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

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Abstract

Using unique 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. AI 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 stock-picking abilities of high-AI funds improve with the availability of big data, such as satellite imagery of parking lots. 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.

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1 Introduction

There is much excitement and speculation about the potential for Artificial Intelligence (AI) to significantly impact GDP growth and productivity, with projections that range from the modest to simply astounding.[1] There is similar uncertainty 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]

In the paper, we study the influence of AI on investment management, specifically its utilization by mutual funds and the impact on their performance. A recent global survey of investment managers suggests that a majority (54%) report making some use of AI in investment strategy or asset class research (Mercer, 2024 survey).[3] 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.

While our paper focuses on the impact of AI on investment performance, we believe that the study can 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 management, or whether we might expect

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

AI and powerful machines to largely displace human skills and judgment in investment professionals (Cao et al., 2024). 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 contribution by human skills and judgment relative to strategies that are less discretionary and more algorithmic and quantitative (Abis, 2022).

We begin by determining the extent of AI utilization by an assessment of the AI skills of individuals hired by mutual fund managers using LinkedIn profile data from Revelio Labs. The dataset provides structured 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 manager (investment adviser) by taking the average of the AI skill levels of all individuals employed by that manager.

Why do certain mutual fund managers 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 managers. For 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 managers. A one percentage point increase in the local supply of AI technologies is associated with a 36 to 55 basis-point increase in the AI utilization by mutual funds. Our results suggest that AI adoption is constrained by the local supply of AI technologies, and mutual fund managers 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. Subsequently, we show that our findings are robust to using the exogenous variation as an instrument for the utilization of AI by investment managers.

We begin our empirical analyses by examining whether the adoption of AI technologies by mutual funds leads to improved fund performance. To this end, we first sort mutual funds into quintiles each month based on their level of investment in AI technologies. We find that high AI funds (top quintile) begin with much higher levels of AI investment from the beginning of our sample. Interestingly, these high AI funds have continued to aggressively adopt AI technologies and have greatly increased the gap with the rest of the funds in the recent years.

For each quintile-sorted portfolio, we compute the equal- and value-weighted averages of fund returns in excess of their prospectus 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 4.3 basis points per month (0.52% annualized), with a t-statistic of 2.46. 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.

AI technologies can also enhance fund performance by reducing expenses, which tend to substantially erode net returns. To assess the impact of AI utilization 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. In additional tests that explicitly control for fund characteristics, including expenses, we find that a one standard deviation increase in mutual fund AI investment leads to 1.7 basis-point higher returns per month.

As noted earlier, one of our objectives is to try to answer whether AI can be expected to enhance human performance or to largely bypass human skills, at least in the area of investment management. Hence, after establishing AI outperformance, we turn to examining which types of funds derive the most value from AI technologies. Are these funds that invest based on human discretion and judgment, or are these funds that rely more on quantitative and algorithmic techniques? Our approach draws upon arguments and modeling in Abis (2022) and Kacperczyk et al. (2016) that time-varying fund manager skill is a human trait. We categorize mutual funds as being quantitative or discretionary by training machine learning models (random forest) on textual data obtained from the Principal Investment Strategy sections of mutual fund prospectuses sourced from SEC filings ((Abis, 2022)).

Our results are quite illuminating and show that AI tends to boost the performance of discretionary rather than quantitative funds. This is consistent with the view that rather than replacing human intelligence, artificial intelligence is more likely to enhance it, consistent with the findings of Cao et al. (2024). Among discretionary funds, high-AI funds outperform low-AI funds by 7.2 basis points per month (0.86% annualized). In contrast, among quantitative funds, AI outperformance is muted and statistically insignificant. Thus, AI technologies appear to have a larger impact on discretionary funds that rely on human judgment than on quantitative funds that rely on algorithms. We further corroborate that AI tends to enhance 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.

We expect AI and machine learning to be particularly powerful in processing unstructured big data, such as satellite imagery. 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. 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.

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. It finds that AI-investing firms experience significantly higher growth, primarily through increased product innovation. Another related paper is Cao et al. (2024), which investigates the issue of 'Man vs. Machine' and provides some of the motivation for our paper. Cao et al. (2024) finds that humans win when institutional knowledge is crucial, though AI wins when information is transparent but voluminous. It documents synergies between humans and machines and informs on how humans can leverage their advantage to better adapt to growing AI prowess.

Our paper is also related to Kacperczyk et al. (2014), which develops a new measure of managerial ability and shows that the same fund managers that pick stocks well in expansions also time the market well in recessions. Kacperczyk et al. (2016) develops an attention allocation model that uses the state of the business cycle to predict information choices by fund managers. Our finding is that these managers with discretionary investment strategies and time-varying skills tend to obtain greater performance benefits from the use of AI.

A paper that provides a machine learning approach to categorize active mutual funds as either quantitative (reliant on computer models and fixed rules) or discretionary (reliant on human judgment) is Abis (2022). The paper provides evidence that quants might have more learning capacity but less flexibility to adapt to changing market conditions than discretionaries. We adopt a similar machine learning approach to classify funds as quantitative or discretionary and show that the performance benefit of AI is primarily evident in discretionary funds. A paper that sheds light on quantitative equity research analysts (Quants) is Birru et al. (2024). The paper provides evidence of their role in discovering market anomalies and moving the markets to greater pricing efficiency.

