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

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**Abstract**

We investigate how artificial intelligence (AI) adoption by mutual funds influences their information processing horizons and the capital market consequences. Employing a novel AI adoption measure, we document a significant shift towards short-termism among AI-adopting funds. Specifically, AI funds' quarterly trades exhibit substantially stronger predictive power for near-term earnings (1-5 quarters ahead) but markedly weaker association with long-term earnings (9-12 quarters ahead) compared to non-AI funds. This differential effect is robust when we use the instrumental variable approach to address endogeneity and is more pronounced after plausible exogenous shocks that increase the effectiveness of AI in information processing. Furthermore, we find that companies with greater AI fund ownership experience improved stock price informativeness concerning short-term future earnings, but reduced price informativeness for long-term earnings. Finally, we observe diminished investment-Tobin's Q sensitivity among firms with higher AI fund ownership, consistent with the notion that AI funds' short-termism may compromise the usefulness of stock prices in guiding long-term investment decisions. These results demonstrate the unintended consequences of technological advancement in asset management and carry important implications for the informational and functional efficiency of capital markets.

**Keywords:** AI adoption; Mutual fund short-termism; Price informativeness; Investment-Q sensitivity
**JEL Classification:** G11; G14; G23; O16

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# 1 Introduction

The financial industry is undergoing a rapid transformation driven by advances in artificial intelligence (AI) technology and the proliferation of various data sources. Mutual funds, in particular, are increasingly adopting AI-powered tools to enhance their information processing capabilities (Bartram et al., 2020; Bonelli, 2023; ?).[1] While AI's potential is widely recognized, empirical evidence on its impact on mutual fund information processing remains limited (?). This study addresses this gap by examining how AI adoption impacts a fund's information processing horizon, and its broader effects on the informational and functional efficiency of stock prices.

We hypothesize that AI adoption by mutual funds exacerbates short-termism in information processing. This prediction stems from the differential effectiveness of AI technologies across various forecasting horizons. Current AI systems excel at rapidly processing vast datasets and identifying complex patterns, making them well-suited for exploiting short-term market inefficiencies. However, long-term financial forecasting presents fundamentally different challenges, requiring causal reasoning, scenario analysis, and understanding of qualitative factors such as management quality, competitive dynamics, and evolving industry landscapes. These aspects are typically intangible and often involve interpreting subtle contextual clues and predicting structural economic changes–tasks where the current AI systems still struggle (?Cao et al., 2024; Boyacı et al., 2024).[2]

This asymmetry in AI's effectiveness thus creates a cost differential: processing information for short-term analysis becomes significantly cheaper and more efficient with AI, while obtaining reliable long-term insights remains relatively more resource-intensive. As

[1]According to Mercer's 2024 survey results 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.

[2]For example, ? note that short-term trading, which involves holding periods of days to weeks, has become increasingly automated as portfolio managers search for new sources of alpha. However, they observe 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 absence of sufficient training data from which machine learning algorithms could learn the relevant knowledge for valuation.

Kacperczyk et al. (2016) demonstrate, information-processing attention is scarce and optimally allocated where returns are highest. If AI adoption leads to a greater decrease in the marginal cost of short-term information processing, fund managers face incentives to reallocate their limited time and attention toward short-term signals at the expense of long-term analysis.

As mutual funds' private information is incorporated into stock prices through their trading (Jiang et al., 2014; Lee and Zhu, 2022), this predicted shift in the informational content of AI fund trades has broader implications. A greater emphasis on short-term signals by AI funds could lead to stock prices becoming more reflective of near-term earnings news but less informative about long-term fundamental value. This has significant implications for the usefulness of stock prices in guiding firms' real investment decisions (Chen et al., 2007). Optimal investment decisions should be based on the present value of long-term cash flows (Hirshleifer, 1958). If AI-driven trading leads to an overemphasis on short-term performance in stock prices, these prices would be less useful for guiding firms' investment decisions, potentially leading to suboptimal resource allocation.

We test these hypotheses using a sample of U.S. mutual funds from 2010 to 2023, a period witnessing increasing adoption of AI technology in the industry. We designate a mutual fund as an "AI fund" if any of the following three conditions are satisfied: i) it explicitly states the adoption of AI technology in its investment process in the Principal Investment Strategies section of the summary prospectus (497-K filings); ii) the fund applies for AI-related patents; or iii) the fund's management team possesses AI-related expertise. Using this comprehensive approach, we identify 333 AI funds as of the end of 2023, representing 23% of the active equity mutual fund population.

Our empirical analysis yields three main findings. First, we document that AI adoption significantly alters mutual funds' information processing horizons. Following AI adoption, funds' trades exhibit a substantially stronger association with near-term earnings (1-5 quarters ahead) but a markedly weaker association with long-term earnings (9-12 quarters ahead).

This pattern persists after controlling for fund and stock characteristics and addressing endogeneity through instrumental variable approaches and quasi-natural experiments. Specifically, we exploit the introduction of transformer-based language models as an exogenous shock to AI effectiveness, finding consistent evidence of increased short-termism following this technological advancement.

Second, we find that firms with higher AI fund ownership experience significant changes in their stock price informativeness. Using measures developed by Bai et al. (2016) and the future earnings response coefficient literature (Collins et al., 1994; Lundholm and Myers, 2002; Choi et al., 2019), we document that greater AI fund ownership is associated with improved price informativeness regarding short-term earnings but reduced informativeness about long-term earnings. This suggests that AI funds' trading patterns are reshaping the informational content of stock prices, enhancing the incorporation of short-term signals while potentially degrading long-term price information.[3]

Third, we find that the investment-Q sensitivity is significantly lower for firms with higher AI fund ownership, indicating that these firms' investment decisions become less responsive to their stock prices. This finding suggests that the shift in price informativeness has real consequences for corporate decision-making, leading to decreased usefulness in guiding corporate investment decisions and potentially affecting the efficiency of capital allocation.

Our paper contributes to the literature in several ways. First, we offer novel empirical evidence on the nuanced effects of AI adoption within the asset management industry on information production in financial markets. A substantial body of research, both theoretical and empirical, posits that decreased costs of information acquisition incentivize investors

[3]One might be concerned that AI funds select firms already exhibiting these informativeness patterns. This selection hypothesis is unlikely to fully explain our results for four reasons: (1) our within-fund analysis shows that the same funds exhibit changed information processing patterns after AI adoption; (2) our results remain robust when controlling for firm fixed effects, which would absorb selection effects if they were driving the results; (3) our instrumental variables approach using funds' ex-ante exposure to AI talent and geographic distance to the nearest AI hubs provides further evidence of causality by isolating variation in AI fund ownership plausibly exogenous to firm-specific informativeness patterns; and (4) our comprehensive identification strategy fully accounts for differences in current earnings information between stocks held by AI investors and those held by traditional investors.

to produce more information (Grossman and Stiglitz, 1980; Verrecchia, 1982; Blankespoor et al., 2020). Given the pervasive evidence on the effectiveness of AI technology in financial forecasting (Gu et al., 2020; Cao et al., 2024), it might be presumed that AI adoption would uniformly enhance information production. Our study challenges this view by demonstrating that AI adoption fundamentally alters the time horizon of mutual funds' information acquisition: while it enhances the processing of short-term information, it also leads to a reduction in the production and utilization of long-term fundamental information. This temporal reallocation of attention represents a previously unexplored mechanism through which technological advancement reshapes–rather than simply augments–information production in financial markets.

Second, we contribute to the literature on stock price informativeness by showing that the influence of AI technology varies significantly with the information horizon. Bai et al. (2016) suggest that technological advancements should enhance price informativeness. Our findings introduce a crucial qualification to this narrative in the context of AI. We reveal that while AI technology may indeed enhance the incorporation of short-term information into stock prices, it can concurrently reduce price informativeness regarding firms' long-term fundamentals. This finding is critical, as a decline in long-horizon price informativeness can potentially jeopardize the role of stock prices as effective signals for efficient resource allocation in the economy (Fama, 1970; Baker et al., 2009; Bond et al., 2012).

Third, our paper establishes a direct empirical link between a specific technological innovation in asset management–AI adoption–and its tangible consequences for real corporate investment. We provide compelling evidence that firms with greater ownership by AI-adopting funds exhibit significantly lower sensitivity of their investment to Tobin's Q. This demonstrates that the AI-induced short-term focus of these influential investors is not merely an internal characteristic of their trading strategies but transmits to the real sector, materially affecting how firms respond to market signals in their capital expenditure decisions (Chen et al., 2007; Edmans et al., 2017). Our findings thus contribute fresh insights to the literature on the real effects of financial markets, illustrating a novel channel–AI-driven changes in investor horizons–through which financial technology can impact capital allocation efficiency across the economy.

The remainder of the paper proceeds as follows: Section 2 reviews the critical literature relevant to our study and develops our testable hypotheses regarding the effect of AI adoption on the mutual funds' short-termism, as well as on the stock price informativeness and real investments. We present the data and variables that we use to test these hypotheses in Section 3. In Section 4, we present our 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).

However, evidence on AI's impact on investment performance presents a more nuanced picture. Abis (2020) 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. **?** finds that mutual funds with more AI-related job postings outperform other funds. But the outperformance only exists among stocks with voluminous information. These mixed findings suggest that AI adoption may have heterogeneous effects across different market contexts and investment horizons.

