

Artificial Intelligence and Stock Liquidity

Sanjay Banerji ^a, Taufiq Choudhry ^b, Wenjing Zhang ^b

^a Business School, University of Nottingham, UK

^b Business School, University of Southampton, UK

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Abstract

This paper examines the effect of firm-level Artificial Intelligence (AI) on stock liquidity. Using résumé and job-posting data to measure AI adoption, we find that higher AI adoption is associated with significantly lower stock illiquidity and narrower bid–ask spreads. Our identification strategy employs an instrument variable using firms’ exposure to the supply of AI graduates from universities. We also exploit a quasi-natural experiment based on AlphaGo’s victory as an exogenous belief shock to AI capabilities. Mechanism analysis shows AI adoption improves stock liquidity because it improves the firm’s information environment and reduce firm risk. Overall, the findings identify AI adoption as an important determinant of stock liquidity and market quality.

Key words: Artificial Intelligence; Stock Liquidity; Earning Management; Volatility

1. Introduction

Artificial Intelligence (AI) is reshaping business practices around the globe (Furman and Seamans, 2019). Firms have invested heavily in AI, transforming how they process information, forecast outcomes, and manage internal operations (Furman and Seamans, 2019; Babina et al., 2024). These changes inside the firm ultimately surface in capital markets. Investors observe shifts in firm fundamentals and disclosure quality, and trade accordingly. A growing literature documents the firm-level consequences of AI adoption, including effects on innovation, productivity, and labor demand (Babina et al., 2024; Acemoglu et al., 2022; Yang, 2022). Recent work shows that AI also affects financial markets through information intermediaries such as analysts (Bertomeu et al., 2025). Whether AI adoption inside the firm shapes capital market quality remains an open question.

We focus on stock liquidity, a central measure of market quality. More liquid stocks carry lower trading costs, better price discovery, and a lower cost of capital (Diamond and Verrecchia, 1991; Kyle, 1985). A substantial literature identifies the macroeconomic and firm-level determinants of stock liquidity (Grullon et al., 2004; Chung et al., 2010; Nagar et al., 2019), but firm-level AI adoption has received no attention. Using large-scale job-posting and resume data, we document that firms with greater AI adoption experience lower stock illiquidity and narrower bid-ask spreads. We provide the first evidence that firm-level AI adoption is a meaningful determinant of stock liquidity.

AI adoption can improve stock liquidity through two channels. First, AI strengthens internal monitoring. Traditional internal controls are largely manual and periodic, leaving well-

documented weaknesses (Beneish et al., 2008). Auditors sample transactions, and checks are performed at fixed intervals. Between review cycles, errors and manipulations can accumulate undetected. Even when controls are applied, they operate within individual systems in isolation. AI transforms previously decentralized data into a centralized information base. Procurement records, expense reports, payroll systems, and operational logs are integrated and monitored together. Cross-referencing these sources in real time leaves little room for inconsistencies to go unnoticed. Unusual accrual patterns, irregular approval sequences, and mismatches between operational activity and reported financials are flagged as they emerge (Zhang et al., 2024; Ashraf, 2025). This constrains managerial discretion and reduces the scope for hidden actions. Improved internal oversight produces more credible disclosures, reducing the information advantage insiders hold over outside investors (Brown and Hillegeist, 2007). Liquidity providers face lower adverse selection costs, leading to tighter spreads and greater market depth.

Second, AI reduces firm risk. As a prediction technology, AI converts large volumes of data into more accurate forecasts of demand, inventories, and operational disruptions. Unlike traditional forecasting models, AI can draw on diverse information sources, including operational records, news, industry trends, and macroeconomic conditions, producing more comprehensive and timely predictions. Firms increasingly rely on machine learning models trained on historical sales data with repeated demand shocks to anticipate demand fluctuations and optimize inventory decisions. Such predictive analytics reduce unexpected shortfalls and stabilize operating performance (Carbonneau et al., 2008; Bertsimas and Kallus, 2020). More stable operations translate into lower earnings volatility. As fundamentals become more predictable, investor uncertainty about firm value narrows and return volatility falls. > Lower return volatility reduces market makers' inventory risk, lowering the compensation they require for providing immediacy (Stoll, 1978; Ho and Stoll, 1981). Both channels predict a negative relation between AI adoption and stock illiquidity.

We measure AI adoption using human capital proxies following Babina et al. (2024). Because AI adoption depends critically on AI-specific human capital, the presence of AI-skilled employees directly reflects a firm's capacity to deploy AI in operations and decision-making. We measure AI adoption using two data sources. Job-posting data from Burning Glass Technologies (BG hereafter) capture firms' demand for AI-related skills. Résumé data from Cognism capture the share of employees whose roles are directly linked to AI activities. Both measures are linked to the Amihud (2002) illiquidity ratio and bid-ask spreads for U.S. listed firms over 2010-2018.

The baseline is a long-differences regression relating the change in stock illiquidity to the change in AI adoption over the sample period. Long differencing absorbs time-invariant firm heterogeneity and is well suited to the gradual, multi-year nature of AI adoption, capturing the cumulative effect of AI buildup on stock liquidity (Acemoglu and Restrepo, 2020). Controls include firm characteristics, commuting-zone conditions, and industry-level wages, alongside 2-digit NAICS industry and state fixed effects. A one-standard-deviation increase in AI adoption is associated with approximately a 15% improvement in the Amihud illiquidity measure. The central empirical challenge is endogeneity. Firms with better future prospects may invest more in AI, creating a selection problem, and firms with higher liquidity may face

lower financing frictions that enable greater technology adoption. This design mitigates time-invariant confounds but cannot rule out that unobserved shocks jointly drive AI adoption and liquidity improvements. We address residual endogeneity using two identification strategies.

The first is an instrumental variable (IV) based on firms' pre-existing ties to universities with established strength in AI research. Firms with historical ties to AI-intensive universities draw from a larger pool of AI-skilled graduates, making them more likely to adopt AI. This supply channel is plausibly exogenous to firms' own liquidity expectations. Universities are classified as AI-strong if, during 2005-2009, they ranked in the top 5% by the share of AI-related publications, before widespread commercial adoption began. Firm-university hiring networks are constructed from pre-2010 resume data. The first-stage F-statistics comfortably exceed conventional thresholds. IV estimates confirm a strong negative effect of AI adoption on stock illiquidity, with coefficients larger in magnitude than OLS. The IV isolates supply-side variation in AI adoption that is plausibly independent of demand-side liquidity determinants. Like all IV designs, this approach rests on an untestable exclusion restriction. We complement the IV with a quasi-experimental design.

The second exploits AlphaGo's defeat of world champion Lee Sedol in March 2016 as an exogenous shock to firms' beliefs about AI capabilities. The event generated extensive global media coverage and was universally recognized as a landmark in AI development. It did not affect firms' operations or financial conditions directly; rather, it updated beliefs about what AI could achieve. East Asian directors share a cultural familiarity with Go, a game embedded in Chinese, Japanese, and Korean traditions for over 2,500 years. Firms with East Asian board members were more likely to grasp the significance of AlphaGo's victory and respond with greater AI adoption than otherwise comparable firms. We implement a difference-in-differences (DID) design comparing firms with and without East Asian board members before and after the event. After the event, firms with East Asian board members show a larger increase in AI-skilled employment and a larger decline in stock illiquidity. Event-study coefficients show no pre-trend divergence and a gradual post-event widening, consistent with a causal interpretation.

To mitigate survivorship bias from requiring firms to survive the full sample period, we estimate panel regressions with firm, state, and industry-by-year fixed effects. These specifications exploit within-firm variation in AI adoption and accommodate firm entry and exit. The negative coefficient on AI adoption holds across rolling one-year changes, three-year horizons, and five-year moving windows, confirming that the result is not specific to the long-run cross-sectional comparison.

The main finding survives a series of specification checks. Alternative AI measures yield similar results: a narrow AI skill set excluding general programming skills, a binary AI job share, and an AI-utilizing worker share based on exposure to external AI software. Replacing Amihud illiquidity with bid-ask spreads leaves the finding intact. Adding controls for non-AI technology adoption, including IT skills, robotics skills, and non-AI data analytics software, does not materially change the estimates, ruling out the interpretation that AI proxies for broader technology adoption. The result is unchanged under detailed industry fixed effects, or

when the IV uses earlier 2000-2004 university research data or excludes any single prominent AI university such as Carnegie Mellon or Stanford.

The liquidity effect is concentrated among larger firms, which generate richer operational data and therefore benefit more from AI adoption in reducing information asymmetry and firm risk. Mechanism tests support both channels. Firms with greater AI adoption exhibit lower real and accrual-based earnings management under both the Jones (1991) and Modified Jones (Dechow et al., 1995) models, consistent with AI tightening internal oversight and reducing managerial discretion in financial reporting. AI adoption is also associated with lower stock return volatility and lower earnings volatility, indicating more stable firm fundamentals. Reduced information asymmetry and lower risk borne by market participants together account for the improvement in stock liquidity.

