Will AI Replace or Enhance Human Intelligence in Asset Management?*

Sanghyun (Hugh) Kim† Vikram Nanda‡

November 7, 2025

Abstract

Using data from LinkedIn profiles, we measure the adoption of AI technologies by mutual fund managers. Compared to low-AI funds, high-AI funds generate superior returns and incur lower expenses. The stock-picking abilities of high-AI funds improve with the availability of big data, such as satellite imagery of parking lots. Consistent with AI complementing investment skills, outperformance is particularly strong among discretionary funds, which rely on human judgment, as opposed to quantitative funds. The greater the AI adoption, the more pronounced the time-varying skill of fund managers across different market conditions. The local availability of AI skills is a key determinant of cross-sectional variation in mutual fund AI investment. Our findings are robust to using geographic variation in AI supply as an instrument for AI utilization by mutual funds.

JEL-Classification: G11, G24.

Keywords: Artificial intelligence, machine learning, big data, mutual funds, fund performance

*We are grateful to Richard Evans, Umit Gurun, Sebastian Krull, Alan Kwan, Si Li, Thomas Maurer, Andriy Shkilko, Shyam Venkatesan, and Qinghai Wang, as well as seminar participants at Western University (Ivey) and Wilfrid Laurier University (Lazaridis), and conference participants at the 2025 German Finance Association Annual Meeting and the 2025 Paris December Finance Meeting for many helpful comments and suggestions. We also thank Arsalan Khan for excellent research assistance. Funding from the Social Sciences and Humanities Research Council of Canada (Insight Development Grant) is gratefully acknowledged.

†Lazaridis School of Business and Economics, Wilfrid Laurier University, shkim@wlu.ca.

‡Jindal School of Management, The University of Texas at Dallas, vikram.nanda@utdallas.edu.

1 Introduction

There is much excitement and uncertainty about the potential for Artificial Intelligence (AI) to significantly impact GDP growth and productivity, with projections that range from the modest to simply remarkable.[1] There is also speculation and misgiving about the effect of AI on different industries and occupations since this depends on the types of human skills that AI might enhance and those it could render obsolete. Evidence is mixed on whether AI enhances skilled work. While research on earlier forms of AI finds that the technology raised wages of skilled workers, other studies indicate that generative AI can serve, at least to some degree, as a complement to low-skilled workers within a given occupation.[2]

Agrawal et al. (2019) conceptualize AI as a general-purpose prediction technology that lowers the cost of inference and reconfigures decision-making and organizational design—complementing evidence that its diffusion is reshaping task content and skill demand. In the same vein, Autor (2015) emphasizes the complementarity between digital tools and analytical occupations, implying that AI is more likely to amplify than to displace professional judgment. While the potential impact on aggregate employment and growth effects is unresolved (Webb, 2019), Acemoglu et al. (2022) find evidence suggesting that the adoption of AI is associated with a change in skill requirements and less hiring in non-AI positions.[3]

In the paper, we study the influence of AI on asset management, specifically its utilization by mutual funds and the impact on their performance. Of particular interest is whether AI tends to complement and enhance human skills in asset management. Our paper is re-

[1]On the high side, an IDC report claims that AI could contribute \$19.9 trillion to the global economy through 2030, accounting for 3.5% of global GDP (IDC Economic Impact `https://my.idc.com/getdoc.jsp?containerId=prUS52600524`). However, MIT economist Daron Acemoglu estimates a more modest GDP increase of 1.1 to 1.6% over 10 years, with an annual productivity gain of only 0.05%.`https://news.mit.edu/2024/what-do-we-know-about-economics-ai-1206`

[2]See, for instance, `https://www.cbo.gov/publication/61147`

[3]Grennan and Michaely (2020) provides evidence of negative consequences for skilled individuals. They find that analysts with portfolios exposed to AI are more likely to reallocate efforts to soft skills, shift coverage towards low AI stocks, and even leave the profession. Similarly, Bonelli and Foucault (2023) suggests that big data has the potential to displace high-skill workers in finance such as portfolio managers.

lated to a growing body of work that links AI to capital-market efficiency and information production.[4] A recent global survey of asset managers suggests that a majority (54%) report making some use of AI in investment strategy or asset class research (Mercer, 2024).[5] The survey suggests that AI is seen as valuable in generating 'alpha', since it facilitates the crunching of massive datasets to detect market trends, in analyzing company financials, and even satellite imagery of parking lots to uncover insights no human could process at scale. It is also lauded for improving cost efficiency and risk mitigation.

Large asset managers are now incorporating AI directly into their investment processes. For instance, BlackRock (2025) reports deploying large language models (LLMs) to analyze corporate earnings call transcripts, news articles, and social media to help inform investment forecasts and uncover potential alpha opportunities.[6] Likewise, Cliff Asness—co-founder of AQR, a quant asset manager with deep academic ties—says the firm has 'surrendered more to the machines,' underscoring the accelerating shift toward AI-driven decision making (Mourselas and Pollard, 2025).[7]

While our paper focuses on the impact of AI on investment performance, we believe that the study can also offer insight into the broader ramifications of AI for human productivity. An issue of keen interest is whether we should expect the AI revolution to complement and strengthen human skills, such as in investment decisions, or whether we might expect AI and powerful machines to largely displace the human skills and judgment of investment professionals (Cao et al., 2024).[8] Hence, as part of our analysis, we examine whether AI tends to have a differential impact on investment strategies in which there is a greater

[4]See, for example, Babina et al. (2024); Abis and Veldkamp (2024); Cao et al. (2024); Lopez-Lira and Tang (2023); Jha et al. (2024); Bonelli and Foucault (2023); Fuster et al. (2022).

[5]`https://www.mercer.com/insights/investments/portfolio-strategies/ai-in-investment-management-survey/`.

[6]`https://www.blackrock.com/us/individual/insights/ai-investing?utm_source=chatgpt.com`.

[7]`https://www.ft.com/content/e62c85cb-e3c8-4df3-b115-e3e11eeaa266`.

[8]Cao et al. (2024) compare the performance of AI and human analysts and find that humans provide significant incremental value in "Man + Machine" settings.

contribution by human skills and judgment relative to strategies that follow systematic rule-based algorithms (Abis, 2020).

We begin by determining the extent of AI adoption by an assessment of the AI skills of individuals hired by mutual fund management companies ("advisers") using LinkedIn profile data from Revelio Labs. The dataset provides detailed information on the employment history of several hundred million individuals across the globe, including job titles and functions, educational background, and firm affiliations. Revelio uses machine learning algorithms to identify and categorize skills associated with each individual based on their listed experiences and roles. For each skill, we compute its AI-relatedness score by the likelihood of its co-occurrence with any of the AI core skills (Babina et al., 2024). Next, we compute the AI skill level of each individual by taking the average of the AI-relatedness scores across all skills associated with that individual. For our main independent variable of interest, we measure the level of investment in AI technologies made by a mutual fund adviser by taking the average of the AI skill levels of all individuals employed by that adviser.

We next assess the performance implications of AI by sorting mutual funds each month into quintiles based on their advisers' investment in AI technologies. By construction, top-quintile ("high-AI") funds enter the sample with markedly greater AI exposure. Moreover, they continue to expand adoption over time, so the dispersion in AI investment relative to lower-quintile funds widens substantially, particularly from the mid-2010s onward. For each quintile-sorted portfolio, we compute the value-weighted averages of fund returns in excess of their benchmark returns, as well as the difference in benchmark-adjusted returns between the highest and lowest quintile (long/short) portfolios. We find that the long/short portfolio has benchmark-adjusted returns of 10.6 basis points per month (about 1.27% per year). The AI outperformance is both economically and statistically significant. We obtain similar results when we compute the alphas (risk-adjusted returns) of benchmark-adjusted returns.

Our results further show that both AI adoption and its performance benefits for mutual funds are concentrated in the latter half of the sample (2016–2023). In this subperiod, the high-minus-low AI return spread approximately doubles—from 7 bps per month to 14.1 bps per month (about 0.84% vs. 1.69% per year). This pattern contrasts sharply with Chen et al. (2025), who examine hedge funds with AI-labeled strategies and document that their outperformance declines after 2015 and disappears by 2020.

AI technologies can also enhance fund performance by reducing expenses, which tend to substantially erode net returns. To assess the impact of AI adoption on fund expenses, we decompose returns (net of expenses) into two components: returns (gross of expenses) and expenses. Indeed, we find that high AI funds incur substantially lower expenses than low AI funds, with expenses being 1.7 basis points per month lower.

To examine the sources of AI outperformance, we leverage the well-documented strength of AI and machine learning in processing unstructured "big data" (e.g., satellite imagery) and use this setting to test whether such capabilities translate into superior investment performance. Using the staggered introduction of satellite imagery of parking lots for retail firms (Katona et al., 2025), we find that the positive impact of AI technologies on stock-picking ability is enhanced by the availability of unstructured big data.[9] Overall, our results suggest that mutual funds utilizing AI technologies are better equipped to process and exploit big data as more unstructured information becomes available. We note that these performance results, since they are consistent with the core benefits of using AI, also validate the measure of AI adoption that we use.

As noted above, a central objective is to assess whether AI enhances human performance or bypasses human skills in asset management. Having established AI outperformance, we ask which funds benefit most: those driven by human discretion and judgment, or those relying on quantitative, algorithmic techniques (Abis, 2020). Put differently, does AI

[9] The use of satellite imagery as an alternative data source is well documented—parking-lot car counts forecast store performance and guide institutional trading (Kang et al., 2021; Katona et al., 2025); more broadly, imagery-based measures such as night lights map to real activity (Henderson et al., 2012).

chiefly make algorithms better at being algorithms, or does it complement human decision-making?

To address this, we classify mutual funds as discretionary or quantitative by training a random-forest classifier on the *Principal Investment Strategy* sections of mutual fund prospectuses obtained from SEC filings, following Abis (2020). The results are informative: AI disproportionately boosts discretionary funds. Among discretionary funds, high-AI funds outperform low-AI funds by 12.9 bps per month (about 1.55% per year). In contrast, among quantitative funds, the AI premium is 7.1 bps per month (about 0.85% per year). These findings align with the view—also supported by Cao et al. (2024)—that, rather than replacing human intelligence, artificial intelligence more often complements it.