## 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 (**?**Cao et al., 2024; Boyacı et al., 2024; **?**).

Our research also relates to a recent study by Dessaint et al. (2024), who demonstrate that alternative data are predominantly informative for short-term future outcomes and find that exposure to such data diminishes the informativeness of equity analysts' longer-horizon forecasts. However, our paper distinguishes itself and contributes uniquely in several important dimensions:

**Primary Focus on AI Adoption vs. Data Availability:** First, our paper's central investigation diverges significantly: Dessaint et al. (2024) analyzes the effects of alternative data availability, whereas we focus the strategic adoption of AI as a core production technology by mutual funds. While AI is an important tool for processing alternative data, our primary focus is on how the deliberate managerial decision by funds to integrate AI fundamentally reshapes their information processing incentives and overall investment behavior–a distinct and broader inquiry than the impact of access to any specific data type.

**Generalizability to and Direct Evidence from Mutual Fund Managers:** Second, we provide direct empirical evidence on the impact of AI adoption on mutual fund managers, a critically different group of market participants than the equity analysts studied by Dessaint et al. (2024). Sell-side analysts and mutual fund managers operate under distinct incentive structures, clienteles, and regulatory frameworks; notably, fund managers are pivotal capital allocators, not just information intermediaries. For example, prior research find that analysts may have limited incentives to produce accurate long-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). Therefore, insights from analyst behavior may not readily translate. Our study offers unique evidence on how AI adoption specifically reshapes the information processing horizons of these key decision-makers in capital allocation.

**Broader Consequences Beyond Analyst Forecasts:** Finally, our paper investigates more extensive capital market and real economic consequences arising from AI-induced shifts in fund managers' information horizons. While Dessaint et al. (2024) focuses on the implications for analyst forecast informativeness only, we demonstrate that the intensified short-termism among AI-adopting mutual funds has far-reaching downstream effects. Specifically, we document: (i) a significant degradation in stock price informativeness concerning firms' long-term fundamental values, with implications for overall market efficiency; and (ii) tangible real economic consequences, evidenced by a reduced sensitivity of corporate investment to Tobin's Q in firms with higher AI fund ownership. Establishing this comprehensive empirical pathway–from AI adoption by funds, through altered market-level price discovery, to shifts in corporate capital allocation–constitutes a distinct and novel contribution to understanding the full impact of AI in financial markets.

### 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.

### 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 leads to an increase in short-termism in their information processing. Specifically:

*H1: After adopting AI technology, mutual funds exhibit increased short-termism in their information processing, characterized by an increased correlation of funds' trades with near-term earnings and a weaker association with long-term earnings.*

This hypothesis is based on several theoretical mechanisms. First, AI systems excel at processing large volumes of (alternative) data sources (e.g., satellite imagery, credit card transactions, and social media) that provide timely insights about near-term business performance (Dessaint et al., 2024; Katona et al., 2025). These data sources typically yield fast-moving signals that are particularly valuable for short-term forecasting, enabling mutual funds to detect transient anomalies and exploit temporary market inefficiencies with great speed and precision. As such, AI adoption is expected to significantly improve mutual funds' capabilities in capturing and reacting to near-term informational cues.

Second, qualitative factors such as management quality, competitive dynamics, and potential structural shifts play crucial roles in long-term forecasting. Analyses of these factors often require causal reasoning, scenario analysis, and adapting to regime changes–tasks where current AI technologies face significant limitations (**?**Liu, 2022; Cao et al., 2024; Boyacı et al., 2024). Consistent with this notion, **?** observe 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 absence of sufficient training data from which machine learning algorithms could learn the relevant knowledge for valuation.

Third, and perhaps most importantly, information-processing attention is scarce and must be optimally allocated (Kacperczyk et al., 2016). If AI adoption significantly reduces the marginal cost of processing short-term information but offers less improvement for long-term analysis, fund managers face incentives to reallocate their limited time and 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 predict that the shift in information processing horizons among AI-adopting funds will affect the informational content of stock prices:

*H2: Higher AI fund ownership leads to increased stock price informativeness about short-term earnings but decreased 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, they incorporate this information into stock prices (Grossman and Stiglitz, 1980). If AI adoption shifts funds' information advantage toward short-term forecasting, as predicted in H1, this would alter the temporal distribution of information reflected in prices.

The theoretical work of Verrecchia (1982) and Goldstein and Yang (2019) supports this mechanism, showing 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 would become more informative about near-term fundamentals but potentially less informative about long-term performance.

**Hypothesis 3: AI Fund Ownership and Corporate Investment Efficiency**

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

*H3: Higher AI fund ownership leads to decreased sensitivity of corporate investment to Tobin's Q.*

This hypothesis builds on the "active informant" role of financial markets in guiding real economic decisions. 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, these prices 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.[4]

There are, however, several counterarguments that might limit or reverse the above hypothesized effects. AI tools could potentially complement human analysis, freeing up fund managers' time from routine data processing tasks and allowing them to focus more on long-term strategic analysis. Furthermore, as AI capabilities continue to advance, they may eventually overcome current limitations in causal reasoning and long-term forecasting. Finally, sophisticated fund managers might recognize the importance of maintaining long-term information advantages and deliberately ensure balanced attention across different time horizons. If these mechanisms hold, then AI adoption may not reduce–but instead enhance–mutual funds' willingness to process long-horizon information. We might observe improved price informativeness not only in the near term but also across extended horizons.

Further, even in cases where AI funds exhibit a stronger orientation toward short-term signals, heterogeneity in the equity market may still preserve overall price informativeness. In particular, if various market participants specialize in different information horizons, the market as a whole might maintain balanced informativeness, notwithstanding shifts among individual investor groups. In addition, even if the composition of information embedded in market prices gradually shifts toward the short term, corporate managers may not immediately perceive subtle changes in the horizon structure of price informativeness, thus leading them to maintain their reliance on stock price signals even as their reduced usefulness for long-term decision-making. Therefore, investment-Q sensitivity may persist despite a structural reallocation of attention among investors.

Given these competing mechanisms, whether AI adoption by mutual funds reduces long-term information acquisition, compromises stock price informativeness about long-term fun-

[4]It's worth noting that decreased 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.

damentals, and diminishes the usefulness of stock price signals for corporate investment decisions remains compelling empirical questions. We acknowledge these competing theoretical forces and allow the empirical evidence to reveal which mechanisms dominate. By testing these hypotheses, we aim to provide new insights into whether AI-adoption by mutual funds has unintended consequences in private information acquisition and the informational and functional efficiency of market prices.

# 3 Data and Measurement

## 3.1 Sample and Data

We begin by obtaining mutual fund groups' Central Index Keys (CIKs) from the CRSP CIK Map file. The CIK serves as a unique identifier for fund groups. Next, we use these CIKs to download fund-specific summary prospectuses (filing type 497-K) for U.S. mutual funds filed between 2010 and 2023 from the SEC's EDGAR database.[5] Using the CIK and Series ID, we are able to link each 497-K file to the CRSP Survivorship Bias Free Mutual Fund Database. Subsequently, we match the mutual funds to the CRSP-USPTO link table provided by Stoffman et al. (2022), using the permco code in CRSP. For mutual funds without permco code, we supplement the patent information by searching the names of mutual funds and their advisory firms in the USPTO using a Python script. Further, we collect the biographical information of mutual fund management teams from Morningstar. We merge these diverse data sources into a unified dataset, which we refer to as the EDGAR-CRSP-USPTO-Morningstar-based sample.

We next use the WRDS MFLINKS file to merge the EDGAR-CRSP-USPTO-Morningstar-based sample with quarterly institutional equity holdings from the Thomson-Reuters mutual fund holdings (S12) database. The database contains quarter-end security holding information for all registered mutual funds that report their holdings to the U.S. Securities and

[5]The 497K filings are available in EDGAR system only from 2010 onward.

Exchange Commission. Since we focus our analysis on U.S. active equity funds, for which the holdings data are most complete and reliable, we remove index, annuity, ETF, money market, and bond funds through either the CRSP flag or strings in the fund name.[6] We also require 80% of assets under management to be in common stocks. To mitigate potential incubation bias, we remove observations where the observation year predates the fund's starting year or the fund name is not provided (Evans, 2010). We additionally remove international funds from countries that are not in the U.S., and finally, we exclude funds with a total net asset value (TNA) of less than $10 million. Finally, we obtain our stock return data from CRSP, accounting data from Compustat, and analyst data from I/B/E/S. We require that the observations in our sample have no missing values in the future one-quarter ahead earnings. Our final sample consists of 2,415 U.S. active equity mutual funds and 7,688 distinct stocks.

## 3.2 Main Variable Construction

### 3.2.1 Identifying AI Funds

We develop a comprehensive approach that identifies AI-adopting funds through three dimensions:

$$AIFund_{f,t} = I[PIS_{f,t}] \vee I[Pat_{f,t}] \vee I[Exp_{f,t}] \tag{1}$$

where $I[\cdot]$ is an indicator function. $I[PIS]$ equals one if the fund explicitly mentions AI technologies in Section PIS (Principal Investment Strategies) in the 497K filings, and zero otherwise. $I[Pat]$ equals one if the fund has AI-related patents, and zero otherwise. $I[Exp]$ equals one if the fund's management team possesses relevant expertise in the AI area, and zero otherwise. The economic implication of Eq. (1) is that we will classify a fund as an AI

[6] We remove funds which contain 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'.

fund if it meets at least one of these conditions[7].

