

AI Adoption, Mutual Fund Short-Termism, and Real Investment*

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Abstract

We examine how AI adoption by mutual funds affects their information acquisition and the ensuing capital market consequences. We document that AI adoption significantly increases mutual funds' acquisition of short-term fundamental information while decreasing long-term fundamental information acquisition. This shift improves the informativeness of stock prices about firms' near-term earnings, but reduces price informativeness about long-term fundamentals and the usefulness of price signals for corporate investment decisions. These results remain robust after addressing endogeneity through instrumental variables and quasi-experiments. Our evidence identifies a technology-induced reallocation of investor attention across horizons, with important consequences for price discovery and corporate investment.

Keywords: AI adoption; Mutual fund short-termism; Price informativeness; Investment-Q sensitivity

JEL Classification: G11; G14; M41; O33

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We examine how AI adoption by mutual funds affects their information acquisition and the ensuing capital market consequences. We document that AI adoption significantly increases mutual funds' acquisition of short-term fundamental information while decreasing long-term fundamental information acquisition. This shift improves the informativeness of stock prices about firms' near-term earnings, but reduces price informativeness about long-term fundamentals and the usefulness of price signals for corporate investment decisions. These results remain robust after addressing endogeneity through instrumental variables and quasi-experiments. Our findings reveal the unintended consequences of AI adoption in asset management and carry important implications for the informational and functional efficiency of capital markets.

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1. Introduction

The financial industry is undergoing rapid transformation driven by advances in artificial intelligence (AI) and the proliferation of data sources. Mutual funds, in particular, increasingly adopt AI-powered tools to enhance their information-processing capabilities (Bartram et al., 2020; Bonelli, 2025; Bank of England, 2025). Despite widespread interest in AI’s potential, systematic evidence on how AI changes mutual fund information processing remains limited (Zhang, 2024). This study addresses this gap by examining how AI adoption affects the horizon of mutual funds’ information processing and the broader implications for the informational and functional efficiency of stock prices.

We hypothesize that AI adoption by mutual funds exacerbates short-termism in information processing—that is, it induces funds to reallocate attention toward short-horizon signals at the expense of long-term fundamentals.¹ This prediction follows from two complementary mechanisms: AI’s differential effectiveness across horizons and the difficulty of monetizing long-horizon information. First, machine-learning algorithms excel at extracting signals from large, high-dimensional, and high-frequency datasets, allowing them to learn from many near-term observations and detect complex patterns quickly—features that make them particularly well suited to exploiting short-term market inefficiencies. Long-horizon forecasting, however, poses different challenges, including fewer independent observations for model training and greater reliance on causal reasoning, scenario analysis, and qualitative assessments such as management quality and competitive dynamics—tasks with which current AI systems still struggle (Sloan, 2019; Cao et al., 2024; Boyacı et al., 2024).²

¹In this paper, “short-termism” refers to a rational reallocation of information-processing resources toward short-term fundamentals in response to AI’s differential effectiveness across forecasting horizons. This represents optimal resource allocation given technological constraints, rather than myopic behavior.

²Our analysis focuses primarily on traditional machine learning and AI technologies, as most of our sample period (2010–2023) predates the widespread diffusion of generative AI systems such as ChatGPT (launched in November 2022). While generative AI may improve the processing of unstructured textual data, its effectiveness in financial forecasting—particularly at long horizons—remains largely untested. Recent work suggests that AI methods still face limitations for long-horizon investing. For example, Dhar and Sedoc (2025) note that short-term trading has become increasingly automated but argue that “so far, AI methods have not been feasible for long-term investing due to the difficulty of creating a suitable knowledge base for investing” and the lack of sufficient training data.

Second, long-horizon information is inherently harder to monetize. Even if AI were to improve forecast accuracy uniformly across horizons, improvements in long-horizon forecasting are associated with longer monetization periods and greater uncertainty. An investor with private information about one-quarter-ahead earnings can profit quickly, with relatively low risk, by positioning ahead of earnings announcements. In contrast, trading on two-year-ahead earnings forecasts exposes the investor to many unpredictable shocks over an extended holding period, making such positions riskier and slower to realize gains. As [Kacperczyk et al. \(2016\)](#) show, attention is scarce and is optimally allocated to activities with the highest marginal returns. If AI adoption increases the marginal returns to short-term information processing—by reducing its cost and facilitating faster, lower-risk monetization—fund managers have incentives to reallocate limited attention toward short-term signals and away from long-term analysis.

Because mutual funds’ private information is incorporated into stock prices through trading ([Jiang et al., 2014](#); [Lee and Zhu, 2022](#)), a shift toward short-term signals by AI funds may cause stock prices to reflect near-term earnings more strongly while becoming less informative about long-term fundamentals. This shift can have real effects because firms learn from stock prices when making investment decisions ([Chen et al., 2007](#)). In particular, efficient investment should be guided by the present value of long-term cash flows ([Hirshleifer, 1958](#)). If AI-driven trading reduces the long-horizon information content of prices, then prices become less useful for managerial learning, potentially worsening investment efficiency and capital allocation.

We test these hypotheses using a sample of U.S. mutual funds from 2010 to 2023, a period characterized by rapid adoption of AI technology in asset management. We construct a comprehensive database of fund manager biographies from Morningstar and supplemental public sources, and we employ large language models (LLMs) to identify managers with AI-related expertise. Using detailed manager-tenure information, we classify a mutual fund

as an “AI-driven fund” starting in the quarter of its first AI-related manager hire.³

Our descriptive evidence indicates that AI-adopting funds differ systematically from other funds. Relative to non-AI funds, AI funds are larger and hold more securities. More importantly, portfolio turnover rises sharply after AI adoption: average turnover increases from 0.598 to 0.811 for AI funds, while matched non-adopting funds exhibit no significant change. Because higher turnover implies shorter holding periods, this pattern is consistent with increased emphasis on short-horizon information and trading following AI adoption. Moreover, because elevated turnover increases transaction costs, these post-adoption changes are difficult to reconcile with an “AI-washing” interpretation in which funds rebrand without meaningfully altering their investment process.

We then formally test our first hypothesis by examining the association between mutual fund trades and future earnings changes across horizons. AI adoption significantly alters funds’ information-processing horizons. Quarterly trades by AI funds exhibit significantly stronger associations with short-term earnings changes (1–4 quarters ahead) but markedly weaker associations with long-term earnings changes (9–12 quarters ahead), relative to non-AI funds.

A concern is that confounding fund characteristics—such as turnover and size—may affect both AI adoption and the information horizon embedded in trading. To address this concern, we conduct a matched-sample difference-in-differences (DiD) analysis. Specifically, we match each AI-adopting fund to a non-AI fund based on pre-adoption characteristics (total net assets, turnover, age, and number of stock holdings) measured one quarter prior to adoption. Relative to these closely matched controls, AI-adopting funds exhibit a significant increase in the trade–earnings association at short horizons and a significant decrease at long horizons.

³Managers are classified as having AI expertise if they meet criteria such as formal education in AI, prior work experience, explicit use of AI in decision-making, or AI-related certifications. We adopt a conservative approach to mitigate Type I error. As a robustness check, we supplement this classification with AI funds identified via textual analysis of fund prospectuses and fund-family AI-related patents; inferences remain unchanged.

A separate concern is that AI adoption may shift funds’ portfolios toward stocks whose fundamentals are inherently more predictable at short horizons, rather than changing how funds process information about a given stock. To address this possibility, we conduct a constant-holding analysis that retains only fund–stock pairs in which the fund holds the same stock continuously throughout both the pre- and post-adoption periods. By fixing the identity of securities, this design isolates changes in information processing from changes in stock selection. Even within this restrictive sample, AI-adopting funds display a significant increase in short-horizon trade–earnings associations and a significant decrease at long horizons relative to matched controls, indicating that the horizon shift reflects a change in information acquisition rather than portfolio recomposition.

To further address endogeneity, we employ instrumental-variable (IV) approaches and quasi-natural experiments. In the IV analysis, we use funds’ exposure to AI talent and their geographic proximity to AI hubs as instruments. Both variables strongly predict AI adoption: AI funds exhibit greater talent exposure and are located closer to AI hubs.⁴ A three-stage probit–2SLS framework confirms that the main patterns—stronger (weaker) trade associations with short-term (long-term) earnings changes for AI funds—remain robust and become economically larger after accounting for endogeneity.

In the quasi-natural experiments, we exploit two plausibly exogenous shocks to AI effectiveness: the introduction of the Transformer architecture (Vaswani et al., 2017) and the staggered rollout of satellite imaging data. The Transformer represents a breakthrough in processing textual and language data, while satellite imagery provides novel input data for AI-enabled investment strategies. Both innovations improved the effectiveness of AI in investment analysis (Huang et al., 2023; Katona et al., 2025) yet were outside individual funds’ control, providing plausibly exogenous variation. Following each shock, AI funds exhibit stronger associations between trades and short-term earnings changes and weaker

⁴Neither instrument predicts the trade–earnings association during the pre-sample period when AI adoption was rare, suggesting they are unlikely to affect information-processing horizons except through AI adoption.

associations with long-term earnings changes.

Having established that AI adoption shifts mutual funds' information horizon, we next examine whether this shift affects stock-price informativeness about future fundamentals across horizons. Using measures from [Bai et al. \(2016\)](#) and the future earnings response coefficient literature ([Collins et al., 1994](#); [Lundholm and Myers, 2002](#)), we find that greater AI-fund ownership is associated with greater price informativeness about short-term earnings but lower informativeness about long-term fundamentals. These results are robust and become stronger when we address endogeneity via IV designs.

To mitigate concerns that AI funds select firms that already exhibit these price-informativeness patterns, we implement a constant-shareholder design. We define treated stocks as those that first gain AI exposure because an incumbent shareholder fund adopts AI, and we match them (one quarter prior to adoption) to control stocks that never have AI-fund shareholders, based on size, leverage, profitability, growth, book-to-market, and analyst coverage. Even in this restrictive sample, treated firms experience increased short-horizon price informativeness and decreased long-horizon price informativeness following AI adoption by an existing investor. These findings indicate that AI-driven information processing and trading can reshape the informational content of stock prices, enhancing incorporation of near-term signals while attenuating long-horizon information.

Finally, we examine whether AI funds' emphasis on short-horizon information reduces the usefulness of stock prices for guiding corporate investment. Prior work shows that firms learn from prices when making long-term investment decisions ([Luo, 2005](#); [Chen et al., 2007](#); [Bond et al., 2012](#)). If prices become disproportionately driven by short-horizon information, they may become less informative for managers assessing investments with near-term costs and long-term payoffs. Consistent with this mechanism, we find that investment- Q sensitivity is significantly lower for firms with greater AI-fund ownership, suggesting that investment becomes less responsive to market-based signals. These results are robust and become stronger with IV designs, and they also hold in a DiD framework that compares

treated firms gaining AI exposure via an incumbent shareholder’s adoption to matched controls without AI-fund shareholders. Overall, the evidence suggests that AI-driven changes in price informativeness have real effects on corporate decision-making, potentially affecting capital allocation efficiency.

This paper contributes to several literatures. First, we provide new evidence on how AI adoption in asset management changes information production in financial markets. Classic models imply that lower information-acquisition costs should increase information production (Grossman and Stiglitz, 1980; Verrecchia, 1982; Blankespoor et al., 2020). Given evidence that AI improves certain forecasting tasks (Gu et al., 2020; Cao et al., 2024), one might expect AI adoption to uniformly enhance information production. We qualify this view by showing that AI adoption changes the *horizon* of information acquisition: it improves processing of short-term information but reduces the production and use of long-horizon fundamental information. This temporal reallocation of attention is a distinct mechanism through which technological progress reshapes—rather than simply augments—information production.

Second, we contribute to the price-informativeness literature by documenting that AI’s effects are horizon-dependent. While technological progress may increase price informativeness in general (Bai et al., 2016), our findings show that AI enhances incorporation of short-term earnings information while reducing informativeness about long-horizon fundamentals. This matters because declines in long-horizon price informativeness can weaken the role of stock prices as signals for efficient resource allocation (Fama, 1970; Baker et al., 2009; Bond et al., 2012).

Third, we establish a link between AI adoption in asset management and corporate investment decisions. Firms with greater AI-fund ownership exhibit significantly lower investment– Q sensitivity, consistent with AI-induced investor short-termism transmitting to the real sector and altering how managers respond to market signals (Chen et al., 2007; Edmans et al., 2017). These results illustrate a novel channel—AI-driven changes in investor

horizons—through which financial technology can affect capital allocation.

The remainder of the paper proceeds as follows. Section 2 reviews the literature and develops testable hypotheses regarding AI adoption’s effects on mutual fund short-termism, price informativeness, and corporate investment. Section 3 describes our data and variable construction. Section 4 presents the main findings. Section 5 concludes.

2. Literature Review and Hypothesis Development

2.1. *AI Adoption in Financial Markets*

The adoption of artificial intelligence in asset management represents a significant shift in how market participants process information and make investment decisions (Bartram et al., 2020). Recent advances in machine learning, natural language processing, and computational capabilities have dramatically expanded AI’s applications in finance, moving well beyond early neural networks (Trippi and Turban, 1992) to sophisticated algorithms that can process vast amounts of structured and unstructured data (Gu et al., 2020; Jiang et al., 2023).⁵

However, evidence on AI’s impact on investment performance presents a more nuanced picture. Abis (2022) finds that quantitative funds outperform during periods of market volatility but underperform in normal market conditions. Grennan and Michaely (2020) document that while AI-using analysts make more accurate forecasts, this does not consistently translate into greater value in their recommendations. Zhang (2024) finds that mutual funds with more AI-related job postings outperform other funds. But the outperformance only exists among stocks with voluminous information. These findings suggest that AI adoption may have heterogeneous effects across different market contexts and investment horizons.

⁵According to Mercer’s 2024 survey of global investment managers, the use of AI in investment strategy and research has expanded well beyond the traditional “quant” group, with only 9% of respondents indicating that they have no plans to use AI within their investment strategy. See *AI integration in investment management: 2024 global manager survey report, Mercer, March 2024*.

2.2. Information Acquisition and Forecast Horizons

The literature on information acquisition in financial markets establishes that investors allocate limited attention and resources across different types of information (Kacperczyk et al., 2016). The classic model of Grossman and Stiglitz (1980) demonstrates that investors rationally acquire information until the marginal cost equals the marginal benefit. Building on this foundation, Verrecchia (1982) and Admati (1985) show that investors may specialize in acquiring specific types of information based on their comparative advantages.

Recent theoretical work suggests that technological innovations can alter information acquisition strategies by changing the relative costs or benefits of different types of information. Farboodi et al. (2022) find that investors increase their data processing substantially for large, high-growth firms (but not for other types of firms) as the benefit of data of these firms is larger for investors. Similarly, Dugast and Foucault (2018) model how technological changes affect the trade-off between fast, low-precision signals and slower, high-precision information, and suggest that improvement in information technologies may reduce price informativeness because a decline in the cost of producing low-precision raw signals may reduce the demand for more precise signals (based on fundamental analysis). These theoretical insights align with the empirical characteristics of current AI technologies. Machine learning algorithms excel at identifying statistical patterns in large datasets but face challenges in causal inference and long-term forecasting that require domain expertise, contextual understanding, and qualitative judgment (Sloan, 2019; Cao et al., 2024; Boyacı et al., 2024; Dhar and Sedoc, 2025).

Our research also relates to Dessaint et al. (2024), who find that alternative data diminishes equity analysts' long-horizon forecast informativeness. However, our paper differs in three key dimensions. First, we study the effect of AI adoption by mutual funds, rather than data availability effects. Second, we focus on mutual fund managers, who serve as capital allocators and may have different incentives from sell-side analysts.⁶ Third, we trace

⁶For example, prior research finds that analysts may have limited incentives to produce accurate long-

the complete pathway from AI adoption through altered price informativeness to real investment effects, whereas [Dessaint et al. \(2024\)](#) examines only analyst forecast accuracy. Our comprehensive approach reveals how technology-driven changes in investor information processing affect both market efficiency and corporate capital allocation.

2.3. The Real Effects of Financial Markets and Corporate Short-termism

A substantial literature examines how stock price informativeness affects corporate decision-making. [Chen et al. \(2007\)](#) demonstrate that firms' investment decisions are more sensitive to stock prices when those prices contain more private information. This sensitivity arises because managers learn from the information aggregated in stock prices when making investment decisions ([Bond et al., 2012](#)).

However, the usefulness of stock prices as signals for investment depends on whether they reflect long-term fundamental value. A growing body of research examines how short-termism in financial markets may distort corporate decision-making. [Bushee \(2001\)](#) finds that high levels of ownership by transient institutional investors are associated with managerial myopia. Similarly, [Cremers et al. \(2020\)](#) document that shorter investor horizons lead to reduced long-term investments by firms.

These concerns about short-termism have gained prominence in policy discussions ([Stein, 1989](#); [Bolton et al., 2006](#)). Recent work by [Asker et al. \(2015\)](#) and [Dow et al. \(2024\)](#) provides evidence that short-term pressure from financial markets can lead to suboptimal investment decisions, particularly regarding long-term, intangible investments such as R&D and organizational capital.

term earnings forecasts, with some studies indicating their long-term forecasts can be less accurate than some naive benchmarks ([Da and Warachka, 2011](#); [Bradshaw et al., 2012](#)).

2.4. Hypothesis Development

Building on the theoretical foundations and empirical evidence presented above, we develop three interconnected hypotheses that examine the effects of AI adoption on information processing horizons, price informativeness, and corporate investment decisions.

Hypothesis 1: AI Adoption and Information Horizon

We hypothesize that AI adoption by mutual funds increases the short-term focus in their information processing. Specifically:

H1: After AI adoption, mutual funds exhibit increased short-termism in their information processing, characterized by stronger correlations between funds' trades and near-term earnings but weaker associations with long-term earnings.

This hypothesis rests on AI's comparative advantage in processing short-term versus long-term information. AI systems excel at processing large volumes of structured and unstructured data (e.g., financial statements, satellite imagery, credit card transactions, social media) that provide timely insights about near-term business performance (Dessaint et al., 2024; Katona et al., 2025). These data sources yield fast-moving signals particularly valuable for short-term forecasting, enabling mutual funds to detect transient anomalies and exploit temporary market inefficiencies with great speed and precision.

In contrast, long-term forecasting depends critically on qualitative factors such as management quality, competitive dynamics, and potential structural shifts. Analyzing these factors requires causal reasoning, scenario analysis, and adaptation to regime changes—tasks where current AI technologies face significant limitations (Sloan, 2019; Liu, 2022; Cao et al., 2024; Boyacı et al., 2024). Several fundamental constraints explain these limitations. First, long-term prediction suffers from acute data scarcity: when forecasting outcomes several years ahead, even decades of historical data yield only a limited number of truly independent observations—insufficient for reliably training complex models without overfitting (Gu et al., 2020).⁷ This sample size problem is exacerbated by structural breaks and regime

⁷For instance, forecasting three years ahead earnings using quarterly data allows fewer than 30 usable

changes that render historical patterns less relevant for distant-future predictions. Second, while AI excels at statistical pattern recognition, it struggles with long-horizon predictions that depend on understanding strategic positioning, adaptability to disruption, and scenario planning rather than extrapolating historical regularities. Third, long-term forecasts are disproportionately sensitive to rare events and paradigm shifts that lie outside models' training distributions, limiting AI's ability to anticipate novel scenarios lacking historical analogues. As [Dhar and Sedoc \(2025\)](#) observe, “*So far, AI methods have not been feasible for long-term investing due to the difficulty of creating a suitable knowledge base for investing*” and the absence of sufficient training data. Moreover, even if AI improved long-term forecasting accuracy equally, monetizing such information involves greater risk and uncertainty, as unpredictable shocks may occur before long-term fundamentals are realized.

