The Growth and Performance of Artificial Intelligence in Asset Management[†]

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Abstract

This paper examines AI adoption in asset management and its investment implications. We document that AI-driven investing is concentrated among hedge funds, particularly those employing macro strategies. AI funds exhibit greater alpha comovement and are launched by investment advisers facing stronger performance incentives. These funds outperformed non-AI hedge funds by approximately 5% annually on a risk-adjusted basis, but this outperformance declined since 2015 and disappeared after 2020, consistent with decreasing returns to scale at the technology level. Despite this trend, AI funds continued to attract significantly greater capital inflows, suggesting persistent investor belief in AI's alpha-generating ability. Our findings highlight both the promise and limitations of AI as a source of investment performance.

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The active asset management industry constantly seeks new sources of performance, as the effectiveness of existing strategies often declines with scale and over time. Traditional sources of performance rely on human expertise and rule-based quantitative methods. In recent decades, however, Artificial Intelligence (AI) has emerged as a promising alternative. By combining advanced statistical techniques and big data, AI offers unprecedented predictive power to inform investment decisions. Its potential to generate superior returns has attracted growing interest from investment advisers and their clients. Despite the proliferation of AI-driven investing since the early 2000s and numerous anecdotal success stories, systematic academic evidence on AI adoption in asset management and its investment implications remains limited.[1]

In this paper, we conduct a systematic examination of AI-driven investing across the asset management industry. The central challenge to our study is identifying where and how AI is being used in actual investment decisions and linking this usage to fund characteristics and performance. We address this challenge through large-scale textual analyses on SEC-registered investment advisers' job postings and tens of thousands of fund-level strategy disclosures. This large body of textual data reveals not only which investment advisers adopt AI, but also which individual funds rely heavily on AI in their portfolio decisions. Our novel top-down approach allows us to make some long-awaited progress in understanding both the alpha-generating ability and scalability of AI technologies in asset management.

Given our focus on investment applications, we consider broadly defined AI technologies, particularly machine learning (ML) techniques that facilitate predictive modeling and trading signal generation. Accordingly, we do not limit our scope to recent developments in generative AI and large language models (LLMs), such as prompt-based chatbot systems (e.g., OpenAI's

[1]Although investment advisers do not disclose the history of their internal operations, multiple accounts suggest that AI-driven investing has been used since well before 2000. For example, Renaissance Technologies reported that it "has been using machine learning as a means for trading for at least 30 years" (U.S. Senate Committee on Homeland Security and Governmental Affairs, 2024). Similarly, in 2018, a D.E. Shaw executive noted that "Over the past few decades we have developed and deployed increasingly sophisticated machine learning techniques".

ChatGPT), which represent a distinct subset of AI with diverse applications.

Our examination shows that, while AI-related job positions have grown rapidly in the US asset management industry, the actual use of AI-driven investing is largely confined to a subset of private funds, namely hedge funds. More importantly, we find that AI adoption is highly concentrated within a narrowly-defined hedge fund category: the Systematic Diversified Macro strategy. As of 2024, 87% of assets managed by hedge funds engaged in AI-driven investing ("AI funds") in our sample fall into this category, which typically involves short-term trading in equities, commodities, and currencies. We further show that AI funds consistently exhibit stronger comovement than non-AI funds, indicating that the use of similar AI models has led to increased homogeneity among hedge funds.[2]

Consistent with the view that AI is being adopted as a tool to enhance investment performance, we find that hedge fund advisers are more likely to launch AI funds when they face stronger performance incentives. Specifically, the number of AI funds created by an adviser is positively associated with incentives embedded in the compensation contracts of its existing funds. On average, these contracts set higher incentive fee rates and are less likely to include high water mark and hurdle rate provisions, making the incentive fees resemble near-the-money options. In addition, these advisers also impose shorter capital lockup periods and looser withdrawal restrictions, which increases the implicit pressure to deliver better performance (Agarwal, Daniel, and Naik, 2009).

Did AI funds deliver superior returns? Our analysis of a large sample of 9,145 US hedge funds between 2001 and 2024 provides nuanced evidence. We show that AI funds significantly outperformed other hedge funds by around 40 basis points per month (roughly 5% annually) on a risk adjusted basis, after controlling for fund size, age, and contractual

[2]This result aligns with a widespread concern that the use of similar AI models may increase homogeneity and herding behaviors, which potentially amplifies market vulnerabilities. For example, see US Homeland Security & Governmental Affairs 2024 Report "AI in the Real World: Hedge Funds' Use of Artificial Intelligence in Trading" (Section V.B.) and OECD Business and Finance Outlook 2021 "AI in Business and Finance" (Section 2.2).

features. However, this outperformance gradually diminished after 2014, and it has become statistically indistinguishable from zero since 2020. Overall, during our 24-year sample period, AI funds delivered only modestly better performance than non-AI funds. Moreover, we find that AI funds performed better compared to non-AI funds managed by the same hedge fund adviser across time periods. This within-adviser comparison accounts for unobserved talents and resources available to an adviser, suggesting that AI technology offers a meaningful edge relative to traditional investment approaches.

Our findings of AI fund performance are consistent with decreasing returns to scale at the *technology* level. During our sample period, the decline in AI fund performance is accompanied by a sharp expansion in AI funds, with their total AUM quadrupled since 2015. Given that many AI funds pursue similar strategies, invest in overlapping asset classes, and likely react to similar signals, the growing scale makes sustaining outperformance increasingly difficult. As such, the future success of AI-driven strategies will depend not only on the advances in predictive power of AI technology, but also on the scale and heterogeneity of its applications within the asset management industry.

A key driving force behind the growing scale of AI funds is investor belief on AI's alpha-generating ability and scalability. To investigate these beliefs, we apply a revealed preference approach and analyze money flows into hedge funds. Our estimates demonstrate that, controlling for realized performance and other fund characteristics, AI funds attracted, on average, 60 basis points more inflows per month (around 7.2% annually) than otherwise similar non-AI funds. This economically significant difference in flows suggests that investors perceived AI technology as a promising source of performance. Notably, these elevated inflows persisted even after AI funds' superior relative performance has declined from their earlier records. This pattern of continued capital allocation towards AI funds despite their declined performance is consistent with slow investor learning about both the alpha and scalability (Pástor and Stambaugh, 2012) in the context of AI technology.

We conduct a broad set of robustness checks. First, hedge funds may drop out of our sample when they get liquidated or stop reporting to the database. We find this potential survivorship bias is unlikely to explain our findings because AI funds and non-AI funds have similar survival rates. Second, we address a potential backfill bias by excluding observations before a fund was added to the database. We find qualitatively and quantitatively similar results on fund performance and flows. Third, we re-estimate time trends in AI fund performance and flows using linear interaction specifications and continue to find the declining patterns over time. Overall, these results further support our interpretation.

This paper is closely related to a recent literature on the applications of AI and big data technologies in delegated investment. Existing studies have developed creative indirect measures of AI-driven investing to evaluate its performance. Bonelli and Foucault (2023) examine mutual fund stock-level investments and find that the performance of traditional fund managers declines after the stock is covered by satellite image data. Sheng, Sun, Yang, and Zhang (2024) infer hedge funds' use of generative AI, a specific type of AI technology, from the association between changes in 13F stock holdings and ChatGPT-generated signals. They show that institutions with a higher reliance on generative AI achieve superior performance. Using labor-based measures of data science and AI adoption, Cen, Han, Han, and Jo (2024) and Zhang (2024) also find positive impacts of these technologies on institution-level investment performance in recent years.