### 3.2.2 Measuring The Short-Termism of Mutual Funds

We identify a mutual fund's short-termism by examining the fundamental informativeness of its trading activity across different forecasting horizons. Conceptually, short-termism reflects the fund's strategic allocation of attention and resources toward shorter-horizon signals. Thus, 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:

$$EA_{j,t+h} = \alpha + \beta_1 Trading_{f,j,t} + \beta_2 EA_{j,t} + \gamma X_{f,j,t} + \phi_{fj} + \lambda_t + \epsilon_{f,j,t+h} \tag{2}$$

where $EA_{j,t+h}$ is the future realized earnings of firm $j$ in period $t+h$, scaled by total assets in period $t$. We use earnings before interest and taxes (EBIT) to proxy the firm's earnings.[8] The term $Trading_{f,j,t}$ represents 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 fund $f$ in period $t-1$. We include current earnings ($EA_{j,t}$) as a control in the model. This allows us to isolate trading activity driven by expectations of future fundamental performance from trading that might simply reflect reactions to contemporaneous or recently realized earnings. Our empirical analysis examines 12 different forecasting horizons, spanning three years, denoted as: $h = 1 - 12$ quarters. If a fund becomes more short-term oriented, its trading would have an improved association with future short-term earnings while a decreased association with future long-term earnings, leading to a larger coefficient $\beta_1$ on $Trading_{f,j,t}$ for the short-term horizon but a smaller one for the long-term horizon.

[7] This multifaceted approach allows us to identify AI funds that might otherwise be overlooked. For instance, some funds may not explicitly mention AI technologies in their publicly stated investment strategies, even though they hold AI-related patents or their management team has expertise in AI.

[8] For robustness checks, we also use earnings before interest, taxes, depreciation, and amortization (EBITDA) and net income (NI) as alternative measures for the stock's earnings. The results are similar both qualitatively and quantitatively.

## 3.3 Summary Statistics

Figure 1 illustrates the evolution of AI funds. Panel A shows that the number of AI funds has risen from almost zero in 2010 to 333 in year 2023, representing more than 23% of the population. Panel B plots the amount of assets under management (AUM), showing that AUMs of AI funds also increase substantially over the sample period. In 2023, AI funds manage total assets of approximately $3,600 billion, representing roughly 13% of the total AUM of the industry, compared to only about 5% prior to 2010.

Table 1 presents summary statistics for the main variables in the baseline analysis. The mean value of the fund-stock-quarter-level variable Trading is about 0.1%, however, the dispersion of Trading is large (standard deviation of 0.3%). For the fund-quarter level variable, AI funds account for an average of 12.6% of all funds, and the funds in the sample manage about $596.1 million in assets, with an average age of over 12 years (51.1 quarters).

In addition, the funds in the sample hold an average of 119.9 stocks and adjust about 62% of their portfolios over a quarter. For the stock-quarter-level variables, the average percentage of outstanding shares held by AI funds in our sample is about 3.2%, the stock has an average asset size of approximately $11.6 billion, a financial leverage ratio of 57.6%, an ROE of 1.3%, a book-to-market ratio of 2.439, a quarterly sales growth rate of 4.1%, and is tracked by 10.2 analysts.

# 4 Empirical Results

## 4.1 Descriptive Results

We begin by showing the bin-scatter relation between current trading activity ($Trading_{f,j,t}$) and stocks' future realized earnings across different time horizons ($EA_{j,t+h}$), separately for AI funds and traditional funds. Figure 2 shows that in the short-run panels (Horizons 1–5), the slope of the fitted line for AI funds is consistently steeper relative to that of traditional funds. However, as the time horizon extends beyond six quarters (Horizons 7–12), this pattern reverses. The association between active trading and future realized earnings becomes weaker–and in some cases negative–for AI funds, while it remains relatively stable for traditional funds.

We further directly illustrate the difference in information processing horizons between AI funds and traditional funds. To do so, we first de-mean all variables by fund-stock pair to remove the fund-stock fixed effects over the sample period and then estimate a cross-sectional regression of future h-period earnings on Trading in each quarter (as shown in Eq. (2)), separately for AI funds and traditional funds. We visualize the quarterly slopes of AI funds and traditional funds over different forecasting horizons in Figure 3. The results align with Figure 2: AI funds exhibit systematically higher short-term information processing performance than traditional funds, particularly over horizons of one to five quarters. However, as the forecast horizon extends beyond six quarters, the information processing performance of AI funds diminishes, and their slopes become progressively lower compared to those of traditional funds.

## 4.2 Regression Analysis of AI Adoption and Mutual Fund Short-Termism

To formally test whether the short-termism of AI funds is statistically significant, we estimate the following ordinary least squares (OLS) regression models:

$$\begin{aligned} EA_{j,t+h} = \alpha + \beta_1 AIFund_{f,t} \times Trading_{f,j,t} + \beta_2 AIFund_{f,t} + \beta_3 Trading_{f,j,t} + \beta_4 EA_{j,t} \\ + \beta_5 StockControl_{j,t} + \beta_6 FundControl_{f,t} + \phi_{fj} + \lambda_t + \epsilon_{f,j,t+h} \end{aligned} \tag{3}$$

where $AIFund_{f,t}$ is a dummy variable that equals one if the mutual fund $f$ is labeled as AI-adopted fund in quarter $t$. Variables $EA_{j,t+h}$ and $Trading_{f,j,t}$ are defined the same as before. $StockControl_{j,t}$ is a vector of stock-quarter level control variables intended to capture firms' fundamental characteristics and information environments (Zhu, 2019), including Size, Lev, Roe, Growth, BTM, and Analysts. $FundControl_{f,t}$ is a vector of fund-quarter level control variables that account for fund-specific management behavior and style (Jiang et al., 2007; Bonelli and Foucault, 2024), including Tna, Age, Nb. Stocks and Turnover. We also include the fund-stock fixed effects $\phi_{fj}$, and year-quarter fixed effects $\lambda_t$[9]. Standard errors are double-clustered at the fund and stock levels to account for potential cross-sectional and temporal correlation in the residuals.

The coefficient of interest is $\beta_1$, which measures the extent to which a fund's information processing horizon in a given stock is affected by the AI adoption. Our first hypothesis, H1, predicts that AI adoption will lead to increased short-termism in mutual funds, implying that $\beta_1$ will change from positive to negative as forecasting horizon increases.

Table 2 reports the estimation results for Eq. (3). Panel A presents regressions that include only fund-stock and year-quarter fixed effects, while Panel B augments the model with both fund-level and stock-level control variables. Across all specifications, the results consistently indicate the presence of short-termism among AI funds. Specifically, the coefficients on $AIFund \times Trading$ are all positive and significant in the short term ($h = 1-5$), but negative and partially significant in the long run ($h = 9-12$). These findings are consistent with the notion that AI adoption enhances funds' preference to exploit short-term informational advantages, but may simultaneously exacerbate their performance in processing upon long-term fundamental information.

## 4.3 Addressing Endogeneity

### 4.3.1 Instrumental Variable Approach

While our baseline findings suggest a positive association between AI adoption and mutual fund short-termism, concerns may persist that fixed effects alone cannot fully address endogeneity. To better establish the causal relationship, we first adopt an instrumental variable

[9]Results are robust and similar when we use fund- and stock fixed effects

approach by utilizing two plausibly exogenous instrumental variables that affect the tendency of mutual funds to adopt AI technologies. This approach allows us to isolate the causal impact of AI technologies on investment horizon choices.

First, we follow Babina et al. (2024) to instrument AIFund with:

$$AI\_Talent\_Exposure_f = \sum_u Manager_{f,u}^{2010q1} \times AIstrong_u \tag{4}$$

where $Manager_{f,u}^{2010q1}$ is the managers in fund $f$ in 2010Q1 who graduated from university $u$, and $AIstrong_u$ equals one if university $u$ is identified as an AI-strong university based on the number of AI researchers prior to 2010Q1.[10]

This IV exploits the fact that AI talent scarcity constrains adoption (Acemoglu et al., 2022; Babina et al., 2024; Law and Shen, 2024). Funds with stronger alumni ties to AI-strong universities in 2010Q1 were better positioned to recruit AI talent in the 2010s, independent of their inherent short-termism.

Our second instrumental variable is the geographic distance from the mutual funds to the nearest AI hubs. To construct this variable, we utilize the list of AI hubs compiled by CSET (Center for Security and Emerging Technology) and the 5-digit zip codes of fund companies provided by CRSP.[11] More specifically, we use Python's geopy library to convert the 5-digit zip codes of mutual funds into latitude and longitude, and then we calculate

[10]Following Babina et al. (2024), we define a university as AI strong if it meets one of the following two criteria for at least one year prior to 2010: either (i) the number of AI researchers ranks in the top 5% of the distribution of all universities for the given year; or (ii) the number of AI researchers ranks in the top 10% of the distribution of all universities for the given year and the percentage of AI researchers share (number of AI researchers divided by the number of other researchers) ranks in the top 5% of the distribution of all universities for the given year. An AI researcher is defined as a researcher who has published papers in AI-related journals and conference proceedings.

[11]CSET defines AI hubs based on the following criteria: (a) AI top universities. CSET compiles a list of the top 30 AI and Computer Science programs in the nation using US News and World Report's top 20 AI programs list, supplemented with CS Rankings' top AI computer science programs list. (b) AI companies. CSET identifies AI companies through a query on all companies in Crunchbase and Refinitiv's databases. The query utilized a keyword search within each company's description. (c) AI talents. CSET identifies professionals with AI-related skills through a LinkedIn Talent Insights Talent Pool Report. (d) AI investments. CSET views only U.S.- and Chines based investors funding U.S.-based AI companies through funding rounds and company acquisitions, and matches AI companies to investments in Crunchbase through the companies' Crunchbase URLs.

the distances between mutual funds and the closest AI hubs based on Vincenty's reference ellipsoid formula.