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2 Data and methodology

2.1 Data contruction

Our source of LinkedIn profile data is Revelio Labs, which provides detailed information on the employment histories of a large sample of individuals. 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 functions.

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 aggregate share-class-level information to the fund (portfolio) level using *crsp_portno*.

We match mutual fund managers (advisers) 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 managers 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 advisers, we use a name-matching algorithm to match mutual fund managers 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 growth/value 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. To avoid the incubation bias (Evans, 2010), we require that funds' TNAs be greater than $5 million at the beginning of the month.

2.2 AI measures

We construct our AI measures 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):

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

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]

For our main independent variable of interest, we measure the level of investment in AI technologies made by each mutual fund investment manager (adviser), AI^{MF}, by taking the average of the AI skill levels of all individuals employed by that adviser. We report some summary statistics in Table 1.

[Insert Table 1]

3 Empirical results

3.1 Does AI investment lead to improved fund performance?

We begin our empirical analyses by examining whether mutual fund AI investment leads to improved fund performance. To this end, we first sort mutual funds into quintiles each month based on their level of investment in AI technologies, AI^{MF}, as defined in Section 2.2. To examine the cross-sectional variation in AI investment, we report the value-weighted 12-month rolling average level of AI investment for each quintile over time in Figure 3.

[Insert Figure 3]

Top quintile AI funds exhibit much higher levels of AI investment from the beginning of our sample period by construction of sorts. However, the gap in the levels of AI investments between high AI funds and the rest has started to increase rapidly in the past few years, suggesting that some mutual funds have started aggressively adopting AI technologies.

Next, for each quintile-sorted portfolio, we compute the equal- and value-weighted averages of fund returns in excess of benchmark returns, as well as the differences in benchmark-adjusted returns between the highest and lowest quintile (long/short) portfolios. For benchmarks, we use Morningstar benchmark indices. We report the time-series averages in Table 2.

[Insert Table 2]

In Panel A, we examine equal-weighted returns and find that the top (bottom) quintile portfolio, sorted by mutual fund AI investment, has the highest (lowest) benchmark-adjusted returns. The long/short portfolio has benchmark-adjusted returns of 4.3 basis points per month (0.52% annualized), with a t-statistic of 2.42. The AI outperformance is both economically and statistically significant. Our results remain similar when we use value-weighted returns in Panel B. Although the statistical significance is slightly lower, the difference in fund performance remains significant at the 10% level and is economically larger when value-weighted. For the remaining analyses, we focus on equal-weighted returns unless otherwise stated, as our focus is on comparing average performance.

For robustness checks, we compute the alphas (risk-adjusted returns) of benchmark-adjusted returns for the long/short portfolio relative to factor models commonly used in evaluating mutual fund performance: the CAPM, the Fama-French 3-factor model (Fama and French, 1993), and the Carhart 4-factor model (Carhart, 1997). We report the results in Table 3. Our results on AI outperformance remain similar when we examine the alphas. High AI funds have 3.3 to 3.5 basis points per month higher alphas than low AI funds. Interestingly, compared to low AI funds, high AI funds tend to load more positively on value and momentum factors, which have consistently higher return premia across diverse markets and asset classes (Asness et al., 2013). Thus, trading risk factors in the right direction partially contributes to the outperformance of high AI funds.

[Insert Table 3]

3.2 Does AI investment lead to reduced expenses?

We expect that AI's contribution to improved performance primarily stems from stock picking and market timing, as we will examine in later subsections. However, AI technologies can also enhance fund performance by reducing expenses, which tend to substantially erode *net* returns. To assess the impact of AI on fund expenses, we decompose returns (net of expenses) into two components: returns (gross of expenses) and expenses. For each of these components, we conduct portfolio sort analyses similar to those in the previous subsection, and report the results in Table 4.

[Insert Table 4]

Our results on net returns (in excess of prospectus benchmark returns) in Panel A of Table 2 are reproduced here for comparison. In terms of gross returns, which exclude the effects of expenses, we still observe that high AI funds outperform low AI funds by 3 basis points per month. The AI outperformance in gross returns is slightly smaller, but still significant, compared to that in net returns, suggesting that AI technologies help funds reduce 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.

3.3 Controlling for fund characteristics

In the previous subsection, we showed that AI technologies tend to reduce expenses, which, in turn, improve fund performance. We also showed that AI outperformance remains robust even when the effects of expenses on fund returns are removed. In this subsection, we examine the impact of AI investment on fund performance while explicitly controlling for fund characteristics, including expenses, to further corroborate our main findings in Section 3.1.

Specifically, we estimate the following linear regression model:

$$BAR_{i,t}\ (Alpha_{i,t}) = \beta AI_{i,t}^{MF} + \gamma\Gamma_{i,t-1} + \theta_{i,t-1} + \varepsilon_{i,t} \tag{2}$$

where i indexes mutual funds and t indexes time in months. $BAR_{i,t}$ denotes the return of fund i in excess of its prospectus 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 $t-1$. $AI_{i,t}^{MF}$ 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). $\theta_{i,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time.

We report the results in Table 5. In columns (1) and (2), we use benchmark-adjusted returns as the dependent variable. In the univariate regression in column (1), we find that $\hat{\beta}$ is positive and statistically significant at the 1% level. A one standard deviation increase in mutual fund AI investment leads to a 1.7 basis-point increase in benchmark-adjusted returns per month ($0.017 = 0.67 \times 0.026$). When we control for fund characteristics in column (2), $\hat{\beta}$ remains positive and statistically significant at the 5% level, although the effect is marginally smaller. Our results remain unchanged when we replace benchmark-adjusted returns with CAPM alphas as the dependent variable in columns (3) and (4). Overall, the results in this subsection are consistent with those based on portfolio sorts in Section 3.1.