We contribute to this literature by providing the first fund-level analysis of AI-driven investing. Unlike prior studies, we directly identify which funds rely on AI for investment decisions. This approach uncovers the use of AI across funds and strategy categories, offering new insights into the performance and scalability of this technology and informing future research on AI in asset management.

Our paper also contributes to the hedge fund literature by exploring AI as an important, yet understudied, source of performance. Prior studies have attributed hedge fund performance to

managerial incentives and discretion (Agarwal, Daniel, and Naik, 2009; Gupta and Sachdeva, 2025), share liquidity restrictions (Aragon, 2007), portfolio disclosure (Shi, 2017). The literature also documents associations between performance and the characteristics of hedge funds and fund managers.[3] We show that AI-driven investing has significant alpha-generating ability, as evidenced by AI fund performance relative to peer funds in earlier years and other funds managed by the same adviser. Consistent with Agarwal, Daniel, and Naik (2009), we find that hedge fund advisers facing stronger performance-based incentives are more likely to adopt AI as a tool to enhance investment performance.

The alpha decay of AI hedge funds as their total assets grow extends earlier research on diseconomies of scale in active asset management. Prior literature has focused on decreasing returns to scale among active equity mutual funds, at both the fund level (Chen, Hong, Huang, and Kubik, 2004; Berk and Green, 2004; Zhu, 2018) and the fund industry level (Pástor and Stambaugh, 2012; Pástor, Stambaugh, and Taylor, 2015). Our findings suggest that the increasing use of AI-driven investing by hedge funds has reduced these funds' strategy distinctiveness (Sun, Wang, and Zheng, 2012), giving rise to decreasing returns to scale at the AI technology level.[4]

Finally, our paper relates to the growing literature on AI's impact across the finance industry. Recent studies examine the effects of AI adoption in public firm disclosures (Cao, Jiang, Yang, and Zhang, 2023; Cao, Jiang, Wang, and Yang, 2024), security trading strategies (Dou, Goldstein, and Ji, 2024; Colliard, Foucault, and Lovo, 2022), lending markets (Fuster, Goldsmith-Pinkham, Ramadorai, and Walther, 2022; Choi, Huang, Yang, and Zhang, 2024; Gambacorta, Sabatini, and Schiaffi, 2024; Piao, Wang, and Weng, 2024), and insurance sales (Liu, 2024). We contribute to this literature by showing that hedge funds explicitly disclosing

[3]For example, see Franzoni and Giannetti (2019), Zheng and Yan (2021), Brown, Lu, Ray, and Teo (2018), Lu and Teo (2022), Lu, Ray, and Teo (2016), Lu, Naik, and Teo (2024), Aggarwal and Jorion (2010), Aggarwal and Boyson (2016), and Li, Zhang, and Zhao (2011)

[4]Although we distinguish between AI-driven investing and general quantitative strategies, the homogeneity of AI funds we document is also consistent with Abis (2020), who shows that quantitative mutual funds engage in more overcrowded trades.

AI use attract significantly higher fund flows than otherwise similar funds, revealing that investors believe in the value of AI integration in investment.

1. Data

We describe in this section the construction of our data sample and provide summary statistics of the main variables.

1.1. Data on Investment Advisers

1.1.1. Form ADV

The regulatory framework established by the *Investment Advisers Act of 1940* requires investment advisers to register with the U.S. Securities and Exchange Commission (SEC) by filing Form ADV. This annual filing provides comprehensive information about an adviser's practices, fees, and business structure. We obtain all Form ADV filings submitted between 2012 and 2024 from the SEC website. Our primary focus is on the following "Items" and corresponding "Schedules" in Part 1A of the form:

- **Item 1** reports the adviser's identifying information, including its name(s), office location(s), and website(s).
- **Item 5** details the adviser's Regulatory Assets Under Management (RAUM), including decomposed values by type of client, such as high net worth individuals, business development companies, investment companies, and pooled investment vehicles (other than investment companies and business development companies).
- **Item 7B** indicates whether the adviser manages private funds. Schedule D of Item 7B provides additional fund-level information, including fund type and gross asset value.

We use the sample starting from 2012, as the significant updates to Form ADV in order to implement the *Dodd-Frank Act* became effective in March 2012. The updates include raising the threshold for registration to $100 million in Regulatory Assets Under Management (RAUM), requiring a decomposition of RAUM by client types, and adding fund-level disclosures for private funds' types, gross asset values, ownership structures, and service providers.[5] In October 2017, the SEC amended Form ADV, leading to changes in the format of several items. For example, prior to 2017Q3, the amount of the adviser's RAUM attributable to a type of client was reported as a categorical range in Item 5D, including "None", "Up to 25%", "Up to 50%", "Up to 75%", and ">75%". After 2017Q3, Item 5A was revised to report the accurate amount of RAUM. To ensure consistency in measuring business dimensions across years, we convert categorical ranges into numerical values by taking the midpoint of the range (e.g., "Up to 50%" becomes 37.5%). Moreover, if the reported RAUM attributable to a type of client is missing, we impute the value as zero.

1.1.2. Job postings from Lightcast

Lightcast (previously known as Burning Glass) aggregates job postings from a variety of online sources, including both job boards and company websites. The dataset includes the full job description and extracted data items such as employer names, job titles, posting dates, sought-after skills, and educational prerequisites. Hershbein and Kahn (2018) find that while Lightcast data focus more on specific occupations and industries, their distribution patterns are relatively consistent over time and align with vacancy trends reported by other major data sources (e.g., Job Openings and Labor Turnover Survey, the Current Population Survey, and Occupational Employment Statistics). Our data from Lightcast's U.S. job postings are

[5]SEC registration is eligible for investment advisers with RAUM of at least $100 million and becomes mandatory for those with RAUM of $110 million or more. In practice, advisers typically register with the SEC once they become eligible, allowing them to avoid the complexities of state-level registration. Moreover, advisers with RAUM below the $100 million threshold may also file Form ADV, even if they are not registered with the SEC. To avoid selection biases, our sample includes Form ADV filings by advisers in years with at least $100 million RAUM.

between 2010 and 2024. We focus on entries with available employer names and exclude internships.

Our key measure of an investment adviser's AI labor intensity is constructed using the skills required for job positions, following the methodology in Babina, Fedyk, He, and Hodson (2024). We also do robustness tests using three measures for an investment adviser's job postings related to AI, old technology (OT), and data management (DM), following Abis and Veldkamp (2024). The detailed steps for constructing the AI labor intensity measure are provided in Internet Appendix IA.2.

1.1.3. Adviser-Year Panel

We construct an adviser-year panel by linking Form ADV filings with Lightcast job postings as follows. First, we retain all filings in which the adviser's total Regulatory Assets Under Management (RAUM) is non-zero and non-missing. For each adviser, uniquely identified by its SEC file number, we keep only the last filing submitted within each calendar year.