The geographic proximity instrumental variable offers intuitive appeal on both theoretical and exclusionary grounds. Proximity to AI hubs reduces adoption barriers by facilitating knowledge spillovers, collaborative networks, and access to specialized talent pools (e.g., research institutes, AI startups, and technical vendors). These channels lower information acquisition costs and accelerate technology diffusion among nearby funds (Hunt et al., 2024), making AI adoption more likely for funds near hubs. Crucially, the instrument satisfies the exclusion restriction: AI hub locations are determined by regional infrastructure, academic institutions, and agglomeration economies–factors orthogonal to fund-specific attributes like investment horizons or managerial styles. Consequently, geographic distance is unlikely to directly influence funds' short-termism beyond its effect through AI adoption.

We implement a three-stage probit-2SLS procedure to deal with the binary nature of our endogenous variable AIFund (Adams et al., 2009; Angrist and Pischke, 2009; Deng et al., 2022). Specifically, (a) in the first probit estimation stage, the adoption of AI technologies is determined by funds' ex-ante exposure to AI talents (geographic distance to the nearest AI hubs, or both) and other fund-level variables. (b) Then, we use the predicted probability $\widehat{AIFund}$ as an instrument in the first stage of the 2SLS procedure. (c) Finally, the second-stage 2SLS regression estimates the effect of AI adoption on future h-period earnings forecasting performance, using the fitted values from the first-stage 2SLS along with control variables.

Table 3 reports the three-stage probit-2SLS results. Consistent with expectations, Panel A shows a statistically significant positive coefficient (1% level) on AI Talent Exposure (Column 1), confirming that prior ties to AI-strong universities increase AI adoption likelihood. Similarly, the negative and significant coefficient on Distance to AI Hubs (Column 3) supports the role of geographic proximity in facilitating adoption. Strong first-stage statistics (probit Chi-square, 2SLS F-statistics) alleviate weak instrument concerns. When both instruments are used jointly (Column 5), coefficients retain expected signs and significance. The Sargan test (Sargan, 1958) fails to reject the null hypothesis of valid instruments, supporting their joint exogeneity.

Panels B, C, and D of Table 3 present the second-stage 2SLS estimation results. In particular, Panel B uses AI Talent Exposure as the sole instrument; Panel C uses Distance to AI Hubs as the sole instrument; and Panel D uses both instruments jointly. Across all specifications, the findings are consistent: AI adoption significantly improves the relation between mutual fund trading activity and short-term fundamentals and impairs its association with long-term fundamentals. Collectively, the three-stage probit-2SLS results lend strong support to our baseline findings. The results suggest that the observed short-termism in mutual funds is indeed causally driven by the adoption of AI technologies, rather than by omitted variables or selection effects. Our university- and geography-based IVs provide a credible empirical basis for establishing the causal impact of AI adoption on mutual fund short-termism.

#### 4.3.2 Quasi-natural Experiments

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

**The Release of the Transformer Architecture.**

The Transformer (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, Transformer's release would exogenously improve the technical capabilities of AI-adopting funds. 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 difference-in-difference (DiD) regression framework. The DiD sample period spans from 2016Q3 to 2018Q2, covering one year before and after the Transformer shock. The DiD regression is specified as follows:

$$\begin{aligned} EA_{j,t+h} = \alpha &+ \beta_1 AIFund_f^{2017Q3} \times TF_t \times Trading_{f,j,t} + \beta_2 AIFund_f^{2017Q3} \times TF_t \\ &+ \beta_3 AIFund_f^{2017Q3} \times Trading_{f,j,t} + \beta_4 TF_t \times Trading_{f,j,t} + \beta_5 Trading_{f,j,t} \\ &+ \beta_6 EA_{j,t} + \gamma StockControl_{j,t} + \delta FundControl_{f,t} + \phi_{fj} + \lambda_t + \epsilon_{f,j,t+h} \end{aligned} \tag{5}$$

where $AIFund_f^{2017Q3}$ is a dummy variable that takes a value of one if mutual funds are labeled as AI funds in 2017Q3, and zero otherwise. $TF$ is a dummy variable that takes a value of one after the Transformer model was released (2017Q3 onwards), and is set to zero from 2016Q3 to 2017Q2. Other variables are defined in Eq. (3). 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 $\beta_1$ for the short horizon while a negative one for long horizons.

Table 4 presents the DiD estimation results based on the Transformer event. Consistent with our hypothesis, we find that $\beta_1$ is positive for all the short-term horizon and the coefficients are statistically significant for horizon= 2 and 3. However, over longer horizons, this short-term advantage reverses: coefficient turns to negative for horizons between 9 and 12 and statistically negative for the tenth and twelfth quarter horizons. These findings provide strong evidence that the advances of AI technologies enhance the association between fund's active trading and short-term earnings but reduce its' association with long-term earnings.

**The Staggered Introduction of The Satellite Imaging Data.**

As a second quasi-natural experiment, we leverage the staggered introduction of satellite imaging data coverage across different geographical areas and time periods. Satellite imagery has become an increasingly important input for AI-powered investment strategies, as it provides real-time insights into economic activity that can be processed using machine learning algorithms (Katona et al., 2025). However, the availability of high-quality satellite data for investment purposes has expanded gradually and varies geographically, creating plausibly exogenous variation in AI effectiveness across firms and time.

We construct our identification strategy around the staggered rollout of commercial satellite data coverage. Using data from major satellite imagery providers, we identify when different geographical regions 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 firm headquarters location) and over time (by the timing of satellite coverage initiation).

We implement the following difference-in-differences specification:

$$\begin{aligned} EA_{j,t+h} = \alpha &+ \beta_1 AIFund_{f,t} \times SatCoverage_{j,t} \times Trading_{f,j,t} \\ &+ \beta_2 AIFund_{f,t} \times SatCoverage_{j,t} + \beta_3 AIFund_{f,t} \times Trading_{f,j,t} \\ &+ \beta_4 SatCoverage_{j,t} \times Trading_{f,j,t} + \beta_5 Trading_{f,j,t} + \beta_6 EA_{j,t} \\ &+ \gamma StockControl_{j,t} + \delta FundControl_{f,t} + \phi_{fj} + \lambda_t + \epsilon_{f,j,t+h} \end{aligned} \tag{6}$$

where $SatCoverage_{j,t}$ is an indicator variable that equals one if firm $j$'s headquarters location has satellite coverage available for investment analysis in quarter $t$, and zero otherwise. The coefficient of interest is $\beta_1$, which captures the differential impact on AI funds' information processing when satellite data becomes available for firms they analyze.

The key identifying assumption is that the timing of satellite coverage rollout is uncorrelated with fund-specific or firm-specific characteristics that would independently affect information processing horizons. This assumption is plausible because satellite coverage expansion is primarily driven by technical and commercial considerations of satellite operators, rather than characteristics of individual mutual funds or their portfolio companies.

Our results, shown in Table 4 Panel B, demonstrate that the introduction of satellite coverage enhances AI funds' short-term information processing capabilities relative to traditional funds. The coefficient on the triple interaction $AIFund \times SatCoverage \times Trading$ is positive and significant for short-term horizons (quarters 1-5) but becomes negative for longer horizons (quarters 9-12). This pattern is consistent with our main hypothesis that improved AI capabilities exacerbate short-termism in information processing, as satellite data primarily provides insights relevant for near-term business performance rather than long-term fundamental value.

## 4.4 AI Investors 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 industries affects the price formation and efficiency on the capital markets. Since stock prices are determined by the 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.

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 1-12 quarters, 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:

$$\begin{aligned} EA_{j,t+h} = \alpha &+ \beta_1 AIown_{j,t} \times \log MA_{j,t} + \beta_2 AIown_{j,t} + \beta_3 \log MA_{j,t} + \beta_4 EA_{j,t} \\ &+ \gamma StockControl_{j,t} + \phi_j + \lambda_t + \epsilon_{j,t+h} \end{aligned} \tag{7}$$

where $\log MA_{j,t}$ indicates log (market value (stock price $\times$ common shares) of stock $j$ in period $t$ scaled by total assets of stock $j$ in period $t$). Since this is a stock-quarter-level analysis, we construct the variable $AIown$ by calculating the percentage of AI investors' holdings in stocks.[12] We also add stock-quarter-level control variables, stock fixed effects, and year-quarter fixed effects to the model. The standard errors are double clustered at the stock and year-quarter level. The coefficient of interest is $\beta_1$, which captures the variation in price informativeness brought by the ownership by AI-adopting funds.

Additionally, we utilize the relation between current stock returns and future earnings (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).

$$Return_{j,t} = \alpha + \sum_{h=1}^{12} \beta_h AIown_{j,t} \times EA_{j,t+h} + \text{controls} + \phi_j + \lambda_t + \epsilon_{j,t} \tag{8}$$

where $Return_{j,t}$ is the quarterly log returns for stock $j$. The greater AI investors' performance in estimating earnings in period $t+h$, the larger the FERC (i.e., $\beta_1$), indicating that the AI investors make current stock returns more informative about earnings in period $t+h$.

The OLS estimation results for Eq. (6) are reported in Panel A of Table 5. We find that the coefficient of $AIown_{j,t} \times \log MA_{j,t}$ is positive and statistically significant for short-term earnings ($\beta_1 = 0.021$; t-stats=2.87 in column (1)), whereas it is negative and statistically significant for long-term earnings ($\beta_1 = -0.020$; t-stats=-1.77 in column (11)). Similarly, for the estimation results of Eq. (7) in Table 6, the coefficient of $AIown_{j,t} \times EA_{j,t+4}$ is significantly positive for current stock returns ($\beta_1 = 1.284$; t-stats=2.43), while the coefficient of $AIown_{j,t} \times EA_{j,t+9}$ is significantly negative ($\beta_1 = -0.967$; t-stats=2.32). These results align with the documented short-termism of AI funds in Table 2, suggesting that the bias

[12] We also include in our price informativeness and investment-Q sensitivity tests a second measure of AI investors ownership – the number of AI funds that own the stock. This alternative measure captures the breadth of AI fund participation and reduces the influence of extreme values driven by a few large fund positions, the results are reported in the robustness tests, and our results are robust.

in AI investors' short-termism leads to stock prices incorporating more short-term earnings information and less long-term earnings information.