[Insert Table 5]

3.4 Instrumenting mutual fund AI investment

One concern in our analyses thus far is that our measure of investment in AI technologies by mutual fund managers is likely to suffer from measurement errors, which may lead to a well-known attenuation bias. For instance, since we only measure investment in human capital likely related to AI technologies, we may miss investment in other types of capital, such as computing capacity and data storage, which are key to the performance of AI and machine learning.

There are also endogeneity concerns related to self-selection and omitted variables that could cause the bias to go in the opposite direction. For instance, why do certain investment managers invest more in AI technologies than others? We address this challenge using instrumental variables (IV) regressions. Although it is *a priori* unclear whether investment managers who are better at generating alphas are also more likely to invest in AI technologies, IV regressions can help mitigate such potential endogeneity concerns.

Why do certain investment managers 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 will be a major determinant of the cross-sectional variation in mutual fund AI investment. Building on this idea, we instrument mutual fund AI investment using the local supply of AI technologies in the areas where investment managers are located.

Specifically, for each metropolitan area, we measure the local supply of AI technologies, AI^{Local}, by taking the average of AI skill levels of all individuals working in that area at that time. For illustrative purposes, we present a map of the local supply of AI technologies in 2023 in Figure 4. The San Jose metropolitan area (a.k.a. Silicon Valley) has the highest local AI supply in the United States, followed by Seattle, San Francisco, Boston, and Austin metropolitan areas. There is substantial variation in the local supply of AI technologies within the same state. In California, San Jose has the highest AI supply in the United States, while Bakersfield has one of the lowest. In Texas, Austin has one of the highest AI supplies in the country, whereas Lubbock has one of the lowest.

[Insert Figure 4]

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

$$AI^{MF}_{i,t} = \beta^1 AI^{Local}_{i,t} + \gamma^1 \Gamma_{i,t-1} + \theta^1_{i,t-1} + \varepsilon^1_{i,t} \quad \text{(first stage)} \tag{3}$$

$$BAR_{i,t}\ (Alpha_{i,t}) = \beta^2 \widehat{AI^{MF}}_{i,t} + \gamma^2 \Gamma_{i,t-1} + \theta^2_{i,t-1} + \varepsilon^2_{i,t} \quad \text{(second stage)} \tag{4}$$

where i indexes mutual funds and t indexes time in months. $BAR_{i,t}$ denotes the return of fund i in excess of its prospectus 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 $t-1$. $AI^{MF}_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, as defined in Section 2.2. $AI^{Local}_{i,t}$ 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). $\theta_{i,t-1}$ denotes category-by-time fixed effects. Standard errors are double-clustered by fund and time.

We report our first-stage results in Table 6. Consistent with our conjecture, the local supply of AI technologies is significantly positively associated with investment in AI technologies by mutual fund managers. A one percentage point increase in the local supply of AI technologies is associated with a 36 to 55 basis-point increase in mutual fund AI investment.

Our results suggest that AI investment is constrained by the local supply of AI technologies, and mutual fund managers located in metro areas with a larger supply of AI technologies tend to invest more in AI. In terms of fund characteristics, mutual funds that are larger, younger, and trade more tend to have higher levels of AI investment. As seen in Section 3.2, the expense ratio is negatively associated with the level of AI investment.

[Insert Table 6]

Finally, we present our second-stage results in Table 7. In columns (1) and (2), we use benchmark-adjusted returns as the dependent variable. In the univariate regression in column (1), we find that $\hat{\beta}^2$ is positive and statistically significant at the 10% level. Our IV estimate is about 4.85 times larger than our OLS estimate reported in Table 5 ($4.85 = 0.126/0.26$), suggesting that measurement errors in our measure of mutual fund AI investment may suffer from attenuation bias. Based on our IV estimate, a one standard deviation increase in AI investment leads to an 8.4 basis-point increase in benchmark-adjusted returns per month (1.01% annualized). Our results remain similar when we control for fund characteristics and replace benchmark-adjusted returns with CAPM alphas. Thus, our IV results suggest that our main findings on AI outperformance are likely causal.

[Insert Table 7]

3.5 Man vs. Machine: Do AI technologies improve the performance of quantitative or discretionary funds?

After establishing AI outperformance, we turn to examining which types of funds derive the most value from AI technologies. Specifically, we aim to answer the following question: Will AI enhance machines to the point where they replace humans (man vs. machine), or will AI improve human performance, enabling humans to coexist with machines (man + machine)?

To address this question, we classify mutual funds into two categories: quantitative funds, which rely on algorithms and signals, and discretionary funds, which rely on human judgment. We train machine learning models (random forest) on textual data obtained from the Principal Investment Strategy sections of mutual fund prospectuses (Abis, 2022).

Mutual funds are double-sorted into two-by-five portfolios based on their quantitative/discretionary classification and their level of AI investment. We report the results in Table 8. Among discretionary funds, high-AI funds outperform low-AI funds by 7.2 basis points per month (0.86% annualized). In contrast, among quantitative funds, AI outperformance is muted and statistically insignificant. Thus, AI technologies appear to have a larger impact on discretionary funds that rely on human judgment than on quantitative funds that rely on algorithms.