Second, we process the private funds data and compute each adviser's total number of private funds and their aggregate gross asset values (GAVs). We also calculate GAVs separately by fund type: Hedge Funds, Private Equity Funds, Real Estate Funds, Securitized Asset Funds, Venture Capital Funds, and other private funds.[6] We then merge private fund variables with the adviser-year panel using the unique filing identifier.

Third, we construct a crosswalk between investment advisers in Form ADV and employers in Lightcast, using Morningstar's PitchBook platform. PitchBook applies a proprietary entity-matching algorithm that incorporates firm name variations (e.g., legal names, trade names, former names), headquarter locations, and website URLs. The algorithm also accounts

[6]Our data cleaning involves three steps. First, we reclassify funds originally labeled as "Other Private Funds" into one of the five core types whenever the fund type description provides a clear mapping. Second, if a private fund has a missing type or is reported as a "Liquidity Fund," we recode it as "Other Private Fund." Third, we ensure consistency between the Item 7B indicator for advising private funds and the presence of private fund data in Schedule D.

for parent-subsidiary relationships.

Figure IA.1 in the Appendix summarizes the annual distribution of linked investment advisers. Nearly the entire population of Form ADV filers is matched to PitchBook entities, and approximately 70% of those are further linked to job postings in Lightcast.[7]

1.2. Data on hedge funds

We use hedge funds' investment strategy descriptions and other information in the HFR database. Agarwal, Daniel, and Naik (2004) compare the number of hedge funds covered in three major databases, HFR, ZCM/MAR, and TASS, during the period 1994–2000, and find that HFR offers the most comprehensive coverage. Given data availability constraints, and after comparing the coverage of HFR and TASS during 2010–2024, a period in which AI-related activities are particularly relevant, we choose to use HFR, which offers superior coverage in recent years.

Our sample consists of USD-nominated US-domiciled hedge funds with at least $1 million in AUM. For each fund's investment strategy description, we use OpenAI's GPT-4o mini large language model to evaluate whether the fund employs Artificial Intelligence, quantitative strategies, or high-frequency trading. The complete AI prompt and classification examples are provided in Internet Appendix IA.1. In addition, the HFR database classifies hedge funds into strategy categories such as Equity Hedge, Event Driven, Macro, Relative Value, Risk Parity, and Crypto/Blockchain.[8]

We assume that a fund's investment strategy, as reported in HFR, applies throughout its history. On the one hand, investment strategy represents a key contractual feature between the fund and its investors, and contractual features are typically established at inception and remain unchanged over the fund's life (Agarwal, Daniel, and Naik, 2009). On the other

[7]PitchBook's coverage is generally more comprehensive for larger investment advisers.

[8]A complete list of HFR strategy categories and definitions is available at: https://www.hfr.com/hfr-indices/hfr-hedge-fund-strategy-classifications/.

hand, in public funds where we have access to historical investment strategy descriptions, we confirm that changes in investment strategy are very rare. We calculate a fund's monthly alpha and risk exposures using the 7-factor model in Fung and Hsieh (2004)[9], including Equity Market Factor, Size Spread Factor, Bond Market Factor, Credit Spread Factor, Bond Trend-Following Factor, Currency Trend-Following Factor, and Commodity Trend-Following Factor. Risk exposures are estimated using 24-month rolling window, requiring at least 12 observations. Monthly alpha is the out of sample residual of the 7-factor model estimation in the next month.

1.3. Data on mutual funds

We collect open-end funds' legally binding investment strategies from Form 497K filings available on the SEC's EDGAR database from 2009 to 2024. Form 497K was introduced following the SEC's adoption of the Summary Prospectus Rule (Rule 498) in 2009, which aimed to improve disclosure clarity in response to concerns that statutory prospectuses were excessively lengthy and difficult to navigate. Since 2010, the use of summary prospectuses has become widespread. Funds using summary prospectuses are required to file Form 497K at least annually and to provide updates when material changes occur. The summary prospectus follows a standardized format and item order. In this study, we focus on the section titled "Principal Investment Strategies of the Fund", which must include any investment techniques that are material to the fund's investment strategy.

We apply the same AI prompt used for hedge fund investment strategy descriptions (see Internet Appendix IA.1) to the investment strategy text of open-end funds. We then match each fund's extracted strategy features and effective date from Form 497K filings with its monthly characteristics from the CRSP Survivorship Bias-Free Mutual Fund database, using fund ticker, fund name, and company name as common identifiers. Following Kacperczyk,

[9]Factor definitions and data are available at: https://people.duke.edu/~dah7/HFRFData.htm

Sialm, and Zheng (2008), we aggregate monthly return and total net asset (TNA) data from the share class level to the fund level and then compute fund flows, winsorized at the 1st and 99th percentiles.

1.4. Summary Statistics

Table 1 reports summary statistics for the adviser-year panel constructed by merging Form ADV disclosures from 2012 to 2023 with job posting data in the next year. By construction, each adviser in the sample manages at least $100 million in regulatory AUM and posts no fewer than five job vacancies in the subsequent year. The median adviser manages $5.6 billion in AUM and serves approximately 200 clients.[10]

We focus on advisers' AUM composition. First, *AUM% Discretionary* measures the proportion of AUM managed on a discretionary basis, where the adviser makes investment decisions without obtaining client approval for each trade. In contrast, non-discretionary management requires client consent prior to execution. Most advisers operate predominantly under discretionary mandates, with a median discretionary AUM share close to 100%.

Second, roughly half of the advisers manage at least one private fund. Private funds refer to pooled investment vehicles other than investment companies and business development companies, including hedge funds, private equity funds, venture capital funds, and other private investment vehicles. These funds are generally exempt from registration under the Investment Company Act of 1940 (e.g., via Sections 3(c)(1) or 3(c)(7)). In contrast, public funds refer to investment companies, such as mutual funds, ETFs, and closed-end funds, which are governed by the Investment Company Act of 1940.

Third, the composition of AUM across different legal structures is rarely 100% in one

[10]The definition of "client" in client count reported by Form ADV differs between individual clients and fund vehicles. Each individual client (e.g., retail or high-net-worth individuals) counts as one client, whereas each fund vehicle (e.g., mutual fund, private equity fund) counts as a single client, regardless of the number of underlying investors.

category, suggesting most advisers serve different clients. *AUM% HighNetWorth* captures the share of AUM managed for high-net-worth individuals, typically defined as clients with at least $1 million in AUM with the adviser or a net worth exceeding $2.1 million (excluding their primary residence). *AUM% Individual* measures the share of AUM from retail investors who fall below the high-net-worth threshold.

Table 2 presents summary statistics for 9,145 hedge funds' monthly observations spanning 2001 to 2024. As mentioned above, the sample includes only USD-nominated US-domiciled hedge funds with at least $1 million in AUM. We focus on the prevalence of AI strategies and compare our sample's fund compensation structures and liquidity restrictions with data samples in the hedge fund performance literature.

Regarding AI strategy's prevalence, the dummy variable *AI Strategy* averages 0.01, indicating that only 1% of fund-month observations explicitly involve AI in investment decision-making. By comparison, 40% of observations are classified as generic quantitative and 1% as high-frequency strategies.