We further examine whether AI enhances human decision-making by drawing on the model and evidence in Kacperczyk et al. (2014, 2016). Their framework posits time-varying managerial skill: fund managers engage in stock picking during normal times and switch to market timing during bad times. Abis (2020) further argues that such state dependence is a hallmark of human decision making. Consistent with this view, we show that AI augments human intelligence in a state-contingent manner: performance improvements are time varying, with high-AI funds exhibiting stronger stock picking in normal times and superior market timing in volatile periods when aggregate risk and investor risk aversion are elevated.[10]

Why do certain mutual fund advisers invest more in AI technologies than others? We conjecture that since AI skills are scarce and geographically concentrated (e.g., in Silicon Valley), the local supply of AI technologies could be a major determinant of the cross-sectional variation in the level of investment in AI technologies by mutual fund advisers. For

[10]These findings contrast with Zhang (2024), who attributes the outperformance of AI-investing funds primarily to enhanced stock picking rather than to market timing. Our results instead indicate that AI can bolster both capabilities, with portfolio managers reweighting signal sets as conditions change; consequently, AI's contribution manifests differently across market regimes.

each metropolitan area, we measure the local supply of AI technologies by taking the average of the AI skill levels of individuals working in that area. Consistent with our conjecture, the local supply of AI technologies is significantly positively associated with the adoption of AI technologies by mutual fund advisers located in that area. Our results suggest that AI adoption is constrained by the local supply of AI technologies, and mutual fund advisers located in metro areas with a larger supply of AI technologies tend to invest more in AI technologies. The geographic variation in the local supply of AI skills provides a source of exogenous variation in the utilization of AI by mutual funds. We show that our findings are robust to using the exogenous variation as an instrument for the utilization of AI by asset managers.

Recent contemporaneous studies provide complementary evidence on how artificial intelligence is transforming the asset management industry. Chen et al. (2025) document that hedge funds with AI-driven strategies initially outperform peers, though the performance premium narrows as adoption becomes widespread. Sheng et al. (2024) focus on generative AI, showing that hedge funds incorporating ChatGPT-based signals earn 2-4 percent higher annualized alphas and improve price efficiency, particularly when analyzing firm-specific information. Zhang (2024) finds that mutual funds with greater AI investment outperform peers through enhanced stock-picking—rather than market timing—especially in information-rich stocks. Cen et al. (2024) link data-science human capital to trading profitability and portfolio concentration, showing that while hiring data scientists improves fund performance, concentrated data-science coverage can reduce market-wide price informativeness.

Our paper is related to recent papers that examine the impact of AI on firm productivity. Among these, Babina et al. (2024) develops some of the AI investment measures that we also employ in our paper. Babina et al. (2024) shows that there is a stark increase in AI investment across sectors and finds that AI-investing firms experience significantly higher growth, primarily through increased product innovation.

Our paper complements and extends this emerging literature in several important ways. First, we show that AI's performance gains are concentrated in discretionary funds—rather than quantitative funds—pinpointing the style margin on which AI complements human judgment and enhances discretionary decision-making. This style-based heterogeneity speaks directly to man+machine synergies (Cao et al., 2024) and addresses a question not explored in the contemporaneous studies, which do not separate investment styles or test this mechanism at the strategy level. Second, by linking AI adoption to both realized fund performance and time-varying managerial skill, we identify when AI augments human intelligence—relaxing information-processing constraints while preserving the flexibility and context sensitivity of human portfolio managers (Kacperczyk et al., 2014, 2016; Abis, 2020). Third, using a broader measure of AI adoption across asset managers, we document a sharpening impact of AI on performance in recent years, underscoring its growing relevance as data intensity rises and tools mature—in contrast to Chen et al. (2025), who, under a narrower definition focused on explicitly AI-labeled investment strategies, document a disappearance of the AI premium post-2020.

2 Data and methodology

2.1 Data contruction

Our source of online resume data is Revelio Labs, which provides detailed information on the employment histories of hundreds of millions of individuals worldwide. Revelio Labs data are derived from publicly available online resumes, primarily sourced from LinkedIn. The dataset provides structured information on employment history, including job titles, firm affiliations, tenure periods, educational background, and job titles.

We obtain mutual fund returns, total net assets (TNA), expenses, and holdings from the CRSP Survivor-Bias-Free Mutual Fund database. CRSP holdings data offer greater coverage than the Thomson/Refinitiv Mutual Fund Holdings (s12) database for our sample period, and holdings are available on a monthly basis for the majority of our sample funds.

We match mutual fund advisers (asset managers) from our mutual fund datasets to companies in the Revelio Labs database using Legal Entity Identifier (LEI) numbers, if available, and company names. For adviser identification, we obtain detailed information on mutual fund advisers as well as sub-advisers directly from SEC filings: Form N-SAR and Form N-CEN. We match funds available in the CRSP dataset with those in the N-SAR filings using a name-matching algorithm (Han et al., 2024), and with funds in the N-CEN filings using the *crsp_cik_map* file made available by CRSP. Form N-SAR filings were discontinued in 2018 and replaced by Form N-CEN filings in 2019.

Form N-CEN filings report advisers' Legal Entity Identifier (LEI) numbers, if available, which are also provided for a subset of companies in the Revelio Labs data. We use LEI numbers to match mutual fund advisers with companies in the Revelio Labs data. We extrapolate LEI numbers for advisers available in both N-CEN and N-SAR filings using SEC file numbers, which consistently identify mutual fund advisers across different SEC filings. For the remaining managers, we use a name-matching algorithm to match mutual fund advisers from our mutual fund datasets with companies in the Revelio Labs data. Since company names may not be reported consistently and tend to be quite similar across subsidiaries and affiliates, we strive to be conservative when in doubt during the name-matching process.

Since we focus on actively managed U.S. domestic equity funds, we require that funds belong to one of the nine Morningstar categories, known as the Morningstar equity style box, defined by the funds' size and style tilts: $\{$Large, Mid-cap, Small$\}$ $\times$ $\{$Growth, Blend, Value$\}$. We obtain Morningstar categories from the Morningstar Direct database. We match funds from CRSP with those from Morningstar based on CUSIP, ticker, and fund name, in that order (Berk and van Binsbergen, 2015; Pástor et al., 2015). We exclude index funds and exchange-traded funds using the fund flags available from CRSP and Morningstar. To avoid the incubation bias (Evans, 2010), we require that funds' TNAs be greater than \$5 million at the beginning of the month. We aggregate share-class-level information to the fund (portfolio) level using Morningstar's *fundid*.

2.2 AI adoption measure

We construct our AI adoption measure using LinkedIn profile data obtained from Revelio Labs. Revelio uses machine learning algorithms to identify and categorize skills associated with each individual (user) based on their listed experiences and roles. For each skill j, we compute its AI-relatedness score by the likelihood of its co-occurrence with any of the AI core skills (Babina et al., 2024):

$$\text{AI relatedness}_j = \frac{\text{Number of individuals with skill } j \text{ and any of the AI core skills}}{\text{Number of individuals with skill } j}, \tag{1}$$

where the average is taken over all individuals associated with skill j. For the AI core skills, we use *Artificial Intelligence*, *Machine Learning*, *Deep Learning*, *Natural Language Processing*, and *Computer Vision*.

We report AI relatedness scores for a few selected skills in Figure 1. Among the top AI-related skills are *Pattern Recognition*, *Data Science*, *Signal Processing*, and *Image Processing*, with AI-relatedness scores of 0.81, 0.66, 0.63, and 0.59, respectively. On the other hand, traditional data analysis skills, such as *Statistics* and *Data Analysis* have relatively low AI-relatedness scores of 0.19 and 0.08, respectively. General-purpose programming languages such as *R* and *Python*, which are widely used in machine learning applications, have relatively high AI-relatedness scores of 0.31 and 0.19, respectively. In contrast, traditional finance skills such as *Corporate Finance* and *Investments* have AI-relatedness scores of virtually zero.

[Insert Figure 1]

Next, we compute the level of AI skills of each individual (employee) by taking the average of the AI-relatedness scores across all skills associated with that individual. To illustrate the roles (positions) of AI skilled workers play within mutual fund investment managers, we report the average level of AI skills of employees for a few selected roles (O*NET titles) in Figure 2. Not surprisingly, *Data Scientists* have the highest level of AI skills. Computer scientists such as *Software Developers*, *Computer Programmers*, and *Computer Systems Analysts* also have high levels of AI skills. In contrast, traditional finance positions such as *Investment Fund Managers* and *Financial and Investment Analysts* have relatively low levels of AI skills.

[Insert Figure 2]

3 AI outperformance

3.1 Does AI adoption improve fund performance?

In this subsection, we test whether AI adoption improves mutual fund performance by sorting funds into monthly quintiles based on advisers' AI adoption level (defined in Section 2.2). To characterize cross-sectional variation in AI adoption, Figure 3 plots the value-weighted 12-month rolling average of the AI adoption level for each monthly quintile. By construction, the top-quintile funds exhibit higher levels of AI adoption from the start of the sample. Notably, the gap between high-AI funds and the rest widens rapidly beginning in the mid-2010s, indicating aggressive adoption by a subset of mutual fund advisers. This widening dispersion in AI adoption is consistent with evidence of heterogeneous AI technology adoption and data-driven practices across firms (Brynjolfsson and McElheran, 2016; Babina et al., 2024).

[Insert Figure 3]

Next, for each quintile portfolio, we compute value-weighted fund returns in excess of benchmark returns and the long–short (Q5–Q1) differences in benchmark-adjusted performance. Benchmarks are Morningstar category indices (Sensoy, 2009). Time-series averages are reported in Table 1. The top (bottom) AI-quintile portfolio delivers the highest (lowest) benchmark-adjusted returns, and the benchmark-adjusted returns. The long–short (Q5–Q1) portfolio earns 10.6 bps per month (1.27% per momth) with a t-stat of 3.85, indicating economically and statistically significant outperformance.

