0.112	0	0	0.012
AI_invest	26,333	0.132	0.199	0	0.025	0.193
Key explanatory variable:						
TPP	26,333	5.201	3.003	3.163	5.123	6.985
Control variables:						
Peers_FinPCA	26,333	0.343	0.277	0.132	0.248	0.478
Peers_Tsim	26,333	3.889	8.348	1.070	1.365	2.632
Size	26,333	6,389	16,311	283	1,103	4,131
LnSize	26,333	6.989	1.971	5.646	7.006	8.326
Lev	26,333	0.448	0.253	0.283	0.420	0.567
MTB	26,333	3.903	7.519	1.622	2.721	4.800
Cash	26,333	0.214	0.191	0.065	0.153	0.306
PPE	26,333	0.166	0.144	0.065	0.122	0.219
ROA	26,333	-0.010	0.217	-0.025	0.037	0.079
Loss	26,333	0.317	0.465	0	0	1
ROAVol	26,333	0.078	0.230	0.017	0.036	0.081
CAPEX	26,333	0.035	0.035	0.014	0.025	0.044
Analysts	26,333	6.210	5.869	2	4	9
LnAnalysts	26,333	1.389	0.977	0.693	1.386	2.197
WWIndex	26,333	-0.334	0.112	-0.410	-0.333	-0.260
MA	26,333	0.221	0.415	0	0	0
GunningFog	26,333	24.009	2.399	22.853	24.705	25.766
LnWordCount	26,333	11.782	1.274	11.572	12.204	12.507
Sentiment	26,333	-0.010	0.023	-0.008	-0.006	-0.003
Uncertainty	26,333	0.010	0.003	0.008	0.010	0.012
LnComplexity	26,333	10.480	1.337	10.249	10.949	11.248

Table 3 Validation Tests of the Discordance Measure

This table presents three validation tests that assess the effectiveness of the *Discordance* measure, which captures the mismatch between a firm's AI disclosure and its actual AI investment. Panel A reports results on a hedge portfolio analysis, in which I form long-short portfolios based on the decile ranking of *Discordance*. To form the hedge portfolio, firm-years in the lowest decile (most likely to engage in AI hushing) are taken in long positions, while those in the highest decile (most likely to engage in AI washing) are taken in short positions. Annual size-adjusted abnormal returns are estimated over one- or two-year horizons following the portfolio formation year. Panel B reports the percentage distribution of securities class action lawsuits related to alleged AI washing across positive *Discordance* quintiles. Panel C reports differences in analyst forecast dispersion and forecast error between firms in the extreme deciles (highest and lowest) and those in the middle deciles. Forecast dispersion (*AF_Dispersion*) is measured as the standard deviation of analyst earnings-per-share (EPS) forecasts for a firm-year, scaled by the absolute value of the mean forecast; forecast error (*AF_Error*) is the absolute difference between a firm's reported EPS and the consensus analyst EPS forecast, scaled by the firm's share price. Panel D estimates a Poisson regression of a sample firm's AI disclosure on its actual AI investment. The test statistics (*t*-statistics or *z*-statistics) are clustered by firm level and included in parentheses. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Hedge portfolio test

	Degree of discordance	
	Year *t*+1	Year *t*+2
Lowest decile (Long)	0.013***	0.010***
	(3.92)	(3.57)
Highest decile (Short)	-0.020***	-0.017***
	(-6.03)	(-5.89)
Hedge	0.033***	0.027***
	(6.81)	(6.02)

Panel B: Percentage distribution of alleged AI washers by positive *Discordance*

Quintile rank of positive *Discordance*	Percentage distribution of alleged AI washing lawsuits
1	0%
2	0%
3	2%
4	11%
5	87%
Total	100%

Panel C: Differences in analyst forecast dispersion/accuracy between extreme and middle deciles

Subsample	*AF_Dispersion*	*AF_Error*
Middle deciles	0.006***	0.007***
	(3.65)	(3.92)
Extreme deciles	0.011***	0.016***
	(4.01)	(4.87)
Difference	0.005***	0.009***
	(5.27)	(6.74)

Panel D: Poisson regression of AI disclosure on actual AI investment

	(1) *AI_disclose*	(2) *AI_disclose*
AI_invest	0.073	0.056
	(0.62)	(0.45)
Controls	Yes	No
Industry×Year FE	Yes	Yes
N	26,334	26,334
Pseudo R2	5.89%	0.02%

Table 4 Baseline Analysis Results

This table presents baseline regression results. Column (1) reports the baseline estimation results of Equation (1). Columns (2) and (3) replace the dependent variable *Discordance* with the disclosure and investment components, respectively, to assess the channels through which TPP influences discordance. Column (2) reports result from estimating Equation (2), with *AI_disclose* as the dependent variable, while column (3) reports result from estimating Equation (3), with *AI_invest* as the dependent variable. All models include the covariates used in the baseline specification, as well as an industry-by-year fixed effects structure. Continuous variables are winsorized at the 1st and 99th percentiles. All variable definitions are provided at Appendix A. Standard errors are clustered at the firm level and the t-values are reported in parentheses. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