Given that information-processing attention is scarce and must be optimally allocated ([Kacperczyk et al., 2016](#)), AI adoption creates incentives to reallocate resources toward activities with the highest marginal returns. AI significantly reduces the marginal cost of processing short-term information while offering smaller improvements for long-term analysis. Furthermore, the marginal benefit of long-term information is inherently lower due to the greater risk and uncertainty associated with monetizing positions held over extended horizons. These dual forces lead fund managers to rationally shift attention toward short-term signals at the expense of long-term information acquisition.

Hypothesis 2: AI Fund Ownership and Stock Price Informativeness

Building on the first hypothesis, we further predict that the shift in information processing horizons among AI-adopting funds affects the informational content of stock prices:

H2: Greater AI fund ownership increases stock price informativeness about short-term earnings but decreases informativeness about long-term earnings.

This hypothesis follows from the role of institutional investors in price formation. When mutual funds trade based on their private information, this information becomes incorporated into stock prices over observations from a decade of history, and far fewer still if requiring non-overlapping samples.

rated into stock prices (Grossman and Stiglitz, 1980). The theoretical work of Verrecchia (1982) and Goldstein and Yang (2019) shows that the composition of informed traders' information sets directly affects the informational content of prices. If AI-adopting funds focus more on short-term signals, stock prices become more informative about near-term fundamentals but less informative about long-term performance.

Hypothesis 3: AI Fund Ownership and Corporate Investment Efficiency

Our final hypothesis connects changes in price informativeness to real corporate decisions:

H3: Greater AI fund ownership reduces the sensitivity of corporate investment to Tobin's Q.

This hypothesis builds on the "active informant" role of financial markets in guiding real economic decisions (Bond et al., 2012). Stock prices aggregate diverse information about firms' prospects, providing signals that inform managerial decision-making. Chen et al. (2007) demonstrate that investment-Q sensitivity is significantly higher when stock prices contain more information that is new to managers.

If AI fund ownership reduces the long-term informativeness of stock prices as predicted in H2, it reduces the revelatory price efficiency (RPE) of the stock markets as discussed in Bond et al. (2012), i.e., stock prices may become less valuable signals for long-term investment decisions. Consequently, the sensitivity of investment to Q would decrease, if managers find stock prices less informative about the long-term payoffs of their investments.⁸

Several counterarguments, however, might limit or reverse these hypothesized effects. AI tools could complement human analysis, freeing fund managers from routine data processing and allowing greater focus on long-term strategic thinking. As AI capabilities advance, they may overcome current limitations in causal reasoning and long-term forecasting. Sophisticated fund managers might also deliberately maintain balanced attention across time horizons, recognizing the value of long-term information advantages. Under these scenarios,

⁸Decreased Investment-Q sensitivity, while indicating that stock prices have become less useful guides for long-term investment decisions, does not necessarily imply reduced investment efficiency. Sophisticated managers might recognize the shift in the informational content of prices and appropriately adjust their decision-making processes, relying more on internal information and alternative sources of long-term insights rather than market signals. This adaptive response could help maintain investment efficiency despite changes in stock price informativeness.

AI adoption could enhance rather than reduce funds' long-horizon information processing, improving price informativeness across all time horizons.

Moreover, even if AI funds shift toward short-term signals, market-level informativeness may remain balanced through specialization. If different market participants focus on different information horizons, aggregate prices could maintain informativeness despite shifts among individual investor groups. Additionally, corporate managers may not immediately perceive subtle changes in the horizon structure of price informativeness, continuing to rely on stock price signals despite their reduced usefulness for long-term decisions. Investment-Q sensitivity might therefore persist despite reallocation of investor attention.

Given these competing mechanisms, whether AI adoption reduces long-term information acquisition, decreases stock price informativeness about long-term fundamentals, and diminishes the usefulness of price signals for corporate investment remains an empirical question. We acknowledge these theoretical tensions and allow the evidence to reveal which forces dominate. By testing our hypotheses, we provide new insights into whether AI adoption by mutual funds has unintended consequences for information acquisition and the informational and functional efficiency of market prices.

3. Data and Measurement

3.1. Sample and Data

We construct our primary dataset by merging fund-level and stock-level data from several standard sources. Our initial sample is drawn from Morningstar, encompassing an expansive universe of 9,399 mutual funds managed by 8,699 distinct fund managers. We merge this Morningstar sample with the CRSP Survivor-Bias-Free US Mutual Fund Database using fund tickers to obtain fund-level characteristic variables. Subsequently, we employ the WRDS MFLINKS file to merge the resulting sample with quarterly institutional equity holdings from the LSEG (formerly Thomson Reuters) mutual fund holdings (S12) database, which

provides quarter-end security holding information for all registered mutual funds.

Because our analysis focuses on U.S. active equity funds, we apply several filters to the data. We remove index funds, annuity funds, ETFs, money market funds, and bond funds using either the CRSP objective flag or identifying strings within the fund name.⁹ We further require that at least 80% of a fund’s assets under management be invested in common stocks. To mitigate potential incubation bias, we exclude observations where the report year predates the fund’s inception year or where the fund name is missing (Evans, 2010). Additionally, we remove international funds domiciled outside the U.S. and exclude funds with a total net asset value (*TNA*) of less than \$10 million.

Finally, we merge our fund data with stock return data from CRSP, accounting data from Compustat, and analyst data from I/B/E/S. We exclude firms operating in the financial services and utilities sectors, as the unique regulatory environments and accounting conventions in these industries often render their fundamentals incomparable to those of other sectors. Furthermore, we require that sample observations have non-missing values for one-year-ahead earnings. Our final sample comprises 3,642 actively managed U.S. equity mutual funds holding 6,626 distinct stocks.

3.2. Main Variable Construction

3.2.1. Identifying AI Funds

Because proprietary AI systems used by mutual funds are unobservable to researchers, we proxy for AI adoption using fund managers’ biographical credentials from Morningstar. Our central identifying assumption is that when a fund’s investment decision makers include managers with demonstrable AI expertise, the fund is more likely to deploy AI methods

⁹Specifically, we first utilize the `index_fund_flag`, `et_flag`, and `vau_fund` to screen for funds that are designated as index funds, ETFs, or annuity funds in their CRSP classification. We further remove funds containing any of the following strings in their name: 'Index', 'Idx', 'Indx', '500', '600', '1000', '1500', '2000', '3000', '5000', 'S&P', 'Dow', 'DJ', 'Dow Jones', 'Nasdaq', 'Barra', 'Powershares', 'Wilshire', 'Russell', 'StreetTRACKS', 'nyse', 'spdr', 'Holdrs', 'ishares', 'ETF', 'Exchange-Traded Fund', 'Exchange Traded Fund', 'Mkt', 'Market', 'Currency', 'Composite', 'bond'.

in portfolio construction and investment decision-making. This assumption is grounded in the view that the effective integration of AI into the investment process requires senior personnel who can select appropriate tools, supervise implementation, and interpret and validate model-driven signals (Sheng et al., 2025).¹⁰

To identify AI expertise, we use GPT-5.1 Mini to evaluate each manager’s publicly available biography along the following four dimensions: i) AI-related education (e.g., degrees or formal training in machine learning, data science, or artificial intelligence), ii) AI/ML work experience (e.g., roles as data scientists or AI researchers, or employment at AI-intensive firms), iii) evidence of applying AI/ML in investment contexts (e.g., references to machine-learning models, natural language processing, or neural networks) and, iv) AI/ML-related credentials such as certifications, publications, or projects. We classify a manager as having AI expertise if at least one criterion is met. To reduce false positives, we explicitly instruct the model to distinguish AI expertise from traditional quantitative methods, so that standard statistical, econometric, or generic “quant” backgrounds are not coded as AI expertise. We then manually verify the model-based classifications to validate accuracy and ensure that the indicator captures substantive AI expertise rather than conventional quantitative skills.¹¹ Using manager-tenure information, we define a fund as “AI-driven” beginning in the quarter in which it first hires an AI-expert manager; otherwise, it is classified as “traditional.” This procedure yields a time-varying fund classification that captures transitions from traditional

¹⁰Alternative proxies for AI adoption exist. Holdings-based measures of reliance on generative AI—such as Sheng et al. (2025), which quantifies the incremental explanatory power of ChatGPT-generated signals for portfolio rebalancing—are well suited to studying LLM/GenAI usage but are not designed to capture broader (“classic”) AI adoption in mutual funds. Hiring-based measures (Zhang, 2024) are informative about AI-related labor investment but may reflect technology and back-office hiring rather than investment decision-making; our approach focuses on the biographies of portfolio decision makers. A further alternative is textual identification from fund prospectuses, but marketing language may reflect “AI-washing” rather than genuine adoption (SEC, 2024; Li, 2025). Our human-capital-based identification strategy, focusing exclusively on fund managers’ AI expertise, helps distinguish between substantive AI adoption and superficial references to AI (Darendeli et al., 2022). Nevertheless, we supplement our primary AI adoption identification approach with AI funds identified via textual analysis of fund prospectuses and fund-family AI-related patents; all inferences remain unchanged. We provide the replication of the baseline model in Section I.2 of the Internet Appendix. The complete set of empirical results is available upon request.

¹¹Internet Appendix Section I.1 reports the full prompt and the model’s structured output, including the AI-expertise indicator and supporting justification.

to AI-driven management over time.

3.2.2. *Measuring The Short-Termism of Mutual Funds*

We measure a mutual fund’s short-termism by examining the fundamental informativeness of its trading activity across different forecasting horizons. As discussed earlier, short-termism reflects the fund’s strategic allocation of attention and resources toward shorter-horizon signals. A fund is considered to exhibit short-termism if its trading activity is more strongly associated with short-term fundamentals while showing weaker association with long-term fundamentals. Empirically, we model this relationship with the following regression:

$$\Delta EA_{j,[h,h+3]} = \alpha + \beta_1 Trading_{f,j,t} + \epsilon_{f,j,t} \quad (1)$$

where $\Delta EA_{j,[h,h+3]}$ represents changes in firm j ’s earnings over quarters h to $h + 3$ relative to the prior four quarters. We compute $\Delta EA_{j,[h,h+3]}$ as the sum of quarterly earnings (EBIT scaled by total assets) from quarter h to $h+3$ minus the sum of earnings over the four quarters immediately preceding quarter h . $Trading_{f,j,t}$ represents the split-adjusted trading value (LSEG S12 item CHANGE*PRC) of fund f for stock j in quarter t , scaled by the total portfolio value of fund f at the end of quarter $t - 1$. A mutual fund exhibiting short-termism is expected to have a larger coefficient β_1 in the regressions corresponding to the near-term earnings horizons ($h=t+1$, or quarters 1–4), indicating stronger alignment of its trading with short-term earnings news, whereas the coefficient would attenuate or even reverse for longer horizons ($h=t+5$, or quarters 5–8, and $h=t+9$, or quarters 9–12), reflecting relatively diminished sensitivity to long-term fundamentals.

3.3. *Summary Statistics*

Figure 1 illustrates the temporal evolution of AI mutual funds. Panel A depicts the count of AI funds, which has increased from negligible levels in 2010 to 172 by 2023, constituting

approximately 8% of the sample population. Panel B plots the aggregate assets under management (AUM). Consistent with the growth in fund count, the capital allocated to AI funds has expanded steadily. By 2023, AI funds managed approximately \$2.2 trillion in assets, representing roughly 5% of the industry’s total AUM, a marked increase from the 0.7% share observed prior to 2010.¹²

Table 1 reports summary statistics for the primary variables used in our baseline analysis. We organize these statistics by the level of aggregation. First, at the fund-stock-quarter level, the variable *Trading* has a mean of 0.044%; however, it exhibits significant dispersion, with a standard deviation of 0.267%.

Second, at the fund-quarter level, AI funds comprise 4.9% of the sample on average. The representative fund in our sample manages \$585.2 million in net assets, has an operational history of over 13 years (53.5 quarters), holds 81.7 distinct stocks, and exhibits a quarterly portfolio turnover rate of 60.3%.

Third, regarding stock-quarter characteristics, the average equity ownership by AI funds is 3.3% of outstanding shares, with an average of 3.9 AI funds holding a given stock. The sample firms are generally large, with an average market capitalization of approximately \$8.0 billion. In terms of fundamentals, the average firm has a financial leverage ratio of 52.2%, a quarterly return on equity (ROE) of 1.0%, a book-to-market ratio of 0.544, and a quarterly sales growth rate of 4.4%. On average, these firms are covered by 8.7 sell-side analysts.

4. Empirical Results

4.1. *Initial Evidence: Portfolio Turnover Before and After AI Adoption*

Before turning to the trade-earnings association, we provide initial evidence on how AI adoption affects funds’ portfolio turnover. If AI shifts funds’ attention toward short-horizon

¹²When we supplement our AI-expertise-based classification with additional AI funds identified via textual analysis of fund prospectuses and fund-family AI-related patents, the number of AI funds in 2023 increases to 239, with total AUM amounting to \$4.5 trillion, representing 9.2% of the market share.

signals, AI-adopting funds should rebalance more frequently. The intuition is that short-horizon signals are time-sensitive; exploiting them requires correspondingly more frequent portfolio adjustment.

Panel A of Table 2 compares key characteristics of AI and non-AI funds. AI funds manage significantly larger assets on average (\$701.3 million vs. \$579.2 million) and maintain more diversified equity portfolios (176 vs. 77 stocks). More importantly, AI funds display markedly higher portfolio turnover (0.811) compared to non-AI funds (0.592), suggesting a baseline difference in trading behavior.

To assess whether turnover increases around the adoption event, we compare changes in turnover for AI-adopting funds to changes for similar non-AI funds in a matched sample. Specifically, prior to the adoption date, we implement one-to-one nearest-neighbor matching: each AI-adopting fund is paired with a non-AI fund based on pre-adoption fund-level covariates, including total net assets, turnover, fund age, and the number of stocks held.

Panel B of Table 2 presents a univariate difference-in-differences (DiD) comparison. In the pre-adoption period, AI funds and their matched counterparts exhibit statistically indistinguishable turnover (0.598 vs. 0.600). Following adoption, turnover increases to 0.811 for AI funds, while remaining relatively stable for matched non-AI funds (0.607). The implied DiD estimate is 0.206 ($t = 10.590$), indicating a sizable increase in portfolio turnover following AI adoption.

Panel C corroborates this pattern in a multivariate regression framework. After controlling for fund characteristics and including the fixed effects specified in Table 2, the DiD coefficient remains positive and statistically significant (coefficient = 0.049, $t = 3.09$). Taken together, these results suggest that AI adoption is associated with higher portfolio turnover, or equivalently, a shorter average holding period, consistent with a shift toward exploiting short-horizon signals and a decrease in trading based on longer-horizon information.

4.2. AI Adoption and a Horizon Shift in the Trade–Earnings Association

In this section, we directly examine whether trades by AI funds are more closely related to short-horizon fundamentals, but less related to longer-horizon fundamentals. We begin by studying the bin-scatter relation between contemporaneous trading and subsequent earnings news, separately for AI and traditional funds. For each fund group and each horizon window, we: (i) sort observations by $Trading_{f,j,t}$ and partition them into 10 equal-sized bins (bin 1 = strongest sells; bin 10 = strongest buys); (ii) compute the mean $\Delta EA_{j,[h,h+3]}$ within each bin; and (iii) plot these bin means, so that each point represents the average future earnings news for a decile of trading activity. Figure 2 shows that at short horizons (quarters 1–4), the fitted line for AI funds is consistently steeper than that for traditional funds. At longer horizons (quarters 5–12), the pattern reverses: the trade–earnings association for AI funds weakens—and in some windows turns negative—while the relation for traditional funds remains comparatively stable.

To formally assess whether AI funds exhibit differential short- versus long-horizon trading informativeness, we estimate the following OLS specification:

$$\begin{aligned} \Delta EA_{j,[h,h+3]} = & \alpha + \beta_1 (AIFund_{f,t} \times Trading_{f,j,t}) + \beta_2 AIFund_{f,t} + \beta_3 Trading_{f,j,t} \\ & + \Pi' StockControl_{j,t} + \Omega' FundControl_{f,t} + \phi_{fj} + \lambda_{kt} + \epsilon_{f,j,t}, \end{aligned} \quad (2)$$

where $AIFund_{f,t}$ is an indicator equal to one if mutual fund f is classified as an AI-adopting fund in quarter t . Variables $\Delta EA_{j,[h,h+3]}$ and $Trading_{f,j,t}$ are defined as in Section 4.1. $StockControl_{j,t}$ is a vector of stock–quarter controls capturing firms’ fundamentals and information environments (Zhu, 2019), including $\log Size$, $Leverage$, ROE , $Growth$, BTM , and $\log \#Analysts$. $FundControl_{f,t}$ is a vector of fund–quarter controls capturing fund characteristics and trading style (Jiang et al., 2007; Bonelli and Foucault, 2024), including $\log TNA$, $\log Age$, $\log \#Stocks$, and $Turnover$.

The specification absorbs time-invariant heterogeneity in fund–stock relationships via

fund–stock fixed effects (ϕ_{fj}) and common shocks at the industry–quarter level via industry–time fixed effects (λ_{kt}). Standard errors are double-clustered at the fund and stock levels. Our hypothesis (H1) predicts a horizon-dependent pattern in β_1 : AI funds’ trading should be more informative about near-term earnings news but less informative about longer-horizon earnings news.

Table 3 reports estimates of Eq. (2) across forecasting horizons. Columns (1), (3), and (5) include fund–stock and industry–time fixed effects; Columns (2), (4), and (6) additionally control for fund- and stock-level characteristics. The interaction coefficient $AIFund \times Trading$ displays a clear horizon pattern consistent with H1. Over short horizons (quarters 1–4), β_1 is positive and highly statistically significant: 0.470 ($t = 10.66$) without controls and 0.475 ($t = 11.07$) with controls, indicating that AI funds’ trades are more strongly associated with near-term earnings news than those of traditional funds. Over medium horizons (quarters 5–8), β_1 becomes negative and statistically significant: -0.110 ($t = -2.08$) and -0.098 ($t = -1.86$). Over long horizons (quarters 9–12), the estimates remain negative and statistically significant: -0.135 ($t = -2.06$) and -0.132 ($t = -2.00$), implying weaker (and relative to traditional funds, lower) long-horizon trading informativeness for AI funds.