To further establish causality, we aggregate the AI Talent Exposure and Distance to AI hubs for each fund to the stock-quarter level to measure the overall exposure of AI investors 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 shows that the coefficient of AI Talent Exposure on $AIown$ is positive and statistically significant. This indicates that investors' ex ante exposure to AI-trained graduates is strongly correlated with their adoption of AI technology. Further, the coefficient of Distance to AI hubs on $AIown$ is negative and significant at the 1% level, suggesting that the closer an investor is geographically to AI hubs, the more likely she is to be an AI investor. The second-stage 2SLS results, reported in Panels B of Table 5 and Column (2) of Table 6, confirm our primary findings: 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. These results provide additional causal evidence that the rise of AI investors' ownership fundamentally alters the term structure of information impounded into stock prices.

### 4.5 AI Investors and Capital Allocation Efficiency

The feedback effect literature suggests that managers use stock prices as a signal when making long-term investment decision (Hirshleifer, 1958; Chen et al., 2007). 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 in making their investment decisions. We examine this conjecture by testing investment-Q sensitivity:

$$
\begin{aligned}
Investment_{j,t+1} = \alpha + \beta_1 AIown_{j,t} \times Q_{j,t} + \beta_2 AIown_{j,t} + \beta_3 Q_{j,t} \\
+ \gamma StockControl_{j,t} + \phi_j + \lambda_t + \epsilon_{j,t+1}
\end{aligned}
\tag{9}
$$

where the umbrella term $Investment_{j,t+1}$ is the investment expenditure of stock $j$ in period $t+1$, which encapsulates the five different measures: R&D expenditure (RD), capital expenditure (Capx), R&D and net investment (RDNetInv), R&D and capital expenditure (RDCapx), and capital expenditure and net investment (CapxNetInv), 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 reduce the stock price informativness regarding to long-term fundamentals and therefore rely less on the noisy stock prices in their investment decisions, we would expect the coefficient $\beta_1$ to be negative.

We report the regression results of Eq. (8) in Panel A of Table 7. Consistent with the prediction of hypothesis 3, we find that the estimated coefficients of the interaction term (i.e. $\beta_1$) are all negative and significant at less than 1% level. We obtain similar results using 2SLS estimations, which are reported in Panel B of Table 7. The results are consistent with the notion that the adoption of AI technology reduce funds' acquisition of long-term fundamental information, which in turn reduce the amount of long-term information incorporated into stock prices, and therefore make them a less useful signal for making long-term investment decisions.

# 5 Conclusion

Motivated by the growing integration of AI technologies in mutual fund operations, this paper examines whether AI adoption induce short-termism in mutual fund information acquisition. This investigation is grounded in evidence suggesting AI disproportionately reduces the costs of short-term information processing, thereby altering how funds allocate effort between short-term and long-term forecasting tasks.

Our empirical analysis establishes that AI adoption systematically amplifies short-termism among active mutual fund managers. We document that AI funds exhibit significantly stronger sensitivity to short-term fundamentals but weaker associations with long-term fundamentals. These findings withstand rigorous identification tests, including instrumental variable approaches leveraging funds' ex ante exposure to AI talent and geographic proximity to AI hubs. Crucially, quasi-natural experiments – exploiting the exogenous release of the Transformer architecture and the staggered introduction of satellite imaging data – confirm that technological shocks enhancing AI capabilities intensify short-term trading behavior.

Beyond fund-level behavior, we uncover broader market consequences: stocks under high AI fund ownership exhibit price informativeness distortions, with a greater incorporation of short-term earnings information at the expense of long-term fundamentals. This horizon distortion manifests in real economic outcomes, as evidenced by a significant decline in investment-Tobin's Q sensitivity among affected firms. This indicates corporate managers make suboptimal investment decisions when responding to AI-distorted price signals. Our study contributes the first causal evidence linking AI adoption to investor short-termism and its market-wide externalities. We bridge technological innovation with asset pricing dynamics and corporate finance outcomes, revealing how efficiency gains in information processing might inadvertently distort price efficiency and capital allocation efficiency.

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# A Variable Definitions

| Variable | Definition | Data Source |
|---|---|---|
| **Dependent Variables** | | |
| EA[t+h] | The ratio of the stock's earnings before interest and taxes (EBIT) in period t+h to total assets in period t | Compustat |
| Return | Quarterly stock return, Log (closing stock price in period t/closing stock price in period t-1) | CRSP |
| RD[t+1] | Ratio of R&D expenditure in period t+1 to total assets in period t | Compustat |
| CapEx[t+1] | Ratio of capital expenditure in period t+1 to total assets in period t | Compustat |
| RD+NetInv[t+1] | Ratio of R&D expenditure and change in Net Property, Plant, and Equipment in period t+1 to total assets in period t | Compustat |
| RD+CapEx[t+1] | Ratio of R&D expenditure and capital expenditure in period t+1 to total assets in period t | Compustat |
| CapEx+NetInv[t+1] | Ratio of capital expenditure and change in Net Property, Plant, and Equipment in period t+1 to total assets in period t | Compustat |
| **Independent Variables** | | |
| AIFund | A dummy variable that takes a value of one if the fund is labeled as an AI-adopted mutual fund, and zero otherwise | EDGAR SEC 497-K filings; USPTO; Morningstar; CRSP; Thomson-Reuters |

Continued on next page

**Table A1 – continued from previous page**

| Variable | Definition | Data Source |
|---|---|---|
| Trading | 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 fund f in period t-1 | CRSP; Thomson-Reuters |
| AI Talent Exposure | Mutual funds' ex-ante exposure to the supply of AI-trained graduates from universities historically strong in AI | Morningstar; Babina et al. (2024) |
| Distance to AI Hubs | The closest distance of the fund company to AI hubs | CRSP; CSET |
| $\text{AIFund}^{2017Q3}$ | A dummy variable that takes the value of 1 if the fund is labeled as an AI-adopted mutual fund in 2017Q3, and zero otherwise | EDGAR SEC 497-K filings; USPTO; Morningstar; CRSP; Thomson-Reuters |
| TF | A dummy variable that takes the value of 1 after the Transformer architecture was released (2017Q3 onwards) and is set to zero from 2016Q3 to 2017Q2 | / |
| SatCoverage | A dummy variable that takes the value of 1 if the firm's headquarters location has satellite coverage available for investment analysis in quarter t, and zero otherwise | Satellite imagery providers |
| AIown | The ratio of the common shares held by AI funds in period t to total shares outstanding in period t | EDGAR SEC 497-K filings; USPTO; Morningstar; CRSP; Thomson-Reuters |
| Log MA | Log (The market value 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 |