	(1) *Discordance*	(2) *AI_disclose*	(3) *AI_invest*
TPP	0.261***	0.050***	0.032***
	(5.46)	(2.99)	(2.97)
Peers_FinPCA	0.519	0.101*	-0.026
	(1.29)	(1.74)	(-0.82)
Peers_Tsim	0.047**	-0.001	-0.005***
	(2.37)	(-1.37)	(-3.84)
LnSize	-0.877***	0.040**	0.056***
	(-5.19)	(2.46)	(3.03)
Lev	-1.087**	-0.074	-0.063
	(-2.38)	(-1.46)	(-1.47)
MTB	-0.015*	0.000	0.002*
	(-1.67)	(0.65)	(1.79)
Cash	-1.723***	0.121*	0.490***
	(-2.66)	(1.67)	(3.35)
PPE	4.796***	0.371**	-0.261***
	(4.45)	(2.37)	(-2.99)
ROA	0.056	-0.091	-0.117
	(0.09)	(-1.30)	(-1.57)
Loss	0.312	0.036	0.045**
	(1.37)	(1.18)	(2.16)
ROAVol	-0.646*	0.058	0.061
	(-1.73)	(0.98)	(1.18)
CAPEX	-5.757	0.746	0.735**
	(-1.40)	(1.16)	(2.44)
LnAnalysts	-0.272**	0.004	0.041***
	(-2.04)	(0.40)	(3.21)
WWIndex	-4.764	0.097	0.104
	(-1.61)	(0.26)	(0.26)
MA	-0.018	-0.011	-0.046***
	(-0.10)	(-0.57)	(-2.90)
GunningFog	-0.071	-0.009*	-0.004
	(-1.29)	(-1.65)	(-0.82)
LnWordCount	3.582**	-0.008	0.123
	(2.49)	(-0.06)	(0.64)
Sentiment	5.305*	-0.150	0.499
	(1.73)	(-0.48)	(1.57)
Uncertainty	-5.513	-1.616	-3.694
	(-1.31)	(-0.44)	(-1.14)
LnComplexity	-3.329**	0.017	-0.113
	(-2.40)	(0.13)	(-0.61)
Industry×Year FE	Yes	Yes	Yes
N	26,333	26,333	26,333
Adjusted R^2	29.7%	21.7%	15.9%

Table 5 Robustness Checks of Baseline Finding

This table presents four robustness tests to assess the validity of the baseline finding. In Panel A, I construct an alternative AI disclosure measure (*AI_disclose_call*) using the presentation section of earnings calls and recalculate *Discordance_call* based on peer decile rankings of disclosure of current AI use and actual AI investment. Panel B uses an alternative AI investment measure (*AI_invest_patent*), defined as the proportion of AI-related patents granted to the firm and constructs *Discordance_patent* accordingly. Panel C replaces the TNIC-based peer identification with 4-digit SIC industry classifications to compute *Discordance_SIC*. Panel D excludes firm-year observations from the COVID-19 period (2020–2021) to mitigate pandemic-related distortions in disclosure and investment behavior. In all panels, I re-estimate the baseline model (1) using the respective discordance measure as the dependent variable. Across all robustness tests, I control for firm-level and industry-level covariates used in the baseline specification and include industry-by-year fixed effect structure. Continuous variables are winsorized at the 1^{st} and 99^{th} percentiles. Standard errors are clustered at the firm level, and *t*-statistics are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Alternative measure of AI disclosure based on earnings calls

	(1) *Discordance_call*	(2) *AI_disclose_call*	(3) *AI_invest*
TPP	0.205***	0.042***	0.033***
	(4.18)	(4.98)	(2.96)
Controls	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
N	20,264	20,264	20,264
Adjusted R^2	29.3%	21.7%	15.9%

Panel B: Alternative measure of AI investment based on patents

	(1) *Discordance_patent*	(2) *AI_disclose*	(3) *AI_invest_patent*
TPP	0.157***	0.050***	0.020***
	(4.28)	(2.99)	(4.25)
Controls	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
N	26,333	26,333	26,333
Adjusted R^2	44.9%	21.7%	48.2%

Panel C: Peer firm identification based on 4-digit SIC industry classification

	(1) *Discordance_SIC*	(2) *AI_disclose*	(3) *AI_invest*
TPP	0.119***	0.050***	0.032***
	(2.51)	(2.99)	(2.97)
Controls	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
N	26,333	26,333	26,333
Adjusted R^2	28.5%	21.7%	15.9%

Panel D: Exclude COVID-19 period

	(1) *Discordance*	(2) *AI_disclose*	(3) *AI_invest*
TPP	0.255***	0.050***	0.030***
	(5.19)	(2.91)	(2.80)
Controls	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
N	23,787	23,787	23,787
Adjusted R^2	30.9%	19.7%	17.0%