This paper makes two contributions. First, we provide causal evidence that AI adoption improves stock liquidity. Prior work documents the role of information transparency and firm risk in shaping liquidity (Glosten and Milgrom, 1985; Kyle, 1985; Diamond and Verrecchia, 1991; Healy and Palepu, 2001). More recent work shows that information-processing technologies can also affect market efficiency: Bertomeu et al. (2025) exploit the unexpected ban of ChatGPT in Italy and show that reduced access to generative AI lowers analysts' forecast frequency and accuracy. This reduction is associated with wider bid-ask spreads, indicating weaker market efficiency. We extend this line of inquiry to the firm level, showing that AI adoption is an important and previously unexplored determinant of stock liquidity. A long-difference baseline, an IV based on university AI research exposure, and a DID design around the AlphaGo event produce convergent estimates, supporting a causal interpretation.

Second, we open the black box by identifying two mechanisms. A growing literature documents the effects of AI on firm productivity, labor markets, and growth (Acemoglu et al., 2022; Babina et al., 2024; Eisfeldt et al., 2023). We extend this literature by focusing on capital market frictions. AI adoption improves the information environment, reducing adverse selection costs, and lowers firm risk, reducing inventory-holding costs. Both channels operate through well-established market microstructure theory, connecting the AI adoption literature to a core question in asset pricing.

The remainder of the paper proceeds as follows. Section 2 develops the hypothesis. Section 3 describes the data and empirical strategy. Sections 4 and 5 present the main results and mechanism analysis. Section 6 concludes.

2. Hypothesis Development

2.1 Theoretical Framework

Stock liquidity reflects the transaction costs investors face when trading a firm's shares. Market microstructure theory identifies three components of these costs: adverse selection, inventory-holding, and order-processing costs (Madhavan, 2000). Order-processing costs are largely determined by trading infrastructure and are stable over time (Nagar et al., 2019). The firm-side determinants are adverse selection and inventory-holding costs. Adverse selection costs arise from information asymmetry between informed and uninformed traders: market makers

widen spreads to protect against trading with better-informed counterparties (Glosten and Milgrom, 1985; Kyle, 1985). Inventory-holding costs arise from the risk that asset values move against the market maker while positions are held (Stoll, 1978; Ho and Stoll, 1981). More credible disclosure reduces information asymmetry, lowering adverse selection costs (Diamond and Verrecchia, 1991). Greater stability in firm fundamentals reduces return volatility, lowering inventory-holding costs. Any firm-level factor that improves information quality or reduces fundamental uncertainty should, all else equal, improve stock liquidity.

2.2 AI Adoption and the Information Environment

AI systems can process large volumes of financial and operational data, detect anomalies, and generate timely internal signals. Traditional internal controls rely on periodic audits and fixed rules. They catch clear violations but miss subtler problems so manipulation that stays within accounting rules goes undetected. AI-powered monitoring operates continuously across structured accounting records, internal communications, procurement logs, and operational reports. Cross-referencing these sources in real time leaves little room for inconsistencies to go unnoticed. Unusual accrual patterns, irregular approval sequences, and mismatches between operational activity and reported financials are flagged as they emerge. These capabilities strengthen internal monitoring and reduce the likelihood that errors or discretionary actions persist undetected (Ashraf, 2025; Zhang et al., 2024). Stronger monitoring improves financial and operational transparency, which decreases information asymmetries between insiders (e.g., managers and large shareholders) and outside investors (e.g., outside owners and liquidity providers), as well as among outside investors (Chung et al., 2010). Lower information asymmetry shrinks the adverse selection component of trading costs, encouraging greater market participation. We therefore predict that AI adoption improves stock liquidity through the information environment channel.

H1: AI adoption is associated with higher stock liquidity through improvements in the firm's information environment.

2.3 AI Adoption and Firm Risk

AI also reduces fundamental uncertainty by improving forecasting accuracy. Traditional forecasting methods rely on linear models and historical averages, which struggle to capture complex relationships across large datasets. AI processes high-dimensional data and identifies patterns that conventional models miss, producing more accurate predictions of demand, inventories, and operational disruptions (Agrawal et al., 2019; Carbonneau et al., 2008). More accurate forecasts stabilize operating performance and reduce earnings volatility. Lower earnings volatility narrows market uncertainty about firm value, dampening return volatility. As market makers face less risk of adverse price movements while holding inventory, they require less compensation for providing immediacy (Stoll, 1978; Ho and Stoll, 1981). Consistent with this logic, Peress (2010) and Kale and Loon (2011) show that lower volatility reduces price impact and improves liquidity. We therefore predict that AI adoption improves stock liquidity through firm risk channel.

H2: AI adoption is associated with higher stock liquidity through reductions in firm risk.

3. Research Design

3.1 Data and sample

The sample covers U.S. listed firms over 2010–2018, the period during which firm-level AI adoption accelerated and human-capital-based measures of AI activity are reliable. We end the sample in 2018 to avoid measurement error from delayed résumé updates and confounding effects from the COVID-19 pandemic. We focus on the adoption of AI technologies rather than their invention, and exclude firms in the technology sector accordingly. Table 1 reports summary statistics.

We measure AI adoption using human capital proxies following Babina et al. (2024), drawing on job-posting data from BG and employee profile data from Cognism. Stock returns, prices, trading volume, and bid-ask spreads are from CRSP. Annual financial data are from Compustat. Commuting-zone characteristics are from the Census American Community Surveys (ACS). Industry-level wages are from the Census Quarterly Workforce Indicators (QWI). Academic publication data are from the Open Academic Graph. Board characteristics are from BoardEx.

3.2 Measure of AI adoption

Following Babina et al. (2024), we measure AI adoption using a data-driven, skill-based approach. The effective deployment of AI depends on AI-specific human capital. Data resources, computing infrastructure, and operational integration all require workers with relevant expertise. Workforce composition therefore directly reflects a firm's actual AI adoption.

More specifically, for each of unique skills from the job postings data, their empirical co-occurrence with unambiguous core AI skills (Artificial Intelligence (AI), machine learning (ML), natural language processing (NLP), and computer vision (CV))¹ is calculated.

$$w_s^{AI} = \frac{\# \text{ of jobs requiring skill } s \text{ and (ML,NLP,CV or AI in required skills or in job title)}}{\# \text{ of jobs requiring skill } s} \quad (1)$$

this measure captures how correlated each skill s is with the core AI skills. A higher value indicates a greater degree of AI-relevant for that skill. The job-posting-level AI-relatedness measure w_j^{AI} for a given job posting j is the mean skill-level measure w_s^{AI} across all skills required by job posting j . The continuous measure w_j^{AI} are aggregated to the firm level as one of the main measure of AI. For robustness, we employ two alternative measures. First, we use a continuous “narrow AI” measure, which restricts AI-relatedness to a refined set of AI-specific skills (e.g., supervised learning, AI software such as Tensorflow) while excluding broader

¹ Artificial Intelligence (AI) is the overarching field concerned with simulating human intelligence in machines, while machine learning (ML) focuses on algorithms that enable systems to learn from data and improve over time without explicit programming. Natural language processing (NLP) addresses the ability of machines to understand and generate human language, and computer vision (CV) involves interpreting and analyzing visual information from images and videos. These areas are considered core AI skills because they form the foundations of how AI systems learn, understand language, and interpret the world, supporting most modern AI applications.

programming or statistical skills². This ensures that the results are not driven by general technical competencies. Second, we construct the AI job share, defined as the proportion of a firm’s job postings in a given year that are classified as AI-related (job posting j is AI-related if the measure w_j^{AI} is above 0.1).

As our second main measure of AI adoption, we use Cognism résumé data to identify employees whose job roles are directly related to AI activities. The starting point are 67 highest skill-level AI-relatedness keywords from job postings data. These 67 skills are shown in Appendix B. Each employment record in the resume data is scanned based on three criteria: (i) the job description directly contains any identified AI keyword; (ii) the individual was granted a patent (within a three-year window) with those keywords; or (iii) the individual authored a publication or received an award (within a two-year window) including those keywords. Meeting any one criterion classifies the person as an AI-related employee for that firm-year. AI adoption intensity is measured as the share of AI-related employees in a firm’s total employees in a given year.

3.3 Measure of Liquidity

The main illiquidity measure follows Amihud (2002), which has been widely adopted in the literature (e.g. Avramov et al., 2006; Ben-Rephael et al., 2015). Since the raw Amihud measure is highly skewed, we use the square root version of the raw measure in our empirical analysis. For every stock in our sample and for every year it is calculated as:

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \sqrt{\frac{|R_{i,d}|}{Vol_{i,d} * P_{i,d-1}}} \quad (2)$$

where D_{it} is the number of trading days for stock i during year t , $R_{i,d}$ is the return on day d , $Vol_{i,d}$ is trading volume in millions of shares, and $P_{i,d-1}$ is the closing stock price. ILLIQ is a price impact measure. It captures the stock return per \$1 million of trading volume.