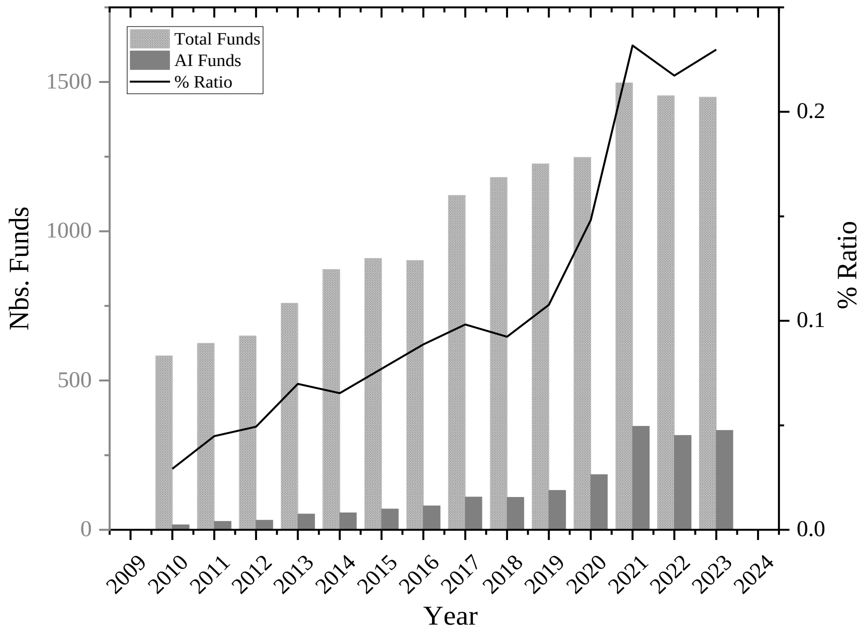
Continued on next page

**Table A1 – continued from previous page**

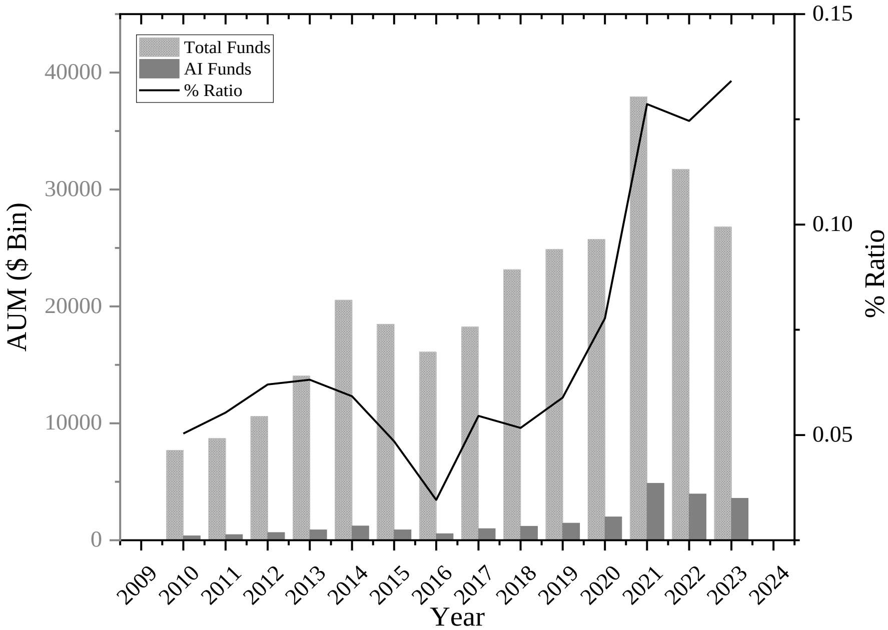
| Variable | Definition | Data Source |
|---|---|---|
| **Control Variables** | | |
| Size | Log (total assets) | Compustat |
| Lev | Ratio of total liabilities to total assets | Compustat |
| ROE | Ratio of net income to average equity value | Compustat |
| Growth | Ratio of change in sales in period t to sales in period t-1 | Compustat |
| BTM | Ratio of book value to market value | Compustat |
| Analysts | 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 |
| Age | Log (current year-quarter - established year-quarter + 1) | CRSP |
| Nb. Stocks | Log (Number of firms held by the fund) | CRSP |
| Turnover | 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), Thomson-Reuters (mutual fund holdings), I/B/E/S (analyst coverage), EDGAR SEC filings (497-K forms), USPTO (patent data), Morningstar (manager biographical information), and CSET (Center for Security and Emerging Technology for AI hub locations). The sample period covers 2010Q1 to 2023Q4 and includes 2,415 U.S. active equity mutual funds holding 7,688 distinct stocks.

Figure 1: Evolution of AI Fund Adoption Over Time



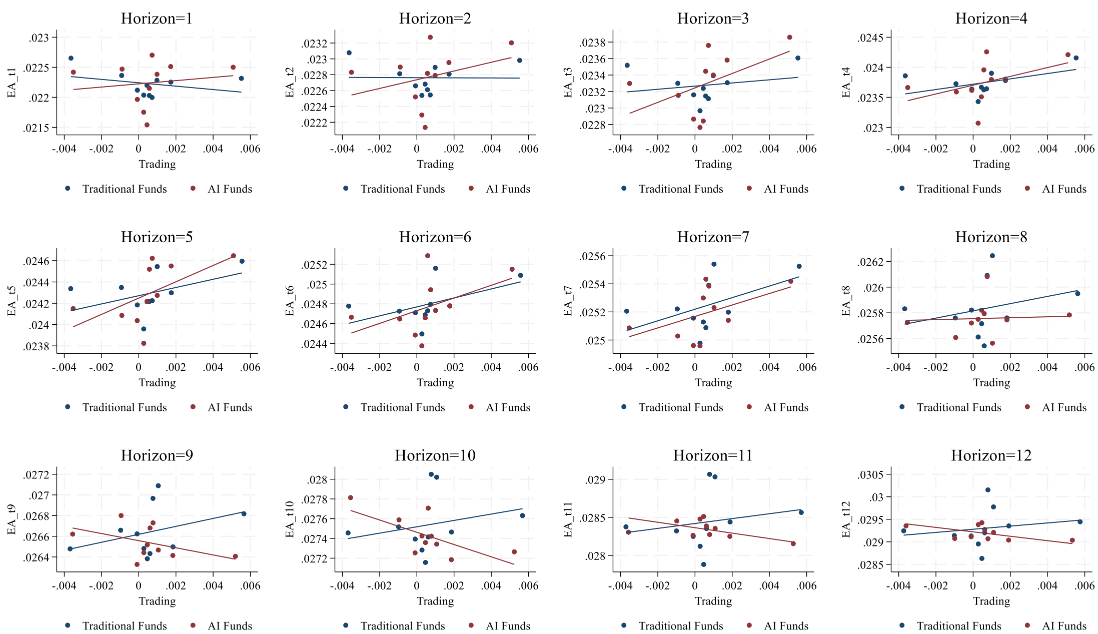

**Panel A:** Number of AI Funds




**Panel B:** Assets Under Management

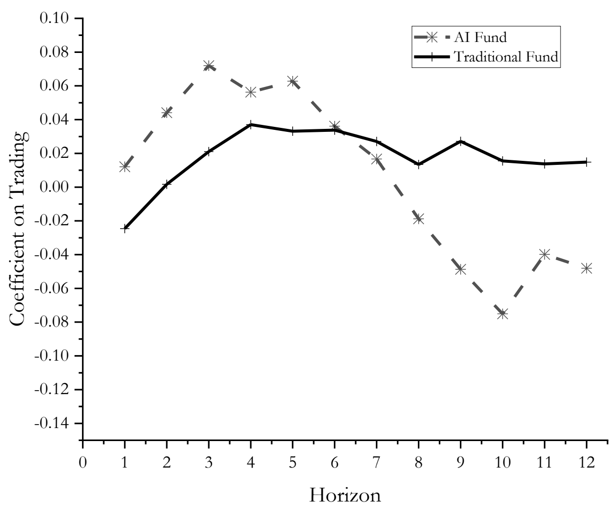
**Notes:** This figure plots the time series evolution of AI fund adoption from 2010 to 2023. Panel A shows the number of AI funds and all funds in our sample. Panel B shows the assets under management (AUM) of AI funds and all funds. AI funds are identified using our comprehensive approach combining textual analysis of 497-K filings, patent records, and managerial expertise. The sample includes 2,415 U.S. active equity mutual funds.

Figure 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 realized earnings ($EA_{j,t+h}$) across different forecasting horizons (1-12 quarters ahead), separately for AI funds and traditional funds. Trading is the split-adjusted trading value scaled by total portfolio value. Future earnings are measured as EBIT scaled by total assets. The analysis includes fund-stock and year-quarter fixed effects. The sample period is 2010-2023.

Figure 3: Information Processing Performance Across Horizons




**Notes:** This figure plots the average coefficients on $Trading_{f,j,t}$ from quarterly cross-sectional regressions of future earnings on trading activity, estimated separately for AI funds and traditional funds across different forecasting horizons (1-12 quarters). Variables are de-meaned by fund-stock pair to remove fixed effects. The analysis shows AI funds' superior short-term information processing performance (quarters 1-5) and deteriorating long-term performance (quarters 6-12) relative to traditional funds.

Table 1: Summary Statistics

| Variable | N | Mean | Std Dev | P25 | P50 | P75 |
|---|---|---|---|---|---|---|
| **Panel A: Fund-Stock-Quarter Level** | | | | | | |
| Trading (%) | 3,927,347 | 0.10 | 0.30 | 0.00 | 0.00 | 0.10 |
| **Panel B: Fund-Quarter Level** | | | | | | |
| AIFund | 50,290 | 0.126 | 0.332 | 0 | 0 | 0 |
| TNA ($million) | 50,290 | 596.1 | 1,739.9 | 48.6 | 109.7 | 301.6 |
| Age (quarters) | 50,290 | 51.1 | 30.9 | 28 | 47 | 67 |
| Nb. Stocks | 50,290 | 119.9 | 241.4 | 32 | 54 | 97 |
| Turnover | 50,290 | 0.621 | 0.598 | 0.250 | 0.450 | 0.770 |
| **Panel C: Stock-Quarter Level** | | | | | | |
| AIown (%) | 180,935 | 3.2 | 6.7 | 0 | 0.4 | 3.1 |
| EA[t] | 181,009 | 1.9 | 4.7 | 0.4 | 1.7 | 3.4 |
| Size ($billion) | 181,009 | 11.6 | 30.5 | 0.5 | 1.9 | 6.8 |
| Leverage | 181,009 | 0.576 | 0.257 | 0.389 | 0.571 | 0.766 |
| ROE | 181,009 | 1.3 | 13.9 | -0.2 | 2.2 | 4.4 |
| Growth | 181,009 | 4.1 | 22.5 | -4.4 | 2.1 | 9.4 |
| BTM | 181,009 | 2.439 | 3.369 | 0.576 | 1.155 | 2.484 |
| Analysts | 181,009 | 10.2 | 8.0 | 4 | 8 | 14 |
| MA | 181,009 | 1.526 | 4.678 | 0.402 | 0.866 | 1.735 |
| Return | 181,008 | 0.000 | 0.253 | -0.099 | 0.016 | 0.123 |
| Tobin's Q | 181,009 | 2.112 | 5.103 | 1.047 | 1.412 | 2.237 |
| R&D[t+1] | 181,009 | 0.9 | 2.3 | 0.0 | 0.0 | 0.7 |
| CapEx[t+1] | 177,915 | 2.3 | 3.8 | 0.2 | 1.1 | 2.8 |
| R&D+NetInv[t+1] | 171,369 | 1.5 | 4.2 | 0.0 | 0.4 | 2.1 |
| R&D+CapEx[t+1] | 177,915 | 3.3 | 4.5 | 0.4 | 1.9 | 4.5 |
| CapEx+NetInv[t+1] | 168,783 | 3.0 | 5.8 | 0.2 | 1.2 | 3.6 |

**Notes:** This table presents summary statistics for the main variables. The sample includes 2,415 U.S. active equity mutual funds holding 7,688 distinct stocks from 2010Q1 to 2023Q4. Panel A shows fund-stock-quarter level variables, Panel B shows fund-quarter level variables, and Panel C shows stock-quarter level variables. Trading is split-adjusted trading value scaled by total portfolio value. AIFund indicates AI-adopting funds. AIown is percentage of shares held by AI funds. EA[t] represents current earnings before interest and taxes, scaled by total assets. Size is total assets in billions. MA is market-to-assets ratio. Investment variables are scaled by lagged total assets and expressed in percentage points. All variables are defined in Appendix A.