[Insert Table 1]

As shown in Figure 3, AI adoption among mutual fund advisers rises sharply beginning in the mid-2010s. We ask whether this widening adoption gap translates into a widening AI premium—the performance spread between high- and low-AI funds. To test this, we split the sample into two subperiods: 2008–2015 and 2016–2023, and report portfolio-sort results separately in Table 2. In the early period (2008–2015; Panel A), the long–short portfolio sorted on AI adoption earns 7 bps per month (0.84% per year; t-stat = 1.91). In the recent period (2016–2023; Panel B), the AI premium roughly doubles to 14.1 bps per month (1.69% per year; t-stat=3.62), indicating that the return advantage associated with AI adoption has strengthened over time.

[Insert Table 2]

These portfolio results are consistent with contemporaneous evidence that AI capability is associated with better performance, while highlighting important differences in what is measured and when. We study capability-based adoption at mutual funds; by contrast, Chen et al. (2025) examine hedge funds explicitly labeled as AI strategies and find initial outperformance that attenuates post-2020 as adoption diffuses. Our results—together with the widening cross-fund dispersion in AI capability (Figure 3)—suggest that depth of organizational AI capacity, rather than strategy labels, underpins persistent gains. Relatedly, Sheng et al. (2024) show hedge funds using LLM-based signals earn higher alphas, reinforcing that AI can raise performance across organizational forms. The stronger post-2015 effects also speak to diffusion dynamics: unlike the attenuation in AI-labeled strategies reported by Chen et al. (2025), capability-based adoption appears to scale with maturing tools and data availability.

For robustness, we estimate alphas (risk-adjusted returns) for the long–short portfolio using the CAPM, the Fama–French three-factor model (Fama and French, 1993), and the Carhart four-factor model (Carhart, 1997). Table 3 reports the results. The AI spread persists: alphas range from 8.9 to 9.4 bps per month.

[Insert Table 3]

3.2 Does AI adoption reduce fund expenses?

We expect the performance gains from AI to stem primarily from enhanced stock picking and market timing—mechanisms we analyze in detail in Section 4.2. That said, AI can also boost performance by lowering expenses, which materially erode net returns. To evaluate this cost channel, we decompose net returns into (i) gross returns and (ii) expenses, and run portfolio sorts for each component using the same procedure as in the previous subsection. Results are reported in Table 4.

[Insert Table 4]

For reference, Panel A of Table 1 (net-of-benchmark returns) is reproduced here. On a gross basis—excluding expenses—high-AI funds still outperform low-AI funds by about 9.2 bps per month (1.10% per year). In addition, high-AI funds bear substantially lower expenses—roughly 1.7 bps per month less—than low-AI funds. A decline of 20.4 bps per year in the expense ratio is economically meaningful relative to the sample's average annual expenses of about 1%—roughly a 20% reduction in expenses. These cost differences are consistent with process efficiencies from data infrastructure and analytics teams. The expense reductions we document suggest that organizational AI capability can deliver both information gains and operational efficiencies.

3.3 Sources of AI outperformance: Evidence from the outer space

Having documented an AI premium, we next examine its underlying sources. This analysis also serves as a validation test for our AI-adoption measure by assessing whether it maps to managers' actual use of AI in investment decisions. Our identification leverages the staggered expansion of satellite imagery coverage of retailer parking lots (Katona et al., 2025), which provides plausibly exogenous variation in the availability of unstructured big data. Because converting raw images into tradable signals requires computer-vision/machine-learning (ML) workflows, funds with stronger AI capabilities should extract more value from this unstructured data.[11] The use of satellite imagery as an alternative data source is well documented—parking-lot car counts forecast store performance and guide institutional trading (Kang et al., 2021; Katona et al., 2025); more broadly, imagery-based measures such as night lights map to real activity (Henderson et al., 2012).

[11] Complementarity between data availability and organizational AI capability is consistent with evidence on data-driven decision-making and AI adoption across firms (Brynjolfsson and McElheran, 2016). Turning raw pixels into signals typically relies on deep-learning models for vision (LeCun et al., 2015); machine-learning methods also deliver sizable gains in return prediction (Gu et al., 2020).

We test our prediction using the following regression specification:

$$
\begin{aligned}
Alpha_{j,t} = {} & \rho\left(Weight_{i,j,t-1} \times AI_{i,t-1} \times \mathbb{1}(Post_{j,t-1})\right) + \delta_1\left(Weight_{i,j,t-1} \times AI_{i,t-1}\right) \\
& + \delta_2\left(Weight_{i,j,t-1} \times \mathbb{1}(Post_{j,t-1})\right) + \delta_3\left(\mathbb{1}(Post_{j,t-1}) \times AI_{i,t-1}\right) \\
& + \beta_1 Weight_{i,j,t-1} + \beta_2 AI_{i,t-1} + \beta_3 \mathbb{1}(Post_{j,t-1}) \\
& + \gamma_1 \Gamma_{i,t-1} + \gamma_2 \Gamma_{j,t-1} + \theta_i + \theta_j + \theta_t + \varepsilon_{i,j,t}
\end{aligned}
\tag{2}
$$

where i indexes mutual funds, j indexes stocks, and t indexes time in months. $Alpha_{j,t}$ is the alpha (idiosyncratic return) of stock j in month t, defined as $R_{j,t} - \beta_{j,t-1}R_{m,t}$, where $R_{j,t}$ and $R_{m,t}$ are the returns of stock j and the market, respectively, in excess of the risk-free rate in month t, and $\beta_{j,t-1}$ is the market beta of stock j, estimated over a 12-month rolling window from month $t-12$ to $t-1$. $Weight_{i,j,t-1} = w_{i,j,t-1} - w_{m,j,t-1}$ is fund i's portfolio weight on stock j in excess of its market weight at the end of month $t-1$. $AI_{i,t-1}$ represents the level of AI adoption by mutual fund i's adviser, as defined in Section 2.2. $\mathbb{1}(Post_{j,t-1})$ is an indicator variable that takes a value of one if firm j is covered by RS Metrics for satellite imagery of parking lots in month $t-1$, and zero otherwise. The timing of satellite imagery availability is sourced from Katona et al. (2025). $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in \$ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\Gamma_{j,t-1}$ is a vector of lagged stock characteristics, including the percentile rankings of market capitalization, book-to-market ratio, and the past 12-month return (excluding the most recent month). θ_i, θ_j, and θ_t represent fund, stock, and time fixed effects, respectively. The sample includes retail firms covered by RS Metrics from 12 months before to 12 months after satellite imagery coverage of parking lots became available. Standard errors are double-clustered by fund and stock.

Table 5 reports the estimates. The coefficient of interest—the triple interaction $\hat{\rho}$ on $Weight \times AI \times \mathbb{1}(Post)$—is positive and statistically significant in column (1), indicating that the stock-picking gap between high- and low-AI funds widens precisely when (Post) and where (treated retail stocks) satellite parking-lot data become available. In short, once imagery rolls out, higher-AI funds extract more signal from this unstructured data and improve selection on the exposed retail stocks relative to their lower-AI peers.

[Insert Table 5]

In addition, the double interaction $\hat{\delta}_1$ on $Weight \times AI$ is small and statistically indistinguishable from zero, indicating no pre-imagery differential in stock picking between high- and low-AI funds on the treated retail stocks. This alleviates concerns that our AI-adoption measure merely proxies for generic stock-picking skill or other fund attributes, isolating complementarities between AI capability and the availability of unstructured data. The absence of pre-period differences also provides informal support for parallel trends, consistent with recommended diagnostics for staggered DiD settings (Roth et al., 2023).

The triple-interaction effect remains similar in magnitude and statistically significant after sequentially adding fund and stock characteristics and comprehensive fixed effects in columns (2)–(4). Taken together, the evidence indicates that AI-intensive funds are better at converting newly available unstructured data into alpha, giving us strong confidence that our measure captures the actual use of AI in investment decisions rather than correlating with unrelated fund traits.

Our results echo recent evidence that AI tools help investors convert unstructured information into tradable signals: hedge funds using generative-AI prompts/LLM-based signals earn higher alphas and improve price efficiency, especially for firm-specific news (Sheng et al., 2024); and mutual funds with stronger AI-related human capital realize superior stock selection in information-rich settings (Zhang, 2024).

4 Inspecting the mechanism

Having documented AI outperformance, we next examine the mechanisms—which funds benefit most from AI? Our central question is whether AI primarily substitutes for human judgment ("man vs. machine") or complements human expertise by elevating decision quality ("man + machine").

4.1 Quantitative vs. discretionary funds

To provide initial evidence on whether AI substitutes for or enhances human decision-making in asset management, we conduct a heterogeneity analysis by fund type. We classify mutual funds into (i) quantitative funds, which employ systematic, rule-based algorithms, and (ii) discretionary funds, which rely primarily on human judgment. Following Abis (2020), we train a random-forest text classifier on the *Principal Investment Strategy* sections of fund prospectuses to assign funds to these categories, and then compare AI effects across the two groups.

We form two-by-five portfolios by double-sorting funds on (i) their quantitative vs. discretionary classification and (ii) the mutual fund adviser's AI adoption quintile, and report results in Table 6. Along quantitative funds, those in the high-AI group outperform their low-AI counterparts by 7.1 bps per month (0.85% annualized). By contrast, within discretionary funds, the AI–return spread nearly doubles to 12.9 bps per month (1.55% per month). This cross-sectional pattern is consistent with AI complementing, rather than replacing, human judgment ("man + machine").

[Insert Table 6]

This style-specific heterogeneity complements Zhang (2024), who find that mutual funds with higher AI investment outperform primarily via stock selection; our results show where this advantage is realized—discretionary strategies that rely on judgment—rather than in rule-based quantitative funds. Taken together, the evidence indicates that AI has a larger impact in discretionary funds—where managerial judgment is central—than in quantitative funds that follow fixed, rule-based algorithms. The double-sort results therefore favor augmentation over substitution: rather than replacing human intelligence, AI appears to complement and enhance it, consistent with Cao et al. (2024).