In addition, following Amihud and Levi (2023), as a robustness test, we replace ILLIQ with logarithm of the bid–ask spread (SPRD). It is computed as the dollar quoted spread divided by the quote midpoint and averaged over all trading days in year t .

3.4 Long-differences Regression

We estimate a long-differences regression relating the 2010–2018 change in stock illiquidity to the change in AI adoption. This design is well-suited to capture the gradual, multi-year nature of AI buildup and its potentially lagged impact (e.g., Acemoglu and Restrepo, 2020). Our estimation is from the following regression:

² To avoid capturing general programming or statistical abilities, skills such as programming languages (e.g., Python) or basic statistical methods (e.g., linear regression) are excluded. Only AI-specific skills are retained, including methodologies or algorithms (e.g., supervised learning) and AI software (e.g., TensorFlow). This screening, conducted by AI-trained personnel at the AI for Good Foundation, identifies 700 skills with an AI-relatedness score above 0.05 and appearing in at least 50 job postings. These are further categorized into “narrow” and “broad” AI skills, with the refinement primarily excluding skills with relatively low AI-relatedness.

$$\Delta ALLIQ_{i[2010,2018]} = \alpha_0 + \alpha_1 \Delta AI_{i[2010,2018]} + \alpha_2 Controls_i + Naics2\ Fixed\ Effects + State\ Fixed\ Effects + \varepsilon_i \quad (3)$$

where the main independent variable, $\Delta AI_{i[2010,2018]}$, captures the change in the AI workers based on the resume and job postings data at firm i from 2010 to 2018, and the main dependent variable is the change of Amihud measure from 2010 to 2018. 2-digit NAICS industry fixed effects and state fixed effects are included. We include a rich set of controls (1) the initial firm-level Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure. (2) commuting-zone (CZ) characteristics, including IT employment share, college-educated workforce share, log average wages, foreign-born worker share, and employment shares in finance and manufacturing and (3) the log industry-average wage.

[Insert Table 1 here.]

4. Empirical results

4.1 Long-differences results

Table 2 reports the main results from long-differences regressions examining the relation between firm-level AI adoption and changes in stock illiquidity from 2010 to 2018. Across all specifications, increases in AI adoption are associated with a statistically significant decline in stock illiquidity.

Columns (1) and (2) use changes in job-postings-based continuous AI measure (BGdata). The coefficient on ΔAI is negative and significant at the 5% and 1% levels, respectively, indicating that firms with larger increases in AI-related job postings experience greater improvements in stock liquidity. The estimates remain stable when state fixed effects are included. Columns (3) and (4) report results using the resume-based share of AI employees (Cognismdata). The estimated coefficients are again negative and highly significant. The magnitude of the effects in Table 2 is economically meaningful, approximately 15% improvement in liquidity change for a one-standard-deviation increase in ΔAI , depending on the AI adoption measure employed.

[Insert Table 2 here.]

4.2 Identification strategy

4.2.1 Instrument Variable (IV)

The long-difference estimates may still reflect unobserved time-varying shocks that jointly drive AI adoption and stock liquidity. To address this, we instrument for AI adoption using firms' pre-existing exposure to the supply of AI graduates from research-intensive universities.

The identification rests on two observations. First, universities with long-standing strength in AI research produce a larger pool of AI-skilled graduates. Second, firms' hiring ties to these universities were established well before AI became commercially widespread, making it unlikely that these connections reflect forward-looking considerations about stock liquidity.

The supply of AI graduates from research-intensive universities therefore provides variation in AI adoption that is plausibly exogenous to liquidity outcomes. The IV compiles two datasets on: (i) the ex-ante strength of AI research in each university, and (ii) firm-university hiring networks.

Open Academic Graph (OAGv2) is used to identify AI-strong universities before 2010. Universities are defined as AI-strong if they rank in the top 5% by the share of researchers whose publications are AI-related during 2005–2009³. Firm–university hiring networks are constructed from resume data, linking firms to the universities from which their employees’ obtained degrees. These pre-2010 hiring ties provide the ex-ante exposure measure for our instrumental variable, as they strongly predict firms’ post-2010 hiring from the same universities. Instrument for firm i are defined as:

$$IV_i = \frac{1}{D_{it}} \sum_u S_{iu}^{2010} AI\ Strong_u \quad (4)$$

where S_{iu}^{2010} is the share of STEM workers in firm i in 2010 who graduated from university u , and $AI\ Strong_u$ equals one if university u is identified as an AI-strong university based on pre-2010 share of AI researchers.

Table 3 reports the IV estimates. The first-stage results show a strong and statistically significant relationship between firms’ exposure to AI-strong universities and subsequent changes in AI adoption. The corresponding first-stage F-statistics exceed conventional thresholds 10, alleviating concerns about weak instruments. The second-stage results indicate that instrumented increases in AI adoption are associated with a significant decline in stock illiquidity. Across specifications, the IV coefficients are negative and larger in magnitude than the main results.

[Insert Table 3 here.]

4.2.2 AlphaGo’s victory as exogenous belief shock

To further strengthen the causal interpretation of our results, we use a DID research design. We exploit AlphaGo’s victory, as a major exogenous shock to firms’ perceptions and adoption of AI. Go is a strategy board game that originated in ancient China more than 2,500 years ago. Known as Weiqi in Chinese, Igo in Japanese, and Baduk in Korean, Go’s enduring legacy is deeply embedded in East Asian cultures. Go was regarded as one of the most challenging board games for AI to master. Unlike chess, which were tackled by brute-force search techniques, the sheer number of possible board configurations in Go makes such approaches infeasible.

³ AI researchers are identified based on publication records in AI- and CS-related journals and conference proceedings. A researcher is classified as an AI researcher if at least one-third of their publications are in AI/CS journals or proceedings and at least half of those appear in explicitly AI-focused journals or proceedings.

At the university level, the share of AI researchers is computed annually. A university is defined as AI-strong if, in any year between 2005 and 2009, it meets either of two criteria: (i) the number of AI researchers ranks in the top 5% across all universities, or (ii) the number of AI researchers ranks in the top 10% while the share of AI researchers (relative to all researchers at that university) ranks in the top 5%.

Consequently, Go requires a nuanced understanding of spatial patterns, balance, and long-term strategy, which is difficult for AI to replicate.

The event we study is AlphaGo's victory over Lee Sedol in March 2016, which marked a breakthrough in AI. The event received extensive global media coverage, including The Wall Street Journal, BBC, and The New York Times, among others. The Financial Times described AlphaGo's victory as "a landmark moment for the development of artificial intelligence." (Financial Times, 2016). AlphaGo's victory was a surprise and updated people's beliefs about AI capabilities. We exploit heterogeneous belief updating from AlphaGo's victory, a particularly salient informational shock for individuals with East Asian cultural backgrounds. AlphaGo's success did not directly affect firms' operations or financial conditions, but instead constituted an informational shock that accelerated firms' learning and adoption of AI. The analysis focuses on board directors, who play a central role in firm decision-making, including strategic adoption in AI.

We construct firm-level board characteristics using BoardEx North America. The sample includes all individuals serving on corporate boards in 2015, prior to AlphaGo's victory. To identify directors' ethnic backgrounds, we infer the country or region of origin from directors' full names using ChatGPT 5.2 (Yao, 2025). A director is classified as ethnically East Asian if the inferred origin is China, Hong Kong, Macao, Taiwan, Japan, or Korea. Approximately 8% of board directors in the sample are classified as East Asian. To ensure that the treated firms and the control firms are comparable, we employ the propensity score matching (PSM) method to construct our empirical sample. We first estimate a full-sample probit model modelling the *East Asian* as a function of the baseline firm-level characteristics in year 2015 as well as industry and state fixed effect. Using the estimated propensity scores, we match each firm in the treated states with a control firm, that has the closest propensity score, requiring that the absolute difference in propensity score between the treatment and matched control firm does not exceed 0.01. The DID model is as follows:

$$AI\ or\ ILLIQ_{it} = \alpha_0 + \alpha_1 After_t * East\ Asian_i + \alpha_2 Controls_{it} + Naics2 * Year\ Fixed\ Effects + State\ Fixed\ Effects + Firm\ Fixed\ Effects + \varepsilon_i \quad (5)$$

The key independent variable in the DID framework is the interaction term $After \times East\ Asian$ Director. *After* is an indicator equal to one for the post-AlphaGo period, and *East Asian Director* captures firms' pre-existing exposure to East Asian board members, measured prior to the event.

[Insert Table 4 here.]