A potential concern is that the baseline trade–earnings associations might reflect pre-existing differences in fund characteristics or investment styles rather than a causal effect of AI adoption on information-processing horizons. For example, funds with higher portfolio turnover might be more likely to adopt AI technology, and these funds also tend to have higher short-term trade informativeness but lower long-term trade informativeness. To mitigate this concern, we implement a matched-sample difference-in-differences (DiD) design analogous to the procedure in Section 4.1. By pairing each AI-adopting fund with a non-adopting peer that exhibits similar pre-adoption characteristics (size, turnover, age, holdings), we control for level differences in investment style and isolate the within-fund change in trading informativeness following AI adoption. This matched framework also fa-

enables a dynamic analysis testing for differential pre-adoption trends. Using this matched sample, we estimate the following difference-in-differences (DiD) specification:

$$\begin{aligned}
\Delta EA_{j,[h,h+3]} = & \beta_1 Treat_f^{Fund} \times Post_t^{Fund} \times Trading_{f,j,t} + \beta_2 Treat_f^{Fund} \times Post_t^{Fund} \\
& + \beta_3 Treat_f^{Fund} \times Trading_{f,j,t} + \beta_4 Post_t^{Fund} \times Trading_{f,j,t} + \beta_5 Trading_{f,j,t} \\
& + \Pi' StockControl_{j,t} + \Omega' FundControl_{f,t} + \phi_{fjc} + \gamma_{ct} + \lambda_{kt} + \epsilon_{f,j,t},
\end{aligned} \tag{3}$$

where $Treat_f^{Fund}$ equals one for an AI-adopting (treatment) fund and zero for its matched non-adopting control fund, and $Post_t^{Fund}$ equals one for periods after the treatment fund's AI-adoption quarter. The dependent variable, $\Delta EA_{j,[h,h+3]}$, measures earnings news over horizon $[h, h + 3]$ as in the main analysis. The specification includes: (i) fund–stock–cohort fixed effects, ϕ_{fjc} , absorbing time-invariant heterogeneity within each adoption cohort; (ii) cohort–time fixed effects, γ_{ct} , absorbing shocks common to a given adoption cohort over time; and (iii) industry–time fixed effects, λ_{kt} , absorbing time-varying industry-level shocks. The coefficient of interest, β_1 , captures the change in the trade–earnings relation for treatment funds after AI adoption relative to matched controls. Under the short-termism hypothesis, we expect $\beta_1 > 0$ at short horizons and $\beta_1 < 0$ at long horizons.

Panel A of Table 4, Columns (1)–(3), reports DiD estimates for the matched sample. Consistent with a post-adoption change rather than a pre-existing style difference, the triple interaction $Treat^{Fund} \times Post^{Fund} \times Trading$ is positive and statistically significant at short horizons (0.499, $t = 4.34$) and negative and significant at long horizons (-0.530 , $t = -3.42$). Because β_1 captures a post-adoption change (relative to matched controls) in the extent to which fund trading predicts subsequent earnings news, these estimates indicate that AI adoption is associated with increased informativeness of trades about near-term earnings news and decreased informativeness about longer-horizon earnings news. This interpretation is further supported by the event-time evidence in Columns (1)–(3) of Panel B, which shows no differential pre-adoption movements in the trade–earnings relation across horizons.

A remaining concern is that these results might be driven by portfolio recomposition rather than changes in information processing horizons. Specifically, AI-adopting funds might shift toward stocks whose fundamentals are inherently more predictable at short horizons, even if the funds’ information-acquisition approach remains unchanged. To rule out this alternative explanation, we perform a “constant-holding” analysis (Panel A, Columns (4)–(6)) that restricts the sample to fund–stock pairs in which the fund continuously holds the same position throughout both the pre- and post-adoption periods.¹³ By fixing the identity of traded securities, this design isolates changes in *how* funds process information about a given stock, holding constant *which* stocks they trade. The results remain qualitatively similar: β_1 is positive and statistically significant at short horizons (0.541, $t = 3.11$) and negative and significant at long horizons (-0.504 , $t = -2.15$). Because these estimates are obtained within the same fund–stock pairs before and after adoption, they indicate that the horizon shift reflects changes in information processing rather than stock selection.

Panel B, Columns (4)–(6), examines the timing of effects in an event-time (dynamic) setting. The pre-adoption interaction terms, $Treat^{Fund} \times Pre_{\#}^{Fund} \times Trading$, are statistically indistinguishable from zero across all horizons, supporting the parallel-trends assumption. In contrast, treatment effects emerge sharply in the post-adoption period, consistent with the shift in trading informativeness occurring as a consequence of AI adoption rather than reflecting pre-existing trends.

In addition to the above, we conduct a battery of further robustness checks. For brevity, we summarize these analyses here and report full details and results in the Internet Appendix.

- While the expertise-based approach to identifying AI funds provides a conservative lower-bound estimate of AI adoption, it may fail to classify funds that adopt AI via organizational capabilities. We therefore augment the baseline measure using two external sources: (i) summary prospectuses (SEC Form 497-K) from EDGAR, which

¹³For example, if Fund A adopts AI in 2015Q1 and holds Stock X continuously throughout the event window, while its matched non-AI counterpart Fund B holds Stock Y continuously over the same window, the observations for (Fund A, Stock X) and (Fund B, Stock Y) form a constant-holding matched set.

describe funds’ principal investment strategies, and (ii) AI-related patent grants from the USPTO. Under this expanded classification, a fund is also labeled as an AI fund if (a) its Form 497-K explicitly references AI in the “Principal Investment Strategies” section, or (b) its advisory firm or fund family holds patents related to AI technologies intended for investment analysis. This broader definition increases the number of AI funds to 239 by 2023, with aggregate assets under management of \$4.5 trillion. Re-estimating our main specification on this expanded sample yields qualitatively similar inferences: as shown in Table I.2, the $AIFund \times Trading$ coefficients continue to decline monotonically with the forecasting horizon.

- We further assess robustness by replacing our baseline measure of future earnings news with two alternative proxies for firm fundamentals: earnings before interest, taxes, depreciation, and amortization (EBITDA) and net income (NI). Table I.3 shows that the horizon pattern documented in our baseline analysis is preserved under both alternative proxies. The interaction term $AIFund \times Trading$ remains positive and statistically significant over short horizons and becomes negative over longer horizons, consistent with AI adoption being associated with a shift in trading informativeness toward near-term fundamentals and away from longer-horizon fundamentals.
- We conduct a specification-curve analysis to evaluate how sensitive our results are to alternative modeling choices. We vary the fixed-effects structure (e.g., fund–stock versus separate fund and stock fixed effects; industry–time versus time fixed effects; and specifications that include fund–time fixed effects) and the clustering of standard errors (e.g., fund–stock, fund–time, stock, and stock–time). Figure I.1 summarizes the estimates across all combinations. The key interaction term, $AIFund \times Trading$, exhibits a consistent horizon pattern: coefficients are positive and statistically significant at short horizons (1–4 quarters ahead) and negative and significant at long horizons (9–12 quarters ahead). Overall, the short-termism pattern remains robust in both

economic magnitude and statistical significance across this broad set of specifications.

- To ensure that our baseline trade–earnings results are not driven by AI funds disproportionately holding AI-related stocks, we re-estimate our main specifications after excluding AI-related firms using three screens. First, we drop firms in the Fama–French 48 industries most directly tied to AI/robotics production. Second, we remove firms appearing on StockAnalysis.com’s curated “Artificial Intelligence Stocks” and “Robotics Stocks” lists. Finally, we apply both filters simultaneously, thereby excluding any AI firm identified through either the industry classification or the thematic list criterion. Table I.4 shows that the horizon pattern is unchanged, indicating that our findings are not driven by AI-stock holdings.

These results collectively deliver a consistent message: AI funds’ informational advantage systematically diminishes as the forecasting horizon extends, ultimately reversing into a significant disadvantage for long-term earnings prediction. This monotonic temporal pattern across all specifications provides compelling evidence that AI adoption fundamentally reshapes the intertemporal allocation of information processing efforts and resources within mutual funds.

4.3. Addressing Endogeneity

4.3.1. Instrumental Variable Approach

To better isolate the causal effect of AI adoption, we implement an instrumental-variable (IV) strategy using two plausibly exogenous sources of variation in funds’ propensity to adopt AI technologies.

Instrument 1: Ex-ante exposure to AI-strong universities. Following [Babina et al. \(2024\)](#), we instrument $AIFund_{f,t}$ with a fund’s pre-2010 exposure to AI talent through its

managers’ alma maters:

$$AI\ Talent\ Exposure_f = \sum_u Manager_{f,u}^{2010q1} \times AIstrong_u, \quad (4)$$

where $Manager_{f,u}^{2010q1}$ counts the managers in fund f in 2010Q1 who graduated from university u , and $AIstrong_u$ equals one if university u is classified as AI strong based on the prevalence of AI researchers prior to 2010Q1.¹⁴ This instrument leverages the idea that scarce AI talent constrains adoption (Acemoglu et al., 2022; Babina et al., 2024; Law and Shen, 2025): funds with stronger pre-existing alumni links to AI-strong universities were better positioned to recruit AI talent in the 2010s, independent of any inherent preference for short-horizon investing.

A potential concern is that AI-strong universities may also proxy for broader computer-science strength or general prestige. To mitigate this, we control for funds’ ex-ante exposure to (non-AI) computer-science-strong universities and to top-ranked universities. Specifically, we include: (i) $\sum_u Manager_{f,u}^{2010q1} \times CSstrong_u$, where $CSstrong_u$ is the average pre-2010 share of non-AI computer science researchers at university u ; and (ii) $\sum_u Manager_{f,u}^{2010q1} \times Top10_u$, where $Top10_u$ equals one if university u is among the top 10 universities in *U.S. News & World Report* (Harvard, Princeton, Yale, University of Pennsylvania, Columbia, MIT, Stanford, Caltech, University of Chicago, and Duke).

Instrument 2: Geographic proximity to AI hubs. Our second instrument is the geographic distance from a fund’s headquarters to the nearest AI hub. Proximity plausibly increases AI adoption through knowledge spillovers, collaboration networks, and access to specialized labor markets (Hunt et al., 2024). Importantly, AI hub locations are shaped by regional infrastructure, academic institutions, and agglomeration forces, and are unlikely

¹⁴Following Babina et al. (2024), a university is defined as AI strong if, for at least one year prior to 2010, it either (i) ranks in the top 5% of universities by number of AI researchers, or (ii) ranks in the top 10% by number of AI researchers and in the top 5% by AI-researcher share (AI researchers divided by non-AI researchers) in that year. AI researchers are identified based on publications in AI-related journals and conference proceedings.

to directly determine a fund’s investment horizon, which is more closely tied to mandates, investment philosophy, and strategy. Thus, distance should affect information-processing horizons primarily through its effect on AI adoption.

To construct this instrument, we use the list of AI hubs compiled by the Center for Security and Emerging Technology (CSET) and fund-company 5-digit ZIP codes from CRSP.¹⁵ We geocode each fund’s ZIP code to latitude–longitude coordinates (Python `geopy`) and compute the distance to the closest hub using Vincenty’s formula.

Assessing the exclusion restriction: pre-period falsification (placebo) test. Our identifying assumption is that the instruments affect funds’ information-processing horizons only through AI adoption. Although the exclusion restriction is not directly testable, we provide suggestive evidence using a pre-period falsification (placebo) test. Specifically, we focus on 2000–2009, a period that predates the majority of AI-adoption events in our sample. If either instrument directly influenced investment horizons through channels other than AI adoption, we would expect to observe a significant relation between the instruments—and their interactions with trading—and future fundamentals in this pre-period. As reported in Table 5, we find no such evidence: the instrument \times trading interaction terms are statistically insignificant across all horizons. This null result in the pre-period increases confidence that the instruments satisfy the exclusion restriction.

Three-stage probit–2SLS analysis. We then implement a three-stage probit–2SLS procedure to accommodate the binary nature of our endogenous variable, *AIFund* (Adams et al., 2009; Angrist and Pischke, 2009; Deng et al., 2022).¹⁶ Specifically: (i) **Stage 1 (probit):** we

¹⁵CSET defines AI hubs using four dimensions: (a) AI top universities (based on *U.S. News* AI program rankings supplemented by CSRankings); (b) AI companies (identified via keyword searches in Crunchbase and Refinitiv); (c) AI talent (based on LinkedIn Talent Insights); and (d) AI investment activity (U.S.- and China-based investors funding U.S.-based AI companies, matched to Crunchbase).

¹⁶Using the nonlinear fitted probabilities from a first-stage probit directly in the outcome regression can generate a “forbidden regression” because the fitted values may be mechanically correlated with the second-stage disturbance (Angrist and Pischke, 2009). The three-stage probit–2SLS approach mitigates this issue by adding an intermediate linearization step: after estimating adoption probabilities in Stage 1, we regress the endogenous binary indicator on these predicted probabilities and controls in Stage 2, producing a linear

estimate a probit model of AI adoption as a function of funds’ ex-ante exposure to AI talent (distance to the nearest AI hubs, or both) and other fund-level covariates; (ii) **Stage 2 (linearization)**: we use the Stage-1 fitted probability, $\widehat{AIFund}_{f,t}$, as an instrument in a linear first-stage regression for $AIFund_{f,t}$ (including the same controls and fixed effects as in the baseline specification); and (iii) **Stage 3 (2SLS outcome)**: we estimate the second-stage 2SLS regression for future earnings news, including the interaction between (instrumented) AI adoption and trading and the full set of controls.

Table 6 reports the three-stage probit–2SLS estimates. Panel A confirms instrument relevance: *AI Talent Exposure* enters positively and significantly (Column 1), and *Distance to AI Hubs* enters negatively and significantly (Column 3), consistent with stronger talent pipelines and geographic proximity facilitating adoption. The probit χ^2 and the first-stage 2SLS F -statistics indicate a strong first-stage fit, alleviating weak-instrument concerns. When both instruments are included jointly (Column 5), coefficients retain the expected signs and remain statistically significant. The Hansen J test fails to reject the null of instrument validity, supporting their joint exogeneity.

Panel B presents the Stage-3 (2SLS) estimates. Columns (1)–(3) use *AI Talent Exposure* as the sole instrument, Columns (4)–(6) use *Distance to AI Hubs* as the sole instrument, and Columns (7)–(9) use both instruments jointly. Across all specifications, AI adoption strengthens the trade–fundamentals relation at short horizons (quarters 1–4), has no impact in the middle horizons (quarters 5–8), and weakens it at longer horizons (quarters 9–12). The consistent horizon pattern of the interaction terms provides evidence that AI adoption causally shifts funds’ information-processing focus toward near-term fundamentals. Overall, the three-stage probit–2SLS results corroborate our baseline findings and reduce concerns that the documented short-termism pattern is driven by omitted variables or selection.

predictor that can be used in a conventional 2SLS framework in Stage 3.

4.3.2. *Quasi-natural Experiments*

To further establish causality, we also attempt to exploit two plausibly exogenous shocks to AI effectiveness. This setting mitigates endogeneity by leveraging variation in AI effectiveness driven externally, unrelated to fund-specific choices.¹⁷

The Release of the Transformer Architecture. The Transformer architecture (Vaswani et al., 2017) revolutionized AI with its multi-head self-attention mechanism, enabling efficient modeling of global dependencies in large-scale datasets. Unlike prior architectures (e.g., LSTM, CNN), it eliminated recurrent structures, allowing parallel processing and superior scalability. This breakthrough rapidly became foundational for state-of-the-art models (e.g., BERT, GPT), accelerating AI adoption across industries. Crucially, its development was driven by academic research—not fund-specific decisions—providing an exogenous shock to adoption incentives. Furthermore, given its profound impact on the performance frontier of AI applications, the release would exogenously improve the technical capabilities of AI-adopting funds. For example, Huang et al. (2023) shows that BERT perform the task of sentiment analysis substantially better than other classic machine learning methods. This plausibly exogenous variation establishes an ideal setting to identify the causal effect of AI adoption on mutual fund short-termism. If it is the adoption of AI technology that leads to the exacerbated short-termism in mutual fund information acquisition, with the enhanced technological effectiveness brought by Transformer, AI funds’ short-termism would become worse. We test this prediction by implementing a DiD regression specified as follows:

¹⁷Both quasi-natural experiments are implemented within a matched-sample framework to enhance comparability between treatment and control groups. For the Transformer shock, each treated AI fund is matched to a control fund using fund-level covariates as before; for the satellite-coverage shock, each treated stock is matched to a control stock using stock-level covariates (size, leverage, ROE, growth, book-to-market, and analyst coverage). Balance tests confirm that the matched treatment and control groups are statistically indistinguishable along these observable dimensions. The results are available upon request.

$$\begin{aligned}
\Delta EA_{j,[h,h+3]} = & \alpha + \beta_1 AIFund_f^{2017Q2} \times TF_t \times Trading_{f,j,t} + \beta_2 AIFund_f^{2017Q2} \times TF_t \\
& + \beta_3 AIFund_f^{2017Q2} \times Trading_{f,j,t} + \beta_4 TF_t \times Trading_{f,j,t} + \beta_5 Trading_{f,j,t} \\
& + \Pi' StockControl_{j,t} + \Omega' FundControl_{f,t} + \phi_{fj} + \lambda_{kt} + \epsilon_{f,j,t}
\end{aligned} \tag{5}$$

where $AIFund_f^{2017Q2}$ is a dummy variable that takes a value of one if mutual funds are labeled as AI funds in 2017Q2 (when Google formally proposed the Transformer architecture), and zero otherwise. TF is a dummy variable that takes a value of one after the Transformer model was released (2017Q2 onwards), and is set to zero otherwise. Other variables are defined in Eq. (2). As discussed above, if it is the adoption and use of AI technology that leads to the exacerbated short-termism in mutual fund information acquisition, we would expect AI funds' short-termism to become worse after the invention of the Transformer, leading to a positive coefficient β_1 for the short horizon while a negative one for long horizons.

Table 7 Panel A presents the DiD estimation results based on the Transformer event. Consistent with our hypothesis, we find that β_1 is positive and statistically significant for the short-term horizons (quarters 1-4). However, over longer horizons, the coefficient turns significantly negative for horizons between 9 and 12. These findings provide strong support for the hypothesis that the advances of AI technologies enhance the association between a fund's trades and short-term earnings but reduce its association with long-term earnings.

The Staggered Introduction of Satellite Imaging Data. As a second quasi-natural experiment, we leverage the staggered introduction of satellite imaging coverage across stocks and time periods. Modern AI systems are data-intensive: their effectiveness scales with access to large, high-frequency datasets that can be processed algorithmically. Satellite imagery is a canonical example of such data—it provides near-real-time signals about economic activity that are difficult to interpret manually but well suited to machine-learning pipelines

(Katona et al., 2025). Importantly, the availability of investment-grade satellite imagery has expanded gradually, creating plausibly exogenous variation in AI effectiveness across firms and time. Using data from RS Metrics, a major satellite imagery provider, we identify when different stocks first gained access to high-frequency, high-resolution satellite coverage suitable for financial analysis. This information allows us to create a treatment indicator that varies both cross-sectionally (by firms) and over time (by the timing of satellite coverage initiation). We implement the following DiD analysis:

$$\begin{aligned}
\Delta EA_{j,[h,h+3]} = & \alpha + \beta_1 AIFund_{f,t} \times SatCoverage_{j,t} \times Trading_{f,j,t} \\
& + \beta_2 AIFund_{f,t} \times SatCoverage_{j,t} + \beta_3 AIFund_{f,t} \times Trading_{f,j,t} \\
& + \beta_4 SatCoverage_{j,t} \times Trading_{f,j,t} + \beta_5 Trading_{f,j,t} \\
& + \Pi' StockControl_{j,t} + \Omega' FundControl_{f,t} + \phi_{fj} + \lambda_{kt} + \epsilon_{f,j,t}
\end{aligned} \tag{6}$$

where $SatCoverage_{j,t}$ is an indicator variable that equals one if firm j has satellite coverage available for investment analysis in quarter t , and zero otherwise (based on the list of covered firms and coverage start dates in Table A1 in Katona et al. (2025)). The coefficient of interest is β_1 , which captures the differential impact on AI funds' information processing when satellite data becomes available for firms they analyze.