4.2 Time-varying managerial skill

Kacperczyk et al. (2014) document time-varying managerial skill: mutual fund managers emphasize stock picking in normal times but shift toward market timing in recessions. To rationalize this pattern, Kacperczyk et al. (2016) develop an attention-allocation model in which skilled managers face limited attention and optimally split it between idiosyncratic (stock-specific) and aggregate (marketwide) signals. In bad times—when both market risk and investors' risk aversion are elevated—the optimal allocation tilts toward aggregate information, making market timing more valuable.

Building on Kacperczyk et al. (2016), Abis (2020) argues that time-varying skill is a hallmark of human portfolio managers: it is pronounced among discretionary funds that rely on judgment and muted among quantitative funds that follow fixed rules and algorithms. Consistent with Section 4.1, if artificial intelligence augments rather than replaces human intelligence, it should amplify this state-contingent skill. We therefore test the prediction that time variation in managerial skill increases with AI adoption in this subsection.

To assess time-varying managerial skill, we construct monthly measures of stock picking (SP) and market timing (MT) as the cross-sectional covariance between a fund's active (excess) weights and, respectively, the idiosyncratic and market components of returns

(Kacperczyk et al., 2014):

$$SP_{i,t} = \sum_{j}^{N_{i,t-1}} \left(w_{i,j,t-1} - w_{m,j,t-1}\right)\left(R_{j,t} - \beta_{j,t-1} R_{m,t}\right) \tag{3}$$

$$MT_{i,t} = \sum_{j}^{N_{i,t-1}} \left(w_{i,j,t-1} - w_{m,j,t-1}\right)\left(\beta_{j,t-1} R_{m,t}\right) \tag{4}$$

where i indexes funds, j indexes stocks, and t indexes time in months. $w_{i,j,t-1} - w_{m,j,t-1}$ represents fund i's portfolio weight on stock j in excess of the market weight at the end of month $t-1$. $R_{j,t}$ and $R_{m,t}$ are the returns on stock j and the market, respectively, during month t. $\beta_{j,t-1}$ is the market beta of stock j, estimated over a 12-month rolling window from month $t-12$ to $t-1$. The summation is taken over all stock holdings of fund i at the end of month $t-1$, $N_{i,t-1}$

Intuitively, stock picking (SP) is high when a fund's active weights covary positively with next-month idiosyncratic returns: the manager overweights stocks that subsequently earn positive alphas and underweights those that deliver negative alphas. Likewise, market timing (MT) is high when active weights move in the same direction as the realized market payoff: the fund tilts toward high-beta stocks before a positive market month and toward low-beta stocks before a negative one.

To test whether AI technologies enhance fund managers' time-varying skills, we estimate the following linear regression model:

$$\begin{aligned} SP_{i,t}\ (MT_{i,t}) = {} & \beta AI_{i,t-1} + \delta\left(AI_{i,t-1} \times \mathbb{1}(\textit{Volatile market}_t)\right) \\ & + \gamma \Gamma_{i,t-1} + \theta_i + \theta_t\ (\theta_{c,t-1}) + \varepsilon_{i,t} \end{aligned} \tag{5}$$

where i indexes mutual funds and t indexes time in months. $AI_{i,t-1}$ represents the level of AI adoption by mutual fund i's adviser, as defined in Section 2.2. $\mathbb{1}(\textit{Volatile market}_t)$ is an indicator variable that takes a value of one if market volatility in month t exceeds its 80th percentile, and zero otherwise. Market volatility is measured as the standard deviation of daily market returns within that month. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in \$ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). θ_i, θ_t, and $\theta_{c,t-1}$ are fund, time, and category-by-time fixed effects, respectively.

We report estimates in Table 7. In columns (1)–(2), where the dependent variable is SP, $\hat{\beta}$ is positive and statistically significant, while $\hat{\delta}$ is negative and significant (albeit marginally). In columns (3)–(4), where the dependent variable is MT, the signs reverse: $\hat{\beta}$ is small and statistically insignificant, and $\hat{\delta}$ is positive and statistically significant. These sign flips are consistent with our prediction: AI adoption strengthens stock picking in normal times and market timing in volatile periods when aggregate market risk and investor risk aversion are elevated.

The state-contingent pattern connects to Zhang (2024), who emphasize stock-picking improvements; our results clarify that AI also aids market timing precisely in volatile states when aggregate information is most valuable. Moreover, the enhanced information processing is also consistent with the price-efficiency gains from LLM-based signals in Sheng et al. (2024).

Overall, our evidence indicates that AI adoption enhances managers' time-varying skills—hallmarks of human discretion (Abis, 2020). Taken together with the double-sort results, the evidence points to augmentation over substitution: artificial intelligence complements, rather than replaces, human judgment, consistent with a "man + machine" equilibrium (Cao et al., 2024).

[Insert Table 7]

5 Addressing endogeneity concerns

5.1 Controlling for fund characteristics

Section 3.2 showed that AI adoption is associated with lower expenses, that these savings improve net performance, and that the AI return premium persists even after stripping out expense effects. In this subsection, we estimate the impact of AI investment on fund performance in a multivariate setting that explicitly controls for fund characteristics—including expenses—to corroborate the baseline portfolio-sorts in Section 3.1. The specification also serves as the reduced-form counterpart to the instrumental-variables (IV) analysis in the subsections that follow.

Specifically, we estimate the following linear regression model:

$$BAR_{i,t}\ (Alpha_{i,t}) = \beta AI_{i,t-1} + \gamma \Gamma_{i,t-1} + \theta_{c,t-1} + \varepsilon_{i,t} \tag{6}$$

where i indexes mutual funds and t indexes time in months. $BAR_{i,t}$ denotes the return of fund i in excess of its benchmark return in month t. $Alpha_{i,t}$ is the CAPM alpha, defined as $R_{i,t} - \beta_{i,t-1} R_{m,t}$, where $R_{i,t}$ and $R_{m,t}$ are the returns of fund i and the market, respectively, in excess of the risk-free rate in month t, and $\beta_{i,t-1}$ is the market beta of fund i, estimated over a 12-month rolling window from month $t-12$ to $t-1$. $AI_{i,t-1}$ represents the level of AI adoption by mutual fund i's adviser, as defined in Section 2.2. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in \$ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\theta_{c,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time.

We report results in Table 9. Columns (1)–(2) use benchmark-adjusted returns as the dependent variable. In the univariate specification in column (1), $\hat{\beta}$ is positive and statistically significant at the 1% level. Adding fund characteristics, including expenses, in column (2) leaves $\hat{\beta}$ positive and statistically significant at the 5% level, with a modest attenuation in magnitude. Replacing benchmark-adjusted returns with CAPM alphas in columns (3)–(4) yields qualitatively similar results. Overall, these regression estimates corroborate the portfolio-sort evidence in Section 3.1.

[Insert Table 9]

5.2 Instrumenting AI adoption

A natural concern with our analyses is measurement error in the adviser's AI adoption proxy, which can induce attenuation bias. Our measure focuses on human-capital investments plausibly tied to AI capabilities; as a result, it may omit other relevant inputs—e.g., computing infrastructure, cloud services, data storage, and data acquisition/licensing—that are central to AI/ML performance. Such omissions, along with potential timing mismatches and reporting noise, would bias estimated effects toward zero and weaken statistical power.

Endogeneity is a second concern: self-selection and omitted variables could bias estimates upward if managers that invest more in AI also differ systematically in unobserved ways. Why do some advisers adopt AI more aggressively than others? Our evidence in Section 3.3 helps alleviate this concern: prior to the availability of satellite imagery of retailer parking lots, high- and low-AI funds did not differentially select retail stocks, suggesting no pre-trend in alpha generation along this margin. To further bolster identification, we employ instrumental-variables (IV) regressions. Although it is *a priori* unclear whether alpha-generating managers are intrinsically more likely to invest in AI, the IV approach mitigates bias from such potential selection and from omitted factors correlated with both AI adoption and performance.

Why do some asset managers invest more in AI than others? We conjecture that, because AI expertise is scarce and geographically concentrated (e.g., Silicon Valley), the local supply of AI technologies is a key driver of cross-sectional differences in adoption across advisers. Building on this idea, we instrument adviser-level AI adoption with the local availability of AI technologies in the areas where asset managers are located.

Specifically, for each metropolitan area and year t, we measure the local supply of AI technologies ($AI^{Local}_{a,t}$) as the average AI-skill score of all individuals employed in area a at time t. For illustration, Figure 4 maps AI^{Local} in 2023. The San Jose metro (Silicon Valley) exhibits the highest local AI supply in the United States, followed by Seattle, San Francisco, Boston, and Austin. The figure also highlights pronounced within-state dispersion: in California, San Jose ranks at the national frontier while Bakersfield is among the lowest; in Texas, Austin is near the top nationally whereas Lubbock sits near the bottom.

[Insert Figure 4]

With our instrument in hand, we estimate the following two-stage least squares (2SLS) model:

$$AI_{i,t-1} = \beta^1 AI^{Local}_{a,t-1} + \gamma^1 \Gamma_{i,t-1} + \theta^1_{c,t-1} + \varepsilon^1_{i,t-1} \quad \text{(first-stage)} \tag{7}$$

$$BAR_{i,t}\ (Alpha_{i,t}) = \beta^2 \widehat{AI}_{i,t-1} + \gamma^2 \Gamma_{i,t-1} + \theta^2_{c,t-1} + \varepsilon^2_{i,t} \quad \text{(second-stage)} \tag{8}$$

where i indexes mutual funds and t indexes time in months. $BAR_{i,t}$ denotes the return of fund i in excess of its benchmark return in month t. $Alpha_{i,t}$ is the CAPM alpha, defined as $R_{i,t} - \beta_{i,t-1} R_{m,t}$, where $R_{i,t}$ and $R_{m,t}$ are the returns of fund i and the market, respectively, in excess of the risk-free rate in month t, and $\beta_{i,t-1}$ is the market beta of fund i, estimated over a 12-month rolling window from month $t-12$ to $t-1$. $AI_{i,t-1}$ represents the level of AI adoption by mutual fund i's adviser, as defined in Section 2.2. $AI^{Local}_{a,t-1}$ is the local supply of AI technologies available to mutual fund i's adviser. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in $ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\theta_{c,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time.