Table 4 reports the DID results examining the effect of AI adoption on stock liquidity using AlphaGo's victory as an exogenous belief shock. Columns (1) and (2) present the results with firm-level AI adoption, measured using resume-based AI employment data from Cognism. The coefficient on the interaction term $After \times East\ Asian$ is positive and statistically significant across specifications. This finding indicates that, following AlphaGo's victory, firms with pre-existing exposure to East Asian directors experience a significantly larger increase in AI-skilled employment relative to control firms. The result is robust to the inclusion of baseline firm characteristics as well as industry-year, state, and firm fixed effects. Columns (3) and (4)

examine the implications of this differential AI adoption for stock liquidity. The coefficient on *After* $\times$ *East Asian* is negative and statistically significant, implying that treated firms experience a larger decline in stock illiquidity in the post-AlphaGo period. This pattern suggests that the increase in AI adoption induced by the belief shock translates into a meaningful improvement in AI adoption and further stock liquidity.

To verify parallel trend, column (4) further replaces the post indicator with a series of interaction terms between East Asian and event-year dummies. The estimates show no statistically significant differences between treated and control firms prior to AlphaGo's victory, providing no evidence of differential pre-trends. In contrast, the coefficients become negative and statistically significant in the years following the event, indicating a gradual divergence in liquidity outcomes that emerges after AlphaGo's victory. This dynamic pattern is consistent with a causal interpretation in which AlphaGo acts as an informational shock that accelerates AI adoption and, in turn, improves stock liquidity among treated firms.

Taken together, the DID results provide complementary evidence that heterogeneous belief updating in response to AlphaGo leads to differential AI adoption across firms. This exogenous variation in AI adoption causally improves stock liquidity.

4.2.3 Panel regressions

The long-difference design restricts the sample to firms that survive throughout the entire 2010–2018 period, which may introduce survivorship bias. To mitigate this concern and following recent firm-level studies of technology adoption (e.g., Oesch and Walser, 2025; Jiang et al., 2025), we adopt a panel-based approach that allows firms to enter and exit the sample.

[Insert Table 5 here.]

Table 5 reports three specifications. Column (1) relates the change in stock illiquidity over a three-year horizon to the lagged level of AI adoption. Column (2) regresses the rolling one-year change in illiquidity on the one-year change in AI adoption. Column (3) uses a five-year moving window of AI adoption as the main independent variable. Across all specifications, the estimated coefficients are negative and significant, consistent with the baseline results.

4.3 Size Effects

We test the size effect of AI adoption and find the liquidity effects of AI are not evenly distributed across firms of different sizes. Firms are sorted into terciles based on employment in 2010 within their 2-digit NAICS industries.

Panel A of Table 6 shows that the liquidity-enhancing effects of AI are concentrated among larger firms. For firms in the largest size tercile, increases in AI are associated with a statistically significant decline in stock illiquidity. In contrast, the estimated effects for firms in the smallest size tercile are close to zero and statistically insignificant. The difference in coefficients between the largest and smallest size terciles is statistically significant. This pattern is consistent across both job postings-based and resume-based measures of AI. The size effect is consistent with differences in data availability. Larger firms generate substantially richer data through their operations, customers, and supply chains. AI relies on high-quality data for

accurate prediction and monitoring (Babina et al., 2024). As a result, AI adoption by large firms is more likely to reduce information asymmetries and firm risk and improve stock liquidity.

To ensure that our findings in main results are not driven by a small number of very large firms, Panel B excludes firms in the top 1% and top 5% of the size distribution. The results remain largely unchanged.

[Insert Table 6 here.]

4.4 Sensitivity analysis

In this section, we check whether the result is consistent with the alternative liquidity and AI adoption measure, alternative sample, alternative IV construction.

We use alternative independent variables in Table 7. For Panel A, the independent variable is a dummy variable for firms having changes in the AI measure in the top 25% of the distribution (in column 3, 4, 7 and 8) or in the top 10% of the distribution (in column 1, 2, 5 and 6). For Panel B, the independent variable is the share of AI worker using job postings-based data (BGdata). We convert the continuous AI score into a binary indicator. A job posting is classified as AI-related if its AI score exceeds 0.1. We then construct the firm-level AI measure as the proportion of job postings that are AI-related for firm f in year t . For Panel C, the independent variable is a continuous measure that focuses on Narrow AI skills, thereby excluding the influence of general programming or statistical skills that are not specific to AI (e.g., Python or linear regression). For Panel D, the independent variable is the change of the share of AI-utilizing workers (including employees with jobs referencing external AI software, such as IBM Watson) using Resume-based AI Measure. We show that our results remain similar when using alternative AI adoption measure.

[Insert Table 7 here.]

As a robustness test, we replace Amihud illiquidity with the bid-ask spread (in logarithm) calculated as the dollar quoted spread divided by the quote's midpoint, averaged over the days of the year. A high spread implies low liquidity. As shown in Table 8, our main results continue to hold with statistical and economic significance for the alternative liquidity measures.

[Insert Table 8 here.]

AI adoption may be correlated with firms' adoption of other technologies, such as information technology or data infrastructure, which could independently affect stock liquidity. To isolate the effect of AI, we control non-AI technology adoption that parallel our AI adoption measures. Specifically, for each firm and year, we include (i) adoption of non-AI IT skills, (ii) adoption of robotics-related skills, (iii) adoption of non-AI data skills (e.g., data cleaning or database management), and (iv) adoption of in non-AI data analytics software as additional controls in our baseline regressions. The results are reported in Table 9. Across all specifications, the estimated relationship between AI adoption and stock liquidity remains quantitatively similar and statistically significant.

[Insert Table 9 here.]

To account for industry-specific shocks, we include detailed industry fixed effects. The estimated effect of changes in AI adoption remains stable, as reported in Table 10.

[Insert Table 10 here.]

We use alternative IV in Table 11. Reverse causality is a potential concern if universities' AI research strength reflects ties to firms providing data and resources. This concern is mitigated by the fact that AI research began well before the broad commercial adoption of AI among non-tech firms in the 2010s. To further address this issue, we measure universities' AI research strength using an earlier period (2000–2004) rather than 2005–2009. The result is shown in Panel A. we also show that our results are not driven by a single prominent university. For Panel B, we drop, one of the top two universities with the largest number of AI faculty—Carnegie Mellon. For Panel C, we drop, one of the top two universities with the largest number of AI faculty—University Stanford University.

[Insert Table 11 here.]

5. Mechanism analysis

Having documented a positive association between AI adoption and stock liquidity, we proceed to explore the underlying economic mechanisms. We argue that the AI adoption lowers liquidity costs due to its role in enhancing the firm's information environment and mitigating firm risk. We examine these possible mechanisms in the following analysis.

5.1. Information environment mechanism

AI adoption can improve stock liquidity by enhancing the information environment faced by investors. As an advanced monitoring and control technology, AI reshapes how firms generate, process, and verify internal information, with important implications for transparency and disclosure credibility. For example, AI-based platforms such as AppZen and BlackLine continuously monitor expense reports and accounts payable transactions, automatically detecting policy violations, duplicate claims, and anomalous spending patterns. This continuous monitoring enhances internal oversight and reduces forgetfulness, mistakes, discretion, and collusion or fraud (Leuz et al., 2003; Ashraf, 2024). The improved financial and operational transparency decreases information asymmetries between insiders and outside investors, and also among outside investors, thereby lowering adverse selection costs and improving liquidity (Leuz and Verrecchia, 2000; Brown and Hillegeist, 2007).

We provide empirical evidence consistent with this mechanism by examining the relation between AI adoption and earnings management. See Appendix A for a detailed description of the earnings management measures. Table 12 reports result for both real earnings management and accrual-based earnings management. As shown in Column (1) and (2) of Panel A and Panel B, increases in AI adoption are associated with statistically significant declines in real earnings management. This finding suggests that AI adoption constrains managers from manipulating firm performance through real operational decisions, such as discretionary expense reductions or the timing of sales. Such actions directly distort the firm's underlying cash flows and

operations Roychowdhury (2006). In addition, according to Column (3) to (6), we find a significant negative relation between AI adoption and accrual-based earnings management, as measured by both the Jones (Jones, 1991) and Modified Jones (Dechow et al., 1995) models. The consistent decline in discretionary accruals indicates that AI adoption also limits managerial discretion in accounting choices and accrual estimation, improving the reliability of reported earnings.

Taken together, the reductions in both real and accrual-based earnings management suggest that AI adoption improves the credibility of financial disclosures. Because reported earnings are more aligned with underlying firm fundamentals, AI adoption enhances the information environment faced by investors, reduces information asymmetries, and contributes to improved stock liquidity.

5.2. Firm risk mechanism

AI adoption can improve stock liquidity by reducing firm risk. Lower fundamental uncertainty reduces the compensation demanded by liquidity providers for bearing inventory risk, lowering inventory-holding costs (Stoll, 1978; Ho and Stoll, 1981; Peress, 2010).