Our results, shown in Table 7 Panel B, demonstrate that the introduction of satellite coverage enhances AI funds' short-term information acquisition, relative to traditional funds. The coefficient on the triple interaction $AIFund \times SatCoverage \times Trading$ is positive and significant for the short-term horizon (quarters 1-4) but becomes negative for longer horizons (quarters 5-12). This pattern is consistent with our main hypothesis that improved AI capabilities exacerbate short-termism in information processing, as the initiation of satellite image data primarily improves AI's effectiveness in forecasting near-term business performance rather than long-term fundamental value.

4.4. *AI-Adoption and Stock Price Informativeness*

In this section, we test our second hypothesis on whether the increased short-termism brought by AI-adoption in the mutual fund industry affects the price formation and efficiency on the capital markets. Since stock prices are determined by investors' expectations of a firm's future earnings through their trading activities, we predict that stock prices will also become short-term focused; i.e., they will become more informative about short-term future fundamentals but less so about long-term future fundamentals among those with high AI fund ownership.

To empirically assess this prediction, we first follow [Bai et al. \(2016\)](#) and measure stock-level price informativeness as the extent to which current market prices reflect the future earnings of the stock, where the future horizon is three combined horizon windows, a high predictive power means that the stock price incorporates more of the future earnings information. Specifically, we run the following regression model to test the hypothesis:

$$EA_{j,[h,h+3]} = \alpha + \beta_1 AIown_{j,t} \times \log MA_{j,t} + \beta_2 AIown_{j,t} + \beta_3 \log MA_{j,t} + EA_{j,t} + \Pi' StockControl_{j,t} + \phi_j + \lambda_{kt} + \epsilon_{j,t} \quad (7)$$

where $\log MA_{j,t}$ is the logarithm of the ratio of the market capitalization of stock j scaled by its total assets at the end of period t . Variable $AIown_{j,t}$ is our primary measure of AI investor presence, defined in two complementary ways: (i) the percentage of outstanding shares of stock j held by AI-adopting mutual funds (share-based measure), and (ii) the number of distinct AI-adopting funds holding stock j (count-based measure). We also include a comprehensive set of stock-quarter-level control variables, stock fixed effects, and industry-time fixed effects. Standard errors are double-clustered at the stock and year-quarter levels. The coefficient of interest is β_1 , which captures the variation in price informativeness associated with AI fund ownership.

We first estimate Eq. (7) using the OLS approach, with the results reported in Panel A

of Table 8. The results show a consistent pattern across both measures of AI ownership. For the share-based measure (*AIown* as percentage held), the coefficient on $AIown \times \log MA$ is positive and statistically significant at the 5% level for short-term earnings (horizons 1-4) with a coefficient of 0.033 and a t-statistic of 2.30. As we increase the horizon, the coefficient turns negative and statistically insignificant for horizons 5-8 (coefficient=-0.024 and t=-1.29), and becomes negative and statistically significant at the 1% level for horizons 9-12 (coefficient=-0.091 and t=-4.27). A very similar pattern is observed for the count-based measure (*AIown* as the number of AI funds).

To further establish causality, we conduct a two-stage least squares regression analysis using instrumental variables. Specifically, we aggregate the *AI Talent Exposure* and *Distance to AI hubs* for each fund to the stock-quarter level to measure the exposure of a firm's investor base to AI-trained graduates and average distance to the nearest AI hubs. We then use these two aggregated variables to instrument *AIown*. The first-stage regression result is provided in Panel B of Table 8. The results for both ownership measures show that the coefficient on $AI\ Talent\ Exposure_{agg}$ is positive and statistically significant at the 1% level (0.006/0.314, t=6.06/29.10), indicating that a firm's ownership by AI-adopting funds is strongly correlated with its investors' ex ante exposure to AI-trained graduates. Further, the coefficient on $Distance\ to\ AI\ hubs_{agg}$ is negative and significant at the 1% level (-0.023/-0.361, t=-12.91/-16.30), suggesting that the closer a firm's investors are to AI hubs, the higher is its ownership by AI-adopting funds.

The second-stage 2SLS results reported in Panel C of Table 8 are largely consistent with, but even stronger than the OLS results. Using the share-based measure, the coefficient on the interaction term $AIown \times \log MA$ is positive and statistically significant at the 1% level for short-term horizons 1-4 (coefficient=0.253, t=5.69), and negative and statistically significant at the 1% level for horizons 9-12 (coefficient=-0.268, t=-3.52). The count-based measure yields a qualitatively identical conclusion, with a positive and significant coefficient for the short horizon (0.010, t=4.98) and a negative and significant coefficient for the long

horizon (-0.015, t=-4.53). These results provide further support for our hypothesis that higher AI fund ownership significantly enhances the extent to which stock prices reflect short-term earnings information, while simultaneously reducing their informativeness about long-term earnings.

We also test the hypothesis by utilizing the future earnings response coefficient (or FERC) as an alternative measure of price informativeness (Collins et al., 1994; Lundholm and Myers, 2002; Choi et al., 2019). Specifically, FERC is estimated with the following regression model:

$$\begin{aligned}
Return_{j,t} = & \alpha + \sum_{k=1}^3 \beta_k AIown_{j,t} \times EA_{j,[4k-3,4k]} + \eta AIown_{j,t} \times EA_{j,t} \\
& + \gamma AIown_{j,t} \times EA_{j,t-1} + \sum_{k=1}^3 \delta_k AIown_{j,t} \times Return_{j,[4k-3,4k]} \\
& + \sum_{k=1}^3 \zeta_k EA_{j,[4k-3,4k]} + \theta EA_{j,t} + \omega EA_{j,t-1} \\
& + \sum_{k=1}^3 \psi_k Return_{j,[4k-3,4k]} + \Pi' StockControl_{j,t} + \phi_f + \lambda_{kt} + \epsilon_{j,t}
\end{aligned} \tag{8}$$

where $Return_{j,t}$ is the stock returns for stock j over quarter t . If AI investors make current stock returns more (less) informative about earnings news over the horizon $[h, h + 3]$, this would lead to a greater (smaller) FERC for that horizon. Hypothesis H2 therefore implies that the coefficient β_1 , should be positive for short horizons but negative for long horizons.

The regression results of Eq. (8) are presented in Table 9. The OLS estimates (columns 1 and 3) show that using the share-based measure, the coefficient on $AIown \times EA_{[1,4]}$ is significantly positive at the 10% level (0.079, t=1.82). The coefficient on $AIown \times EA_{[9,12]}$ is negative but statistically insignificant. The pattern is more pronounced and statistically stronger when using the count-based measure (column 3), with significant positive coefficients for the short and medium horizons and a significant negative coefficient for the long horizon.

The second-stage IV results (columns 2 and 4) further sharpen this finding. After controlling for endogeneity, the coefficients on $AIown \times EA$ using the share-based measure are

positive and statistically significant at the 1% level for the short-horizon (0.362 for horizons 1-4, $t=4.20$), and turn negative and insignificant for the long horizon (-0.015, $t=-0.26$). The results using the count-based measure in the IV specification (column 4) remain robust: the coefficient is positive and significant for the short horizon (0.012, $t=3.83$) and negative and significant for the long horizon (-0.004, $t=-1.65$). These findings are consistent with the altered information processing horizons of AI funds documented in Table 3. The rational reallocation of AI funds’ attention toward short-term signals—where their technological advantage is greatest—increases the price informativeness regarding short-term earnings but reduces the information content of stock price regarding long-term earnings.

4.5. *Constant Shareholder Analysis: Price Informativeness*

A legitimate concern is that our estimates may reflect endogenous stock selection rather than a causal effect of AI adoption. If AI-adopting investors disproportionately hold—or tilt their portfolios toward—stocks whose prices are intrinsically more informative about near-term earnings and less informative about longer-horizon fundamentals, then the observed horizon pattern could arise mechanically from changes in portfolio composition rather than from a change in the horizon of investors’ information processing.

To further mitigate this selection-based explanation, we implement a constant-shareholder DiD design at the stock level. This approach parallels the logic of the fund–stock constant-holding test but changes the unit of analysis to the stock. Specifically, we compare the evolution of price informativeness for (i) firms that, for the first time, become exposed to an AI-driven shareholder because an incumbent shareholder fund adopts AI (treatment group) and (ii) otherwise similar firms that never have an AI-fund shareholder during the sample period (control group).¹⁸ Because AI exposure arises from an existing shareholder’s technological transition—rather than from the entry of a new AI fund—any ensuing change in the

¹⁸To ensure economic relevance, we require that the adopting fund holds at least a 1% ownership stake in the firm prior to its AI adoption. One quarter before the adoption event, we implement one-to-one nearest-neighbor matching using stock-level covariates (size, leverage, ROE, growth, book-to-market, and analyst coverage) to improve comparability and support parallel pre-trends.

firm’s information environment can be more plausibly attributed to the shareholder’s use of AI.

We estimate a DiD version of Eq. (7), where the coefficient of interest is the triple interaction $Treat^{Stock} \times Post^{Stock} \times \log MA$. Panel A of Table 10 confirms our main findings. The coefficient on the triple interaction is positive and statistically significant at short horizons ([1, 4]: 0.042, $t = 2.81$) and negative and highly significant at long horizons ([9, 12]: -0.050 , $t = -2.37$). This pattern indicates that, following an incumbent shareholder’s AI adoption, the treated firm’s stock price becomes more informative about short-term earnings and less informative about long-term earnings. Panel B reports the dynamic (event-time) analysis and shows no statistically significant pre-period differences, supporting the parallel-trends assumption. Overall, these results strengthen the causal interpretation that investor AI adoption alters the horizon of price informativeness.

In Internet Appendix Section I.6, we provide complementary evidence by applying the same constant-shareholder DiD design to the FERC model (Eq. (8)). The results in Table I.5 corroborate our price-informativeness findings: the triple interaction $Treat^{Stock} \times Post^{Stock} \times EA_{[1,4]}$ is significantly positive, whereas $Treat^{Stock} \times Post^{Stock} \times EA_{[9,12]}$ is significantly negative. These estimates indicate that, following an incumbent shareholder’s transition to AI, stock returns load more on near-term earnings news and less on longer-horizon earnings news, consistent with a shift in the horizon of information impounded into prices.

4.6. AI-Adoption and Investment-Q Sensitivity

The literature suggests that managers use stock prices as a signal when making long-term investment decisions (Luo, 2005; Chen et al., 2007; Bond et al., 2012). However, if stock prices are dominated by short-term information, they would become less useful for long-term investment decision-making, as these decisions are based on the tradeoff between the cost of investment projects and the present value of their long-term payoffs. Consequently, decreased stock price informativeness regarding long-term future fundamentals would lead

managers to rely less on the price signals when making their investment decisions. We test this hypothesis by examining investment-Q sensitivity:

$$\begin{aligned}
Investment_{j,t+1} = & \alpha + \beta_1 AIown_{j,t} \times Q_{j,t} + \beta_2 AIown_{j,t} + \beta_3 Q_{j,t} \\
& + \Pi' StockControl_{j,t} + \phi_j + \lambda_{kt} + \epsilon_{j,t}
\end{aligned}
\tag{9}$$

where $Investment_{j,t+1}$ is the investment of stock j in period $t + 1$, which encapsulates the three different measures: R&D expenditure ($R\&D$), capital expenditure ($CapEx$), and R&D plus capital expenditure ($R\&D + CapEx$), all scaled by lagged total assets. $Q_{j,t}$ denotes Tobin's Q (market value of the firm's equity plus book value of assets minus book value of equity, scaled by book value of assets) of stock j in period t . If managers understand that greater ownership by AI funds reduces the stock price informativeness regarding long-term fundamentals and therefore rely less on the noisy stock prices in their investment decisions, we would expect the coefficient β_1 to be negative.

We report the OLS regression results of Eq. (9) in Panel A of Table 11. Consistent with Hypothesis 3, the estimated coefficients on the interaction term (β_1) using the share-based measure are negative and statistically significant at the 1% level across all investment measures: -0.009 for $R\&D$ ($t=-7.24$), -0.007 for $CapEx$ ($t=-3.63$), and -0.018 for $R\&D + CapEx$ ($t=-6.96$). A consistent pattern emerges when using the count-based measure, with coefficients of -0.001 ($t=-12.86$), -0.002 ($t=-9.33$), and -0.004 ($t=-13.94$), respectively.

To address potential endogeneity concerns, we implement the instrumental variable approach following the same procedure as in Panel B of Table 8. The second-stage 2SLS results, reported in Panel B of Table 11, confirm and strengthen our findings. Using the share-based measure, the coefficients on $AIown \times Q$ remain negative and statistically significant at the 1% level for all investment categories, with magnitudes substantially larger than the OLS estimates: -0.033 for $R\&D$ ($t=-10.86$), -0.034 for $CapEx$ ($t=-6.09$), and -0.074 for $R\&D + CapEx$ ($t=-10.23$). The results using the count-based measure are similarly robust and significant: -0.002 ($t=-14.50$), -0.002 ($t=-7.22$), and -0.004 ($t=-12.88$), respectively. The

heightened significance and magnitude after correcting for endogeneity provide strong causal evidence.

Taken together, these results support the view that AI adoption alters the information production process in capital markets. By rationally reallocating attention toward short-term fundamentals—where AI provides the greatest efficiency gains—AI funds reduce the incorporation of long-term information into stock prices. Consequently, stock prices become less informative signals for managers making long-term investment decisions, leading to the observed decline in investment- Q sensitivity.

4.7. *Constant Shareholder Analysis: Investment- Q Sensitivity*

We also extend the constant-shareholder DiD framework to further examine whether investor AI adoption affects firms' reliance on stock prices for investment decision-making. Following the logic of Hypothesis 3, if an incumbent shareholder's AI adoption reduces the long-horizon informativeness of the firm's stock price, managers should place less weight on this noisier signal when making investment decisions. We test this prediction using a DiD specification based on Eq. (9), where the coefficient of interest is the triple interaction $Treat^{Stock} \times Post^{Stock} \times Q$.

Panel A of Table 12 reports the results. Consistent with our hypothesis, the coefficient on $Treat^{Stock} \times Post^{Stock} \times Q$ is negative and statistically significant for both R&D expenditure (-0.001 , $t = -1.89$) and capital expenditure (-0.007 , $t = -2.25$), with a similarly negative effect for total investment ($R\&D + CapEx$: -0.009 , $t = -2.80$). These estimates indicate that, after an incumbent shareholder adopts AI, the sensitivity of corporate investment to stock-price signals (Tobin's Q) declines. Panel B presents the dynamic (event-time) analysis and shows no statistically significant pre-period differences, supporting the parallel-trends assumption. Overall, this evidence further mitigates selection concerns and is consistent with a causal channel from AI-driven changes in the horizon of price informativeness to real corporate investment decisions.

5. Conclusion

Motivated by the growing integration of AI technologies in mutual fund operations, this paper examines whether AI adoption induces short-termism in mutual funds' information acquisition—that is, whether funds reallocate attention toward short-term signals at the expense of long-term fundamentals. The analysis builds on the premise that AI disproportionately lowers the cost of processing short-horizon information, thereby reshaping how funds allocate effort between near-term and long-term forecasting.

Our empirical results indicate that AI adoption causally amplifies short-termism among active mutual fund managers. After adoption, AI funds' trades become more strongly associated with short-term fundamentals and less associated with long-term fundamentals. These findings are robust to multiple identification strategies, including an instrumental-variable design based on funds' ex ante exposure to AI talent and geographic proximity to AI hubs. We further exploit quasi-natural experiments—the release of the Transformer architecture and the staggered introduction of satellite imaging data—and show that exogenous improvements in AI capability intensify short-horizon trading behavior.

We also document broader market implications. Stocks with high ownership by AI-adopting funds exhibit a horizon-dependent shift in price informativeness: prices incorporate more short-term earnings information but less long-term fundamental information. This shift has real effects on corporate decision-making. In particular, firms exposed to AI-adopting shareholders experience a decline in the sensitivity of investment to Tobin's Q , consistent with managers placing less weight on stock prices when those prices become more short-term oriented. Overall, our results provide evidence that investor AI adoption increases short-term focus in information acquisition and can generate market-wide externalities. More broadly, the findings connect advances in information-processing technology to asset-pricing efficiency and corporate investment efficiency, highlighting that efficiency gains in processing near-term signals may come at the cost of reduced long-horizon price informativeness.

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Appendix A. Variable Definitions

Variable	Definition	Data Source
Dependent Variables		
$EA_{[h,h+3]}$	The sum of earnings for stock j from quarter h to h+3, where earnings are defined as EBIT scaled by total assets.	Compustat
$\Delta EA_{[h,h+3]}$	The sum of earnings from quarter h to h+3 minus the sum of earnings from the past four quarters	Compustat
<i>Return</i>	Quarterly stock return	CRSP
<i>R&D</i>	Ratio of R&D expenditure in period t+1 to total assets in period t	Compustat
<i>CapEx</i>	Ratio of capital expenditure in period t+1 to total assets in period t	Compustat
<i>RD+CapEx</i>	Ratio of R&D expenditure and capital expenditure in period t+1 to total assets in period t	Compustat
Independent Variables		
<i>AIFund</i>	A dummy variable that takes a value of one if the fund is labeled as an AI-adopted mutual fund, and zero otherwise	Morningstar; LinkedIn profiles; Google search
<i>Trading</i>	The split-adjusted trading value (LSEG S12 item CHANGE*PRC) of fund f for stock j in period t, scaled by the total portfolio value of fund f in period t-1	CRSP; LSEG
<i>AI Talent Exposure</i>	Fund-level ex-ante exposure to AI-trained graduates from historically AI-strong universities.	Morningstar; Babina et al. (2024)
<i>AI Talent Exposure_{agg}</i>	Firm-level aggregation of <i>AI Talent Exposure</i> across all funds holding the stock in a given quarter.	LSEG; Morningstar; Babina et al. (2024)
<i>CS Strong Exposure</i>	Fund-level ex-ante exposure to computer science-strong universities.	Morningstar; Babina et al. (2024)
<i>CS Strong Exposure_{agg}</i>	Firm-level aggregation of <i>CS Strong Exposure</i> across all funds holding the stock in a given quarter.	LSEG; Morningstar; Babina et al. (2024)
<i>Top 10 Exposure</i>	Fund-level ex-ante exposure to top-10 universities.	Morningstar; U.S. News & World Report; Babina et al. (2024)

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Table A1 – continued from previous page

Variable	Definition	Data Source
$Top\ 10\ Exposure_{agg}$	Firm-level aggregation of <i>Top 10 Exposure</i> across all funds holding the stock in a given quarter.	LSEG; Morningstar; U.S. News & World Report.; Babina et al. (2024)
$Distance\ to\ AI\ Hubs$	Fund-level geographic distance to the nearest AI hub.	CRSP; CSET
$Distance\ to\ AI\ Hubs_{agg}$	Firm-level aggregation of <i>Distance to AI Hubs</i> across all funds holding the stock in a given quarter.	LSEG; CRSP; CSET
$AIFund^{2017Q2}$	A dummy variable that takes the value of 1 if the fund is labeled as an AI-adopting mutual fund in 2017Q2, and zero otherwise	Morningstar; LinkedIn profiles; Google search
TF	A dummy variable that takes the value of 1 after the Transformer architecture was released (2017Q2 onwards) and is set to zero from 2016Q2 to 2017Q1	/
$SatCoverage$	A dummy variable that takes the value of 1 if firm j has satellite coverage available for investment analysis in quarter t , and zero otherwise	Katona et al. (2025)
$AIown\ (Share-based)$	The percentage of shares outstanding of a stock held by AI-adopting mutual funds at the end of quarter t .	Morningstar; LinkedIn profiles; Google search; LSEG
$AIown\ (Count-based)$	The number of distinct AI-adopting mutual funds holding a stock at the end of quarter t .	Morningstar; LinkedIn profiles; Google search; LSEG
$Log\ MA$	Log (The market capitalization of the firm in period t / the total assets of the firm in period t)	Compustat
Q	(Market value of the firm's equity + book value of assets - book value of equity)/book value of assets	Compustat
DiD Variables		
$Treat^{Fund}$	A dummy variable equal to one for AI-adopting (treatment) funds, and zero for matched non-AI (control) funds.	Morningstar; LinkedIn profiles; Google search
$Post^{Fund}$	A dummy variable equal to one for the adoption quarter and all subsequent periods, and zero otherwise.	Morningstar; LinkedIn profiles; Google search
Pre^{Fund}_k	Event-time dummy variables indicating the k -th quarter ($k = 1, 2, 3$) before the AI fund's adoption quarter.	Morningstar; LinkedIn profiles; Google search