Table 10 reports the first-stage regressions linking adviser-level AI adoption to local AI supply. Consistent with our conjecture, the coefficient on the local supply of AI technologies is positive and statistically significant. This pattern suggests that AI adoption is constrained by local availability of AI talent/technology, with advisers in metros richer in AI resources investing more in AI. Regarding fund controls, larger, younger, and higher-turnover funds exhibit greater AI adoption, while expense ratios are negatively related to adoption (consistent with Section 3.2).

[Insert Table 10]

Finally, Table 11 reports the second-stage estimates. Columns (1)–(2) use benchmark-adjusted returns as the dependent variable. In the univariate second stage in column (1), the IV coefficient $\hat{\beta}^{IV}$ is positive and statistically significant at the 10% level. Its magnitude is about 4.85 times the corresponding OLS estimate in Table 9 ($4.85 = 0.126/0.026$), consistent with attenuation from measurement error in our AI investment proxy. Results are similar when adding fund characteristics in column (2) and when replacing benchmark-adjusted returns with CAPM alphas in columns (3)–(4). Taken together, the IV results reinforce our earlier findings and suggest a causal AI outperformance effect.

[Insert Table 11]

6 Conclusion

In the paper, we study the influence of AI on investment management, specifically its utilization by mutual fund managers and its impact on their performance. In addition, the study provides insight into the broader implications of AI for human productivity and displacement. The issue is whether we should expect the AI revolution to complement and strengthen human skills, such as in investment management, or whether we might expect AI and powerful machines to largely replace human skills and judgment in these endeavors.

Using unique data from LinkedIn profiles, we measure the adoption of AI technologies among mutual fund management companies. This is done by computing the AI skill level of each individual by taking the average of AI-relatedness scores across all skills associated with that individual. The level of investment in AI technologies made by a mutual fund advisor is measured by the average of the AI skill levels of all individuals employed by that advisor. Among our results, we show the local supply of AI technologies is a major determinant of the cross-sectional variation in mutual fund AI investment. The geographic variation in the local supply of AI skills provides a source of exogenous variation in the utilization of AI by mutual funds. We show our findings are robust to using the exogenous variation as an instrument for the utilization of AI by funds.

Compared to low-AI funds, high-AI funds earn superior benchmark-adjusted returns and incur lower expenses. The long/short portfolio has benchmark-adjusted returns of 4.3 basis points per month (0.52% annualized). The AI outperformance is both economically and statistically significant. We obtain similar results when we compute the alphas (risk-adjusted returns) of benchmark-adjusted returns.

Our results are quite instructive in their implications for human-machine complementarity. In particular, our results show that AI tends to boost the performance of discretionary funds that invest based on human skills and judgment — relative to funds that rely more on quantitative and algorithmic techniques. Among discretionary funds, high-AI funds outperform low-AI funds by 8.8 basis points per month (1.06% annualized). In contrast, among quantitative funds, AI outperformance is muted and statistically insignificant. This is in keeping with the view that rather than replacing human intelligence, artificial intelligence is more likely to augment it, consistent with the findings of Cao et al. (2024). We further corroborate that AI tends to augment human intelligence by showing that the source of the improved performance is time-varying and is evident in stock-picking and market-timing skills conditional on market conditions. The stock-picking skills of high-AI funds improve with the availability of big data, such as satellite imagery of parking lots for retailers.

References

Abis, Simona, 2020, Man vs. machine: Quantitative and discretionary equity management, Working paper.

Abis, Simona, and Laura Veldkamp, 2024, The changing economics of knowledge production, *Review of Financial Studies* 37, 89–118.

Acemoglu, Daron, David Autor, Jonathon Hazell, and Pascual Restrepo, 2022, Artificial intelligence and jobs: Evidence from online vacancies, *Journal of Labor Economics* 40, S293–S340.

Agrawal, Ajay, Joshua S Gans, and Avi Goldfarb, 2019, Artificial intelligence: The ambiguous labor market impact of automating prediction, *Journal of Economic Perspectives* 33, 31–50.

Autor, David H, 2015, Why are there still so many jobs? The history and future of workplace automation, *Journal of Economic Perspectives* 29, 3–30.

Babina, Tania, Anastassia Fedyk, Alex He, and James Hodson, 2024, Artificial intelligence, firm growth, and product innovation, *Journal of Financial Economics* 151, 103745.

Berk, Jonathan B, and Jules H van Binsbergen, 2015, Measuring skill in the mutual fund industry, *Journal of Financial Economics* 118, 1–20.

BlackRock, 2025, How AI is transforming investing, August 27, 2025.

Bonelli, Maxime, and Thierry Foucault, 2023, Displaced by big data: Evidence from active fund managers, Working paper.

Brynjolfsson, Erik, and Kristina McElheran, 2016, The rapid adoption of data-driven decision-making, *American Economic Review* 106, 133–139.

Cao, Sean, Wei Jiang, Junbo Wang, and Baozhong Yang, 2024, From man vs. machine to man + machine: The art and AI of stock analyses, *Journal of Financial Economics* 160, 103910.

Carhart, Mark M, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.

Cen, Ling, Bing Han, Yanru Han, and Chanik Jo, 2024, Data scientists on wall street, Working paper.

Chen, Shuang, Clemens Sialm, and David X. Xu, 2025, The growth and performance of artificial intelligence in asset management, Working paper.

Evans, Richard B, 2010, Mutual fund incubation, *Journal of Finance* 65, 1581–1611.

Fama, Eugene F, and Kenneth R French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3–56.

Fuster, Andreas, Paul Goldsmith-Pinkham, Tarun Ramadorai, and Ansgar Walther, 2022, Predictably unequal? The effects of machine learning on credit markets, *Journal of Finance* 77, 5–47.

Grennan, Jillian, and Roni Michaely, 2020, Artificial intelligence and high-skilled work: Evidence from analysts, Working paper.

Gu, Shihao, Bryan Kelly, and Dacheng Xiu, 2020, Empirical asset pricing via machine learning, *Review of Financial Studies* 33, 2223–2273.

Han, Munhee, Sanghyun Kim, and Vikram K Nanda, 2024, Institutional brokerage networks: Facilitating liquidity provision, *Review of Financial Studies* 37, 2903–2935.

Henderson, J Vernon, Adam Storeygard, and David N Weil, 2012, Measuring economic growth from outer space, *American Economic Review* 102, 994–1028.

Jha, Manish, Jialin Qian, Michael Weber, and Baozhong Yang, 2024, ChatGPT and corporate policies, Working paper.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2014, Time-varying fund manager skill, *Journal of Finance* 69, 1455–1484.

Kacperczyk, Marcin, Stijn Van Nieuwerburgh, and Laura Veldkamp, 2016, A rational theory of mutual funds' attention allocation, *Econometrica* 84, 571–626.

Kang, Jung Koo, Lorien Stice-Lawrence, and Yu Ting Forester Wong, 2021, The firm next door: Using satellite images to study local information advantage, *Journal of Accounting Research* 59, 713–750.

Katona, Zsolt, Marcus O Painter, Panos N Patatoukas, and Jean Zeng, 2025, On the capital market consequences of big data: Evidence from outer space, *Journal of Financial and Quantitative Analysis* 60, 551–579.

LeCun, Yann, Yoshua Bengio, and Geoffrey Hinton, 2015, Deep learning, *Nature* 521, 436–444.

Lopez-Lira, Alejandro, and Yuehua Tang, 2023, Can ChatGPT forecast stock price movements? Return predictability and large language models, Working paper.

Mercer, 2024, AI integration in investment management.

Mourselas, Costas, and Amelia Pollard, 2025, We have 'surrendered more to the machines', says quant fund titan Cliff Asness, *Financial Times* June 4, 2025.

Pástor, L'uboš, Robert F Stambaugh, and Lucian A Taylor, 2015, Scale and skill in active management, *Journal of Financial Economics* 116, 23–45.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe, 2023, What's trending in difference-in-differences? A synthesis of the recent econometrics literature, *Journal of Econometrics* 235, 2218–2244.

Sensoy, Berk A, 2009, Performance evaluation and self-designated benchmark indexes in the mutual fund industry, *Journal of Financial Economics* 92, 25–39.

Sheng, Jinfei, Zheng Sun, Baozhong Yang, and Alan L Zhang, 2024, Generative AI and asset management, Working paper.

Webb, Michael, 2019, The impact of artificial intelligence on the labor market, Working paper.

Zhang, Yiming, 2024, Do mutual funds benefit from the adoption of AI technology?, Working paper.