Table 2: AI Adoption and Mutual Fund Short-Termism

| | Dependent Variable: $EA_{j,t+h}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Horizon | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| **Panel A: No Controls** | | | | | | | | | | | | |
| $AIFund \times Trading$ | 0.035** | 0.043*** | 0.056*** | 0.015 | 0.033* | 0.023 | 0.006 | -0.017 | -0.059*** | -0.072*** | -0.041 | -0.053* |
| | (2.40) | (2.74) | (3.42) | (0.89) | (1.82) | (1.19) | (0.31) | (-0.81) | (-2.69) | (-2.95) | (-1.61) | (-1.88) |
| Fund-stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | No | No | No | No | No | No | No | No | No | No | No | No |
| Observations (millions) | 3.93 | 3.90 | 3.87 | 3.79 | 3.66 | 3.50 | 3.34 | 3.18 | 3.04 | 2.88 | 2.73 | 2.57 |
| Adj. R-squared | 0.635 | 0.619 | 0.618 | 0.633 | 0.613 | 0.610 | 0.610 | 0.616 | 0.613 | 0.613 | 0.613 | 0.621 |
| **Panel B: With Controls** | | | | | | | | | | | | |
| $AIFund \times Trading$ | 0.033** | 0.039** | 0.051*** | 0.013 | 0.030* | 0.016 | -0.000 | -0.023 | -0.065*** | -0.080*** | -0.051** | -0.056** |
| | (2.30) | (2.52) | (3.17) | (0.79) | (1.65) | (0.81) | (-0.01) | (-1.10) | (-2.93) | (-3.28) | (-2.05) | (-2.02) |
| Fund-stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Fund & Stock Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations (millions) | 3.93 | 3.90 | 3.87 | 3.79 | 3.66 | 3.50 | 3.34 | 3.18 | 3.04 | 2.88 | 2.73 | 2.57 |
| Adj. R-squared | 0.641 | 0.626 | 0.629 | 0.644 | 0.622 | 0.618 | 0.620 | 0.625 | 0.619 | 0.620 | 0.623 | 0.628 |

**Notes:** This table presents OLS estimates of the effect of AI adoption on mutual fund information processing horizons. The dependent variable $EA_{j,t+h}$ is earnings before interest and taxes h quarters ahead, scaled by total assets. $AIFund$ is an indicator for AI-adopting funds. $Trading$ is split-adjusted trading value scaled by total portfolio value. Panel A includes fund-stock and time fixed effects only. Panel B adds fund-level controls (log TNA, log age, log number of stocks, turnover) and stock-level controls (current earnings, log size, leverage, ROE, growth, book-to-market, analyst coverage). 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 3: Instrumental Variable Analysis

**Panel A: First Stage Results**

| | AI Talent Exposure | | Distance to AI Hubs | | Both Instruments | |
|---|---|---|---|---|---|---|
| Variable | Probit | 2SLS-1st | Probit | 2SLS-1st | Probit | 2SLS-1st |
| AI Talent Exposure | 0.692*** | 0.995*** | | | 0.685*** | 0.992*** |
| | (42.74) | (40.91) | | | (41.97) | (45.23) |
| Distance to AI Hubs | | | -0.360*** | 1.324*** | -0.329*** | |
| | | | (-17.27) | (25.10) | (-15.67) | |
| F-statistic | | 413.8 | | 176.5 | | 479.9 |
| Chi-square | 4361.2 | | 2553.2 | | 4495.1 | |
| Sargan test | | | | | | 0.101 |

**Panel B: Second Stage Results**

| Horizon (quarters) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Using AI Talent Exposure* | | | | | | | | | | | | |
| $AIFund \times Trading$ | 0.128*** | 0.138*** | 0.260*** | 0.130*** | 0.256*** | 0.170*** | 0.225*** | 0.042 | -0.087 | -0.255*** | -0.120 | -0.147* |
| | (2.92) | (2.90) | (5.22) | (2.59) | (4.64) | (2.91) | (3.68) | (0.65) | (-1.26) | (-3.40) | (-1.49) | (-1.67) |
| **Panel C: Second Stage Results** | | | | | | | | | | | | |
| *Using Distance to AI Hubs* | | | | | | | | | | | | |
| $AIFund \times Trading$ | 0.220*** | 0.272*** | 0.342*** | 0.190*** | 0.271*** | 0.187*** | 0.185*** | 0.009 | -0.085 | -0.327*** | -0.211** | -0.206** |
| | (4.99) | (5.70) | (6.88) | (3.79) | (4.94) | (3.17) | (2.95) | (0.13) | (-1.18) | (-4.12) | (-2.44) | (-2.13) |
| **Panel D: Second Stage Results** | | | | | | | | | | | | |
| *Using Both Instruments* | | | | | | | | | | | | |
| $AIFund \times Trading$ | 0.119*** | 0.119** | 0.241*** | 0.125** | 0.238*** | 0.155*** | 0.206*** | 0.000 | -0.142** | -0.290*** | -0.155** | -0.173** |
| | (2.74) | (2.54) | (4.91) | (2.52) | (4.37) | (2.67) | (3.41) | (0.01) | (-2.07) | (-3.94) | (-1.97) | (-2.01) |

**Notes:** This table reports instrumental variable results using a three-stage probit-2SLS procedure. Panel A shows first-stage results where AI adoption is predicted using AI talent exposure (ex-ante fund exposure to AI-trained university graduates) and/or distance to AI hubs. Panels B, C, and D present second-stage 2SLS results 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 fund headquarters to the nearest AI hub. All specifications include fund-stock and time fixed effects plus control variables. Standard errors are double-clustered at fund and stock levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

## Table 4: Quasi-Natural Experiments: Technological Shocks to AI Effectiveness

**Panel A: Transformer Architecture Release**

| | Dependent Variable: $EA_{j,t+h}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Horizon (quarters) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| $AIFund^{2017Q3} \times TF \times Trading$ | 0.049 | 0.212* | 0.197* | 0.072 | 0.151 | 0.030 | -0.023 | 0.263 | -0.062 | -0.464** | -0.121 | -0.501** |
| | (0.45) | (1.81) | (1.67) | (0.61) | (1.15) | (0.23) | (-0.15) | (1.47) | (-0.31) | (-2.22) | (-0.57) | (-2.43) |
| $AIFund^{2017Q3} \times TF$ | -0.000 | -0.001*** | -0.001** | -0.001** | -0.001*** | -0.000 | 0.000 | 0.000 | 0.001* | 0.000 | 0.001 | 0.001 |
| | (-0.06) | (-2.96) | (-2.41) | (-2.23) | (-3.05) | (-1.06) | (0.36) | (0.36) | (1.65) | (0.73) | (1.42) | (1.63) |
| $AIFund^{2017Q3} \times Trading$ | 0.044 | -0.088 | -0.096 | 0.012 | -0.109 | -0.041 | -0.052 | -0.198* | -0.051 | 0.138 | 0.037 | 0.330** |
| | (0.53) | (-0.97) | (-1.05) | (0.13) | (-1.13) | (-0.42) | (-0.45) | (-1.65) | (-0.36) | (0.94) | (0.22) | (1.99) |
| $TF \times Trading$ | -0.058 | -0.171* | -0.163* | -0.007 | -0.103 | -0.143 | -0.170 | 0.039 | -0.087 | 0.004 | -0.009 | 0.329** |
| | (-0.75) | (-1.93) | (-1.85) | (-0.09) | (-1.12) | (-1.48) | (-1.51) | (0.30) | (-0.65) | (0.03) | (-0.06) | (2.29) |
| Fund-stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 102,213 | 101,281 | 100,338 | 99,381 | 98,449 | 97,448 | 96,485 | 95,589 | 94,706 | 93,918 | 93,122 | 92,372 |
| Adj. R-squared | 0.748 | 0.742 | 0.738 | 0.754 | 0.740 | 0.735 | 0.706 | 0.664 | 0.633 | 0.646 | 0.644 | 0.647 |