[Insert Table 8]

Our double-sort results suggest that, rather than replacing human intelligence, artificial intelligence is more likely to augment it, consistent with the findings of Cao et al. (2024). To corroborate our claim that AI is likely to augment human intelligence, we examine the time-varying fund manager skill in the next sub-section.

3.6 Time-varying fund manager skill

Kacperczyk et al. (2014) find that mutual fund managers exhibit time-varying skills, engaging in stock picking during normal times and switching to market timing during bad times. Kacperczyk et al. (2016) propose a rational attention allocation model to explain these empirical results. In their model, skilled fund managers have limited attention and, as a result, rationally allocate it between two types of information: idiosyncratic shocks and aggregate shocks. Paying attention to aggregate shocks becomes more important in bad times, when both the amount of market risk and investors' risk aversion increase.

Building on the model of Kacperczyk et al. (2016), Abis (2022) argue that time-varying fund manager skill is a human trait. She finds that this trait is more pronounced among discretionary funds that rely on human judgment and is muted among quantitative funds that rely on algorithms. As shown in the previous subsection, if artificial intelligence indeed augments rather than replaces human intelligence, we would expect that time-varying fund manager skill improves with the use of AI technologies. We test this prediction in this subsection.

To do so, we define the stock picking (SP) and market timing (MT) skills of mutual funds as the covariance between fund excess weights and idiosyncratic returns and market returns, respectively, following Kacperczyk et al. (2014):

$$SP_{i,t} = \sum_{j}^{N_{i,t-1}} (w_{i,j,t-1} - w_{m,j,t-1}) (R_{j,t} - \beta_{j,t-1} R_{m,t}) \tag{5}$$

$$MT_{i,t} = \sum_{j}^{N_{i,t-1}} (w_{i,j,t-1} - w_{m,j,t-1}) (\beta_{j,t-1} R_{m,t}) \tag{6}$$

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) skill is higher if the fund tends to overweight (underweight) stocks with positive (negative) alphas in the following month. Similarly, market timing (MT) skill is higher if the fund tends to overweight high (low) beta stocks when the market return is positive (negative) in the following month.

To test whether AI technologies improve time-varying fund manager skill, we estimate the following linear regression model:

$$
\begin{aligned}
SP_{i,t}\ (MT_{i,t}) = \beta AI_{i,t}^{MF} + \delta \left(AI_{i,t}^{MF} \times \mathbb{1}(\textit{Volatile market}_t) \right) \\
+ \gamma \Gamma_{i,t-1} + \theta_i + \theta_t\ (\theta_{i,t-1}) + \varepsilon_{i,t}
\end{aligned}
\tag{7}
$$

where i indexes mutual funds and t indexes time in months. $AI_{i,t}^{MF}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, 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 $\theta_{i,t-1}$ are fund, time, and category-by-time fixed effects, respectively.

We present the results in Table 9. In columns (1) and (2), where the dependent variable is SP, we find that $\hat{\beta}$ is positive and statistically significant, while $\hat{\delta}$ is negative and statistically significant. The signs of $\hat{\beta}$ and $\hat{\delta}$ reverse in columns (3) and (4), where the dependent variable is MT. These results support our prediction: high-AI funds demonstrate better stock picking during normal times and superior market timing during volatile periods when aggregate market risk and investor risk aversion are elevated.

Overall, our findings suggest that AI technologies enhance time-varying skills – traits traditionally associated with human discretion (Abis, 2022). Thus, our results across this and the previous subsection support the view that artificial intelligence augments human intelligence rather than replaces it, pointing to a "man + machine" equilibrium (Cao et al., 2024).

[Insert Table 9]

3.7 Satellite imagery of parking lots for retailers

Thus far, we have shown that mutual fund AI investment lead to improved fund performance in terms of benchmark-adjusted returns, alphas, and time-varying stock-picking and market-timing skills. In this subsection, we take a closer look at the source of the improved performance of high-AI funds.

We expect that AI and machine learning will be particularly powerful in processing unstructured big data, such as satellite imagery of parking lots for retailers. To test our hypothesis, we estimate the following linear regression model:

$$\begin{aligned} Alpha_{j,t} = {} & \rho\left(Weight_{i,j,t-1} \times \mathbb{1}(Post_{j,t-1}) \times AI^{MF}_{i,t}\right) + \delta_1\left(Weight_{i,j,t-1} \times \mathbb{1}(Post_{j,t-1})\right) \\ & + \delta_2\left(Weight_{i,j,t-1} \times AI^{MF}_{i,t}\right) + \delta_3\left(\mathbb{1}(Post_{j,t-1}) \times AI^{MF}_{i,t}\right) \\ & + \beta_1 Weight_{i,j,t-1} + \beta_2 \mathbb{1}(Post_{j,t-1}) + \beta_3 AI^{MF}_{i,t} + \gamma_1 \Gamma_{i,t-1} + \gamma_2 \Gamma_{j,t-1} + \theta_i + \theta_j + \theta_t + \varepsilon_{i,j,t} \end{aligned} \quad (8)$$

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). $AI^{MF}_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, 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.

We present the results in Table 10. Our main variable of interest is the triple interaction term, which captures the effect of AI on stock picking following the availability of satellite imagery of parking lots. In column (1), $\hat{\rho}$ is positive and statistically significant, suggesting that the positive impact of AI technologies on stock selection is enhanced by the availability of big data, such as satellite imagery of parking lots. Our findings remain robust to the inclusion of fund and stock characteristics in columns (2) through (4). Overall, our results suggest that funds utilizing AI technologies are better equipped to process and exploit big data as more unstructured information becomes available.