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Table A1 – continued from previous page

Variable	Definition	Data Source
$Current^{Fund}$	Event-time dummy variable indicating the AI fund's adoption quarter.	Morningstar; LinkedIn profiles; Google search
$Post^{Fund}_{1+}$	Event-time dummy variable indicating all quarters <i>after</i> the AI fund's adoption quarter.	Morningstar; LinkedIn profiles; Google search
$Treat^{Stock}$	A dummy variable equal to one for stocks that first gain an AI-fund shareholder due to an existing fund's AI adoption (treatment group), and zero for matched stocks that never have an AI-fund shareholder (control group).	LSEG; Morningstar; LinkedIn profiles; Google search
$Post^{Stock}$	A dummy variable equal to one for the quarter in which a stock first gains an AI-fund shareholder and all subsequent periods, and zero otherwise.	LSEG; Morningstar; LinkedIn profiles; Google search
Pre^{Stock}_k	Event-time dummy variables indicating the k -th quarter ($k = 1, 2, 3$) <i>before</i> the quarter a stock first gains an AI-fund shareholder.	LSEG; Morningstar; LinkedIn profiles; Google search
$Current^{Stock}$	Event-time dummy variable indicating the quarter in which a stock first gains an AI-fund shareholder.	LSEG; Morningstar; LinkedIn profiles; Google search
$Post^{Stock}_{1+}$	Event-time dummy variable indicating all quarters <i>after</i> a stock first gains an AI-fund shareholder.	LSEG; Morningstar; LinkedIn profiles; Google search
Control Variables		
$Size$	Total assets	Compustat
$Leverage$	Ratio of total liabilities to total assets	Compustat
ROE	Ratio of net income to the common equity	Compustat
$Growth$	Ratio of change in sales in period t to sales in period $t-1$	Compustat
BTM	Ratio of book value of equity to market value of equity.	Compustat
$\#Analyst$	Number of analysts tracking the stock	I/B/E/S
TNA	The sum of assets under management across all share classes of a fund	CRSP

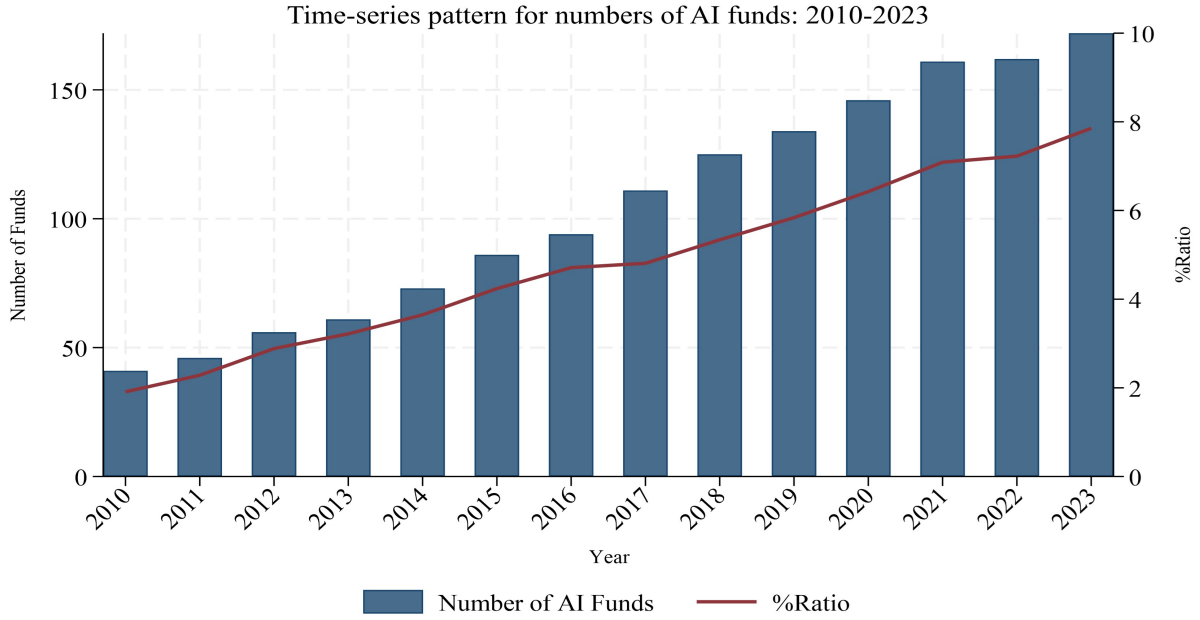
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Table A1 – continued from previous page

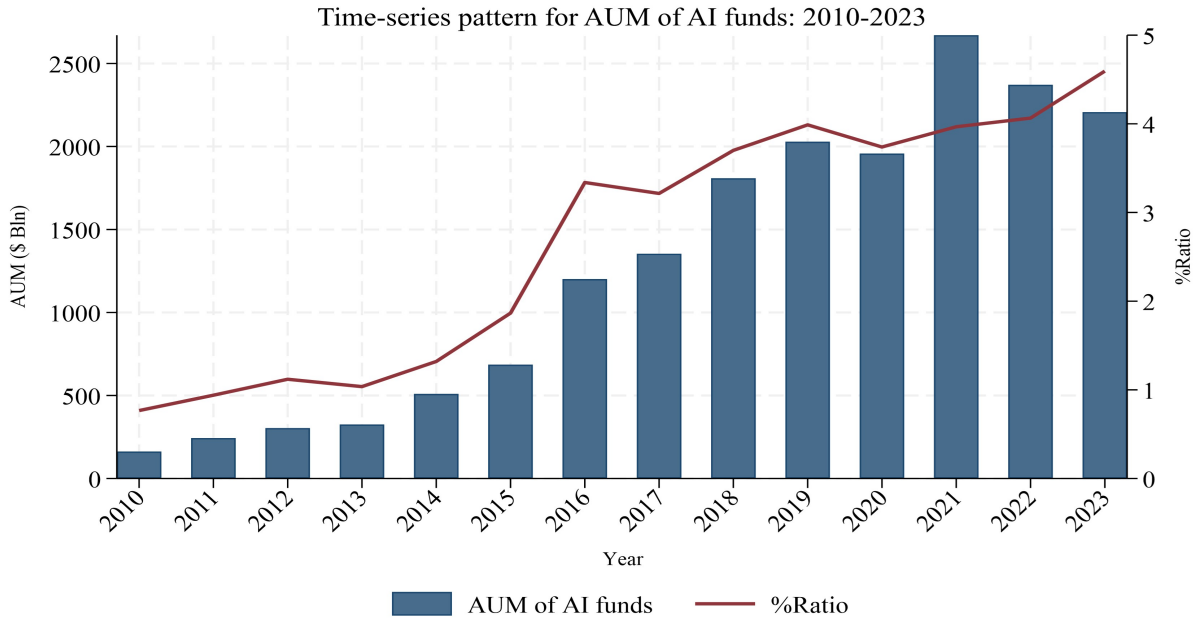
Variable	Definition	Data Source
<i>Age</i>	Current year-quarter - established year-quarter + 1	CRSP
<i>#Stocks</i>	Number of firms held by the fund	CRSP
<i>Turnover</i>	Minimum of aggregated sales or aggregated purchases of securities, divided by the average 12-month Total Net Assets of the fund	CRSP

Notes: This table provides detailed definitions of all variables used in the empirical analysis. Variables are grouped into dependent variables, independent variables, and control variables. Data sources include CRSP (Center for Research in Security Prices), Compustat (quarterly accounting data), LSEG (mutual fund holdings), I/B/E/S (analyst coverage), Morningstar (manager biographical information), and CSET (Center for Security and Emerging Technology for AI hub locations).

Fig. 1: Evolution of AI Fund Adoption Over Time



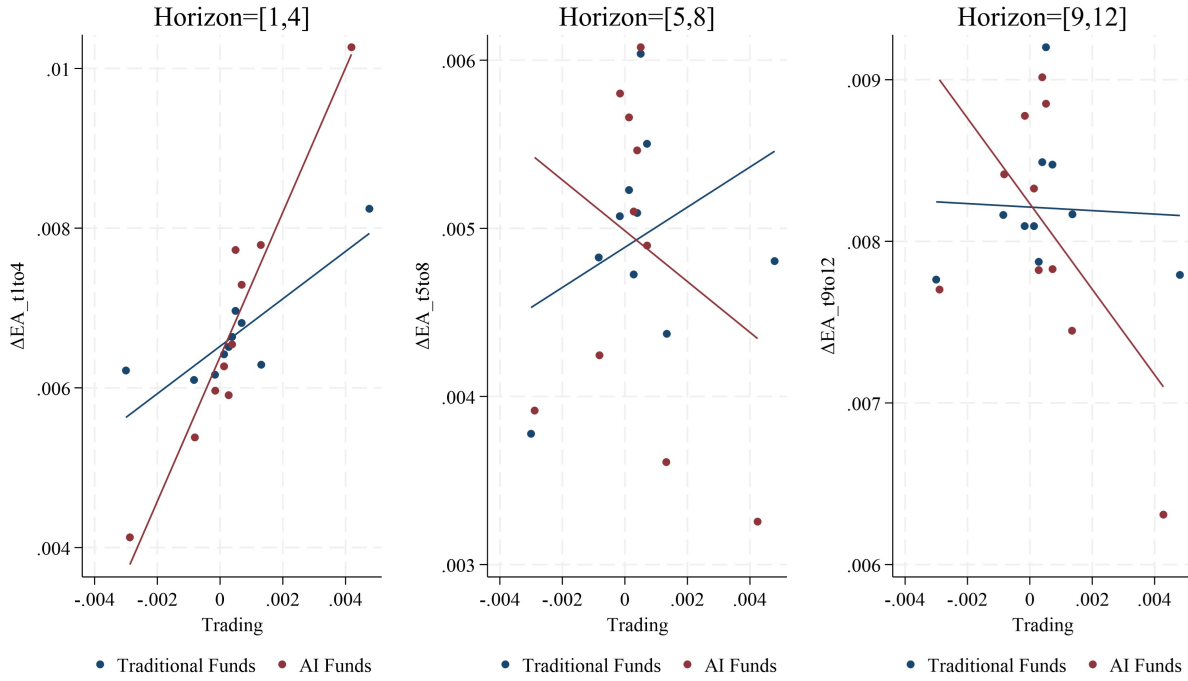
Panel A: Number of AI Funds



Panel B: Assets Under Management

Notes: This figure plots the time series evolution of AI fund adoption from 2010 to 2023. Panel A shows the number of AI funds and all funds in our sample. Panel B shows the assets under management (AUM) of AI funds and all funds. AI funds are identified using the managerial AI expertise. The sample includes 3,642 U.S. active equity mutual funds.

Fig. 2: Trading Activity and Future Earnings: Bin-Scatter Analysis



Notes: This figure shows bin-scatter plots relating current trading activity ($Trading_{f,j,t}$) to future earnings news ($\Delta EA_{j,[h,h+3]}$) across different forecasting horizons (1-12 quarters ahead), separately for AI funds and traditional funds. $Trading$ is the split-adjusted trading value scaled by lagged total portfolio value. The sample period is 2010Q1-2023Q4.

Table 1: Summary Statistics

Variable	N	Mean	Std Dev	P25	P50	P75
Panel A: Fund-Stock-Quarter Level						
<i>Trading</i> (%)	8,005,682	0.044	0.267	-0.003	0.000	0.026
Panel B: Fund-Quarter Level						
<i>AIFund</i>	105,507	0.049	0.216	0	0	0
<i>TNA</i> (\$million)	105,507	585.160	1,598.450	51.238	116.575	332.900
<i>Age</i> (quarters)	105,507	53.479	30.523	31	49	69
<i>#Stocks</i>	105,507	81.664	151.704	26	46	77
<i>Turnover</i>	105,507	0.603	0.502	0.260	0.460	0.780
Panel C: Stock-Quarter Level						
<i>AIown</i> (share-based %)	162,398	3.334	6.041	0	0.827	3.695
<i>AIown</i> (count-based #)	162,398	3.884	4.816	0	2	6
$\Delta EA_{[1,4]}$	162,465	0.007	0.106	-0.028	0.006	0.040
$\Delta EA_{[5,8]}$	139,915	0.006	0.116	-0.029	0.006	0.042
$\Delta EA_{[9,12]}$	119,502	0.007	0.127	-0.030	0.007	0.046
<i>Size</i> (\$billion)	162,465	8.027	23.719	0.326	1.251	4.570
<i>Leverage</i>	162,465	0.522	0.252	0.339	0.512	0.674
<i>ROE</i>	162,465	0.010	0.157	-0.011	0.020	0.046
<i>Growth</i>	162,465	0.044	0.244	-0.053	0.021	0.103
<i>BTM</i>	162,465	0.544	0.463	0.217	0.427	0.761
<i>#Analysts</i>	162,465	8.693	8.079	3	7	13
<i>MA</i>	162,465	1.819	7.144	0.554	1.011	1.925
<i>Return</i> (%)	162,465	1.133	8.473	-2.723	1.134	4.683
<i>Q</i>	162,465	2.365	8.171	1.111	1.530	2.417
<i>R&D</i> _{t+1} (%)	162,465	1.111	2.542	0	0	1.116
<i>CapEx</i> _{t+1} (%)	159,324	2.682	4.046	0.441	1.330	3.199
<i>R&D</i> _{t+1} + <i>CapEx</i> _{t+1} (%)	159,324	3.823	4.773	0.848	2.388	5.039

Notes: This table presents summary statistics for the main variables. The sample includes 3,642 active equity funds and 6,626 distinct stocks, spanning 56 quarters from 2010Q1 through 2023Q4. Panel A reports fund-stock-quarter level variables, Panel B reports fund-quarter level variables, and Panel C reports stock-quarter level variables. *Trading* is the split-adjusted trading value scaled by the fund's lagged total portfolio value. *AIFund* is an indicator equal to one for funds that adopt AI technologies. *AIown* is measured both as the percentage of shares outstanding held by AI funds and as the number of AI funds holding the stock. Variable definitions for all firm characteristics and investment measures (*R&D*_{t+1}, *CapEx*_{t+1}) are provided in Appendix A.

Table 2: AI Funds vs. Non-AI Funds

Panel A: Difference between AI funds and non-AI funds								
Variables	AI Funds			Non-AI Funds			Mean diff	t-stats
	Mean	Sd	Median	Mean	Sd	Median		
<i>TNA(\$million)</i>	701.324	1706.486	128.700	579.178	1592.468	116.087	122.146***	5.357
<i>Age(quarters)</i>	54.019	29.402	49.568	53.922	30.639	49.486	0.097	0.222
<i>#Stocks</i>	175.816	207.017	106.000	76.815	146.672	45.000	99.001***	46.207
<i>Turnover</i>	0.811	0.532	0.700	0.592	0.498	0.450	0.218***	30.579

Panel B: Portfolio Turnover Comparison: Univariate Analysis				
	AI Funds	Matched Non-AI Funds	Diff (AI - Non-AI)	t-stat
Before Adoption	0.598	0.600	-0.002	-0.132
After Adoption	0.811	0.607	0.204***	18.645
Diff (After – Before)	0.213***	0.007	0.206***	10.590
t-stat	13.727	0.593	10.590	

Panel C: Portfolio Turnover Comparison: Regression Analysis		
Variable	(1)	(2)
	<i>Turnover</i>	<i>Turnover</i>
$Treat^{Fund} \times Post^{Fund}$	0.049*** (3.09)	0.041*** (2.59)
$\log TNA$		-0.050*** (-8.24)
$\log Age$		-0.027** (-2.19)
$\log \#Stocks$		0.067*** (3.81)
Fund-cohort FE	Yes	Yes
Time-cohort FE	Yes	Yes
Observations	12,574	12,574
Adj. R^2	0.694	0.699

Notes: Panel A reports the differences in characteristics between AI funds and non-AI funds. Panel B compares average portfolio turnover for AI funds and matched non-AI funds before and after AI adoption. Each AI fund is matched to a non-AI fund based on ex-ante fund-level covariates, including total net assets, turnover, age, and number of stocks. The row “Diff (After – Before)” reports the within-group changes, and the resulting DiD estimate is reported in the column “Diff (AI – Non-AI)”. Panel C presents regression results where the dependent variable is portfolio turnover. $Treat^{Fund}$ is an indicator for AI-adopting (treatment) funds, and $Post^{Fund}$ indicates periods after AI adoption. All specifications include fund-cohort and time-cohort fixed effects. Standard errors are clustered at the fund and year-quarter level. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

Table 3: AI Adoption and Mutual Fund Short-Termism

Horizon (quarters)	Dependent Variable: $\Delta EA_{j,[h,h+3]}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	[1, 4]		[5, 8]		[9, 12]	
<i>AIFund</i> × <i>Trading</i>	0.470*** (10.66)	0.475*** (11.07)	-0.110** (-2.08)	-0.098* (-1.86)	-0.135** (-2.06)	-0.132** (-2.00)
<i>AIFund</i>	0.002*** (3.85)	0.001 (1.33)	0.000 (0.24)	-0.001 (-0.87)	-0.001 (-0.97)	-0.001 (-1.21)
<i>Trading</i>	0.160*** (15.14)	0.090*** (8.67)	0.048*** (3.81)	0.009 (0.69)	0.042*** (2.81)	0.027* (1.82)
Fund-stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock Controls	No	Yes	No	Yes	No	Yes
Observations (millions)	8.01	8.01	7.10	7.10	6.19	6.19
Adj. R^2	0.277	0.319	0.277	0.285	0.274	0.275

Notes: This table presents OLS estimates of the effect of AI adoption on mutual fund information processing horizons. The dependent variable $\Delta EA_{j,[h,h+3]}$ represents the change in earnings for stock j , defined as the sum of earnings ($EBIT$ scaled by total assets) from quarter h to $h+3$ minus the sum of earnings from the past four quarters. *AIFund* is an indicator for AI-adopting funds. *Trading* is the split-adjusted trading value scaled by the fund's total portfolio value. All specifications include fund-stock and industry-time (i.e., industry-by-quarter) fixed effects. Columns (2), (4), and (6) include the full set of fund- and stock-level control variables as defined in Appendix A. Standard errors are double-clustered by fund and stock. t-statistics are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels.