As a prediction technology, AI improves forecasting accuracy across a range of operational decisions, including demand forecasting, inventory management, resource allocation, and operational planning. More accurate forecasts stabilize operating performance and reduce earnings volatility. As earnings become more predictable, investor uncertainty about firm fundamentals narrows, dampening return volatility. Lower return volatility reduces the risk of adverse price movements while market makers hold inventory, requiring less compensation for providing immediacy.

We provide evidence consistent with this mechanism by examining the relation between AI adoption and firm-level volatility. Like Bae et al. (2004), we calculate the stock return volatility, by taking a logarithmic transformation of squared monthly returns for each year and averaging this measure for the year. Earnings volatility based on the standard deviation of quarterly earnings (Hasan et al., 2014). Table 12 reports the results. Panel C and D report results for stock return volatility and earnings volatility using job postings-based and resume-based measures of AI adoption, respectively. Using the résumé-based measure, increases in AI adoption are associated with significant declines in both return volatility and earnings volatility, consistent with the firm risk channel. The job-posting-based measure yields weaker and insignificant effects. This divergence likely reflects the distinction between hiring intentions and realized AI deployment: job postings capture demand for AI skills, while résumé data capture the actual stock of AI-skilled employees (Babina et al., 2024). Taken together, the evidence indicates that AI adoption reduces firm risk, contributing to improved stock liquidity through lower inventory-holding costs.

[Insert Table 12 here.]

6. Conclusion

This paper examines how firm-level AI adoption affects stock liquidity. Using human-capital-based measures of AI adoption drawn from job-posting and résumé data, we document that firms with greater AI adoption have lower stock illiquidity and narrower bid-ask spreads among U.S. public firms.

We establish the baseline using a long-difference regression that absorbs time-invariant firm heterogeneity and captures the cumulative, multi-year nature of AI adoption. To address residual endogeneity, we employ two identification strategies. An IV based on firms' pre-existing exposure to AI graduates from research-intensive universities provides exogenous variation in AI adoption. A DID design exploiting AlphaGo's defeat of world champion Lee Sedol as an exogenous belief shock offers an independent quasi-experimental test. Both designs produce estimates consistent with the baseline, supporting a causal interpretation.

We identify two mechanisms through which AI adoption improves stock liquidity. First, AI adoption improves the information environment. Firms with greater AI adoption exhibit lower real and accrual-based earnings management, consistent with stronger internal monitoring and more credible financial disclosures. Lower information asymmetry reduces adverse selection costs, improving liquidity. Second, AI adoption reduces firm risk. Firms with greater AI adoption experience lower return volatility and earnings volatility, consistent with more stable operating performance. Lower fundamental uncertainty reduces inventory-holding costs for liquidity providers, improving liquidity. The findings connect the emerging literature on AI adoption to the determinants of stock liquidity and trading costs.

Table 1. Summary Statistics

This table presents summary statistics for the firms included in baseline regressions. The sample comprises 870 firms in the specifications using the job-postings-based measure and 932 firms in specifications using the résumé-based measure. The number of observations, the mean, the standard deviation, the 25th, 50th and 75th percentiles are reported.

Panel A: Summary Statistics for Burning Glass sample

Variables	N	Mean	SD	p25	p50	p75
Change in Amihud measure	870	-0.022	0.063	-0.025	-0.0074	-0.00094
Change in Bid-Ask spread measure	870	-0.54	0.82	-1.063	-0.67	-0.081
Change in share of AI workers (Burning Glass)	870	0.0013	0.0038	-0.00038	0.00035	0.0019
Change in Real Earning Management	654	0.011	0.28	-0.13	0.011	0.15
Change in Accrual-Based Earnings Management (Jones)	668	-0.0033	0.13	-0.053	0.00024	0.05
Change in Accrual-Based Earnings Management (Modified Jones)	667	-0.0044	0.14	-0.053	0.00022	0.049
Change in stock return volatility	870	-0.0034	0.024	-0.007	-0.0022	0.0015
Change in sd of quarterly earnings ratio	862	0.0039	0.062	-0.0025	0.00041	0.0056
Log market value as of 2010	870	7.68	1.77	6.51	7.57	8.87
Log number of non-AI job positions as of 2010	870	4.86	2.3	3.22	4.96	6.41
Log sales as of 2010	870	7.47	1.77	6.26	7.41	8.69
Ratio of tangible assets as of 2010	870	0.25	0.23	0.075	0.17	0.35
Revenue-based Total Factor Productivity as of 2010	870	-0.059	0.79	-0.74	-0.042	0.63
Markup ratio as of 2010	870	0.58	0.48	0.26	0.45	0.78
Capital Expenditure to asset ratio as of 2010	870	0.04	0.046	0.013	0.027	0.051
Log R&D expenditure as of 2010	870	1.95	2.43	0	0	3.8

Panel B: Summary Statistics for Cognism sample

Variables	N	Mean	SD	p25	p50	p75
Change in Amihud measure	933	-0.022	0.073	-0.027	-0.0076	-0.00094
Change in Bid-Ask spread measure	933	-0.53	0.84	-1.072	-0.67	-0.0771
Change in share of AI workers (Cognism)	933	0.001	0.0021	0	0.00026	0.0012
Change in Real Earning Management	702	0.011	0.28	-0.13	0.011	0.15
Change in Accrual-Based Earnings Management (Jones)	716	-0.0052	0.14	-0.053	0.00024	0.051
Change in Accrual-Based Earnings Management (Modified Jones)	715	-0.006	0.14	-0.054	0.00022	0.05
Change in stock return volatility	933	-0.0033	0.024	-0.007	-0.0022	0.0017
Change in sd of quarterly earnings ratio	923	0.0034	0.06	-0.0026	0.00041	0.0059
Log market value as of 2010	933	7.63	1.78	6.45	7.49	8.84

Log number of non-AI job positions as of 2010	933	7.77	1.6	6.66	7.61	8.75
Log sales as of 2010	933	7.4	1.81	6.19	7.34	8.62
Ratio of tangible assets as of 2010	933	0.25	0.23	0.072	0.17	0.35
Revenue-based Total Factor Productivity as of 2010	933	-0.063	0.79	-0.74	-0.043	0.62
Markup ratio as of 2010	933	0.57	0.49	0.26	0.45	0.78
Capital Expenditure to asset ratio as of 2010	933	0.039	0.041	0.013	0.027	0.051
Log R&D expenditure as of 2010	933	1.91	2.38	0	0	3.71

Table 2. Main Result

AI adoption and stock illiquidity: Long-differences Estimates. This table reports the results from long-differences regressions of stock illiquidity change from 2010 to 2018 on the contemporaneous firm-level changes in AI adoption among U.S. public firms (in non-tech sectors). We consider two measures of AI adoption: changes in job postings-based continuous AI measure (BGdata) (columns 1 and 2), and changes in Resume-based share of AI employee measure (Cognismdata). (columns 3 and 4). The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects and baseline controls: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 2 and 4 also include the state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1)	(2)	(3)	(4)
	BGdata		Cognismdata	
ΔAI	-1.061** (-2.41)	-1.277*** (-2.68)	-1.303*** (-3.11)	-1.696*** (-3.55)
Observations	841	832	931	923
R-squared	0.276	0.344	0.187	0.212
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes

Table 3. IV Results

AI adoption and stock illiquidity: IV Estimate. This table shows the relationship between AI adoption stock illiquidity, where firm AI adoption are instrumented with ex-ante firm-level exposure to AI-strong universities. The independent variables is the change in continuous AI measure based on job postings data from 2010 to 2018 in columns 1 to 4 and the share of AI workers from 2010 to 2018 based on the resume data in columns 5 to 8. The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects, ex-ante exposure to universities that are strong in computer science research as well as top 10 universities, and baseline control: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 3–4 and 7–8 also include state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	BGdata				Cognismdata			
	First Stage	Second	First Stage	Second Stage	First Stage	Second	First Stage	Second
Instrument	0.010*** (4.18)		0.011*** (5.23)		0.007*** (3.92)		0.007*** (4.36)	
Δ AI		-3.153** (-2.16)		-4.232** (-2.09)		-3.540* (-1.94)		-5.424** (-2.05)
Observations	841	841	832	832	931	931	923	923
F-statistics	17.457		27.356		15.374		18.967	
R-squared	0.531	0.21	0.598	0.185	0.485	0.144	0.568	0.13
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 4. DID Results

AI adoption and stock illiquidity: DID results. This table estimates the relationship between AI adoption and the stock illiquidity using AlphaGo's victory as exogenous shock. The dependent variables is the share of AI workers based on the resume data in Column 1 and 2. The dependent variables is the Amihud illiquidity in Column 3 and 4. The main independent variable is the interaction term After $\times$ East Asian in column 1 to 3. The main independent variables are interactions between East Asian and variables indicating three years before and two years after the events. All specifications control for the 2-digit NAICS industry sector $\times$ year, state and firm fixed effect. Control variables include firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) AI	(2) AI	(3) ILLIQ	(4) ILLIQ
After* East Asian	0.001** (2.16)	0.001** (2.26)	-0.003** (-2.17)	
Year2013* East Asian				0.000 (0.44)
Year2014* East Asian				-0.002 (-1.60)
Year2015* East Asian				-0.002 (-1.65)
Year2017* East Asian				-0.004** (-2.00)
Year2018* East Asian				-0.004** (-2.16)
Observations	1,758	1,691	1,691	1,691
R-squared	0.807	0.853	0.886	0.887
Baseline Controls	No	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes

Table 5. Panel regression Results

AI adoption and stock illiquidity: Panel regression Results. This table shows the panel regression results of the relationship between AI adoption and the stock illiquidity. The dependent variables is the share of AI workers based on the resume data in Column 1 and 2. The dependent variables is the Amihud illiquidity in Column 3 and 4. The main independent variable is the interaction term After $\times$ East Asian in column 1 to 3. The main independent variables are interactions between East Asian and variables indicating three years before and two years after the events. All specifications control for the 2-digit NAICS industry sector $\times$ year, state and firm fixed effect. Control variables include firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). The t-statistics based on robust standard errors are reported in parentheses.

*, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) $\Delta \text{ILLIQ}(i[t+3,t])$	(2) $\Delta \text{ILLIQ}(i[t,t-1])$	(3) $\Delta \text{ILLIQ}(i[t,t-1])$
AI(i, t-1)	-1.008*** (-2.75)		
$\Delta \text{AI}(i[t,t-1])$		-0.812** (-2.07)	
Mean AI(i[t,t-5])			-0.842*** (-3.35)
Observations	9,796	11,080	11,080
R-squared	0.409	0.237	0.238
Baseline Controls	Yes	Yes	Yes
Industry*Year FE	Yes	Yes	Yes
State FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes

Table 6. Size Effect of AI effect

This table shows results from long-differences regressions of the change of stock illiquidity on contemporaneous changes in AI adoption from 2010 to 2018, separately for each tercile of initial firm size. In Panel A, firms are divided into terciles based on employment in 2010. We consider two measures of AI adoption: changes in job postings-based continuous AI measure (BGdata) (columns 1 and 2), and changes in Resume-based share of AI employee measure (Cognismdata) (columns 3 and 4). The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. Columns 2, 4, also include state interacted with initial firm size tercile fixed effects. In Panel B, we exclude the largest firms. We consider two measures of AI adoption: changes in job postings-based continuous AI measure (BGdata) (columns 1 and 2), and changes in Resume-based share of AI employee measure (Cognismdata) (columns 3 and 4). In each measure, we exclude firms in the top 1% and 5% of the size distribution in terms of 2010 sales respectively. All specifications control for the 2-digit NAICS industry sector interacted with initial firm size tercile fixed effects and baseline control: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). The t-statistics based on robust standard errors are reported in parentheses. At the bottom of the table, we report t-statistics and p-values from tests of the difference between the coefficients on $\Delta \text{AI Size q1}$ and $\Delta \text{AI Size q3}$. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: Heterogeneous Relationship between AI adoption and stock illiquidity

VARIABLES	(1) BGdata	(2) BGdata	(3) Cognismdata	(4) Cognismdata
$\Delta \text{AI Size q1}$	0.987 (1.31)	1.751 (1.53)	4.429** (1.97)	3.639 (1.39)

Δ AI Size q2	-2.613 (-1.46)	-2.235 (-1.61)	-0.62 (-0.52)	-0.455 (-0.33)
Δ AI Size q3	-0.777*** (-3.13)	-0.947*** (-2.64)	-1.390*** (-2.98)	-1.603*** (-3.04)
Observations	837	798	928	896
R-squared	0.312	0.437	0.241	0.313
Baseline Controls	Yes	Yes	Yes	Yes
Industry*Size tercile FE	Yes	Yes	Yes	Yes
State*Size tercile FE	No	Yes	No	Yes
T-test statistics	5.08	5.18	6.27	3.75
T-test p value	0.025	0.023	0.013	0.053

Panel B. AI adoption and stock illiquidity Excluding the Largest Firms

VARIABLES	BGdata				Cognismdata			
	Drop Top 1%		Drop Top 5%		Drop Top 1%		Drop Top 5%	
ΔAI	-1.145**	-1.312**	-1.579***	-1.563***	-1.348***	-1.619***	-2.197***	-2.197***
	(-2.38)	(-2.47)	(-2.84)	(-2.60)	(-3.14)	(-3.42)	(-4.84)	(-4.07)
Observations	832	823	798	789	921	913	884	876
R-squared	0.277	0.346	0.309	0.372	0.187	0.213	0.236	0.261
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 7. Robustness test: Alternative independent variable

This table shows the results from long-differences regressions of stock illiquidity change from 2010 to 2018 on the contemporaneous firm-level changes in AI adoption using alternative independent variable. For Panel A, the Independent variable is a dummy variable for firms having changes in the AI measure in the top 25% of the distribution (in column 3, 4, 7 and 8) or in the top 10% of the distribution (in column 1, 2, 5 and 6). For Panel B, the Independent variable is the share of AI worker using job postings-based data (BGdata). For Panel C, the independent variable is continuous measure based on Narrow AI skills. For Panel D, the independent variable is the growth in the share of AI-utilizing workers using Resume-based AI measure. The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects and baseline controls: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Alternative independent variable: dummy variable indicating high AI change

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		BGdata				Cognismdata		
Top 10% in Δ	-0.006** (-2.00)	-0.007** (-2.15)			-0.008** (-2.43)	- (-2.76)		
Top 25% in Δ			-0.005** (-2.20)	-0.006** (-2.13)			-0.006* (-1.83)	-0.008** (-2.58)
Observations	841	832	841	832	931	923	931	923
R-squared	0.268	0.335	0.268	0.335	0.185	0.210	0.184	0.210
Baseline	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B Alternative independent variable: Share of AI workers based on BG

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			First Stage	Second Stage	First Stage	Second Stage
Instrument			0.043*** (3.34)		0.042*** (4.23)	
Alt. Δ AI	-0.261*** (-3.41)	-0.287*** (-3.12)		-0.914* (-1.95)		-1.250* (-1.91)
Observations	841	832	841	841	832	832
F-statistics			11.425		17.548	
R-squared	0.274	0.339	0.5	0.199	0.558	0.156
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	Yes

Panel C Alternative independent variable: Continuous Narrow AI measure on BG

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			First Stage	Second Stage	First Stage	Second Stage
Instrument			0.010*** (3.47)		0.010*** (4.47)	
Alt. Δ AI	-1.238*** (-3.04)	-1.405*** (-2.98)		-4.014** (-2.00)		-5.449** (-1.97)
Observations	841	832	841	841	832	832
F-statistics			12.378		20.052	
R-squared	0.275	0.341	0.537	0.205	0.594	0.169
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	Yes

Panel D Alternative independent variable: share of AI-utilizing workers on Cognism

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
			First Stage	Second Stage	First Stage	Second Stage
Instrument			0.008*** (4.11)		0.008*** (5.06)	
Alt. Δ AI	-1.303*** (-3.11)	-1.696*** (-3.55)		-3.540* (-1.94)		-5.424** (-2.05)
Observations	931	923	931	931	923	923
F-statistics			15.374		18.967	
R-squared	0.187	0.212	0.48	0.144	0.559	0.13
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	No	Yes	Yes

Table 8. Robustness test: Alternative dependent variable

This table shows the results from long-differences regressions of stock illiquidity change from 2010 to 2018 on the contemporaneous firm-level changes in AI using alternative dependent variable bid-ask spread. We consider two measures of AI adoption: changes in job postings-based continuous AI measure (BGdata) (columns 1 and 2), and changes in Resume-based share of AI employee measure (Cognismdata). (columns 3 and 4). The main dependent variable is the bid-ask spread from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects and baseline controls: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 2 and 4 also include the state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

VARIABLES	(1) Bgdata	(2) Bgdata	(3) Cognismdata	(4) Cognismdata
ΔAI	-25.102** (-2.22)	-27.964** (-1.98)	-32.157** (-2.01)	-30.748** (-2.04)
Observations	870	862	933	926
R-squared	0.411	0.540	0.227	0.378
Baseline Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes

Table 9. Robustness test: Controlling for Other Technologies

This table shows the results from long-differences regressions of stock illiquidity change from 2010 to 2018 on the contemporaneous firm-level changes in AI adoption, controlling for adoption of non-AI-specific technologies. Columns 1 and 2 control for the 2010-2018 change in the firm's share of non-AI IT jobs, columns 3 and 4 control for the change in the share of robot-related jobs, columns 5 and 6 control for the change in the share of non-AI data-related jobs, and columns 7 and 8 control for the changes in the share of non-AI data analysis jobs. Detailed definitions are provided in Babina et al. (2024). Panel A looks at the job-posting-based measure, while Panel B considers the resume-based measure of the share of AI workers. The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects and baseline controls: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 2, 4, 6 and 8 also include the state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Additional controls using Job postings-based continuous AI measure (BGdata)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
					BGdata			
Δ AI	-0.833*** (-2.64)	-0.969** (-2.58)	-1.103** (-2.36)	-1.306*** (-2.60)	-0.865*** (-3.15)	-0.952*** (-2.66)	-1.098*** (-2.72)	-1.240*** (-2.79)
Δ Non-AI IT Workers %	-0.022 (-1.11)	-0.035 (-1.63)						
Δ Robot Workers %			0.144 (0.85)	0.116 (0.61)				
Δ Non-AI Data Workers %					-0.030 (-0.56)	-0.053 (-0.93)		
Δ Non-AI Analysis Workers %							0.009 (0.31)	-0.012 (-0.29)
Observations	841	832	841	832	841	832	841	832
R-squared	0.281	0.353	0.276	0.344	0.278	0.348	0.276	0.344
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes

Panel B Additional controls using Resume-based share of AI employee measure (Cognismdata)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
				Cognismdata				
Δ AI	-0.966*** (-2.59)	-1.321*** (-3.20)	-0.960*** (-2.66)	-1.413*** (-3.36)	-0.867** (-2.33)	-1.123*** (-2.84)	-0.835** (-2.21)	-1.117*** (-2.82)
Δ Non-AI IT Workers %	-0.020* (-1.93)	-0.024** (-2.33)						
Δ Robot Workers %			-0.084 (-0.61)	0.075 (0.51)				
Δ Non-AI Data Workers %					-0.026 (-1.31)	-0.045** (-1.97)		
Δ Non-AI Analysis Workers %							-0.042 (-1.24)	-0.080** (-2.09)
Observations	868	859	868	859	868	859	868	859
R-squared	0.185	0.221	0.178	0.212	0.181	0.219	0.181	0.221
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes

Table 10. Robustness test: Detailed industry fixed effects

This table shows the results from long-differences regressions of stock illiquidity change from 2010 to 2018 on the contemporaneous firm-level changes in AI adoption, with detailed industry fixed effects. Columns 1 and 2 control for 3-digit NAICS industry sector fixed effects, columns 3 and 4 control for 4-digit NAICS industry sector fixed effects, and columns 5 and 6 control for 5-digit NAICS industry sector fixed effects. Panel A looks at the job-posting-based measure, while Panel B considers the resume-based measure of the share of AI workers. The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications include baseline controls: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 2, 4 and 6 also include the state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Detailed industry fixed effects using Job postings-based continuous AI measure (BGdata)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	BGdata					
ΔAI	-1.501*** (-2.67)	-1.589*** (-2.60)	-0.623** (-2.03)	-0.571 (-1.61)	-0.689** (-2.51)	-0.664** (-2.05)
Observations	833	824	781	770	714	701
R-squared	0.382	0.435	0.586	0.623	0.604	0.656
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Naics3 FE	Yes	Yes	No	No	No	No
Naics4 FE	No	No	Yes	Yes	Yes	Yes
Naics5 FE	No	No	No	No	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

Panel B Detailed industry fixed effects using Resume-based share of AI employee measure (Cognismdata)

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	Cognismdata					
ΔAI	-1.602*** (-3.19)	-2.176*** (-3.39)	-2.153*** (-3.63)	-2.650*** (-3.74)	-2.058*** (-3.45)	-2.711*** (-3.49)
Observations	926	918	880	871	804	796
R-squared	0.233	0.266	0.337	0.368	0.396	0.424
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes
Naics3 FE	Yes	Yes	No	No	No	No
Naics4 FE	No	No	Yes	Yes	Yes	Yes
Naics5 FE	No	No	No	No	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

Table 11. Robustness test: Alternative Instrumental variable

This table shows the relationship between stock illiquidity and AI adoption, using alternative variable. For Panel A, we measure universities' AI research strength using an earlier period from 2000 to 2004 instead of 2005–2009. For Panel B, we drop, one of the top two universities with the largest number of AI faculty—Carnegie Mellon. For Panel C, we drop, one of the top two universities with the largest number of AI faculty—University Stanford University. The independent variables is the change in continuous AI measure based on job postings data from 2010 to 2018 in columns 1 to 4 and the share of AI workers from 2010 to 2018 based on the resume data in columns 5 to 8. The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects, ex-ante exposure to universities that are strong in computer science research as well as top 10 universities, and baseline control: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 3–4 and 7–8 also include state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A AI Hubs Before 2005

VARIABLES	BGdata				Cognismdata			
	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage	First Stage	Second Stage
Alt. Instrument	0.011*** (4.18)		0.011*** (5.65)		0.007*** (3.95)		0.007*** (4.56)	
ΔAI		-2.558** (-2.01)		-4.071** (-2.00)		-3.506* (-1.83)		-4.690* (-1.93)
Observations	841	841	832	832	931	931	923	923
F-statistics	17.501		31.907		15.569		20.808	
R-squared	0.520	0.230	0.603	0.193	0.500	0.145	0.574	0.143
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel B Drop Carnegie Mellon

	BGdata	Cognismdata
1	1	1
2	1	1
3	1	1
4	1	1
5	1	1
6	1	1
7	1	1
8	1	1
9	1	1
10	1	1
11	1	1
12	1	1
13	1	1
14	1	1
15	1	1
16	1	1
17	1	1
18	1	1
19	1	1
20	1	1
21	1	1
22	1	1
23	1	1
24	1	1
25	1	1
26	1	1
27	1	1
28	1	1
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31	1	1
32	1	1
33	1	1
34	1	1
35	1	1
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40	1	1
41	1	1
42	1	1
43	1	1
44	1	1
45	1	1
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59	1	1
60	1	1
61	1	1
62	1	1
63	1	1
64	1	1
65	1	1
66	1	1
67	1	1
68	1	1
69	1	1
70	1	1
71	1	1
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73	1	1
74	1	1
75	1	1
76	1	1
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80	1	1
81	1	1
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83	1	1
84	1	1
85	1	1
86	1	1
87	1	1
88	1	1
89	1	1
90	1	1
91	1	1
92	1	1
93	1	1
94	1	1
95	1	1
96	1	1
97	1	1
98	1	1
99	1	1
100	1	1

VARIABLES	First Stage	Second	First	Second Stage	First Stage	Second Stage	First Stage	Second Stage
Alt. Instrument	0.011*** (4.00)		0.010*** (4.96)		0.007*** (3.89)		0.006*** (4.38)	
ΔAI		-3.284** (-2.17)		-4.360** (-2.07)		-3.791** (-1.98)		-5.713** (-2.10)
Observations	841	841	832	832	931	931	923	923
F-statistics	15.979		24.595		15.132		19.178	
R-squared	0.524	0.204	0.593	0.179	0.481	0.141	0.565	0.124
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes

Panel C Drop University Stanford University

VARIABLES	BGdata				Cognismdata			
	First Stage	Second	First Stage	Second Stage	First Stage	Second	First Stage	Second
Alt. Instrument	0.011*** (4.20)		0.010*** (5.17)		0.007*** (3.86)		0.007*** (4.22)	
ΔAI		-3.112** (-2.15)		-4.293** (-2.11)		-3.493* (-1.88)		-5.334** (-2.01)
Observations	841	841	832	832	931	931	923	923
F-statistics	17.624		26.741		14.867		17.784	
R-squared	0.530	0.211	0.596	0.182	0.483	0.145	0.567	0.132
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes

Table 12. Mechanism Analysis

AI adoption and Earning Management, firm risk. This table shows the results from long-differences regressions of stock illiquidity change from 2010 to 2018 on the contemporaneous firm-level changes in Earning Management and firm risk. The dependent variables are real earnings management by the method of Roychowdhury (2006), accrual-based earnings management as estimated by Jones model and accrual-based earnings management as estimated by modified Jones model respectively. In panel A, we consider changes in job postings-based continuous AI measure. In Panel B, we consider changes in Resume-based share of AI employee measure. The main dependent variable is the Amihud illiquidity measure from 2010 to 2018. Regressions are weighted by the number of job positions in 2010. All specifications control for the 2-digit NAICS industry sector fixed effects and baseline controls: firm-level characteristics (Log market value, Log number of non-AI job positions, Log sales, Ratio of tangible assets, Revenue-based Total Factor Productivity, Markup ratio, capital expenditure ratio and Log R&D expenditure), log industry wage, and commuting-zone level characteristics (the share of workers in finance and manufacturing industries, the share of workers in IT-related worker, the share of college-educated workers, the share of foreign-born workers and log average wage). Columns 2, 4, 6 also include the state fixed effects. The t-statistics based on robust standard errors are reported in parentheses. *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A Earning Management Channel using Job postings-based continuous AI measure (BGdata)