[Insert Table 10]

4 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.

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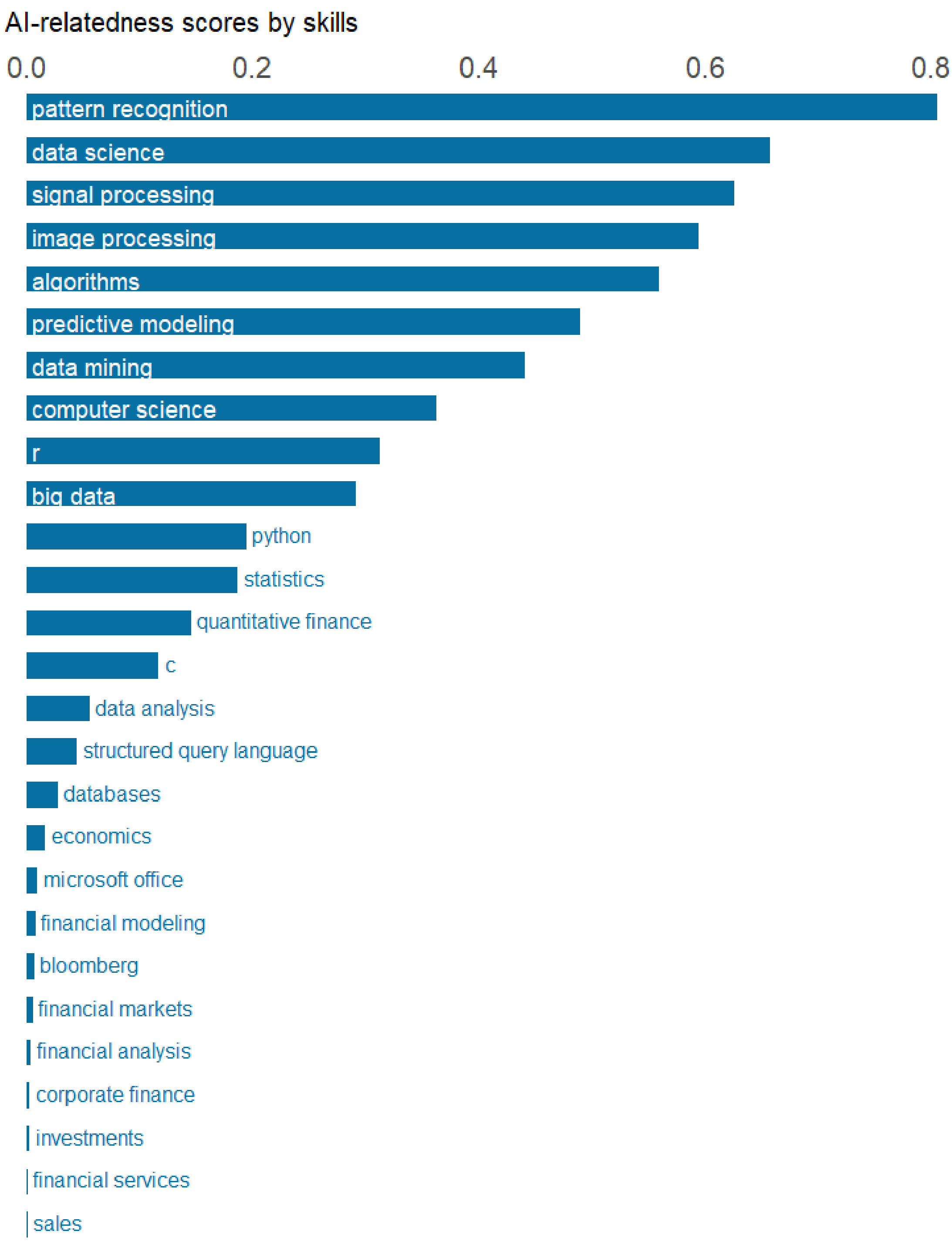

Figure 1: This figure shows the AI-relatedness scores for a few selected skills.