Table 4: Matched Sample and Constant Holding Sample Analysis

Dependent Variable: $\Delta EA_{j,[h,h+3]}$						
	Matched Sample			Constant Holdings Sample		
	(1)	(2)	(3)	(4)	(5)	(6)
Horizon (quarters)	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]
Panel A: DiD Regression						
$Treat^{Fund} \times Post^{Fund} \times Trading$	0.499*** (4.34)	-0.006 (-0.05)	-0.530*** (-3.42)	0.541*** (3.11)	-0.084 (-0.42)	-0.504** (-2.15)
$Treat^{Fund} \times Trading$	0.036 (0.36)	-0.275** (-2.48)	0.327*** (2.59)	0.088 (0.69)	-0.206 (-1.44)	0.277* (1.72)
$Post^{Fund} \times Trading$	-0.051 (-0.64)	0.031 (0.34)	0.120 (1.11)	-0.000 (-0.00)	0.078 (0.57)	0.182 (1.14)
$Treat^{Fund} \times Post^{Fund}$	-0.002** (-2.09)	-0.004*** (-3.72)	-0.000 (-0.04)	-0.002* (-1.86)	-0.004*** (-3.58)	-0.000 (-0.01)
$Trading$	0.021 (0.32)	0.146** (1.98)	-0.030 (-0.36)	-0.055 (-0.61)	0.066 (0.65)	-0.017 (-0.15)
Observations (millions)	1.39	1.21	1.05	0.374	0.341	0.304
Adj. R^2	0.327	0.293	0.284	0.263	0.241	0.236
Panel B: Dynamic effect						
$Treat^{Fund} \times Pre^{Fund}_{.3} \times Trading$	-0.106 (-0.27)	0.047 (0.11)	0.417 (0.81)	-0.317 (-0.75)	-0.206 (-0.42)	0.496 (0.87)
$Treat^{Fund} \times Pre^{Fund}_{.2} \times Trading$	-0.569 (-1.46)	0.418 (0.93)	-0.311 (-0.61)	-0.708* (-1.70)	0.252 (0.52)	-0.457 (-0.84)
$Treat^{Fund} \times Pre^{Fund}_{.1} \times Trading$	0.012 (0.03)	-0.582 (-1.16)	0.084 (0.15)	-0.322 (-0.77)	-0.740 (-1.42)	0.225 (0.39)
$Treat^{Fund} \times Current^{Fund} \times Trading$	-0.156 (-0.51)	0.045 (0.13)	-0.753* (-1.70)	-0.023 (-0.05)	0.005 (0.01)	-0.940 (-1.55)
$Treat^{Fund} \times Post^{Fund}_{.1+} \times Trading$	0.474*** (3.81)	0.004 (0.03)	-0.489*** (-2.94)	0.462** (2.38)	-0.136 (-0.62)	-0.435* (-1.71)
Observations (millions)	1.39	1.21	1.05	0.374	0.341	0.304
Adj. R^2	0.327	0.293	0.284	0.263	0.241	0.236
Fund-stock-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-cohort FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents results of matched sample and constant holding sample analysis. The dependent variable $\Delta EA_{j,[h,h+3]}$ represents the change in earnings, defined as the sum of earnings ($EBIT$ scaled by total assets) from quarter h to $h+3$ minus the sum of earnings from the past four quarters. $Treat^{Fund}$ is an indicator for AI-adopting (treatment) funds, and $Post^{Fund}$ indicates periods after AI adoption. $Trading$ is the split-adjusted trading value scaled by the fund's lagged total portfolio value. Panel A reports the baseline DiD estimates. Columns (1)-(3) use the matched sample. Columns (4)-(6) restrict the sample to fund-stock pairs where the fund's position in that stock exists continuously in both the pre- and post-adoption periods (constant holdings sample). Panel B examines the dynamic effects around AI adoption using the both matched sample and constant holdings sample. All specifications include fund-stock-cohort, time-cohort, and industry-time fixed effects, as well as fund- and stock-level controls. Standard errors are double-clustered by fund and stock. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 5: Pre-period Placebo Test for the Instrument Variables

	Dependent Variable: $\Delta EA_{j,[h,h+3]}$					
	(1)	(2)	(3)	(4)	(5)	(6)
Horizon (quarters)	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]
<i>AI Talent Exposure</i> \times <i>Trading</i>	-0.042 (-0.65)	-0.023 (-0.33)	0.003 (0.03)			
<i>Distance to AI Hubs</i> \times <i>Trading</i>				0.067 (1.26)	0.004 (0.06)	-0.026 (-0.31)
<i>Trading</i>	0.094*** (4.07)	0.018 (0.73)	-0.016 (-0.45)	0.070*** (2.61)	0.014 (0.51)	-0.008 (-0.20)
Fund-stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock & University Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations (millions)	3.19	3.03	2.88	3.19	3.03	2.88
Adjusted R^2	0.379	0.353	0.345	0.379	0.353	0.345

Notes: This table presents pre-trend tests for the validity of the instrumental variables. We conduct this test using a sample from 2000-2009, a period preceding the majority of AI adoption events in our data. If the instruments had a direct effect on horizons, we would observe a significant relationship in this pre-period (2000-2009). *AI Talent Exposure* is defined as the fund's exposure to AI-strong universities. *Distance to AI Hubs* is the geographic distance from the fund headquarters to the nearest AI hub. All specifications include fund-stock and industry-time fixed effects, along with the standard fund & stock controls and controls for funds' ex-ante exposure to (i) computer science-strong universities and (ii) top-10 universities. Standard errors are double-clustered at the fund and stock levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Instrumental Variable Analysis

Panel A: Results of Stage 1 and Stage 2									
IV(s) Variable	(1)	(2)	(3)	(4)	(5)	(6)			
	AI Talent Exposure		Distance to AI Hubs			Both Instruments			
	Probit	2SLS-1st	Probit	2SLS-1st	Probit	2SLS-1st			
<i>AI Talent Exposure</i>	0.700*** (4.08)						0.725*** (4.01)		
<i>Distance to AI Hubs</i>			-0.751*** (-4.44)				-0.755*** (-4.47)		
\widehat{AIFund}		0.808*** (6.25)		0.760*** (6.64)				0.860*** (7.63)	
F-statistic		47.654		48.451					50.041
Chi-square	708.187		635.581		679.164		0.855		
Hansen J statistics									
Observations	105,507	105,507	105,507	105,507	105,507	105,507			105,507
Pseudo R ² / Adj. R ²	0.253	0.185	0.260	0.188	0.273	0.197			
P-value	0.000	0.000	0.000	0.000	0.000	0.000			0.000

Panel B: Results of Stage 3									
IV(s) Horizon (quarters)	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	AI Talent Exposure			Distance to AI Hubs			Both Instruments		
	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]
<i>AIFund</i> × <i>Trading</i>	0.890*** (8.46)	-0.014 (-0.11)	-0.485*** (-3.16)	0.857*** (8.19)	-0.036 (-0.29)	-0.481*** (-3.14)	0.820*** (7.86)	-0.028 (-0.23)	-0.477*** (-3.14)
<i>AIFund</i>	0.012*** (2.72)	0.001 (0.26)	0.024*** (3.81)	0.018*** (3.15)	0.010 (1.55)	0.037*** (4.53)	0.012*** (2.66)	0.005 (1.00)	0.026*** (4.18)
<i>Trading</i>	0.066*** (5.73)	0.004 (0.28)	0.041** (2.47)	0.067*** (5.77)	0.003 (0.25)	0.038** (2.29)	0.069*** (6.07)	0.004 (0.29)	0.040** (2.42)
Fund-stock FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock & University Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations (millions)	8.01	7.10	6.19	8.01	7.10	6.19	8.01	7.10	6.19
Adj. R ²	0.319	0.285	0.274	0.319	0.285	0.274	0.319	0.285	0.274

Notes: This table reports instrumental variable results using a three-stage probit-2SLS procedure. Panel A presents results from the probit stage (Stage 1) and the first-stage 2SLS (Stage 2). Panel B presents the second-stage 2SLS results (Stage 3) for selected horizons using different instrument combinations. *AI Talent Exposure* measures funds' connections to AI-strong universities prior to 2010. *Distance to AI Hubs* is the geographic distance from the fund headquarters to the nearest AI hub. All specifications include fund-stock and industry-time fixed effects, along with the standard fund & stock controls and controls for funds' ex-ante exposure to (i) computer science-strong universities and (ii) top-10 universities. Standard errors are double-clustered at the fund and stock levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: Quasi-Natural Experiments: Technological Shocks to AI Effectiveness

	Dependent Variable: $\Delta EA_{j,[h,h+3]}$		
	(1)	(2)	(3)
Horizon (quarters)	[1, 4]	[5, 8]	[9, 12]
Panel A: Transformer Architecture Release			
$AIFund^{2017Q2} \times TF \times Trading$	0.455* (1.93)	0.288 (0.99)	-0.848** (-2.20)
$AIFund^{2017Q2} \times TF$	-0.002* (-1.93)	-0.000 (-0.45)	-0.002 (-1.37)
$AIFund^{2017Q2} \times Trading$	-0.220 (-1.20)	-0.196 (-0.93)	0.435 (1.57)
$TF \times Trading$	-0.054 (-0.31)	-0.306 (-1.40)	0.002 (0.01)
$Trading$	0.203 (1.54)	0.189 (1.22)	-0.032 (-0.16)
Observations	255,985	244,598	234,577
Adj. R^2	0.458	0.434	0.431
Panel B: Staggered Introduction of Satellite Imaging Data			
$AIFund \times SatCoverage \times Trading$	1.124*** (3.62)	-1.265*** (-3.01)	-0.543 (-0.85)
$SatCoverage \times Trading$	0.107* (1.65)	0.471*** (5.21)	-0.320** (-2.50)
$AIFund \times SatCoverage$	0.003 (1.54)	-0.006* (-1.91)	0.010*** (3.57)
$AIFund \times Trading$	0.430 (1.27)	0.001 (0.00)	-0.530 (-0.85)
$SatCoverage$	-0.004*** (-5.86)	0.012*** (9.32)	-0.010*** (-8.64)
$Trading$	-0.081 (-1.21)	-0.140* (-1.77)	0.366*** (3.66)
Observations	334,351	308,968	280,955
Adj. R^2	0.402	0.370	0.340
Fund-stock FE	Yes	Yes	Yes
Industry-time FE	Yes	Yes	Yes
Fund & Stock Controls	Yes	Yes	Yes

Notes: This table reports average effects across three forecast horizons in two quasi-natural experiment settings. Panel A examines the release of the Transformer architecture (June 2017), comparing AI vs non-AI funds. Panel B examines the staggered introduction of satellite imaging data availability. Key coefficients reflect the interaction between AI fund designation, information innovation, and trading exposure. All specifications include fund-stock and time fixed effects and relevant controls. Standard errors are double-clustered at the fund and stock levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 8: AI Fund Ownership and Stock Price Informativeness

Panel A: OLS Estimates						
	Dependent Variable: $EA_{j,[h,h+3]}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Share-based measure			Count-based measure		
Horizon (quarters)	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]
$AIown \times \log MA$	0.033** (2.30)	-0.024 (-1.29)	-0.091*** (-4.27)	0.004*** (2.98)	-0.001 (-0.67)	-0.006*** (-2.79)
$AIown$	0.033*** (6.94)	0.034*** (5.32)	0.046*** (5.95)	0.008*** (15.41)	0.005*** (7.21)	0.006*** (6.96)
$\log MA$	0.021*** (19.24)	0.014*** (9.65)	0.015*** (7.60)	0.019*** (17.17)	0.013*** (8.71)	0.013*** (6.63)
Stock FE/Industry-time FE/Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162,398	139,854	119,478	162,398	139,854	119,478
R^2	0.766	0.712	0.708	0.766	0.712	0.708
Panel B: First Stage IV Results						
	Dependent Variable: $AIown$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Share-based measure			Count-based measure		
$AI Talent Exposure_{agg}$	0.006*** (6.06)		0.007*** (6.93)	0.314*** (29.10)		0.320*** (32.54)
$Distance to AI Hubs_{agg}$		-0.023*** (-12.91)	-0.024*** (-12.54)		-0.361*** (-16.30)	-0.401*** (-19.99)
Stock FE/Industry-time FE/Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162,398	162,398	162,398	162,398	162,398	162,398
Adj. R^2	0.501	0.502	0.504	0.866	0.851	0.869
F-statistics	45.014	55.406	55.885	626.196	324.868	671.262
Hansen J statistics			0.000			0.001
Panel C: Second Stage IV Results						
	Dependent Variable: $EA_{j,[h,h+3]}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Share-based measure			Count-based measure		
Horizon (quarters)	[1, 4]	[5, 8]	[9, 12]	[1, 4]	[5, 8]	[9, 12]
$AIown \times \log MA$	0.253*** (5.69)	-0.001 (-0.02)	-0.268*** (-3.52)	0.010*** (4.98)	-0.004 (-1.49)	-0.015*** (-4.53)
$AIown$	0.308*** (17.15)	0.223*** (9.23)	0.230*** (7.81)	0.012*** (13.59)	0.007*** (6.14)	0.008*** (5.30)
$\log MA$	0.018*** (15.61)	0.012*** (7.71)	0.012*** (6.14)	0.018*** (16.20)	0.012*** (8.24)	0.013*** (6.42)
Stock FE/Industry-time FE/Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	162,398	139,854	119,478	162,398	139,854	119,478
R^2	0.767	0.712	0.708	0.766	0.712	0.708

Notes: This table presents results on how AI fund ownership affects stock price informativeness about future earnings, following [Bai et al. \(2016\)](#). The dependent variable $EA_{j,t+h}$ is the sum of earnings over the specified horizon. $AIown$ is measured as the percentage of shares held by AI funds (share-based) in columns (1)-(3) and as the number of AI funds holding the stock (count-based) in columns (4)-(6). $\log MA$ is the log market-to-assets ratio. Panel A reports OLS estimates. Panel B presents the first-stage IV results, where the aggregated $AI Talent Exposure$ and $Distance to AI Hubs$ are used as instruments for $AIown$. Panel C reports the corresponding second-stage IV results. All specifications include stock fixed effects, industry-time fixed effects, and stock-level controls (current earnings, log size, leverage, ROE, growth, book-to-market, and analyst coverage). Standard errors are double-clustered at the stock and year-quarter level. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 9: Future Earnings Response Coefficient Analysis

Variables	Dependent Variable: Stock Return			
	Share-based measure		Count-based measure	
	(1)	(2)	(3)	(4)
	OLS Estimates	Second Stage IV Results	OLS Estimates	Second Stage IV Results
$AIown \times EA_{[1,4]}$	0.079* (1.82)	0.362*** (4.20)	0.012*** (4.43)	0.012*** (3.83)
$AIown \times EA_{[5,8]}$	0.064 (1.62)	0.093 (1.26)	0.005* (1.88)	0.004 (1.37)
$AIown \times EA_{[9,12]}$	-0.034 (-1.09)	-0.015 (-0.26)	-0.004** (-2.10)	-0.004* (-1.65)
Stock FE	Yes	Yes	Yes	Yes
Industry-time FE	Yes	Yes	Yes	Yes
Stock Controls	Yes	Yes	Yes	Yes
Other FERC Components	Yes	Yes	Yes	Yes
Observations	119,448	119,448	119,448	119,448
Adj. R^2	0.373	0.368	0.373	0.366

Notes: This table presents future earnings response coefficient (FERC) analysis examining how current stock returns reflect information about future earnings. The dependent variable is the quarterly stock return. $AIown$ is measured as the percentage of shares held by AI funds (share-based) in columns (1)-(2) and as the number of AI funds holding the stock (count-based) in columns (3)-(4). $EA_{[h,h+3]}$ represents the sum of earnings from quarter h to $h+3$. Columns (1) and (3) show OLS estimates, while columns (2) and (4) show second stage IV results using the aggregated *AI Talent Exposure* and *Distance to AI Hubs* as instruments. All specifications include stock and industry-time fixed effects, stock-level controls, and the full set of FERC components (main effects, lagged earnings interactions). Standard errors are double-clustered at the stock and year-quarter level. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 10: Constant Shareholder Analysis: Price Informativeness

Horizon (quarters)	Dependent Variable: $EA_{j,[h,h+3]}$		
	[1, 4]	[5, 8]	[9, 12]
Panel A: DiD Estimates			
$Treat^{Stock} \times Post^{Stock} \times \log MA$	0.042*** (2.81)	-0.018 (-1.07)	-0.050** (-2.37)
$Treat^{Stock} \times \log MA$	0.007 (0.65)	0.003 (0.20)	-0.009 (-0.63)
$Post^{Stock} \times \log MA$	-0.051*** (-4.32)	0.004 (0.28)	0.019 (1.08)
$Treat^{Stock} \times Post^{Stock}$	-0.037*** (-6.04)	-0.045*** (-5.94)	-0.056*** (-5.93)
$\log MA$	0.038*** (4.32)	0.029*** (2.91)	0.035*** (2.78)
Observations	7357	6588	5839
Adj. R^2	0.811	0.792	0.793
Panel B: Dynamic effect			
$Treat^{Stock} \times Pre^{Stock}_{.3} \times \log MA$	0.029 (0.83)	0.028 (0.71)	-0.046 (-0.92)
$Treat^{Stock} \times Pre^{Stock}_{.2} \times \log MA$	0.050 (1.59)	-0.010 (-0.29)	-0.034 (-0.82)
$Treat^{Stock} \times Pre^{Stock}_{.1} \times \log MA$	0.038 (1.28)	-0.009 (-0.28)	-0.063 (-1.28)
$Treat^{Stock} \times Current^{Stock} \times \log MA$	0.063** (2.05)	-0.021 (-0.65)	-0.071 (-1.49)
$Treat^{Stock} \times Pos^{Stock}_{t-1+} \times \log MA$	0.058*** (3.38)	-0.013 (-0.67)	-0.060** (-2.56)
Observations	7357	6588	5839
Adj. R^2	0.812	0.793	0.794
Fund-stock-cohort FE	Yes	Yes	Yes
Time-cohort FE	Yes	Yes	Yes
Industry-time FE	Yes	Yes	Yes
Fund & Stock Controls	Yes	Yes	Yes

Notes: This table presents constant shareholder analysis at the stock level to address selection concerns, focusing on price informativeness. The treatment group consists of stocks that first gain an AI-fund shareholder due to an existing fund's AI adoption. The control group consists of matched stocks that never have an AI-fund shareholder. The key coefficient is the triple interaction $Treat^{Stock} \times Post^{Stock} \times \log MA$, which captures the DiD effect on price informativeness. All specifications include fund-stock-cohort, time-cohort, and industry-time fixed effects. Stock-level controls are included. Standard errors are double-clustered at the stock and year-quarter level. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 11: AI Fund Ownership and Investment-Q Sensitivity