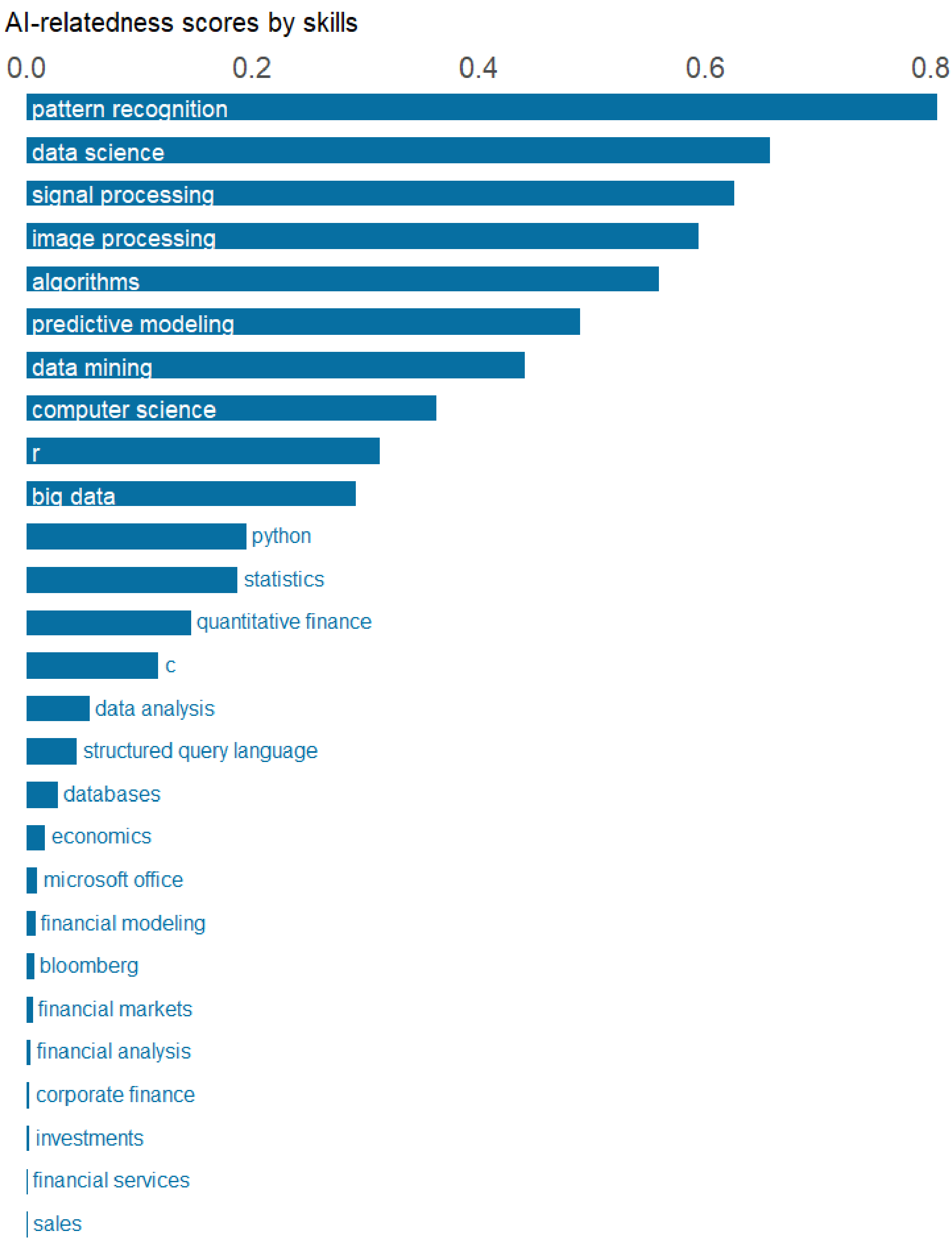

Figure 1: This figure shows the AI-relatedness scores for a few selected skills.

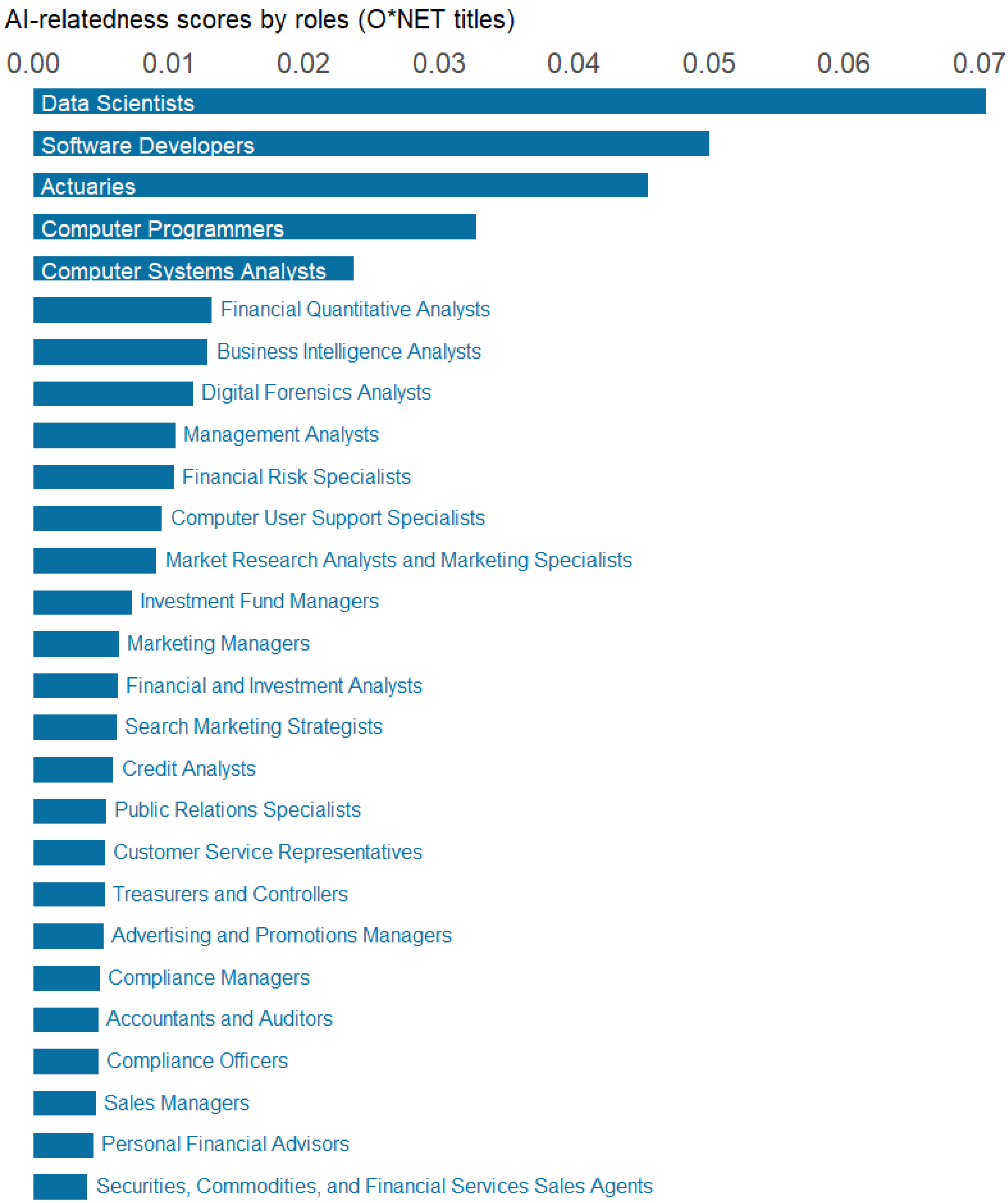

Figure 2: This figure shows the AI-relatedness scores for a few selected roles (O*NET titles).

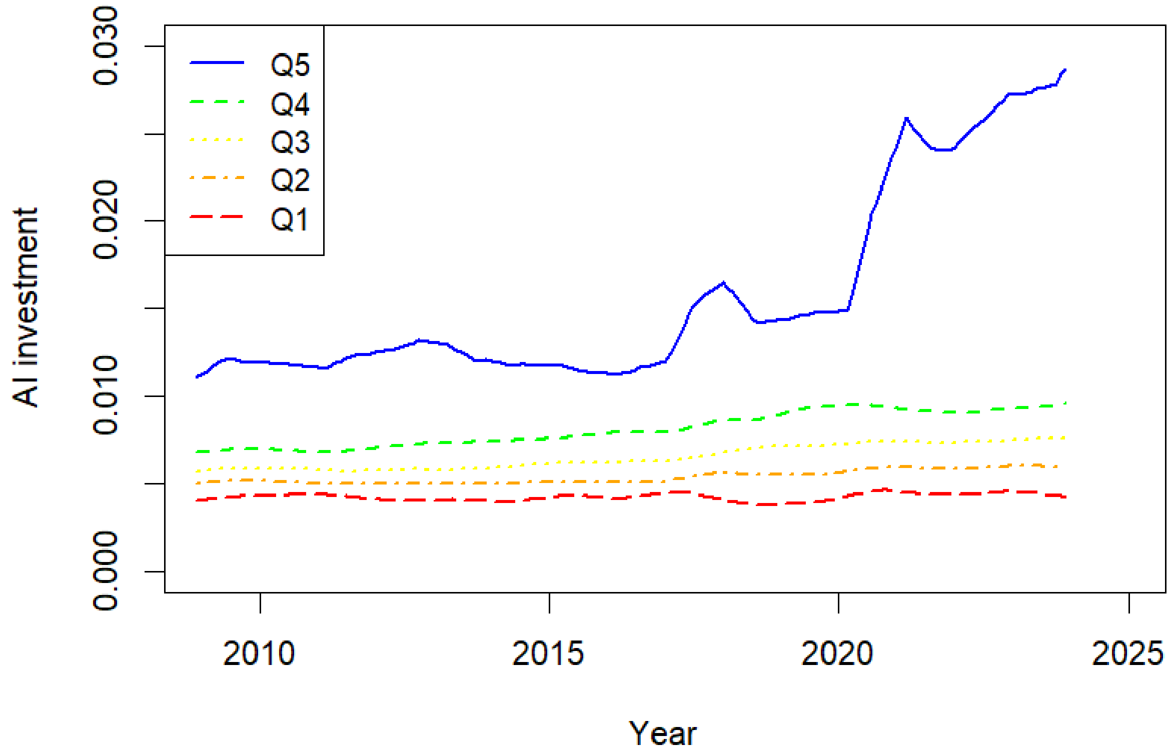

Figure 3: This figure shows the value-weighted average level of investment in AI technologies by mutual fund investment advisers, sorted into quintiles each month.