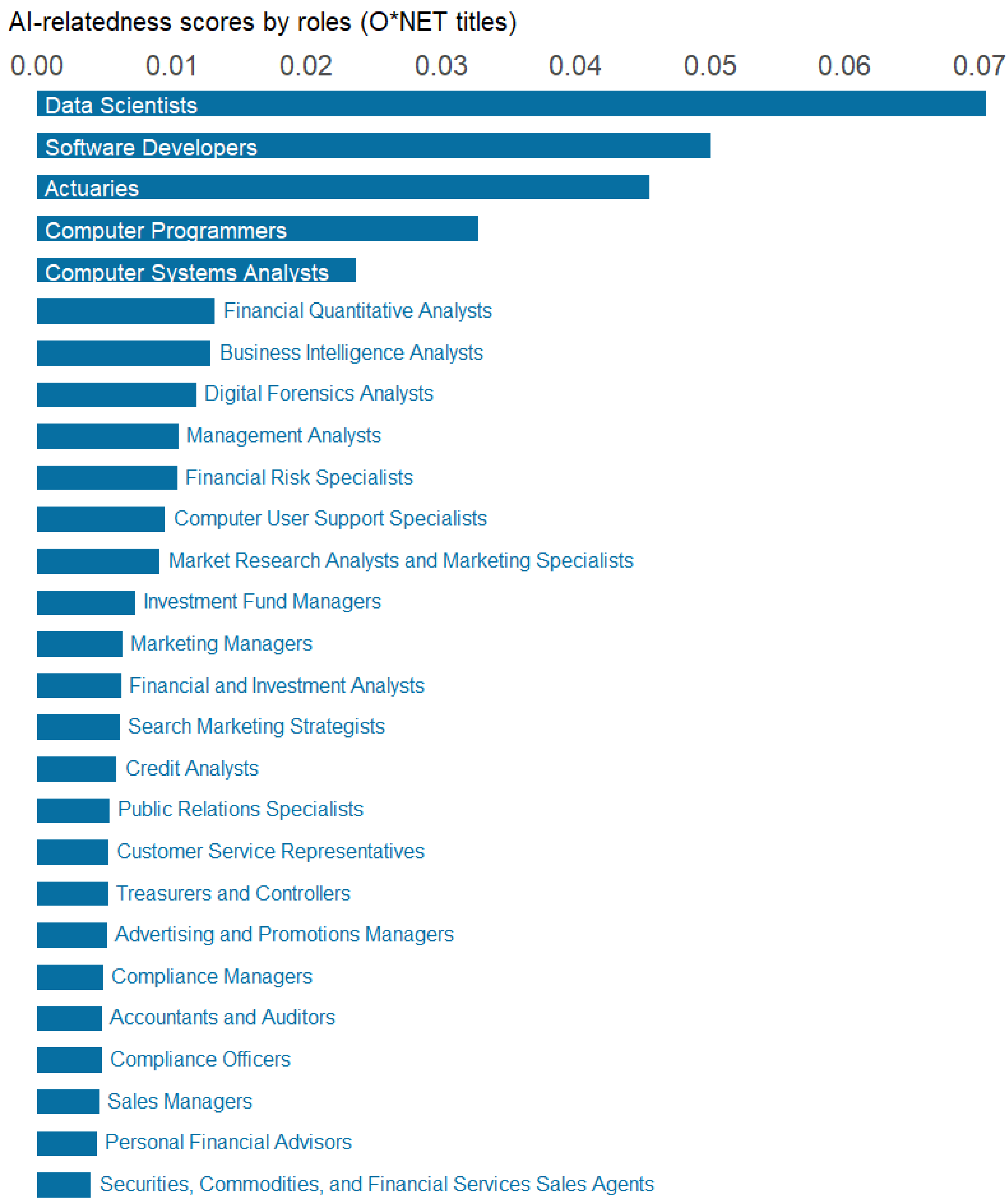

Figure 2: This figure shows the AI-relatedness scores for a few selected roles (O*NET titles).

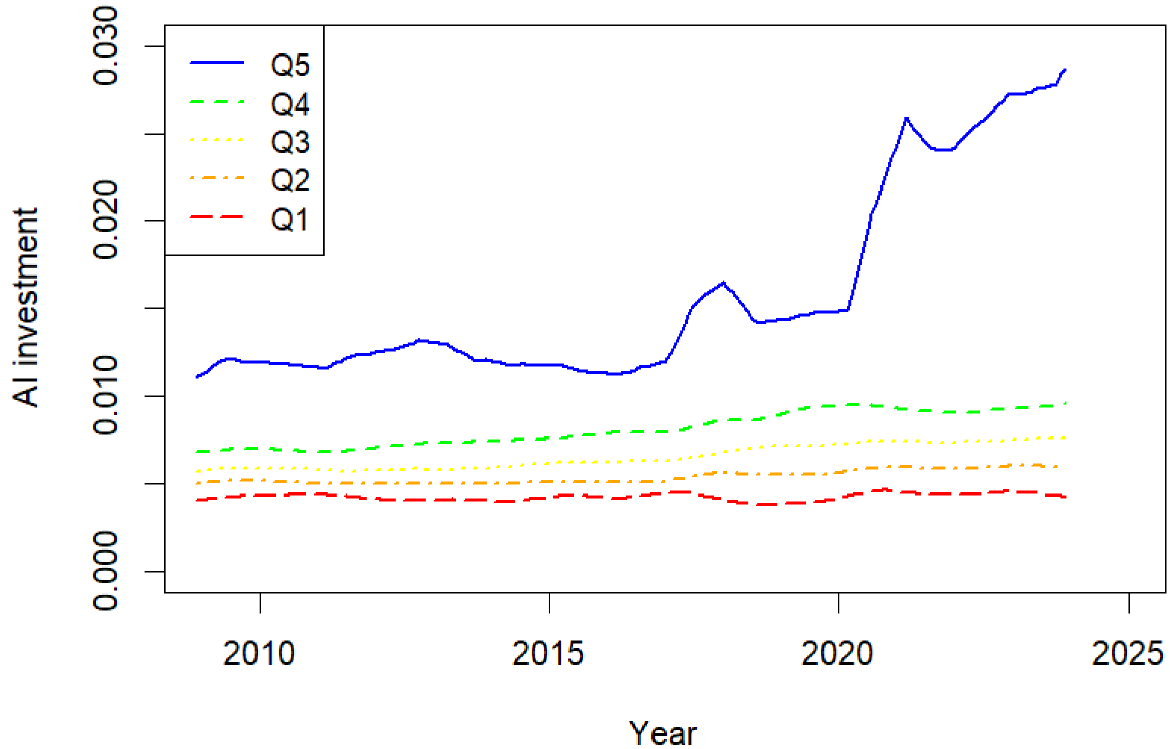

Figure 3: This figure shows the value-weighted average level of investment in AI technologies by mutual fund investment managers, sorted into quintiles.