Regarding compensation structure, the average incentive fee among hedge funds in our sample is 15.7%, closely matching the 16.3% reported in Agarwal, Daniel, and Naik (2009). High-water mark provisions are present in 85% of fund-month observations, consistent with the 80.1% prevalence in their sample. However, hurdle rate provisions appear far less frequently in our data, only 13%, compared to 60.8% in Agarwal, Daniel, and Naik (2009), suggesting a possible shift away from this investor-protection clause over time.

Regarding liquidity restrictions, the average lock-up period is 4.83 months, shorter than the 0.8 years (or 9.6 months) reported by Agarwal, Daniel, and Naik (2009). Conversely, the average restriction period is 4.35 months, closely aligning with the 0.3 years (3.6 months) in their study.

2. Which Funds Use AI-Driven Investing?

This section provides a top-down analysis of which funds use AI, beginning with broad fund classifications based on legal structure, then moving to more detailed classifications based on target assets, and finally to the most granular classifications based on investment strategy.

First, to gain a high-level view of the asset management industry, we obtain each investment adviser's AUM composition by legal structure from Form ADV. For example, Form ADV provides the percentage of AUM managed in investment companies regulated under the Investment Company Act of 1940 (i.e., public funds) versus the percentage managed in pooled investment vehicles other than investment companies and business development companies, which are exempt from registration under the Act (i.e., private funds). We examine whether an adviser's AUM concentration in a particular fund legal structure predicts its AI labor intensity in the following year.

Second, we zoom into a more detailed breakdown of private funds based on the fund's target assets, as reported in Form ADV. We analyze whether an adviser's gross asset value (GAV)[11] concentration in a specific target asset class predicts its AI labor intensity in the next year.

Third, considering potential variation in AI usage within an adviser's funds with the same legal structure and investing in the same asset class, we directly examine each fund's disclosed investment strategy to identify funds that use AI in investment decisions. We then describe the key characteristics of the identified AI funds.

[11]GAV and AUM often align in value for private funds. AUM is measured net of liabilities, reflecting the fair market value of assets under continuous and regular management, whereas GAV is reported gross, before deducting any liabilities.

2.1. The growth of investment advisers' AI jobs postings

As companies rarely disclose their capital expenditures on AI, the literature[12] typically measures company-level AI intensity from the labor perspective. We follow the literature by examining each investment adviser's AI labor intensity revealed through their job postings. Figure 1 presents the time trend in AI-related job postings across investment advisers, Compustat financial firms, and Compustat non-financial firms. While the average share of AI-related job postings among all job postings remains below 4% across all three groups, it rises sharply beginning in 2017, with investment advisers consistently exhibiting slightly higher AI labor intensity than the other groups following this take-off. In 2023, a notable decline in AI labor intensity is observed among Compustat non-financial firms, potentially reflecting widespread layoffs in the IT sector, whereas investment advisers and Compustat financial firms are less affected. The annual averages for Compustat firms in our sample closely align with the patterns reported by Babina et al. (2024).

To provide further insight into the roles AI labor performs within investment advisers, we present time trends of AI-related job postings across different functional areas, including investment, data management, IT, client communication, and those referencing generative AI keywords, in Internet Appendix Figure IA.2. By 2024, investment and IT roles together account for over half of all AI-related job postings. Following the release of ChatGPT in November 2022, which marked a major breakthrough in generative AI, AI-related job postings that contain generative AI keywords increased sharply in 2023 and 2024, surpassing the number in data management roles or client communication roles in 2024.

[12] Acemoglu, Autor, Hazell, and Restrepo (2022), Babina, Fedyk, He, and Hodson (2023), Babina, Fedyk, He, and Hodson (2024), Eisfeldt, Schubert, and Zhang (2023)

2.2. Investment advisers' fund composition and AI job postings

We examine whether variations in an investment adviser's AI labor intensity are associated with variations in the composition of the funds it manages. Specifically, we leverage the detailed fund compositions reported in Form ADV Item 5, Item 7, and Section 7B(1) of Schedule D to obtain Table 3.

In Panel A, the natural logarithm of an investment adviser's total AUM is positively and significantly associated with the share of AI-related job postings in the following year, suggesting that firm scale is a key driver of AI labor intensity. In contrast, the natural logarithm of total client count is negatively associated with AI labor intensity, indicating that, for a given level of AUM, advisers with more clients (implying lower average AUM per client) tend to invest less in AI labor.[13] Figure IA.3 in the Internet Appendix visualizes these two correlations using a heatmap that double-sorts investment advisers by AUM and client count. Darker cell shading indicates higher AI labor intensity in the subsequent year, confirming that larger AUM and fewer clients are associated with greater AI labor intensity.

Columns 3 and 4 highlight a positive relationship between managing private funds and subsequent AI labor intensity. In Column 3, the coefficient on the dummy variable indicating whether the adviser manages at least one private fund is 0.739, implying that private-fund advisers exhibit a 0.739-percentage-point increase in next-year AI labor intensity. This effect is economically meaningful, amounting to 61.58% of the sample mean and 15.40% of the sample standard deviation of AI labor intensity. Column 4 confirms this relationship using the continuous measure of AUM percentage allocated to private funds. A one-standard-deviation increase in this share (equal to 38.8 percentage points) is associated with a 0.5432-percentage-point increase in AI labor intensity in the following year ($38.8 \times 0.014 = 0.5432$). This

[13] Since advisory services for high-net-worth individuals or other individual clients count each person as a separate client, whereas managing a public or private fund counts each fund product as a single client, the negative coefficient is likely driven by advisers with a larger number of individual clients using less AI labor. Panel B presents a similar pattern using the number of private funds, where the definition of private fund is consistent across advisers.

corresponds to 45.27% of the sample mean and 11.32% of the standard deviation. Figure IA.4 in the Internet Appendix confirms this relationship with heatmaps.

Given the evidence in Panel A that deeper involvement in private fund management is strongly associated with greater AI-related human capital investment, we further investigate this relationship by focusing on the subsample of advisers that manage at least one private fund. Specifically, we examine whether target asset types of private funds are differentially associated with variations in AI labor intensity. Form ADV Schedule D Section 7B(1) requires each private fund to disclose fund type and GAV, specifying whether it is a fund of funds, hedge fund, liquidity fund, private equity fund, real estate fund, securitized asset fund, or venture capital fund.

In Panel B,[14] the variable *log(GAV)* consistently exhibits a statistically significant positive coefficient across all columns, indicating that advisers managing larger aggregate private fund assets tend to allocate more resources to AI-related labor. In contrast, *log(Number of Private Fund)* shows a significant negative association with AI labor intensity, suggesting that AI investments are more concentrated in advisers overseeing fewer, larger private funds. These results echo the patterns documented in Panel A, where *log(AUM)* is positively and *log(Client)* negatively correlated with AI labor intensity.

Further, Column 4 shows that the composition of private fund assets also matters: a higher percentage of GAV allocated to hedge funds is positively associated with subsequent AI labor intensity, whereas a higher share in securitized asset funds is significantly negatively associated. Specifically, a one-standard-deviation increase in *GAV% Hedge Fund* (42.6 percentage points) predicts a 0.852-percentage-point increase in AI labor intensity ($42.6 \times 0.020 = 0.852$), equivalent to 71% of the sample mean and 17.75% of its standard deviation. This relationship is also visualized in Figure IA.5 in the Internet Appendix.