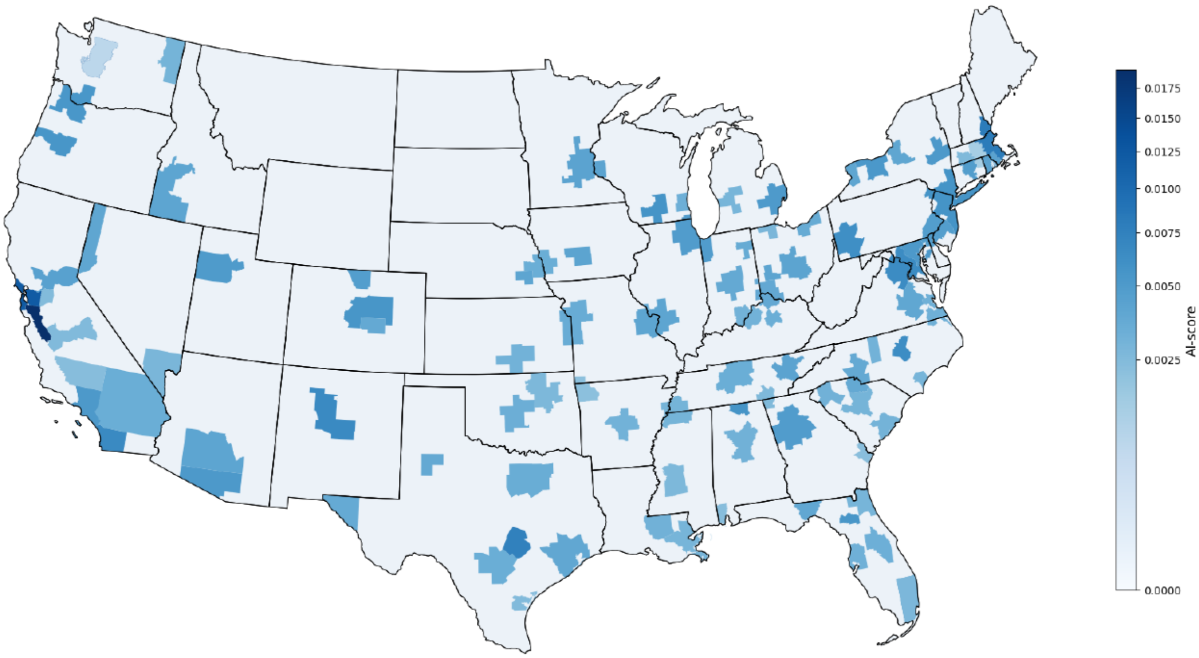

Figure 4: This figure shows the local supply of AI technologies in 2023.

Table 1: Does AI adoption improve fund performance?

This table presents the results of portfolio sorts based on AI adoption. First, we sort the funds into quintile portfolios each month based on the level of investment in AI technologies by mutual fund management companies ("investment advisers"), as defined in Section 2.2. Next, we compute the value-weighted average returns of the funds in each quintile, as well as the difference between the extreme quintile portfolios (long-short portfolio). Fund returns are reported as excess returns relative to their benchmark returns. t-statistics, based on Newey-West standard errors with five lags, are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 − Q1
-0.164^{***}	-0.100^{***}	-0.117^{***}	-0.097^{***}	-0.058^{*}	0.106^{***}
(−4.05)	(−3.57)	(−3.81)	(−2.65)	(−1.84)	(3.85)

Table 2: AI outperformance over time

This table reports portfolio-sort results by AI adoption for two subperiods. We re-estimate the specifications in Table 1 separately for the early (2008–2015) and recent (2016–2023) periods. t-statistics, based on Newey-West standard errors with five lags, are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

Panel A: Early period (2008–2015)

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 − Q1
−0.116*	−0.077**	−0.108**	−0.089	−0.046	0.070*
(−1.86)	(−2.02)	(−2.28)	(−1.40)	(−0.87)	(1.91)

Panel B: Recent period (2016–2023)

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 − Q1
−0.212***	−0.124***	−0.126***	−0.106***	−0.071**	0.141***
(−4.41)	(−3.12)	(−3.36)	(−2.86)	(−2.02)	(3.62)

Table 3: Can AI outperformance be explained by common risk factors?

This table presents the results of the following linear regression model:

$$R_{p,t} = \alpha_p + b_p MKT_t + s_p SMB_t + h_p HML_t + u_p UMD_t + \varepsilon_{p,t}$$

where $R_{p,t}$ represents the value-weighted average benchmark-adjusted return of the long-short portfolio, which is sorted into quintiles based on the level of investment in AI technologies by mutual fund investment advisers, as defined in Section 2.2. MKT_t, SMB_t, HML_t, and UMD_t are the factor returns on the market, size, value, and momentum (Fama and French, 1993; Carhart, 1997). t-statistics, based on Newey and West standard errors with five lags, are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

	Benchmark-adjusted returns		
	(1)	(2)	(3)
Alpha	0.094***	0.091***	0.089***
	(3.52)	(3.47)	(3.28)
MKT	0.014	0.018*	0.023**
	(1.64)	(1.94)	(2.55)
SMB		−0.018*	−0.014
		(−1.88)	(−1.48)
HML		−0.001	0.004
		(−0.10)	(0.36)
UMD			0.016**
			(2.28)

Table 4: Does AI adoption reduce fund expenses?

This table presents the results of portfolio sorts based on AI adoption. First, we sort the funds into quintile portfolios each month based on the level of investment in AI technologies by mutual fund investment advisers, as defined in Section 2.2. Next, we compute the value-weighted average returns (both before and after expenses) and expenses for the funds in each quintile, as well as the difference between the extreme quintile portfolios (long-short portfolio). Fund returns are reported as excess returns relative to their benchmark returns. t-statistics, based on Newey-West standard errors with five lags, are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

Panel A: Net returns

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
−0.164***	−0.100***	−0.117***	−0.097***	−0.058*	0.106***
(−4.05)	(−3.57)	(−3.81)	(−2.65)	(−1.84)	(3.85)

Panel B: Gross returns

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
−0.093**	−0.038	−0.039	−0.033	−0.001	0.092***
(−2.26)	(−1.37)	(−1.24)	(−0.89)	(−0.05)	(3.32)

Panel C: Expenses

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
0.074***	0.067***	0.077***	0.070***	0.057***	−0.017***
(29.19)	(66.13)	(32.24)	(20.34)	(22.22)	(−12.92)

Table 5: Stock picking with satellite imagery of parking lots

This table presents the results of the following linear regression model:

$$\begin{aligned} Alpha_{j,t} = {} & \rho\left(Weight_{i,j,t-1} \times AI_{i,t-1} \times \mathbb{1}(Post_{j,t-1})\right) + \delta_1\left(Weight_{i,j,t-1} \times AI_{i,t-1}\right) \\ & + \delta_2\left(Weight_{i,j,t-1} \times \mathbb{1}(Post_{j,t-1})\right) + \delta_3\left(\mathbb{1}(Post_{j,t-1}) \times AI_{i,t-1}\right) \\ & + \beta_1 Weight_{i,j,t-1} + \beta_2 AI_{i,t-1} + \beta_3 \mathbb{1}(Post_{j,t-1}) + \gamma_1 \Gamma_{i,t-1} + \gamma_2 \Gamma_{j,t-1} + \theta_i + \theta_j + \theta_t + \varepsilon_{i,j,t} \end{aligned}$$

where i indexes mutual funds, j indexes stocks, and t indexes time in months. $Alpha_{j,t}$ is the alpha (idiosyncratic return) of stock j in month t, defined as $R_{j,t} - \beta_{j,t-1} R_{m,t}$, where $R_{j,t}$ and $R_{m,t}$ are the returns of stock j and the market, respectively, in excess of the risk-free rate in month t, and $\beta_{j,t-1}$ is the market beta of stock j, estimated over a 12-month rolling window from month $t-12$ to $t-1$. $Weight_{i,j,t-1} = w_{i,j,t-1} - w_{m,j,t-1}$ is fund i's portfolio weight on stock j in excess of its market weight at the end of month $t-1$. $\mathbb{1}(Post_{j,t-1})$ is an indicator variable that takes a value of one if firm j is covered by RS Metrics for satellite imagery of parking lots in month $t-1$, and zero otherwise. The timing of satellite imagery availability is sourced from Katona et al. (2025). $AI_{i,t-1}$ represents the level of investment in AI technologies by mutual fund i's investment adviser, as defined in Section 2.2. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in \$ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\Gamma_{j,t-1}$ is a vector of lagged stock characteristics, including the percentile rankings of market capitalization, book-to-market ratio, and the past 12-month return (excluding the most recent month). θ_i, θ_j, and θ_t represent fund, stock, and time fixed effects, respectively. The sample includes retail firms covered by RS Metrics from 12 months before to 12 months after satellite imagery coverage of parking lots became available. Standard errors are double-clustered by fund and stock, and t-statistics are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

Table 5–*Continued*

	Alpha			
	(1)	(2)	(3)	(4)
Weight × AI × Post	0.21**	0.21**	0.24**	0.24**
	(2.38)	(2.36)	(2.34)	(2.41)
Weight × AI	−0.04	−0.04	−0.03	−0.03
	(−0.60)	(−0.54)	(−0.39)	(−0.43)
Weight × Post	−0.13	−0.12	0.01	−0.004
	(−0.95)	(−0.92)	(0.05)	(−0.04)
Post × AI	−0.07	−0.06	−0.17**	−0.17**
	(−0.99)	(−0.91)	(−2.11)	(−2.19)
Weight	−0.31***	−0.32***	−0.26***	−0.25***
	(−4.45)	(−4.61)	(−3.95)	(−4.10)
AI	0.08	0.08	0.12	0.12
	(0.63)	(0.58)	(0.93)	(0.92)
Post	−0.72	−0.75	−0.85	−0.87
	(−1.02)	(−1.06)	(−1.13)	(−1.15)
Fund fixed effects	Yes	Yes	Yes	Yes
Stock fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Fund characteristics		Yes		Yes
Stock characteristics			Yes	Yes
Observations	85,620	80,865	85,600	80,846
Adjusted R^2	0.24	0.24	0.26	0.26