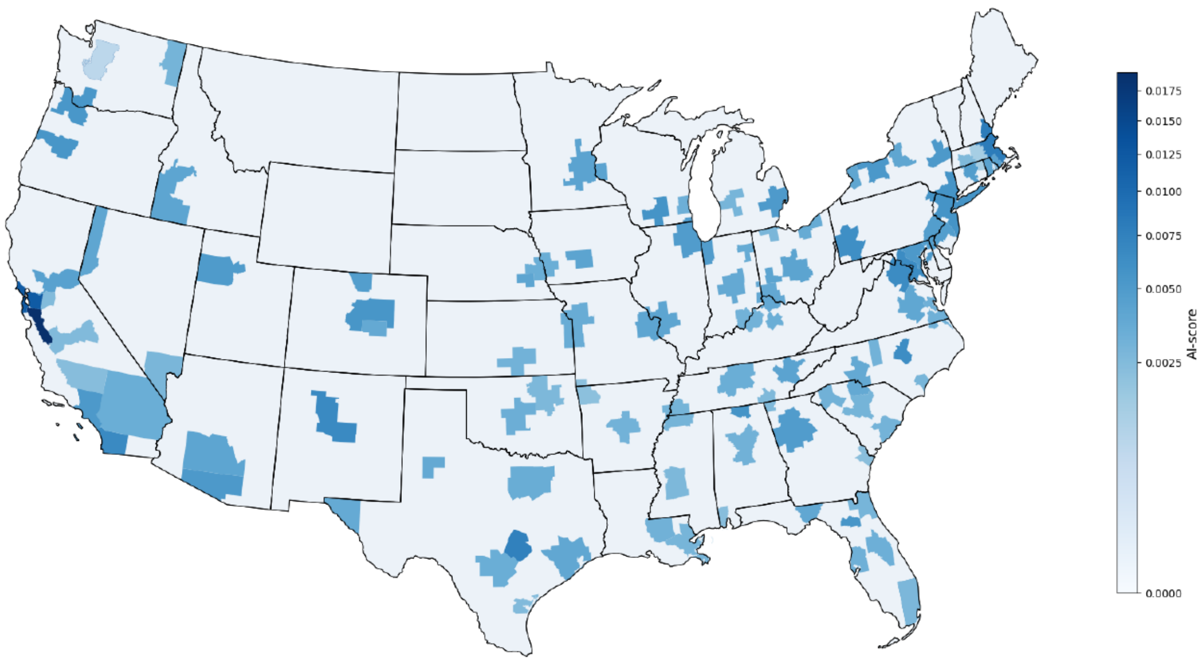

Figure 4: This figure shows the local supply of AI technologies in 2023.

Table 1: Summary statistics

This table presents summary statistics for the key variables used in our analyses. All variables are indexed by mutual fund i and time t in months. AI^{MF} and AI^{Local} represent our measures of mutual fund investment in, and local supply of, AI technologies, respectively, as defined in Section 2.2. $BAR_{i,t}$ denotes fund i's return in excess of its prospectus 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 on 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 $t-1$. $SP_{i,t}$ 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 (5) and (6) in Section 3.6 for details. The remaining variables represent lagged fund characteristics, including total net assets (TNA, in $ billions), expense ratio (in percent), turnover ratio, and fund age (in years). Share-class-level variables are aggregated to the fund (portfolio) level using *crsp_portno*, by summing TNAs, taking value-weighted averages of the expense and turnover ratios, and measuring fund age as the time elapsed between the end of month $t-1$ and the inception date of the oldest share class.

Statistic	N	Mean	St. Dev.	Pctl(25)	Median	Pctl(75)
AI^{MF}	145,742	0.85	0.67	0.52	0.67	0.87
AI^{Local}	145,742	0.57	0.14	0.47	0.53	0.64
BAR	145,742	−0.12	1.65	−0.97	−0.11	0.73
Alpha	145,742	−0.24	2.02	−1.26	−0.17	0.84
SP	157,437	−0.13	1.73	−0.97	−0.07	0.78
MT	157,437	0.86	3.55	−1.12	0.96	2.87
TNA	145,742	2.29	4.99	0.16	0.59	1.91
Expense ratio	138,155	0.99	0.32	0.81	0.99	1.17
Turnover ratio	138,174	0.57	0.46	0.26	0.45	0.73
Fund age	145,742	19.11	13.84	9.77	17.07	24.56

Table 2: Does AI investment lead to improved fund performance?