Variables	Dependent Variable: Investment $_{j,t+1}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	Share-based measure			Count-based measure		
	R&D	CapEx	R&D+CapEx	R&D	CapEx	R&D+CapEx
Panel A: OLS Estimates						
$AI_{own} \times Q$	-0.009*** (-7.24)	-0.007*** (-3.63)	-0.018*** (-6.96)	-0.001*** (-12.86)	-0.002*** (-9.33)	-0.004*** (-13.94)
AI_{own}	0.003*** (4.68)	0.006*** (3.08)	0.011*** (4.72)	0.001*** (9.35)	0.001*** (5.05)	0.002*** (7.91)
Q	0.005*** (20.12)	0.007*** (19.60)	0.013*** (25.47)	0.007*** (21.73)	0.010*** (19.01)	0.017*** (25.56)
Observations	162,398	159,257	159,257	162,398	159,257	159,257
Adj. R^2	0.850	0.659	0.667	0.850	0.659	0.668
Panel B: Second Stage IV Results						
$AI_{own} \times Q$	-0.033*** (-10.86)	-0.034*** (-6.09)	-0.074*** (-10.23)	-0.002*** (-14.50)	-0.002*** (-7.22)	-0.004*** (-12.88)
AI_{own}	0.012*** (4.89)	0.030*** (4.48)	0.046*** (5.87)	0.001*** (7.92)	0.002*** (5.58)	0.003*** (7.92)
Q	0.006*** (20.79)	0.009*** (16.87)	0.016*** (23.42)	0.008*** (21.93)	0.009*** (16.30)	0.018*** (23.51)
Observations	162,398	159,257	159,257	162,398	159,257	159,257
Adj. R^2	0.850	0.659	0.667	0.850	0.659	0.667
Stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time FE	Yes	Yes	Yes	Yes	Yes	Yes
Stock Controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table examines how AI fund ownership affects the sensitivity of corporate investment to Tobin's Q. The dependent variables are various investment measures in period $t + 1$: R&D expenditure, capital expenditure ($CapEx$), and R&D plus $CapEx$, all scaled by lagged total assets. AI_{own} is measured as the percentage of shares held by AI funds (share-based) in columns (1)-(3) and as the number of AI funds holding the stock (count-based) in columns (4)-(6). Q is Tobin's Q (market value of equity plus book value of assets minus book value of equity, divided by book value of assets). Panel A shows OLS estimates and Panel B shows second-stage IV estimates using the aggregated AI Talent Exposure and Distance to AI Hubs as instruments. All specifications include stock fixed effects, industry-time fixed effects, and stock-level controls (log size, leverage, ROE, growth, book-to-market, and analyst coverage). Standard errors are double-clustered at the stock and year-quarter level. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 12: Constant Shareholder Analysis: Investment–Q Sensitivity

	Dependent Variable: Investment _{j,t+1}		
	R&D	CapEx	R&D+CapEx
Panel A: DiD Estimates			
$Treat^{Stock} \times Post^{Stock} \times Q$	-0.001*	-0.007**	-0.009***
	(-1.89)	(-2.25)	(-2.80)
$Treat^{Stock} \times Q$	0.001	0.003	0.004
	(1.52)	(0.67)	(0.85)
$Post^{Stock} \times Q$	0.001*	0.006**	0.007**
	(1.93)	(2.43)	(2.41)
$Treat^{Stock} \times Post^{Stock}$	0.000	0.002	0.002
	(1.00)	(0.70)	(1.06)
Q	0.001***	0.007*	0.009**
	(2.85)	(1.93)	(2.42)
Observations	7357	7171	7171
Adj. R^2	0.932	0.781	0.794
Panel B: Dynamic Effect			
$Treat^{Stock} \times Pre^{Stock}_{-3} \times Q$	0.001	-0.003	-0.005
	(0.85)	(-0.39)	(-0.65)
$Treat^{Stock} \times Pre^{Stock}_{-2} \times Q$	0.000	0.012*	0.006
	(0.12)	(1.93)	(0.96)
$Treat^{Stock} \times Pre^{Stock}_{-1} \times Q$	0.003	0.001	0.001
	(1.64)	(0.20)	(0.17)
$Treat^{Stock} \times Current^{Stock} \times Q$	0.002	0.005	0.003
	(1.44)	(0.61)	(0.33)
$Treat^{Stock} \times Post^{Stock}_{-1+} \times Q$	-0.001	-0.006*	-0.009**
	(-1.45)	(-1.77)	(-2.43)
Observations	7357	7171	7171
Adj. R^2	0.932	0.782	0.795
Stock-cohort FE	Yes	Yes	Yes
Time-cohort FE	Yes	Yes	Yes
Industry-time FE	Yes	Yes	Yes
Stock Controls	Yes	Yes	Yes

Notes: This table presents constant shareholder analysis at the stock level, focusing on Investment–Q sensitivity. The treatment group consists of stocks that first gain an AI-fund shareholder due to an existing fund’s AI adoption. The control group consists of matched stocks that never have an AI-fund shareholder. The key coefficient is the triple interaction $Treat^{Stock} \times Post^{Stock} \times Q$, which captures the DiD effect on the sensitivity of corporate investment (R&D, CapEx, and their sum) to stock prices (Tobin’s Q). All specifications include stock-cohort, time-cohort, and industry-time fixed effects. Stock-level controls are included. Standard errors are double-clustered at the stock and year-quarter level. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Internet Appendix for AI Adoption, Mutual Fund Short-Termism, and Real Investment

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I.1. Illustrative Examples of AI Fund Managers from Manager Profiles

This section describes our procedure for classifying mutual fund managers as AI adopters based on their biographies. We implement a pre-specified rule set using a large language model (ChatGPT 5.1 Mini) to evaluate each manager’s biographical text and return a structured classification output. The prompt instructs the model to flag biographies that contain evidence of (i) AI/ML-related education, (ii) AI/ML-related work experience, (iii) use of AI/ML methods in investment processes, or (iv) AI/ML-related publications, certifications, or projects, while explicitly excluding general quantitative or statistical expertise. The exact prompt used for this classification is reproduced below:

```
Forget your previous instructions. You are an expert analyst evaluating whether a fund manager possesses AI-related skills. Based on the biography provided below, determine if the manager has AI capabilities by checking for:
```

1. AI-related educational background (e.g., degrees in Machine Learning, Data Science, Artificial Intelligence)
2. Work experience involving AI/ML technologies (e.g., roles as data scientist, AI researcher, or positions at AI-intensive companies)
3. Evidence of applying AI/ML techniques in investment strategies (e.g., mentions of machine learning models, natural language processing, neural networks)
4. Certifications, publications, or projects related to AI/ML

```
IMPORTANT DISTINCTION:
```

- Traditional quantitative methods are NOT considered AI-related expertise.

```
Please analyze the biography carefully, and you must return your answer in EXACTLY in the following format:
```

```
"response_example": {
  "has_ai_expertise": "[Yes/No]",
  "reasoning": "[...]"
}
```

```
Current manager biography is: {"Biography"}
```

We present representative cases in Table I.1 that illustrate how the model operationalizes the above criteria. These examples provide qualitative support for the construct validity of our classification and highlight the range of AI-related profiles captured by our measure.

- The PXIIX manager case demonstrates our methodology’s ability to identify managers based on explicit organizational roles. The manager’s position within the “Voya Machine Intelligence (VMI) team” provides clear evidence of institutional commitment to AI technologies.
- The GAFCX managers illustrate how our methodology captures both educational and professional AI specialization. One manager’s Harvard statistics background with a focus on “statistical machine learning” represents formal training in core AI methodologies. The other manager’s explicit work in “development of new trading strategies, machine learning, and global markets analysis” at AlphaSimplex demonstrates applied AI expertise in investment contexts.
- The VC SOX manager case showcases our methodology’s sensitivity to advanced technical credentials. The manager’s “Diplôme d’Ingénieur des Grandes Écoles in Artificial Intelligence and Robotics” and “Ph.D. in Artificial Intelligence and Distributed Systems” represent the substantial educational backgrounds in AI technologies.
- The SVTAX manager example demonstrates identification of hands-on AI implementation experience. The manager’s research focus on “applications of machine learning and pattern recognition technologies”, combined with previous work at the “MIT Ar-

tificial Intelligence Laboratory,” provides compelling evidence of both theoretical and practical AI capabilities in investment management.

- The EISVX, PIPJX, and PPSIX examples illustrate that skills such as “quantitative analytic specialist”, “developing quantitative models,” or “statistical analysis” are correctly excluded. This confirms that ChatGPT targets the unique credentials of modern AI/ML rather than general quantitative or statistical expertise.

Collectively, these cases—spanning explicit AI team roles, specialized education, and applied AI/ML implementation—support the validity of our classification approach and increase confidence in the AI-fund measures used in the main analyses.

I.2. Alternative Measurement of AI Funds

We construct a multidimensional AI-fund classification to address potential under-identification. While our baseline, skill-based approach provides a conservative (lower-bound) measure of AI adoption, it may miss funds that adopt AI through organizational resources rather than manager backgrounds. We therefore expand the definition using two additional data sources: (i) summary prospectuses (SEC Form 497-K) from EDGAR, which describe funds’ Principal Investment Strategies (PIS), and (ii) patent grants from the USPTO. We use a large language model to review the text of the 497-K PIS sections and patent abstracts and to flag explicit references to AI applications in investment research or portfolio management. Under this expanded definition, a fund is classified as an AI fund if it satisfies at least one of the following criteria: (a) its 497-K filing explicitly references AI adoption in the PIS section; (b) its adviser or fund family holds patents directly related to AI technologies used for investment analysis; or (c) its portfolio managers exhibit demonstrable AI expertise based on biographies. Applying this definition increases the number of AI funds to 239 by the end of 2023, with aggregate assets under management of \$4.5 trillion (9.2% of the mutual fund market).

As shown in Table I.2, our main results are robust to this alternative definition. The horizon pattern is qualitatively unchanged: trading by AI funds (as reclassified) remains more strongly associated with short-horizon earnings news and substantially less associated with longer-horizon fundamentals.

I.3. Alternative Measures of Earnings

We also assess robustness to alternative proxies for future firm fundamentals—earnings before interest, taxes, depreciation, and amortization (EBITDA) and net income (NI). Specifically, we re-estimate our baseline regressions after replacing the future earnings-news dependent variable with future EBITDA and, separately, future NI, while keeping the econometric specification and control set unchanged. These tests assess whether the documented horizon patterns persist across alternative measures of firm performance.

The results in Table I.3 are consistent with our primary findings for both alternative outcomes. The interaction term $AIFund \times Trading$ remains positive and statistically significant at short horizons and negative at longer horizons. Together, these estimates support our interpretation that AI adoption is associated with a temporal reallocation of mutual fund managers' information processing toward short-horizon fundamentals.

I.4. Alternative Model Specifications

We conduct a specification-curve analysis to assess the sensitivity of our estimates to alternative modeling choices and to ensure that the results are not driven by a particular set of econometric assumptions. We vary both the fixed-effects structure and the clustering of standard errors.

We consider several alternative fixed-effects specifications: (i) replacing fund–stock fixed effects with separate fund and stock fixed effects; (ii) replacing industry–time fixed effects with time fixed effects; and (iii) incorporating fund–time fixed effects to absorb time-varying

fund characteristics, either in place of industry–time fixed effects or in addition to them. For each fixed-effects specification, we additionally vary the clustering of standard errors (fund–stock, stock, fund–time, and stock–time) to accommodate alternative within-sample correlation structures.

Figure 1.1 summarizes the results across all combinations of fixed effects and clustering choices. The upper panel reports coefficient estimates for the key interaction term ($AIFund \times Trading$), with blue dots indicating point estimates and gray bars denoting 95% confidence intervals; the black dashed line marks zero. The lower panel records the corresponding modeling choices for each specification (horizon, fixed effects, and clustering). Across specifications, we observe a consistent horizon pattern: the coefficients at short horizons (1–4 quarters ahead) are positive and statistically significant, whereas the coefficients at longer horizons (9–12 quarters ahead) are negative and statistically significant. Thus, the short-horizon versus long-horizon contrast in earnings-information processing by AI funds remains robust in both economic magnitude and statistical significance across a wide range of specifications, suggesting that the pattern is not an artifact of particular fixed-effects or clustering choices.

I.5. Ruling Out Confounding from AI-Related Holdings

If AI-adopting funds disproportionately hold AI-related stocks, whose valuations may be more sensitive to short-term growth signals, then the observed trade-earnings pattern could reflect portfolio characteristics rather than a change in information acquisition horizon following AI adoption. To rule out this alternative explanation, we exclude AI-related firms from the sample using two complementary screens. First, we remove firms classified in the Fama–French 48 industry groups most directly linked to AI and robotics technology

production.¹ Second, we remove any firm identified on the curated thematic “Artificial Intelligence Stocks” and “Robotics Stocks” lists published by StockAnalysis.com.² Finally, we apply both filters simultaneously, thereby excluding any AI firm identified through either the industry classification or the thematic list criterion.

Re-estimating our main specifications on these restricted samples yields results that are qualitatively and statistically indistinguishable from our baseline findings. Table I.4 shows that the coefficient on $AIFund \times Trading$ remains significantly positive for short-term earnings horizons (quarters 1–4) and significantly negative for long-term horizons (quarters 9–12). The persistence of our core result after removing AI-related stocks provides strong evidence that the documented shift in trading informativeness is not mechanically driven by funds holding AI-related stocks.

I.6. Constant Shareholder Analysis: Future Earnings Response Coefficient (FERC)

We apply the constant-shareholder difference-in-differences (DiD) design to the FERC model. As detailed in the main text, this design identifies firms that become exposed to AI through an incumbent shareholder’s adoption (treatment group) and matches them to otherwise similar firms that experience no such exposure (control group). Because treatment is triggered by an incumbent shareholder’s AI adoption—rather than by AI funds initiating new positions—this approach mitigates endogenous stock-selection concerns.

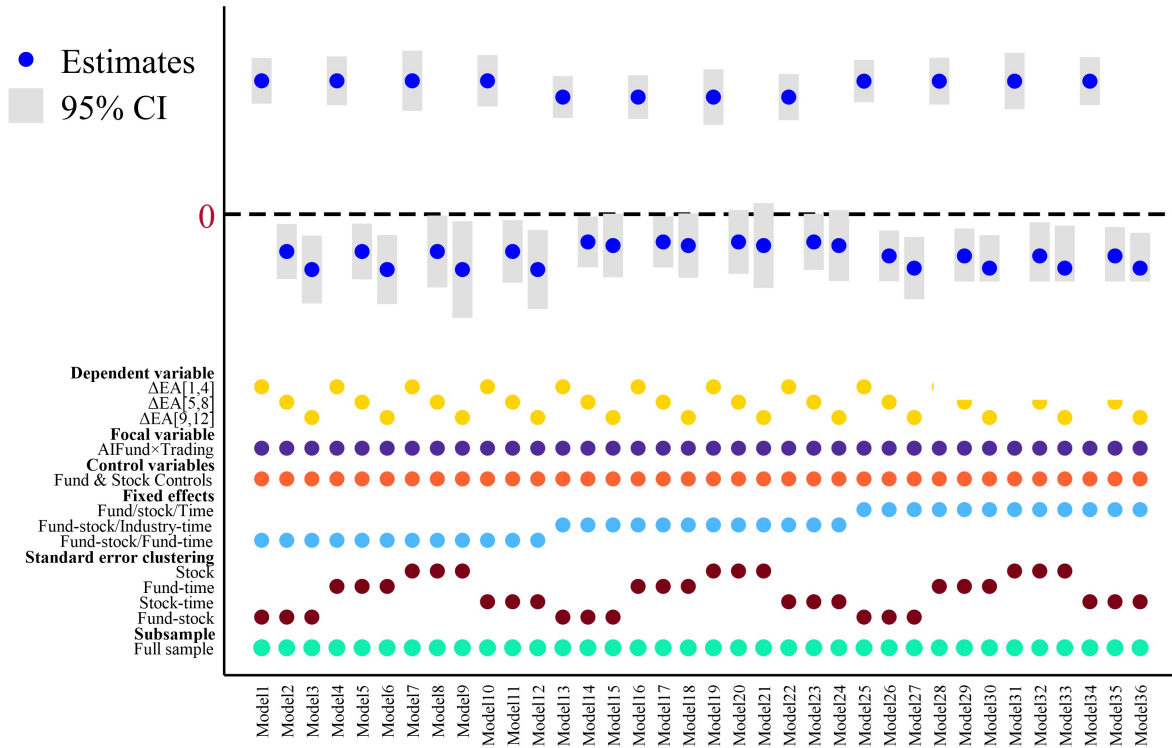
Table I.5 presents the results. In Panel A, the coefficient on $Treat^{Stock} \times Post^{Stock} \times EA_{[1,4]}$ is significantly positive, whereas the coefficient on $Treat^{Stock} \times Post^{Stock} \times EA_{[9,12]}$ is significantly negative. Panel B reports a dynamic specification and finds no statistically

¹Specifically, firms classified in the “Computers” (industry code 35), “Electronic Equipment” (36), and “Measuring and Control Equipment” (37) sectors.

²These thematic lists are maintained and updated by StockAnalysis.com. For reference, see <https://stockanalysis.com/list/>.

significant differential pre-trends, supporting the parallel-trends assumption. Overall, the estimates indicate that, following an incumbent shareholder's transition to AI, stock returns become more reflective of short-horizon earnings news and less reflective of long-horizon earnings news.

Fig. I.1: Alternative model specifications



Notes: This figure reports the robustness checks of using alternative model specifications, including: fund/stock/time, fund-stock/time, fund-stock/fund-time, and fund-stock/industry-time/fund-time fixed effects, as well as clustering standard errors at different dimensions, such as fund-stock level, stock level, fund-time level, and stock-time level. The upper panel plots the coefficient estimates of $AIFund \times Trading$ in various model specifications, and the associated 95% confidence intervals. The lower panel reports the exact specification for each model, where colored dots indicate the choices from various specification alternatives.