VARIABLES	(1) Real Earning Management	(2) Real Earning Management	(3) Jones Model	(4) Jones Model	(5) Modified Jones Model	(6) Modified Jones Model
ΔAI	-15.995** (-2.22)	-11.330** (-2.19)	-3.906** (-2.47)	-3.562** (-2.53)	-4.745** (-2.31)	-4.208** (-2.42)
Observations	633	625	645	636	644	635
R-squared	0.385	0.68	0.243	0.447	0.237	0.442
Baseline	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

Panel B Earning Management Channel using Resume-based share of AI employee measure (Cognismdata)

VARIABLES	(1) Real Earning	(2) Real Earning	(3) Jones Model	(4) Jones Model	(5) Modified Jones Model	(6) Modified Jones Model
ΔAI	-34.920*** (-2.71)	-24.095*** (-3.09)	-7.412*** (-4.20)	-6.687*** (-3.32)	-9.176*** (-3.75)	-7.936*** (-3.17)
Observations	699	691	713	704	712	703
R-squared	0.438	0.611	0.267	0.372	0.287	0.386
Baseline	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

Panel C Volatility Channel using Job postings-based continuous AI measure (BGdata)

VARIABLES	(1) Return Volatility	(2) Return Volatility	(3) Earning Volatility	(4) Earning Volatility
ΔAI	-0.054 (-0.30)	-0.027 (-0.14)	-0.028 (-0.09)	-0.100 (-0.37)
Observations	870	862	885	877

R-squared	0.270	0.470	0.191	0.596
Baseline Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes

Panel D Volatility Channel using Resume-based share of AI employee measure (Cognismdata)

VARIABLES	(1) Return Volatility	(2)	(3) Earning Volatility	(4)
ΔAI	-0.395** (-2.03)	-0.463* (-1.79)	-0.956** (-2.42)	-0.975** (-2.47)
Observations	933	926	948	941
R-squared	0.083	0.150	0.071	0.152
Baseline Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes

Appendix A. Measure of earning management

A.1 Real earnings management

To measure real earnings management, we adopt established approaches from the literature (Roychowdhury, 2006). We capture real activities manipulation using three abnormal components: cash flow from operations (CFO), discretionary expenses (DiscExp), and production costs (PROD).

We first estimate the normal levels of cash flow from operations, discretionary expenses, and production costs following Dechow et al. (1998) and Roychowdhury (2006). Normal cash flow from operations is modeled as a linear function of sales and changes in sales and is estimated using cross-sectional regressions by industry and year:

$$\frac{CFO_{it}}{Assets_{it-1}} = k_1 \frac{1}{Assets_{it-1}} + k_2 \frac{Sales_{it}}{Assets_{it-1}} + k_3 \frac{\Delta Sales_{it}}{Assets_{it-1}} + \varepsilon_{it}$$

$Assets_{it-1}$ represents the total assets of firm i in period $t - 1$. $\Delta Sales_{it}$ is the change in sales for firm i in period t .

PROD are defined as the sum of cost of goods sold and change in inventory during the year. We estimate the normal level of PROD as:

$$\frac{PROD_{it}}{Assets_{it-1}} = k_1 \frac{1}{Assets_{it-1}} + k_2 \frac{Sales_{it}}{Assets_{it-1}} + k_3 \frac{\Delta Sales_{it}}{Assets_{it-1}} + k_4 \frac{\Delta Sales_{it-1}}{Assets_{it-1}} + \varepsilon_{it}$$

DiscExp represents the discretionary expenditures in period t , defined as the sum of advertising expenses, R&D expenses and SG&A. We model the normal level of discretionary expenses as:

$$\frac{DiscExp_{it}}{Assets_{it-1}} = k_1 \frac{1}{Assets_{it-1}} + k_2 \frac{Sales_{it-1}}{Assets_{it-1}} + \varepsilon_{it}$$

For each year, we estimate the above models for every industry classified by its two-digit SIC code. The abnormal CFO (RCFO), abnormal production costs (RPROD) and abnormal discretionary expenses (RDISX) are computed as the difference between the actual values and the normal levels predicted from above Equations. To capture the effects of real earnings management as a single measure, we define:

$$REM_{it} = RPROD_{it} - RCFO_{it} - RDISX_{it}$$

A.2 Jones' Standard Model

Following Jones (1991) and Dechow et al. (1995), total accrual adjustments (TA) are defined as:

$$TA_{it} = [(\Delta CA_{it} - \Delta CASH_{it}) - (\Delta CL_{it} - \Delta RLTP_{it})] - \Delta DA_{it}$$

where ΔCA_{it} represents the change in current assets; $\Delta CASH$ reflects the change in cash held and in short-term financial investments; ΔCL_{it} is the change in current liabilities; $\Delta RLTP_{it}$ is the change in reclassified long-term obligations; ΔDA_{it} is the depreciation and amortization; i represents the company and t represents the year.

We use a cross-sectional model of discretionary accruals, where for each year we estimate the model for every industry classified by its two-digit SIC code to separate the discretionary component and the non-discretionary one:

$$\frac{TA_{it}}{Assets_{it-1}} = k_1 \frac{1}{Assets_{it-1}} + k_2 \frac{\Delta Sales_{it}}{Assets_{it-1}} + k_3 \frac{PPE_{it}}{Assets_{it-1}} + \varepsilon_{it}$$

Where $Assets_{it-1}$ represents the total assets of firm i in period $t - 1$. $\Delta Sales_{it}$ is the change in sales for firm i in period t . PPE_{it} it represents the property, plant and equipment of firm i in period t . ε_{it} represents the discretionary accrual adjustments for firm i in year t .

A.3 Modified Jones Model (Dechow et al. 1995)

In the modified Jones model (Dechow et al. 1995), it is assumed that not all sales are necessarily non-discretionary, and that this will depend on the item to be received.

$$\frac{TA_{it}}{Assets_{it-1}} = k_1 \frac{1}{Assets_{it-1}} + k_2 \frac{\Delta Sales_{it} - \Delta AR_{it}}{Assets_{it-1}} + k_3 \frac{PPE_{it}}{Assets_{it-1}} + \varepsilon_{it}$$

ΔAR_{it} is the change in accounts receivable. ε_{it} represents the discretionary accrual adjustments for firm i in year t under modified Jones model.

Appendix B: Skills with Highest AI-Relatedness Measures in Burning Glass Job Postings

This table lists the top 67 skills based on the skill-level AI measure w_s^{AI} .

#	Skills	AI-relatedness
1	Artificial Intelligence	1

2	Computer Vision	1
3	Machine Learning	1
4	Natural Language Processing	1
5	NDAJ (software)	0.979
6	Kernel Methods	0.979
7	Microsoft Cognitive Toolkit	0.975
8	Xgboost	0.972
9	Sentiment Classification	0.971
10	Long Short-Term Memory (LSTM)	0.97
11	Libsvm	0.968
12	Semi-Supervised Learning	0.968
13	Recurrent Neural Network (RNN)	0.965
14	Word2Vec	0.956
15	MXNet	0.953
16	Caffe Deep Learning Framework	0.95
17	Autoencoders	0.949
18	MLPACK (C++ library)	0.942
19	Keras	0.941
20	Theano	0.94
21	Torch (Machine Learning)	0.932
22	Wabbit	0.929
23	Boosting (Machine Learning)	0.905
24	TensorFlow	0.903
25	Vosvoal	0.903
26	Convolutional Neural Network (CNN)	0.897
27	Jung Framework	0.894
28	OpenNLP	0.894
29	Natural Language Toolkit (NLTK)	0.892
30	Unsupervised Learning	0.891
31	Dlib	0.891
32	Scikit-learn	0.889
33	Latent Semantic Analysis	0.889
34	Latent Dirichlet Allocation	0.889
35	Stochastic Gradient Descent (SGD)	0.881
36	Gradient boosting	0.872
37	Dimensionality Reduction	0.861
38	Deep Learning	0.859
39	DBSCAN (Density-Based Spatial Clustering of Applications with	0.855
40	AI ChatBot	0.844
41	Recommender Systems	0.842
42	Random Forests	0.84
43	Deeplearning4j	0.839
44	Support Vector Machines (SVM)	0.817
45	Unstructured Information Management Architecture	0.806
46	Apache UIMA	0.805
47	Maximum Entropy Classifier	0.799
48	Hidden Markov Model (HMM)	0.796
49	Pybrain	0.786
50	Computational Linguistics	0.78
51	Naive Bayes	0.768
52	H2O (software)	0.763
53	Expectation-Maximization (EM) Algorithm	0.763
54	WEKA	0.74
55	Clustering Algorithms	0.74

56	Matrix Factorization	0.739
57	Object Recognition	0.727
58	Classification Algorithms	0.721
59	Information Extraction	0.72
60	Image Recognition	0.708
61	Genetic Algorithm	0.705
62	Supervised Learning (Machine Learning)	0.695
63	OpenCV	0.688
64	K-Means	0.683
65	Sentiment Analysis / Opinion Mining	0.679
66	Machine Translation (MT)	0.655
67	Neural Networks	0.64

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