Overall, Table 3 highlights that future AI labor intensity among investment advisers is

[14]Fund-of-funds and liquidity funds are not separately reported due to their limited presence in the sample.

positively linked to advising private funds, especially hedge funds. Advisers managing larger assets, especially those concentrated in fewer funds, will integrate AI labor more extensively.

2.3. The growth of AI funds

To examine variation in AI usage among funds with the same legal structure and asset class, we identify whether a given hedge fund or open-end public fund employs AI in its investment decision-making, based on its investment strategy description. Figure 2 presents the time series growth of hedge funds and public funds that use AI for investment decisions from 2000 to 2024. Each panel shows total net assets (TNA) in USD billions on the left vertical axis with gray bars and the number of funds on the right vertical axis with the red line.

Panel A shows a rapid increase in both the number and total assets of hedge funds using AI from 2016 to 2021. The number of such funds peaks at over 100 in 2021, before declining to fewer than 60 by 2024. However, TNA continues to grow after 2021, reaching approximately $13 billion by 2024, suggesting an increasing concentration of assets among a smaller set of AI hedge funds. This rapid growth in assets since 2016 coincides with the rise in average AI labor intensity among investment advisers shown in Figure 1. Panel B shows a slower and much more modest growth pattern among open-end public funds using AI. AI for investment decisions in this segment remains limited, with the number of AI public funds rising gradually to around 20 by 2024 and TNA approaching $2 billion. Overall, these trends indicate that AI adoption in investment strategies is much more prevalent among hedge funds than among public funds.

2.4. Investment strategies of AI funds

A fund's investment strategy category, such as equity active, event-driven, or index, plays a crucial role in shaping the feasibility and application of AI algorithms. For instance, strategies operating in signal-rich environments like global macro or short-horizon equity trading are

naturally more amenable to data-intensive AI techniques, whereas illiquid or event-driven strategies provide fewer high-frequency observations, limiting the applicability of such models.

We map the distribution of AI adoption across strategy types in Figure 3, drawing from HFR hedge fund classifications and CRSP public fund strategy categories. Each of the four panels compares the proportion of AI funds (blue bars) and non-AI funds (white bars) in a specific investment strategy category. The height of the blue bars indicates the share of AI funds allocated to each strategy, while the white bars represent the corresponding distribution among non-AI funds. This comparison reveals which investment environments are more conducive to or compatible with AI-driven decision-making.

Panels (a) and (b) of Figure 3 focus on hedge funds. In terms of fund counts, AI hedge funds are disproportionately concentrated in Macro strategies, while being notably underrepresented in Relative Value and Fund of Funds categories. Equity Hedge strategies also feature prominently among AI funds, although their relative share closely mirrors that observed in non-AI hedge funds. When measured by total net assets, the concentration becomes even more pronounced: over 80% of AI hedge fund assets are allocated to Macro strategies, suggesting that AI hedge funds within the Macro category tend to be substantially larger than their counterparts in other strategy categories.

Panels (c) and (d) display corresponding distributions for open-end public funds. Among public funds employing AI in investment decisions, a significant majority, approximately 70% by number of funds and nearly 90% by TNA, are actively managed equity funds. A limited number of AI public funds pursue index strategies, either in equities or mixed-asset portfolios, though their contribution to total assets under management remains marginal.

Figure 4 shows the time-series evolution of AI hedge funds' strategy composition, segmented by the three most prevalent AI fund categories and further broken down by sub-strategies within the Macro classification. Panel (a) reveals that Macro strategies have consistently dominated the AI hedge fund landscape, accounting for over 60% of AI hedge

fund TNA in most years. A brief exception occurs around 2006, during which the share of Equity Hedge strategies temporarily rises before rapidly contracting in 2007. This transitory shift corresponds to the underperformance of Macro funds in 2006 and their subsequent recovery in 2007, alongside the quant crisis of August 2007 and the early stages of the global financial crisis that adversely affected equity hedge strategies. Crypto/Blockchain strategies emerge only after 2019 and, while still small, exhibit a gradually increasing footprint.

Panel (b) disaggregates the Macro category into sub-strategies, comparing AI (blue bars) and non-AI (white bars) funds. Among AI Macro hedge funds, assets are overwhelmingly concentrated in the Systematic Diversified sub-strategy, which accounts for over 90% of their TNA. This strong preference underscores the alignment between AI technologies and rule-based, model-driven trading frameworks. In contrast, non-AI Macro funds exhibit a more balanced distribution across sub-strategies. AI funds show minimal participation in Discretionary Thematic strategies, reinforcing the notion that AI is predominantly adopted in systematic, data-rich environments rather than in discretionary investment styles.

2.5. Characteristics of AI Funds

Table 4 presents factor loadings that help elucidate the sources of risk and associated compensation for AI funds, relative to their non-AI counterparts. These loadings are derived from seven-factor models estimated using 24-month rolling windows and offer insight into how AI strategies are positioned across major risk dimensions.

Panel A focuses on hedge funds and highlights two distinguishing traits of AI strategies. First, AI hedge funds exhibit significantly lower exposure to small-cap equity risk, measured by the return spread between the Russell 2000 and the S&P 500, compared to non-AI hedge funds. This suggests that AI funds are less reliant on idiosyncratic small-firm information or stock-picking among small-cap equities. Second, AI funds show a modestly higher loading on commodity trend-following returns (PTFS Commodity), pointing to a stronger emphasis

on systematic macro signals. Together, these patterns align with earlier evidence that AI adoption is most concentrated in macro hedge fund strategies, which are naturally suited to data-intensive and model-driven investment approaches.

Panel B turns to open-end public funds and uncovers a different profile. AI public funds display substantially higher market beta (0.878 vs. 0.604), implying that these funds are more exposed to systematic equity market movements and possibly more aggressive in their positioning. They also exhibit a less negative loading on the interest rate factor, suggesting a reduced sensitivity to rising rates. However, exposures to traditional style factors such as size, value, and momentum are statistically similar between AI and non-AI public funds. This implies that AI public funds do not fundamentally diverge from standard factor-based investing in terms of cross-sectional tilts.

Overall, the factor loadings suggest that AI-driven funds differ in their exposure to key systematic risks, with AI hedge funds leaning toward macro-oriented strategies and AI public funds exhibiting greater market sensitivity without diverging from traditional equity style factors.

3. Which Hedge Fund Advisers Create AI Funds?

To examine which investment advisers are better positioned to make the up-front investment in AI talent and infrastructure, we regress a hedge fund adviser's next-year AI fund count on its current-year adviser-level average fund characteristics.

Poisson regressions in Table 5 show that advisers with higher incentive fees, weaker investor-protection clauses (e.g., lower high-water marks and hurdle rates), and fewer liquidity constraints (e.g., shorter lock-up and restriction periods) are more likely to launch AI funds.