This table presents the results of portfolio sorts based on AI investment. First, we sort the funds into quintile portfolios each month based on the level of investment in AI technologies by mutual fund managers (investment advisers). Next, we compute the equal- and 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 prospectus 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: Benchmark-adjusted returns (equal-weighted)

Portfolios sorted on AI investment					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
-0.119^{***}	-0.092^{***}	-0.110^{***}	-0.099^{**}	-0.076^{**}	0.043^{**}
(-3.33)	(-2.74)	(-3.19)	(-2.55)	(-2.21)	(2.46)

Panel B: Benchmark-adjusted returns (value-weighted)

Portfolios sorted on AI investment					
Q1	Q2	Q3	Q4	Q5	Q5 – Q1
-0.122^{***}	-0.119^{***}	-0.112^{***}	-0.091^{**}	-0.070^{**}	0.052^{*}
(-2.98)	(-4.37)	(-3.63)	(-2.47)	(-2.20)	(1.77)

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 managers (investment advisers). 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	0.035**	0.035**	0.033*
	(2.06)	(2.09)	(1.95)
MKT	0.009**	0.010***	0.015***
	(2.01)	(2.64)	(3.67)
SMB		−0.009	−0.006
		(−1.21)	(−0.74)
HML		0.006	0.011*
		(0.97)	(1.82)
UMD			0.016***
			(3.71)

Table 4: Does AI investment lead to reduced expenses?

This table presents the results of portfolio sorts based on AI investment. First, we sort the funds into quintile portfolios each month based on the level of investment in AI technologies by mutual fund managers (investment advisers). Next, we compute the equal-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 prospectus 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 investment					
	Q1	Q2	Q3	Q4	Q5	Q5 – Q1
Net returns	-0.119^{***}	-0.092^{***}	-0.110^{***}	-0.099^{**}	-0.076^{**}	0.043^{**}
	(-3.33)	(-2.74)	(-3.19)	(-2.55)	(-2.21)	(2.46)
Gross returns	-0.034	-0.007	-0.018	-0.016	-0.004	0.030^{*}
	(-0.92)	(-0.21)	(-0.52)	(-0.40)	(-0.10)	(1.68)
Expenses	0.090^{***}	0.085^{***}	0.089^{***}	0.085^{***}	0.074^{***}	-0.017^{***}
	(56.12)	(82.06)	(43.11)	(47.14)	(21.21)	(-6.70)

Table 5: Controlling for fund characteristics

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

$$BAR_{i,t}\ (Alpha_{i,t}) = \beta AI^{MF}_{i,t} + \gamma\Gamma_{i,t-1} + \theta_{i,t-1} + \varepsilon_{i,t}$$

where i indexes mutual funds and t indexes time (in months). $BAR_{i,t}$ denotes the return of fund i in excess of its prospectus 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 $t-1$. $AI^{MF}_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, 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). $\theta_{i,t-1}$ 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^{MF}	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 6: Determinants of mutual fund AI investment

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

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

where i indexes mutual funds and t indexes time in months. $AI^{MF}_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment adviser, as defined in Section 2.2. $AI^{Local}_{i,t}$ 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). $\theta_{i,t-1}$ 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^{MF}					
	(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 7: Instrumental variables (IV) regressions

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

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

where i indexes mutual funds and t indexes time in months. $BAR_{i,t}$ denotes the return of fund i in excess of its prospectus 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 $t-1$. $AI^{MF}_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, as defined in Section 2.2. $AI^{Local}_{i,t}$ 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). $\theta_{i,t-1}$ 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)
$\widehat{\text{AI}^{\text{MF}}}$	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

Table 8: Man vs. Machine: Do AI technologies improve the performance of quantitative or discretionary funds?

This table presents the results of double sorts based on quantitative fund classification and AI investment. First, we sort the funds into two-by-five portfolios each month, based on the fund's quantitative/discretionary classification (Abis, 2022) and the level of investment in AI technologies by the fund's investment adviser. 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 prospectus 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 investment					
	Q1	Q2	Q3	Q4	Q5	Q5 − Q1
Discretionary	-0.125^{***}	-0.087^{*}	-0.087^{**}	-0.091^{**}	-0.053	0.072^{*}
	(-2.75)	(-1.67)	(-2.24)	(-1.98)	(-1.32)	(1.96)
Quantitative	-0.138^{***}	-0.156^{***}	-0.156^{***}	-0.124^{***}	-0.083^{**}	0.055
	(-3.67)	(-5.25)	(-4.07)	(-3.01)	(-2.40)	(1.33)

Table 9: Time-varying fund manager skill

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

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

where i indexes mutual funds and t indexes time in months. $AI_{i,t}^{MF}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, 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 (5) and (6) in Section 3.6 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 $\theta_{i,t-1}$ 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^{MF}	0.031*	0.020**	−0.032	−0.018
	(1.76)	(2.16)	(−1.52)	(−1.52)
$\text{AI}^{\text{MF}} \times \mathbb{1}(\text{Volatile market})$	−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 10: Stock picking with satellite imagery of parking lots

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

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

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). $AI^{MF}_{i,t}$ represents the level of investment in AI technologies by mutual fund i's investment advisers, 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 10–*Continued*

	Alpha			
	(1)	(2)	(3)	(4)
Weight × Post × AI^{MF}	0.21**	0.21**	0.24**	0.24**
	(2.38)	(2.36)	(2.34)	(2.41)
Weight × Post	−0.13	−0.12	0.01	−0.004
	(−0.95)	(−0.92)	(0.05)	(−0.04)
Weight × AI^{MF}	−0.04	−0.04	−0.03	−0.03
	(−0.60)	(−0.54)	(−0.39)	(−0.43)
Post × AI^{MF}	−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)
Post	−0.72	−0.75	−0.85	−0.87
	(−1.02)	(−1.06)	(−1.13)	(−1.15)
AI^{MF}	0.08	0.08	0.12	0.12
	(0.63)	(0.58)	(0.93)	(0.92)
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