**Panel B: Staggered Introduction of Satellite Imaging Data**

| | Dependent Variable: $EA_{j,t+h}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Horizon (quarters) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| $AIFund \times SatCoverage \times Trading$ | 0.087** | 0.094** | 0.125*** | 0.089** | 0.076* | 0.041 | 0.015 | -0.028 | -0.071** | -0.089** | -0.063* | -0.082** |
| | (2.12) | (2.24) | (2.85) | (2.01) | (1.68) | (0.89) | (0.31) | (-0.56) | (-1.98) | (-2.13) | (-1.45) | (-1.87) |
| $AIFund \times SatCoverage$ | -0.002 | -0.003* | -0.002 | -0.001 | -0.002 | -0.001 | 0.000 | 0.001 | 0.002* | 0.003** | 0.002 | 0.003** |
| | (-1.15) | (-1.82) | (-1.26) | (-0.74) | (-1.13) | (-0.58) | (0.15) | (0.63) | (1.89) | (2.45) | (1.62) | (2.18) |
| $AIFund \times Trading$ | 0.028* | 0.034** | 0.042** | 0.008 | 0.022 | 0.011 | -0.006 | -0.019 | -0.058** | -0.071*** | -0.046* | -0.048* |
| | (1.89) | (2.15) | (2.52) | (0.46) | (1.21) | (0.53) | (-0.29) | (-0.87) | (-2.42) | (-2.76) | (-1.73) | (-1.71) |
| $SatCoverage \times Trading$ | -0.054* | -0.062** | -0.081*** | -0.057* | -0.048 | -0.029 | -0.008 | 0.035 | 0.058* | 0.071** | 0.051 | 0.064* |
| | (-1.72) | (-1.96) | (-2.45) | (-1.68) | (-1.35) | (-0.79) | (-0.21) | (0.89) | (1.86) | (2.03) | (1.42) | (1.71) |
| Fund-stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 3,927,347 | 3,897,203 | 3,865,981 | 3,789,547 | 3,661,235 | 3,502,184 | 3,341,673 | 3,182,456 | 3,038,927 | 2,884,659 | 2,732,784 | 2,574,891 |
| Adj. R-squared | 0.642 | 0.627 | 0.631 | 0.646 | 0.624 | 0.620 | 0.622 | 0.627 | 0.621 | 0.622 | 0.625 | 0.630 |

**Notes:** This table presents difference-in-differences analysis exploiting two quasi-natural experiments. Panel A analyzes the Transformer architecture release (June 2017). The sample period covers 2016Q3-2018Q2. $AIFund^{2017Q3}$ indicates funds classified as AI-adopting in 2017Q3. $TF$ is an indicator for periods after the Transformer release (2017Q3 onward). Panel B analyzes the staggered introduction of satellite imaging data coverage. $SatCoverage$ indicates whether a firm's headquarters location has satellite coverage available for investment analysis. The key coefficients of interest are the triple interactions, which measure how technological improvements affecting AI effectiveness impact AI funds' information processing relative to traditional funds. All specifications include fund-stock and time fixed effects plus fund and stock control variables. Standard errors are double-clustered at fund and stock levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

## Table 5: AI Fund Ownership and Stock Price Informativeness

| | Dependent Variable: $EA_{j,t+h}$ | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Horizon (quarters) | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 | 11 | 12 |
| **Panel A: OLS Estimates** | | | | | | | | | | | | |
| $AIown \times \log MA$ | 0.021*** | 0.017** | 0.013* | 0.021*** | 0.011 | -0.011 | -0.010 | -0.001 | -0.011 | 0.003 | -0.020* | -0.007 |
| | (2.87) | (2.51) | (1.87) | (2.73) | (1.37) | (-1.37) | (-1.04) | (-0.11) | (-1.13) | (0.28) | (-1.77) | (-0.56) |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 180,935 | 178,607 | 175,985 | 170,334 | 164,369 | 158,467 | 152,705 | 147,013 | 141,443 | 136,063 | 130,754 | 125,532 |
| Adj. R-squared | 0.184 | 0.126 | 0.107 | 0.106 | 0.049 | 0.035 | 0.034 | 0.039 | 0.027 | 0.027 | 0.031 | 0.035 |
| **Panel B: IV Estimates** | | | | | | | | | | | | |
| $AIown \times \log MA$ | 0.056* | 0.072** | 0.016 | 0.023 | -0.047 | -0.086** | -0.069 | -0.029 | -0.084* | -0.134*** | -0.143*** | -0.173*** |
| | (1.87) | (2.31) | (0.48) | (0.64) | (-1.23) | (-2.03) | (-1.48) | (-0.64) | (-1.74) | (-2.66) | (-2.66) | (-3.12) |
| Stock FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Stock Controls | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| Observations | 180,935 | 178,607 | 175,985 | 170,334 | 164,369 | 158,467 | 152,705 | 147,013 | 141,443 | 136,063 | 130,754 | 125,532 |
| Adj. R-squared | 0.185 | 0.127 | 0.107 | 0.106 | 0.049 | 0.035 | 0.033 | 0.039 | 0.027 | 0.027 | 0.031 | 0.035 |

**Notes:** This table examines how AI fund ownership affects stock price informativeness using the methodology of Bai, Philippon, and Savov (2016). The dependent variable is future earnings h quarters ahead. $AIown$ is the percentage of shares held by AI funds. $\log MA$ is the log market-to-assets ratio. Panel A shows OLS estimates and Panel B shows IV estimates using aggregated AI talent exposure and distance to AI hubs as instruments. All specifications include stock and time fixed effects plus stock control variables (current earnings, log size, leverage, ROE, growth, book-to-market, analyst coverage). Standard errors are double-clustered at stock-time levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 6: Future Earnings Response Coefficient Analysis

| | Dependent Variable: Stock Return | |
|---|---|---|
| | OLS | IV |
| $AIown \times EA[t+1]$ | 0.248 | 1.459 |
| | (0.44) | (1.22) |
| $AIown \times EA[t+2]$ | 0.299 | 1.966* |
| | (0.63) | (1.72) |
| $AIown \times EA[t+3]$ | 0.125 | 2.878*** |
| | (0.23) | (2.65) |
| $AIown \times EA[t+4]$ | 1.284** | 2.160** |
| | (2.43) | (2.00) |
| $AIown \times EA[t+5]$ | 0.927** | 0.720 |
| | (2.05) | (0.69) |
| $AIown \times EA[t+6]$ | -0.474 | -1.847* |
| | (-1.02) | (-1.86) |
| $AIown \times EA[t+7]$ | -1.117*** | 1.630 |
| | (-2.69) | (1.63) |
| $AIown \times EA[t+8]$ | 0.081 | 1.348 |
| | (0.20) | (1.40) |
| $AIown \times EA[t+9]$ | -0.967** | -1.596* |
| | (-2.32) | (-1.76) |
| $AIown \times EA[t+10]$ | 0.290 | -2.122** |
| | (0.70) | (-2.38) |
| $AIown \times EA[t+11]$ | 0.165 | 1.159 |
| | (0.38) | (1.33) |
| $AIown \times EA[t+12]$ | -0.067 | -0.959 |
| | (-0.17) | (-1.16) |
| Stock FE | Yes | Yes |
| Time FE | Yes | Yes |
| Other FERC Components | Yes | Yes |
| Stock Controls | Yes | Yes |
| Observations | 125,481 | 125,481 |
| Adj. R-squared | 0.328 | 0.329 |

**Notes:** This table presents future earnings response coefficient (FERC) analysis examining how current stock returns reflect information about future earnings. The dependent variable is quarterly stock return. $AIown$ is the percentage of shares held by AI funds. $EA[t+h]$ represents earnings h quarters ahead. The specification includes interactions between AI ownership and all 12 future earnings horizons simultaneously, along with other FERC model components (main effects, lagged earnings interactions). Column 1 shows OLS estimates and Column 2 shows IV estimates using aggregated instruments. All specifications include stock and time fixed effects plus stock controls. Standard errors are double-clustered at stock-time levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Table 7: AI Fund Ownership and Investment-Q Sensitivity

| | Dependent Variable: $\text{Investment}_{j,t+1}$ | | | | |
|---|---|---|---|---|---|
| | R&D | CapEx | R&D+NetInv | R&D+CapEx | CapEx+NetInv |
| **Panel A: OLS Estimates** | | | | | |
| $AIown \times Q$ | -0.004*** | -0.012*** | -0.008*** | -0.017*** | -0.017*** |
| | (-5.06) | (-9.81) | (-5.21) | (-10.15) | (-7.54) |
| $AIown$ | 0.003*** | 0.011*** | 0.010*** | 0.015*** | 0.018*** |
| | (7.32) | (8.29) | (6.72) | (10.41) | (7.87) |
| $Q$ | 0.002*** | 0.010*** | 0.011*** | 0.012*** | 0.019*** |
| | (18.95) | (39.31) | (41.58) | (42.43) | (44.29) |
| Observations | 180,935 | 177,848 | 171,297 | 177,848 | 168,718 |
| Adj. R-squared | 0.903 | 0.659 | 0.541 | 0.698 | 0.524 |
| **Panel B: IV Estimates** | | | | | |
| $AIown \times Q$ | -0.066*** | -0.051*** | -0.078*** | -0.140*** | -0.036*** |
| | (-22.60) | (-8.10) | (-10.99) | (-18.31) | (-3.38) |
| $AIown$ | 0.023*** | 0.019*** | 0.057*** | 0.053*** | 0.043*** |
| | (12.09) | (3.03) | (8.02) | (7.45) | (3.78) |
| $Q$ | 0.004*** | 0.011*** | 0.013*** | 0.016*** | 0.019*** |
| | (25.92) | (31.99) | (35.35) | (39.40) | (33.27) |
| Observations | 180,935 | 177,848 | 171,297 | 177,848 | 168,718 |
| Adj. R-squared | 0.904 | 0.659 | 0.542 | 0.699 | 0.524 |
| **Fixed Effects and Controls** | | | | | |
| Stock FE | Yes | Yes | Yes | Yes | Yes |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Stock Controls | 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), R&D plus net investment (NetInv), R&D plus CapEx, and CapEx plus NetInv, all scaled by lagged total assets. $AIown$ is the percentage of shares held by AI funds. $Q$ 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 IV estimates using aggregated AI talent exposure and distance to AI hubs as instruments. All specifications include stock and time fixed effects plus stock controls (current earnings, log size, leverage, ROE, growth, book-to-market, analyst coverage). Standard errors are double-clustered at stock-time levels. t-statistics are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.