First, incentive fees are positively and significantly associated with AI adoption across all specifications. In Column (3), a one standard deviation increase in the incentive fee (7.59

percentage points) is associated with a 2.19-fold increase[15] in the expected number of AI funds launched in the following year ($\exp(7.59 \times 0.103) \approx 2.19$). This is consistent with the idea that greater payoff convexity, i.e., stronger upside optionality, encourages advisers to adopt high-risk, high-reward technologies such as AI. Supporting this view, Agarwal et al. (2009) find that hedge funds with higher managerial ownership and greater total delta (i.e., pay-for-performance sensitivity) deliver significantly better performance, suggesting that performance-based compensation aligns incentives with skill acquisition.

Second, investor-protection provisions, such as high-water marks and hurdle rates, are negatively associated with future AI fund launches. The literature offers mixed interpretations of these clauses. Arya and Mittendorf (2005) argue that option-based compensation can screen for more skilled managers willing to accept higher payoff variability. Panageas and Westerfield (2009) show that high-water mark contracts can reduce risk-taking by introducing intertemporal tradeoffs in compensation. Empirically, Agarwal, Daniel, and Naik (2009) find high-water marks are associated with improved fund performance, while hurdle rates have mostly insignificant effects.

Our findings suggest a complementary channel: these provisions may reduce the delta of the incentive fee option, weakening the link between performance and compensation. This muted incentive can dissuade managers from undertaking costly, uncertain investments such as AI adoption. If the compensation structure reduces the potential reward for innovation, managers may avoid AI, even if it has positive expected value, due to the asymmetric downside risks and upfront costs.

Third, lockup and restriction periods appear to deter AI adoption. Column (3) shows that both lock-up and restriction periods are negatively associated with the expected number of AI funds launched in the following year. This relationship may reflect competing mechanisms. Longer lock-up periods reduce short-term redemption pressure and may give managers greater

[15]Because Poisson regression models the log of the expected count, exponentiating the coefficient converts it back to the multiplicative effect on the count.

flexibility to absorb temporary losses, potentially enabling experimentation with frontier technologies such as AI. However, they also reduce the incentive to innovate or differentiate from peers, since capital is committed for extended periods regardless of performance. Our empirical evidence supports this latter interpretation: managers facing more flexible redemption terms, i.e., shorter lock-up and restriction periods, are more likely to launch AI-driven funds. This suggests that the implicit performance pressure associated with shorter capital commitment horizons encourages AI adoption.

Finally, adviser total hedge fund AUM positively predicts AI adoption. By contrast, adviser age, management fees, and current-year average net returns are not significantly correlated with AI fund counts in the next year.

We further validate whether a hedge fund adviser's declared use of AI strategies reflects genuine technological capability by examining the relationship between the number of AI hedge funds and the adviser's AI labor intensity. Internet Appendix Table IA.1 shows that each additional AI fund is associated with a 0.074 to 0.080 percentage point increase in the share of AI-related job postings in the subsequent year. The coefficients remain positive, though attenuated, after including adviser fixed effects, indicating that even within the same adviser, launching more AI funds corresponds to greater demand in AI-specific human capital. This pattern supports the interpretation that AI-labeled strategies are, on average, accompanied by organizational commitments, rather than serving merely as marketing devices.[16]

[16]Concerns about "AI-washing", the practice of labeling products as AI-driven without substantive backing, have recently attracted regulatory attention. See https://www.sec.gov/newsroom/press-releases/2024-36. Notably, the two advisers charged by the SEC for AI-washing, Delphia and Global Predictions, are not present in our sample.

4. The Performance and Flows of AI Hedge Funds

This section investigates whether hedge funds that employ AI techniques generate superior risk-adjusted returns and how capital flows respond to such strategies over time. These questions are central to understanding the mechanisms of AI technological diffusion within asset management. Our tests build on the theoretical framework of Pástor and Stambaugh (2012), which models how decreasing returns to scale influence the equilibrium size of the active management industry. According to their model, while fund manager skill can yield alpha, growth in industry size eventually dilutes these gains through decreasing returns to scale. We extend this framework to the context of AI hedge funds, conceptualizing AI capability as a form of investment skill whose marginal value declines as more capital is allocated to AI-driven strategies.

4.1. Investment performance of AI hedge funds

In our baseline result, Table 6, we benchmark AI strategy against other systematic strategies, including quantitative strategy and high frequency trading, to assess whether AI represents new technology or merely re-packaged traditional systematic strategies. To filter out the overall time trend documented by Bollen, Joenväärä, and Kauppila (2021) and to mitigate potential return inflation in December, as noted by Agarwal, Daniel, and Naik (2011), we include time-fixed effects in our analysis.

Firstly, after controlling for both strategy-month[17] and adviser-month fixed effects, AI hedge funds earn an additional 19 basis points in raw returns (Column (3)) and 25 basis points in seven-factor alpha (Column (6)) per month. In contrast, generic quantitative and high-frequency trading strategies either underperform or deliver no significant alpha, highlighting the specificity of the AI advantage. Notably, when only month fixed effects

[17]The strategy classifications follow those in Figure 3, encompassing Equity Hedge, Event Driven, Macro, Relative Value, Crypto/Blockchain, Risk Parity, and Fund of Funds strategies.

(Column (1)) or strategy-month fixed effects (Column (2)) are included, the performance premium of AI strategies becomes statistically insignificant. This pattern suggests that the documented outperformance is not universal but arises only when comparing AI funds to the same adviser's non-AI funds within the same strategy category. The AI advantage is adviser- and strategy-specific rather than industry-wide.

Scale diseconomies at the individual hedge fund level are also evident: larger and older funds exhibit significantly lower alpha in Column (6). Incentive fee, lockup period, restriction period, and management fee are positively associated with performance in some columns without adviser-month fixed effects. However, these effects vanish once adviser-by-month fixed effects are introduced. This attenuation likely reflects the limited within-adviser variation in compensation structure in the same month. Overall, these findings underscore that AI strategies generate incremental alpha even after controlling for a wide range of fund-level, time-level, and adviser-level characteristics.

To examine temporal heterogeneity in AI strategy performance, Table 7 reports heterogeneity tests across early (2001–2014), mid (2015–2019), and recent (2020–2024) adoption periods. AI hedge funds in the early period earn between 39 and 45 basis points in monthly alpha. These effects diminish during the mid-period, with alpha estimates around 25 basis points and are only marginally significant in the model specification of Column (5). In the post-2020 period, AI funds show no significant alpha, with some specifications yielding negative point estimates.

This decay in alpha is consistent with the sharp increase in total net assets managed by AI hedge funds during the same period, as illustrated in Figure 2. The concentration of AI assets in Macro: Systematic Diversified strategies likely contributes to this pattern. These strategies typically involve short holding periods and liquid instruments,[18] making them especially susceptible to strategy crowding.

[18]A detailed description of the Macro: Systematic Diversified strategy is available at https://www.hfr.com/hfr-indices/hfr-hedge-fund-strategy-classifications/.

Due to data limitations, we only have access to each fund's most recent investment strategy description from the HFR database and apply it retrospectively to all historical months, which raises the concern that hedge funds with strong past performance may then update their strategy to include AI, potentially driving the observed outperformance of AI funds. On the one hand, Joenväärä et al. (2019) collect investment strategy snapshots at several time points starting in 2007 from various hedge fund databases, including HFR, and find that strategy descriptions rarely change across successive snapshots. On the other hand, Lynch and Musto (2003) demonstrate that investment strategy changes only occur after bad performance, which runs counter to the pattern of AI funds' outperformance. Moreover, this explanation cannot explain the disappearance of hedge funds' outperformance in the most recent period.