Table I.1: Illustrative Examples of AI Fund Managers from Manager Profiles

Fund name	Manager Biography (Anonymized)	GPT Response
PXIIX: Virtus KAR Equity Income I	<p>██████████ is a portfolio manager with the Voya Machine Intelligence (VMI) team at Voya Investment Management. Prior to joining Voya, he was a senior portfolio manager at Franklin Templeton, managing smart beta and active multi-factor equity strategies. Prior to that, ██████████ worked at QS Investors (a Legg Mason affiliate) as head of equity portfolio management and trading. Previously, he was a lead portfolio manager with the diversification based investing equity and tax managed equity strategies at Deutsche AM Quantitative Strategies group. ██████████ earned a BBA with honors in finance and a minor in economics from Pace University. He is a CFA[®] Charterholder.</p>	<p>Yes; Reason: ██████████ works as a portfolio manager with the Voya Machine Intelligence (VMI) team, which directly indicates involvement in AI/ML-driven investment strategies. His role within the Voya Machine Intelligence team suggests that he is applying machine learning techniques in portfolio management. Additionally, his previous experience in managing smart beta and multi-factor equity strategies at Franklin Templeton, as well as his work at QS Investors in equity portfolio management, further supports his expertise in quantitative and data-driven investment strategies, which are often powered by AI/ML.</p>
GAFCX: Virtus AlphaSimplex Global Alts C	<p>As a Senior Research Scientist and Portfolio Manager at AlphaSimplex, Mr. ██████████ serves as a co-portfolio manager for the AlphaSimplex Managed Futures Strategy. In this role, he is focused on portfolio management, applied research, and overall capability development. Mr. ██████████ joined AlphaSimplex in 2009. He specializes in trend-following, term-structure, and pattern-based trading strategies, as well as trade execution optimization. He holds two patents in risk-managed index design. Mr. ██████████ earned both an A.B. and an A.M. in Statistics from Harvard University, where he focused on statistical machine learning, capital markets, and time series analysis. Mr. ██████████ is also a CAIA[®] Charterholder.</p>	<p>Yes; Reason: Mr. ██████████ has an educational background in Statistics from Harvard University, where he focused on statistical machine learning, which is highly relevant to AI/ML techniques. His work experience includes applied research in trend-following, pattern-based trading strategies, and trade execution optimization, which suggests the use of machine learning or AI-related techniques in investment strategies. Additionally, he holds patents related to risk-managed index design, indicating involvement in advanced algorithmic work that may align with AI/ML methods. His work at AlphaSimplex, particularly in strategy development, further supports the likelihood of AI/ML application in his portfolio management activities.</p>
GAFCX: Virtus AlphaSimplex Global Alts C	<p>Mr. ██████████ joined AlphaSimplex in 2016 and currently serves as Senior Research Scientist, focusing on the development of new trading strategies, machine learning, and global markets and macro analysis. Before working at AlphaSimplex, Mr. ██████████ was Partner and Managing Director of Risk Management and Quantitative Research at Aurora Investment Management. Prior to Aurora, he held a similar role at Man Investments USA Corp. Mr. ██████████ earned a B.A. from Western Michigan University and an M.F.A. from the University of Iowa. In addition, he earned an M.B.A. in Analytical Finance and an M.S. in Financial Mathematics from the University of Chicago. Mr. ██████████ is a CFA[®] Charterholder and an author of multiple articles on investing.</p>	<p>Yes; Reason: Mr. ██████████ has significant experience in machine learning, having worked on the development of trading strategies involving machine learning at AlphaSimplex. Additionally, his background includes roles in risk management and quantitative research, which often involve advanced analytics and data-driven approaches. His expertise in machine learning and financial mathematics, combined with his focus on global markets and macro analysis, suggests strong AI/ML capabilities applied to investment strategies.</p>

Continued on next page

Table I.1 – continued from previous page

Fund name	Manager Biography (Anonymized)	GPT Response
VC SOX: VALIC Company I Intl Selly Rspnb	██████████, PhD, CFA Managing Director, Global Multi-Asset PineBridge Investments, Sydney. Dr. ██████████ joined the firm in 1999. As part of the Global Multi-Asset team, Dr. ██████████ is responsible for multi-asset research, offering differentiated investment point of view through research & development papers and presentations. She is also the Asia Pacific Portfolio Manager for the Global Multi-Asset products. She has been working in the area of quantitative investment strategies since 1994 covering equity instruments as well as fixed income instruments, derivatives instruments, and currencies. She has worked in a quantitative capacity at American General Investment Management, Loomis Sayles, US West Investment, Citibank and Warburg. Dr. ██████████ received a Diplôme d'Ingénieur des Grandes Écoles in Artificial Intelligence and Robotics from Toulouse, France . She received her Ph.D. in Artificial Intelligence and Distributed Systems from University College London and is also a CFA charterholder.	Yes; Reason: Dr. ██████████ has a relevant AI-related educational background, including a Diplôme d'Ingénieur des Grandes Écoles in Artificial Intelligence and Robotics and a Ph.D. in Artificial Intelligence and Distributed Systems . Additionally, her work in quantitative investment strategies, including her role in multi-asset research, suggests she may have applied AI/ML techniques in her investment strategies. Her advanced education and experience in AI and quantitative strategies strongly suggest AI-related expertise.
SVTAX: SEI Global Managed Volatility F (SIMT)	██████████ joined Acadian in August 2006 and is a member of the Research and Portfolio Management Team, where he contributes to improving our investment processes, portfolio management, and supporting marketing and client service. His research focus at Acadian spans areas such as applications of machine learning and pattern recognition technologies, and frontier markets investing . Prior to Acadian, he was with the AlphaSimplex Group in Cambridge, where he developed news-based and high-frequency trading strategies, among other projects. He has also worked with iSpheres, Kana Communications, the MIT Artificial Intelligence Laboratory , and BBN Systems and Technology.	Yes; Reason: The biography clearly indicates that ██████████ has experience in applying machine learning techniques, specifically in areas such as pattern recognition and high-frequency trading strategies. His research focus includes applications of machine learning, and his previous roles at AlphaSimplex Group and the MIT Artificial Intelligence Laboratory demonstrate direct involvement with AI/ML technologies. Additionally, his work with iSpheres and BBN Systems and Technology further supports his experience in AI-related projects.
EISVX: Carillon ClariVest International Stock Fund Class R-6	██████████ is a Portfolio Manager on the investment team at ClariVest Asset Management LLC, focusing on non-U.S. and Global strategies. Prior to joining ClariVest in 2008, Mr. ██████████ was a Quantitative Analytic Specialist at FactSet Research System, where he co-managed sales and support for all of FactSet's quantitative products on the West Coast as well as worked closely with investment firms in developing quantitative models and implementing risk control strategies . His work experience includes roles as a FactSet Consultant, an Assistant Actuary, and a Technical Writer for a technology company. Mr. ██████████ earned a Bachelor of Science in Business Administration with an emphasis in Finance from University of California, Berkeley. He began his investment career in 2005.	No; Reason: While ██████████ has experience as a Quantitative Analytic Specialist and has worked with quantitative models, there is no direct mention of AI-related education or specific work with AI/ML technologies. The biography highlights his work with quantitative models and risk control strategies, but traditional quantitative methods are not considered AI-related expertise. No evidence of applying AI/ML techniques (e.g., machine learning models, algorithmic trading, neural networks) in investment strategies is mentioned. Therefore, he does not appear to have AI capabilities.
PIPJX: Principal Inflation Protection Fund Class J	██████████, Managing Director, is a member of the Multi-Sector Mutual Fund team within BlackRock's Global Fixed Income Group. He is a portfolio manager of BlackRock's Core Bond, Inflation Protected, Total Return, and Strategic Income Opportunities Funds. Mr. ██████████ focuses on broad macro positioning, with specialties in interest rates, inflation, and volatility trading. Mr. ██████████ joined Fixed Income in 2009. Previously, he was a member of BlackRock's Multi Asset Strategies group, where he developed quantitative models and advised insurance companies, pension funds, and banks on asset-allocation.	No; Reason: The biography does not mention any AI-related educational background, work experience with AI/ML technologies, or the application of AI/ML techniques in investment strategies. While Mr. ██████████ has experience in developing quantitative models, this is not the same as applying machine learning or AI techniques. His expertise focuses on macro positioning, interest rates, inflation, and volatility trading, which does not indicate the use of AI/ML methods such as machine learning models or algorithmic trading. Additionally, there is no mention of AI certifications or projects.

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Table I.1 – continued from previous page

Fund name	Manager Biography (Anonymized)	GPT Response
PPSIX: Principal Spectrum Preferred and Capital Securities Income Fund Class Institutional	<p>■■■■■■■■ joined Spectrum in 2012. Previously, Mr. ■■■■■■■ had been a Guaranteed Introducing Broker with MF Global through Nugent Investment Group, LLC, since 2002. Additionally, since 2007 he has been a portfolio manager at Huntington Bay Capital Management and HFP Investment Management, with an emphasis on trading a proprietary volatility strategy for a hedge fund. He has held senior positions at Smith Barney, UBS and Prudential Securities where he developed low risk market strategies by using a proprietary trading model and statistical analysis. He also has extensive experience in developing various hedging strategies for commercial and institutional clients. Mr. ■■■■■■■ graduated in 1981 with a Bachelor of Arts degree from Ohio Wesleyan University. He holds a Series 3 (National Commodities Futures) license. He is NASD Series 65 (Uniform Investment Advisor Law Examination) examination qualified.</p>	<p>No; Reason: ■■■■■■■'s biography does not indicate any AI-related educational background, work experience, or the use of AI/ML technologies. His experience focuses on trading strategies, volatility strategies for hedge funds, and statistical analysis, which are more aligned with traditional quantitative methods rather than AI or machine learning techniques. There is no mention of machine learning models, algorithmic trading, natural language processing, or neural networks in his career. Additionally, his qualifications, including Series 3 and Series 65 licenses, do not suggest a connection to AI or machine learning.</p>

Notes: This table presents illustrative examples of mutual fund managers identified as AI adopters through our text analysis methodology. Manager biographies are sourced from Morningstar Direct. The GPT Analysis Response column indicates whether GPT-5.1 mini classifies the manager as an AI adopter, along with the reasoning. Names and identifying details have been anonymized to maintain confidentiality.

Table I.2: Alternative Measures of AI fund

Dependent Variable: $\Delta EA_{j,[h,h+3]}$						
	(1)	(2)	(3)	(4)	(5)	(6)
Horizon (quarters)	[1, 4]		[5, 8]		[9, 12]	
<i>AIFund</i> \times <i>Trading</i>	0.083*** (8.64)	0.083*** (8.89)	-0.027** (-2.44)	-0.027** (-2.40)	-0.027* (-1.91)	-0.026* (-1.89)
<i>AIFund</i>	0.000 (0.38)	0.000 (0.38)	-0.000 (-1.33)	-0.000 (-1.14)	-0.000 (-0.85)	-0.000 (-0.80)
<i>Trading</i>	0.171*** (16.37)	0.089*** (8.66)	0.047*** (3.78)	0.019 (1.54)	0.040*** (2.68)	0.031** (2.07)
Fund-stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock Controls	No	Yes	No	Yes	No	Yes
Observations (millions)	8.01	8.01	7.10	7.10	6.19	6.19
Adj. R^2	0.277	0.318	0.277	0.282	0.274	0.274

Notes: This table presents robustness checks using an alternative measure of AI adoption. A fund is classified as an AI fund if it meets any of the following criteria: (1) its SEC Form 497-K explicitly lists AI adoption in its “Principal Investment Strategies” section; (2) its advisory firm or fund family holds patents directly related to AI technologies for use in investment analysis; or (3) its portfolio managers possess demonstrable AI expertise. The dependent variable $\Delta EA_{j,[h,h+3]}$ is the change in earnings, defined as the sum of earnings (EBIT scaled by total assets) from quarter h to $h+3$ minus the sum of earnings from the past four quarters. *Trading* is the split-adjusted trading value (Thomson Reuters S12 item CHANGE*PRC) of fund f for stock j in period t , scaled by the fund’s total portfolio value in period $t - 1$. Stock-level control variables include: current earnings, log size, leverage, ROE, growth, book-to-market, and analyst coverage. Fund-level control variables include: log TNA, log age, log number of stocks, and turnover. All variables are defined in Appendix A. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table I.3: Alternative Measures of Earnings

		Dependent Variable: $\Delta EA_{j,[h,h+3]}$					
		(1)	(2)	(3)	(4)	(5)	(6)
Horizon (quarters)		[1, 4]		[5, 8]		[9, 12]	
Panel A: EBITDA							
<i>AIFund</i> × <i>Trading</i>		0.416*** (7.03)	0.419*** (7.24)	-0.093 (-1.52)	-0.075 (-1.25)	-0.168** (-2.21)	-0.163** (-2.14)
<i>AIFund</i>		0.003** (2.48)	0.001 (1.11)	0.001 (0.97)	-0.000 (-0.57)	-0.000 (-0.23)	-0.001 (-0.88)
<i>Trading</i>		0.184*** (11.27)	0.086*** (5.50)	0.068*** (4.80)	0.015 (1.04)	0.046*** (2.69)	0.017 (0.98)
Observations (millions)		8.01	8.01	7.10	7.10	6.19	6.19
Adj. R^2		0.659	0.664	0.243	0.251	0.236	0.238
Panel B: Net Income							
<i>AIFund</i> × <i>Trading</i>		0.445*** (11.68)	0.446*** (12.11)	-0.062 (-1.37)	-0.055 (-1.21)	-0.111* (-1.95)	-0.107* (-1.89)
<i>AIFund</i>		0.002*** (3.59)	0.001 (1.02)	-0.000 (-0.63)	-0.001 (-1.31)	-0.002** (-2.35)	-0.002** (-2.34)
<i>Trading</i>		0.126*** (13.91)	0.068*** (7.65)	0.013 (1.20)	-0.011 (-1.01)	0.032** (2.47)	0.028** (2.11)
Observations (millions)		8.01	8.01	7.10	7.10	6.19	6.19
Adj. R^2		0.264	0.317	0.266	0.276	0.264	0.265
Fund-stock FE		Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE		Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock Controls		No	Yes	No	Yes	No	Yes

Notes: This table presents the robustness checks of using alternative measures of stocks' earnings. Panel A uses the earnings before interest, taxes, depreciation, and amortization (*EBITDA*). Panel B uses net income (*NI*). The independent variable *AIFund* is a dummy variable that takes a value of one if the fund is labeled as an AI-adopted mutual fund, and zero otherwise. *Trading* is the split-adjusted trading value (Thomson Reuters S12 item CHANGE*PRC) of fund *f* for stock *j* in period *t*, scaled by the total portfolio value of the fund *f* in period *t* - 1. Stock-level control variables include: current earnings, log size, leverage, ROE, growth, book-to-market, and analyst coverage; Fund-level control variables include: log TNA, log age, log number of stocks, and turnover. Standard errors are double-clustered at the fund and stock levels across all columns. All the variables are defined in Appendix A. t-statistics are in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

Table I.4: Ruling Out Confounding from AI-Related Holdings

Dependent Variable: $\Delta EA_{j,[h,h+3]}$						
	(1)	(2)	(3)	(4)	(5)	(6)
Horizon (quarters)	[1, 4]		[5, 8]		[9, 12]	
Panel A: Industry Classification-Based Exclusion						
<i>AIFund</i> × <i>Trading</i>	0.435*** (9.39)	0.444*** (9.85)	-0.116** (-2.11)	-0.106* (-1.94)	-0.118* (-1.74)	-0.114* (-1.67)
<i>AIFund</i>	0.002*** (3.65)	0.001 (1.02)	-0.000 (-0.20)	-0.001 (-1.35)	-0.001 (-0.95)	-0.001 (-1.29)
<i>Trading</i>	0.178*** (16.15)	0.107*** (9.83)	0.034** (2.56)	-0.002 (-0.16)	0.035** (2.19)	0.020 (1.25)
Observations (millions)	7.13	7.13	6.33	6.33	5.51	5.51
Adj. R^2	0.283	0.325	0.284	0.292	0.281	0.282
Panel B: Lists-Based Exclusion						
<i>AIFund</i> × <i>Trading</i>	0.454*** (9.91)	0.456*** (10.26)	-0.128** (-2.33)	-0.118** (-2.16)	-0.135** (-2.01)	-0.132* (-1.96)
<i>AIFund</i>	0.003*** (4.32)	0.001* (1.79)	0.000 (0.51)	-0.000 (-0.60)	-0.001 (-0.89)	-0.001 (-1.18)
<i>Trading</i>	0.164*** (14.96)	0.090*** (8.36)	0.055*** (4.21)	0.015 (1.13)	0.042*** (2.72)	0.026* (1.67)
Observations (millions)	7.55	7.55	6.70	6.70	5.84	5.84
Adj. R^2	0.277	0.319	0.277	0.283	0.274	0.275
Panel C: Combined Exclusion (Industry + Lists)						
<i>AIFund</i> × <i>Trading</i>	0.432*** (8.89)	0.437*** (9.26)	-0.121** (-2.09)	-0.112* (-1.94)	-0.143** (-2.00)	-0.138* (-1.93)
<i>AIFund</i>	0.002*** (3.87)	0.001 (1.23)	0.000 (0.03)	-0.001 (-1.09)	-0.001 (-0.86)	-0.001 (-1.21)
<i>Trading</i>	0.178*** (15.25)	0.102*** (8.96)	0.042*** (3.04)	0.005 (0.35)	0.034** (2.03)	0.017 (1.05)
Observations (millions)	6.76	6.76	5.99	5.99	5.23	5.23
Adj. R^2	0.282	0.327	0.284	0.292	0.281	0.282
Fund-stock FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Fund & Stock Controls	No	Yes	No	Yes	No	Yes

Notes: This table presents robustness checks addressing the potential confounding effect of AI-adopting funds' holdings in AI-related stocks. Panel A excludes stocks from the Fama–French 48 industries most directly associated with producing AI and robotics: Computers (35), Electronic Equipment (36), and Measuring and Control Equipment (37). Panel B excludes stocks identified as AI and Robotics companies according to the lists from [StockAnalysis.com](https://www.stockanalysis.com). Panel C applies both filters simultaneously. The dependent variable is the change in earnings ($\Delta EA_{j,[h,h+3]}$). All specifications include the full set of controls and fixed effects as in our baseline model. Standard errors are double-clustered at the fund and stock levels. t -statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table I.5: Constant Shareholder Analysis: Future Earnings Response Coefficient (FERC)

Panel A: DiD Estimates	
Dependent Variable: Stock Return	
	(1)
$Treat^{Stock} \times Post^{Stock} \times EA_{[1,4]}$	0.104* (1.74)
$Treat^{Stock} \times Post^{Stock} \times EA_{[5,8]}$	-0.044 (-0.80)
$Treat^{Stock} \times Post^{Stock} \times EA_{[9,12]}$	-0.064* (-1.70)
$Treat^{Stock} \times EA_{[1,4]}$	-0.091** (-1.99)
$Treat^{Stock} \times EA_{[5,8]}$	0.082** (1.97)
$Treat^{Stock} \times EA_{[9,12]}$	0.047* (1.65)
$Post^{Stock} \times EA_{[1,4]}$	-0.116** (-2.44)
$Post^{Stock} \times EA_{[5,8]}$	0.037 (0.80)
$Post^{Stock} \times EA_{[9,12]}$	0.029 (0.98)
Observations	5835
Adj. R^2	0.452

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Panel B: Dynamic Effect	
	Dependent Variable: Stock Return
	(1)
$Treat^{Stock} \times Pre^{Stock}_{.3} \times EA_{[1,4]}$	-0.074 (-0.66)
$Treat^{Stock} \times Pre^{Stock}_{.3} \times EA_{[5,8]}$	0.124 (1.26)
$Treat^{Stock} \times Pre^{Stock}_{.3} \times EA_{[9,12]}$	-0.108 (-1.62)
$Treat^{Stock} \times Pre^{Stock}_{.2} \times EA_{[1,4]}$	-0.079 (-0.58)
$Treat^{Stock} \times Pre^{Stock}_{.2} \times EA_{[5,8]}$	-0.013 (-0.08)
$Treat^{Stock} \times Pre^{Stock}_{.2} \times EA_{[9,12]}$	0.124 (1.01)
$Treat^{Stock} \times Pre^{Stock}_{.1} \times EA_{[1,4]}$	-0.178 (-1.35)
$Treat^{Stock} \times Pre^{Stock}_{.1} \times EA_{[5,8]}$	0.004 (0.03)
$Treat^{Stock} \times Pre^{Stock}_{.1} \times EA_{[9,12]}$	0.039 (0.41)
$Treat^{Stock} \times Current^{Stock} \times EA_{[1,4]}$	0.234* (1.69)
$Treat^{Stock} \times Current^{Stock} \times EA_{[5,8]}$	-0.170 (-1.22)
$Treat^{Stock} \times Current^{Stock} \times EA_{[9,12]}$	0.136 (1.63)
$Treat^{Stock} \times Post^{Stock}_{.1+} \times EA_{[1,4]}$	0.115* (1.84)
$Treat^{Stock} \times Post^{Stock}_{.1+} \times EA_{[5,8]}$	-0.001 (-0.03)
$Treat^{Stock} \times Post^{Stock}_{.1+} \times EA_{[9,12]}$	-0.102** (-2.43)
Observations	5835
Adj. R^2	0.455
Stock-cohort FE	Yes
Time-cohort FE	Yes
Industry-time FE	Yes
Other FERC Components	Yes
Stock Controls	Yes

Notes: This table presents constant shareholder analysis at the stock level, focusing on the Future Earnings Response Coefficient (FERC). The treatment group consists of stocks that first gain an AI-fund shareholder due to an existing fund's AI adoption. The control group consists of matched stocks that never have an AI-fund shareholder. The key coefficients are the triple interactions $Treat^{Stock} \times Post^{Stock} \times EA_{[h,h+3]}$, which capture the DiD effect on the stock return's responsiveness to earnings news over different horizons. All specifications include stock-cohort, time-cohort, and industry-time fixed effects, along with the full set of FERC control components and stock-level controls. Standard errors are double-clustered at the stock and year-quarter level. t -statistics are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.