Table 6 Reverse Causality Test

This table reports the results of analyses that address reverse causality between technological peer pressure and AI washing. Panel A reports the results from panel vector autoregression (PVAR) model of discordance between firm AI disclosure and actual AI investment (measured by *Discordance*), technological peer pressure (measured by *TPP*), and respective control variables used in my baseline model specification. *Discordance* and *TPP* are treated as endogenous variables, and controls are treated as exogenous variables in PVAR. I include the first-order lag of endogenous variables in the PVAR and use the first four lags of endogenous variables as instruments in the model both to minimize the modified Bayesian information criterion and the modified Quinn information criterion (Abrigo and Love 2016) and to mitigate the model overfitting issues (Arnerić and Situm 2022). Panel B reports the Chi-square statistics for the Granger causality Wald tests of the null hypothesis that the excluded variable does not Granger-cause equation variable. Appendix A provides variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The test statistics are presented in parentheses calculated using standard errors clustered by firm level. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Panel vector autoregression coefficient estimates

	(1) $Discordance_t$	(2) TPP_t
$Discordance_{t-1}$	0.563***	0.020
	(3.66)	(0.39)
TPP_{t-1}	0.328***	1.356***
	(3.98)	(4.63)
Controls	Yes	Yes

Panel B: Granger causality test

Equation variable	Excluded variable	Chi-square
(1) *Discordance*	*TPP*	6.698***
(2) *TPP*	*Discordance*	0.329

Table 7 Two-stage Least Squares Analysis

This table presents results from a two-stage least squares (2SLS) analysis designed to address endogeneity concerns in the relation between technological peer pressure (TPP) and the discordance between firm AI disclosure and actual AI investment (*Discordance*). Column (1) re-estimates the baseline model specification using the reduced 2SLS sample. Column (2) reports the first-stage regression, where the endogenous variable TPP is instrumented using *TaxCredit*, which captures peer firms' exposure to state-level R&D tax credits. Specifically, *TaxCredit* is constructed as the sum of R&D stocks of peer firms headquartered in states that offer R&D tax credits, weighted by their product market similarity to the focal firm. Column (3) reports the second-stage regression, where the predicted values of *TPP* from the first stage are used to estimate its effect on *Discordance*. All regressions include the firm- and industry-level covariates and industry-by-year fixed effects as the baseline model. Continuous variables are winsorized at the 1st and 99th percentiles. Standard errors are clustered at the firm level, and *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	OLS	IV 1st stage	IV 2nd stage
	$Discordance_{t+1}$	TPP_{t+1}	$Discordance_{t+1}$
$TaxCredit_t$		0.183*	
		(1.81)	
TPP_t	0.220***		0.264**
	(5.12)		(2.50)
Controls	Yes	Yes	Yes
Industry×Year FE	Yes	Yes	Yes
N	17,044	17,044	
Adjusted R^2	29.2%	26.7%	
Wu–Hausman F-statistic		45.38***	
First-stage F-statistic		36.25***	

Table 8 Cross-section Variation Analysis

This table presents the results of estimating Equation (4) to examine cross-sectional variation in the effect of technological peer pressure (*TPP*) on the discordance between firm AI disclosure and actual AI investment (*Discordance*). In Panel A, I conduct cross-sectional analyses related to managers' opportunistic overstatement of AI investment. I test whether the main effect is more pronounced for firms with more boilerplate disclosure language (*Boilerplate*) or those operating in less transparent information environments (*LowInfoEnviron*). In Panel B, I conduct cross-sectional analyses related to capital market benefits. I test whether the effect is more pronounced for firms more pronounced for firms with a lower implied cost of equity (*LowCOE*) or firms with higher stock liquidity (*HighLiquidity*). In Pane C, I conduct cross-sectional analyses related to strategic competition advantages. I test whether the effect is more pronounced for firms with greater technological proximity to their peers (*TechProximity*) or those positioned as either AI frontrunners (*Frontrunner*) or laggards (*Laggard*). Appendix A provides all variable definitions. All continuous variables are winsorized at the 1st and 99th percentiles. The t-values are presented in parentheses calculated using standard errors clustered by firm. *, **, and *** indicate $p < 0.10$, $p < 0.05$, and $p < 0.01$, respectively.

Panel A: Cross-sectional variation in opportunistic overstatement of AI investment

	(1)	(2)
	Discordance	
Boilerplate×TPP	0.267***	
	(4.99)	
LowInfoEnviron×TPP		0.148**
		(2.34)
Industry×Year FE	Yes	Yes
N	26,333	26,333
Adjusted R^2	30.4%	31.8%

Panel B: Cross-sectional variation in capital market benefits

	(1)	(2)
	Discordance	
LowCOE×TPP	0.210***	
	(4.43)	
HighLiquidity×TPP		0.218***
		(3.46)
Industry×Year FE	Yes	Yes
N	26,333	26,333
Adjusted R^2	30.5%	30.3%

Panel C: Cross-sectional variation in strategic competition advantages

	(1)	(2)	(3)
		Discordance	
TechProximity×TPP	0.258***		
	(3.52)		
Frontrunner×TPP		0.125***	
		(2.50)	
Laggard×TPP			0.265**
			(2.10)
Industry×Year FE	Yes	Yes	Yes
N	26,333	26,333	26,333
Adjusted R^2	30.2%	31.7%	55.0%