Figure 5 presents the co-movement of hedge fund performance by displaying the proportion of the variance in monthly fund alpha explained by the first and second principal components derived from a principal component analysis (PCA). The PCA is conducted using 24-month rolling windows and is implemented separately for AI and non-AI hedge funds. To ensure meaningful estimates, we restrict the analysis to the post-2010 period, as the number of AI hedge funds with non-missing alpha observations is limited in earlier years. While there are at least 17 AI hedge funds with non-missing alpha data in 2010, only 4 such funds are available in 2003.

Panel A shows that the first principal component consistently explains a substantially larger share of alpha variation among AI funds than among non-AI funds. This suggests a higher degree of commonality or shared dynamics among AI strategies, beyond what is captured by the seven-factor model used to estimate alpha. The disparity is especially pronounced during the 2010–2014 period, indicating a period of particularly strong clustering in AI fund behavior during the early phase of adoption. The gap subsequently narrows in more recent years, as the explanatory power of the first principal component for AI

funds declines. This pattern is consistent with the notion that, as more assets flow into AI strategies, funds may experience diminishing returns to scale and respond by differentiating their investment approaches. An exception to the declining trend in the explanatory power of the first principal component for AI funds occurs during the 2020–2021 period, when both AI and non-AI funds exhibit a sharp rise in commonality. This spike is attributable to the construction of the alpha measure, which is based on a 24-month rolling average of factor exposures. Consequently, abrupt and systematic shifts in hedge fund risk exposures, such as those induced by the COVID-19 shock, are not fully captured by the factor model and are instead absorbed into the alpha term, artificially inflating the observed degree of co-movement.

Panel B incorporates both the first and second principal components and exhibits a similar pattern. This finding reinforces the interpretation that AI hedge fund alphas are more strongly driven by common underlying factors, which potentially comes from greater homogeneity in AI modeling frameworks or reliance on shared data inputs across AI hedge funds. These results highlight the concern raised in OECD (2021) and U.S. Senate Committee on Homeland Security and Governmental Affairs (2024) that the widespread use of similar AI algorithms could lead to increased homogeneity and herding behaviors.

4.2. Money Flows to AI Hedge Funds

Investor capital allocation does not necessarily follow realized alpha. As highlighted by the puzzle in Pástor and Stambaugh (2012), active fund management remains popular despite its poor performance track record. Pástor and Stambaugh (2012) attribute this to investors' slow learning about fund manager skill and the rate at which alpha decays with scale. To examine investor beliefs about AI's alpha-generating potential, we test whether the AI label itself attracts capital inflows beyond what can be explained by historical performance.

Table 8 shows that AI hedge funds receive 0.600-0.984% higher monthly net inflows than

otherwise similar funds, even after conditioning on past returns or seven-factor alphas. The sensitivity of flows to performance remains positive and significant, as expected. Among the control variables, fund flows decline with fund size and age, and higher incentive fees deter flows when comparing funds within the same strategy and time period. Across all specifications, investors are especially attracted to AI strategies, independent of performance.

To analyze how this flow premium evolves over time, Table 9 reports regressions that interact the AI strategy dummy with indicator variables for early (2001–2014), mid (2015–2019), and recent (2020–2024) adoption periods. When AI funds are compared to all other funds, or to non-AI funds within the same strategy, the flow premium is significantly positive prior to 2020 and disappears thereafter. By contrast, compared with other funds offered by the same adviser in the same month, the AI flow premium is insignificant during the 2001–2014 and 2015–2019 periods when most advisers offer only non-AI funds and thus provide little within-adviser variation. However, the flow premium becomes significantly positive in the 2020–2024 period, indicating that investors distinguish between AI and non-AI funds offered by the same adviser.

This pattern reflects a two-stage diffusion process. In the early stage, investors direct capital toward AI funds across different firms, responding broadly to the novelty of AI technology. In the later stage, as AI becomes more widely adopted across the industry, investors no longer allocate more to AI funds in general but instead show a preference for AI funds over non-AI funds within the same adviser's offerings.

5. Conclusion

This paper provides the first comprehensive analysis of AI adoption in asset management. By integrating adviser-level fund composition from regulatory filings, AI labor intensity inferred from job postings, and fund-level investment strategy disclosures for both hedge

funds and open-end public funds, we document a highly uneven pattern of AI uptake. AI use is concentrated among large advisers managing private funds, particularly hedge funds employing systematic macro strategies. Moreover, hedge fund advisers with higher incentive fees, weaker investor-protection clauses (e.g., lower high-water marks and hurdle rates), and fewer liquidity constraints (e.g., shorter lock-up and restriction periods) are more likely to launch AI funds.

Our hedge fund performance and flow analysis reveals the diseconomies of scale framework in Pástor and Stambaugh (2012) at the AI hedge fund sector level. Early adopters of AI (2001–2014) earn significant alphas of 39–44 basis points per month, but this advantage declines for mid-period adopters (2015–2019) and disappears entirely post-2020, coinciding with a sharp rise in total AI hedge fund assets since 2016. Controlling for historical performance, AI hedge funds receive 0.6–0.98% higher monthly flows than similar non-AI funds. This flow premium is widespread before 2020 but becomes concentrated within advisers thereafter, reflecting persistent investor preference for AI-labeled strategies, consistent with slow investor learning about AI's alpha and scalability.

The results have implications for asset managers, investors, and researchers. For asset managers, successful AI integration requires not only technical infrastructure but also incentive-aligned compensation schemes, to support the high-risk, high-investment nature of AI adoption. For fund investors, we highlight the need to assess whether a fund's claim of AI use converts into actual benefits. Our findings also suggest new directions for researchers. The concentration of AI in macro strategies invites further study on how AI affects intertemporal risk pricing and market efficiency beyond the widely studied stock market. The observed alpha decay over time reinforces the relevance of scale constraints in modern asset management, and raises broader questions about how technological innovation interacts with competition and industry dynamics. As AI continues to evolve, its deployment offers a valuable lens for studying the organizational and economic limits of financial innovation.