Table 6: Quantitative vs. discretionary funds

This table presents the results of double sorts based on quantitative/discretionary fund classification and AI adoption. First, we sort the funds into two-by-five portfolios each month, based on the fund's quantitative/discretionary classification (Abis, 2020) and the level of investment in AI technologies by its adviser, as defined in Section 2.2. Next, we compute the value-weighted average return of the funds in each portfolio, as well as the difference between the extreme quintile portfolios (long-short portfolio) for each classification. Fund returns are reported as excess returns relative to their benchmark returns. t-statistics, based on Newey-West standard errors with five lags, are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

Panel A: Quantitative funds

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 − Q1
−0.114***	−0.123***	−0.165***	−0.090**	−0.043	0.071**
(−3.48)	(−3.68)	(−4.98)	(−2.47)	(−1.29)	(2.22)

Panel B: Discretionary funds

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 − Q1
−0.192***	−0.102***	−0.098**	−0.102**	−0.063*	0.129***
(−3.73)	(−3.25)	(−2.41)	(−2.17)	(−1.81)	(3.21)

Table 7: Time-varying fund manager skill

This table presents the results of the following linear regression model:

$$SP_{i,t}\ (MT_{i,t}) = \beta AI_{i,t-1} + \delta\,(AI_{i,t-1} \times \mathbb{1}(\textit{Volatile market}_t)) + \gamma\Gamma_{i,t-1} + \theta_i + \theta_t\ (\theta_{c,t-1}) + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in months. $AI_{i,t-1}$ represents the level of investment in AI technologies by mutual fund i's investment adviser, as defined in Section 2.2. $SP_{i,t}$ and $MT_{i,t}$ capture the stock picking and market timing skills of mutual funds, defined as the covariance between fund weights (in excess of the market) and the idiosyncratic returns (alphas) and systematic returns of the stock holdings, respectively (Kacperczyk et al., 2014). See Equations (3) and (4) in Section 4.2 for details. $\mathbb{1}(\textit{Volatile market}_t)$ is an indicator variable that takes a value of one if market volatility in month t exceeds its 80th percentile, and zero otherwise. Market volatility is measured as the standard deviation of daily market returns within that month. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in \$ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). θ_i, θ_t, and $\theta_{c,t-1}$ are fund, time, and category-by-time fixed effects, respectively. Standard errors are double-clustered by fund and time, and t-statistics are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

	SP		MT	
	(1)	(2)	(3)	(4)
AI	0.031*	0.020**	−0.032	−0.018
	(1.76)	(2.16)	(−1.52)	(−1.52)
AI × $\mathbb{1}$(Volatile market)	−0.045	−0.030*	0.133**	0.086**
	(−1.42)	(−1.70)	(2.20)	(2.50)
log(TNA)	−0.142***	−0.113***	−0.011	0.001
	(−5.27)	(−10.15)	(−0.96)	(0.14)
Expense ratio	−0.086	−0.012	0.022	0.036
	(−1.47)	(−0.28)	(0.84)	(1.24)
Turnover ratio	−0.146***	−0.090***	0.063***	0.030***
	(−4.54)	(−4.79)	(3.15)	(2.81)
log(Fund age)	0.042	0.032**	0.027**	0.013
	(1.51)	(2.09)	(2.07)	(1.33)
Fund fixed effects	Yes	Yes	Yes	Yes
Time fixed effects	Yes		Yes	
Category-by-time FEs		Yes		Yes
Observations	149,332	149,332	149,332	149,332
Adjusted R^2	0.22	0.58	0.91	0.96

Table 8: STEM vs. non-STEM managers

This table presents the results of double sorts on manager STEM designation and AI adoption. We classify a fund as STEM-run if at least one manager has an educational background in science, technology, engineering, or mathematics. Each month, funds are assigned to two-by-five portfolios based on the manager's STEM status (STEM vs. non-STEM) and the adviser's level of AI adoption (quintiles). Next, we compute the value-weighted average return of the funds in each portfolio, as well as the difference between the extreme quintile portfolios (long-short portfolio) for each classification. Fund returns are reported as excess returns relative to their benchmark returns. t-statistics, based on Newey-West standard errors with five lags, are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

Panel A: STEM managers

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
-0.180^{***}	-0.081^{*}	-0.141^{***}	-0.112^{**}	-0.037	0.143^{***}
(-3.57)	(-1.68)	(-3.32)	(-1.99)	(-1.14)	(3.18)

Panel B: Non-STEM managers

Portfolios sorted on AI adoption					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
-0.175^{***}	-0.129^{***}	-0.118^{***}	-0.084^{**}	-0.081^{**}	0.094^{**}
(-3.93)	(-3.38)	(-3.34)	(-2.24)	(-2.06)	(2.43)

Table 9: Controlling for fund characteristics

This table presents the results of the following linear regression model:

$$BAR_{i,t}\ (Alpha_{i,t}) = \beta AI_{i,t-1} + \gamma\Gamma_{i,t-1} + \theta_{c,t-1} + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time (in months). $BAR_{i,t}$ denotes the return of fund i in excess of its benchmark return in month t. $Alpha_{i,t}$ is the CAPM alpha, defined as $R_{i,t} - \beta_{i,t-1}R_{m,t}$, where $R_{i,t}$ and $R_{m,t}$ are the returns of fund i and the market, respectively, in excess of the risk-free rate in month t, and $\beta_{i,t-1}$ is the market beta of fund i, estimated over a 12-month rolling window from month $t-12$ to $t-1$. $AI_{i,t-1}$ represents the level of investment in AI technologies by mutual fund i's investment adviser, as defined in Section 2.2. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in $ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\theta_{c,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time, and t-statistics are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

	BAR		Alpha	
	(1)	(2)	(3)	(4)
AI	0.026***	0.019**	0.026***	0.018*
	(2.73)	(2.10)	(2.69)	(1.91)
log(TNA)		−0.003		0.002
		(−0.66)		(0.38)
Expense ratio		−0.119***		−0.110***
		(−4.89)		(−3.98)
Turnover ratio		−0.052*		−0.076***
		(−1.66)		(−2.81)
log(Fund age)		0.004		−0.017*
		(0.39)		(−1.91)
Category-by-time FEs	Yes	Yes	Yes	Yes
Observations	145,742	138,152	145,742	138,152
Adjusted R^2	0.16	0.16	0.58	0.57

Table 10: Determinants of mutual fund AI adoption

This table presents the results of the following linear regression model:

$$AI_{i,t} = \beta AI^{Local}_{a,t} + \gamma \Gamma_{i,t-1} + \theta_{c,t-1} + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time in months. $AI_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment adviser, as defined in Section 2.2. $AI^{Local}_{a,t}$ is the local supply of AI technologies available to mutual fund i's investment adviser. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in $ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\theta_{c,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time, and t-statistics are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

	AI					
	(1)	(2)	(3)	(4)	(5)	(6)
AI^{Local}	0.551*	0.500*	0.397*	0.476*	0.569*	0.359*
	(1.91)	(1.90)	(1.76)	(1.70)	(1.94)	(1.67)
log(TNA)		0.030**				0.027**
		(2.45)				(2.09)
Expense ratio			−0.416***			−0.359***
			(−2.69)			(−2.72)
Turnover ratio				0.060*		0.091***
				(1.69)		(2.65)
log(Fund age)					−0.061*	−0.069**
					(−1.83)	(−2.08)
Category by time FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	145,742	145,742	138,155	138,174	145,742	138,152
Adjusted R^2	0.09	0.09	0.12	0.09	0.09	0.13

Table 11: Instrumental variables (IV) regressions

This table presents the results of the following two-stage least squares model:

$$AI_{i,t-1} = \beta^1 AI^{Local}_{a,t-1} + \gamma^1 \Gamma_{i,t-1} + \theta^1_{c,t-1} + \varepsilon^1_{i,t-1} \quad \text{(first stage)}$$
$$BAR_{i,t}\ (Alpha_{i,t}) = \beta^2 \widehat{AI}_{i,t-1} + \gamma^2 \Gamma_{i,t-1} + \theta^2_{c,t-1} + \varepsilon^2_{i,t} \quad \text{(second stage)}$$

where i indexes mutual funds and t indexes time in months. $BAR_{i,t}$ denotes the return of fund i in excess of its benchmark return in month t. $Alpha_{i,t}$ is the CAPM alpha, defined as $R_{i,t} - \beta_{i,t-1}R_{m,t}$, where $R_{i,t}$ and $R_{m,t}$ are the returns of fund i and the market, respectively, in excess of the risk-free rate in month t, and $\beta_{i,t-1}$ is the market beta of fund i, estimated over a 12-month rolling window from month $t-12$ to $t-1$. $AI_{i,t-1}$ represents the level of investment in AI technologies by mutual fund i's investment adviser, as defined in Section 2.2. $AI^{Local}_{a,t-1}$ is the local supply of AI technologies available to mutual fund i's investment adviser. $\Gamma_{i,t-1}$ is a vector of lagged fund characteristics, including the natural logarithm of total net assets (TNA, in \$ million), expense ratio (in percent), turnover ratio, and the natural logarithm of fund age (in years). $\theta_{c,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time, and t-statistics are reported in parentheses, with statistical significance at the 10%, 5%, and 1% levels indicated by *, **, and ***, respectively.

	BAR		Alpha	
	(1)	(2)	(3)	(4)
$\widehat{\text{AI}}$	0.126*	0.205*	0.114*	0.197*
	(1.88)	(1.80)	(1.84)	(1.91)
log(TNA)		−0.009		−0.003
		(−1.38)		(−0.30)
Expense ratio		−0.050		−0.043
		(−1.26)		(−0.95)
Turnover ratio		−0.072*		−0.094***
		(−1.95)		(−3.10)
log(Fund age)		0.016		−0.005
		(1.31)		(−0.30)
Category by time FEs	Yes	Yes	Yes	Yes
Observations	145,742	138,152	145,742	138,152
Adjusted R^2	0.16	0.15	0.58	0.57