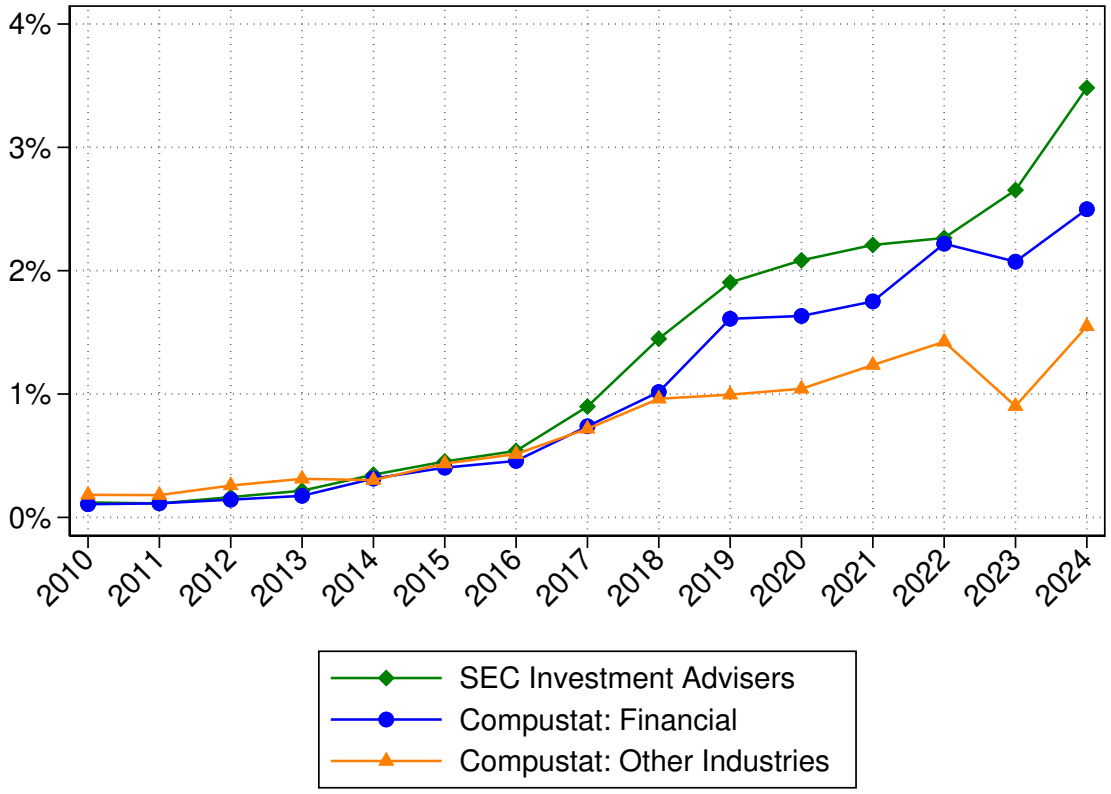
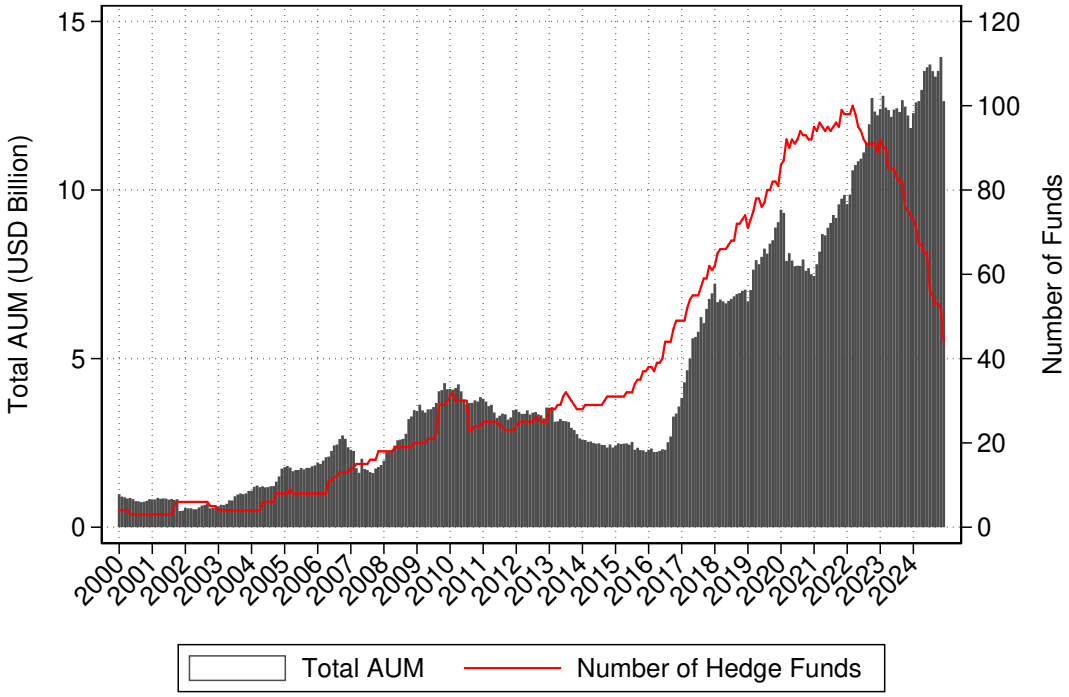


Figure 1: **AI Job Postings by Investment Advisers and Compustat Firms.**
This figure presents the annual percentages of AI-related jobs among total job postings by each of three groups of firms: SEC registered investment advisers, financial industry firms in Compustat, and non-financial firms in Compustat.

(a) Hedge Funds Using AI Strategies



(b) Mutual Funds Using AI Strategies

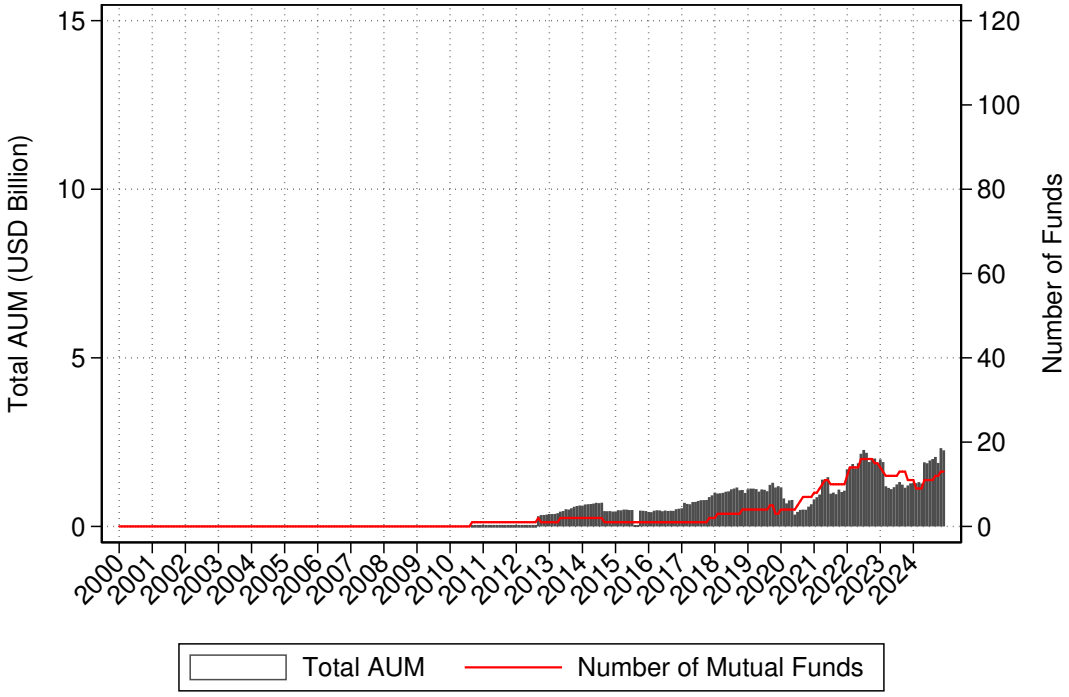


Figure 2: **The Growth of Funds that Use AI Strategies.**
This figure presents the number and total AUM of hedge funds and open-end mutual funds (including ETFs) that use AI-driven investment strategies.

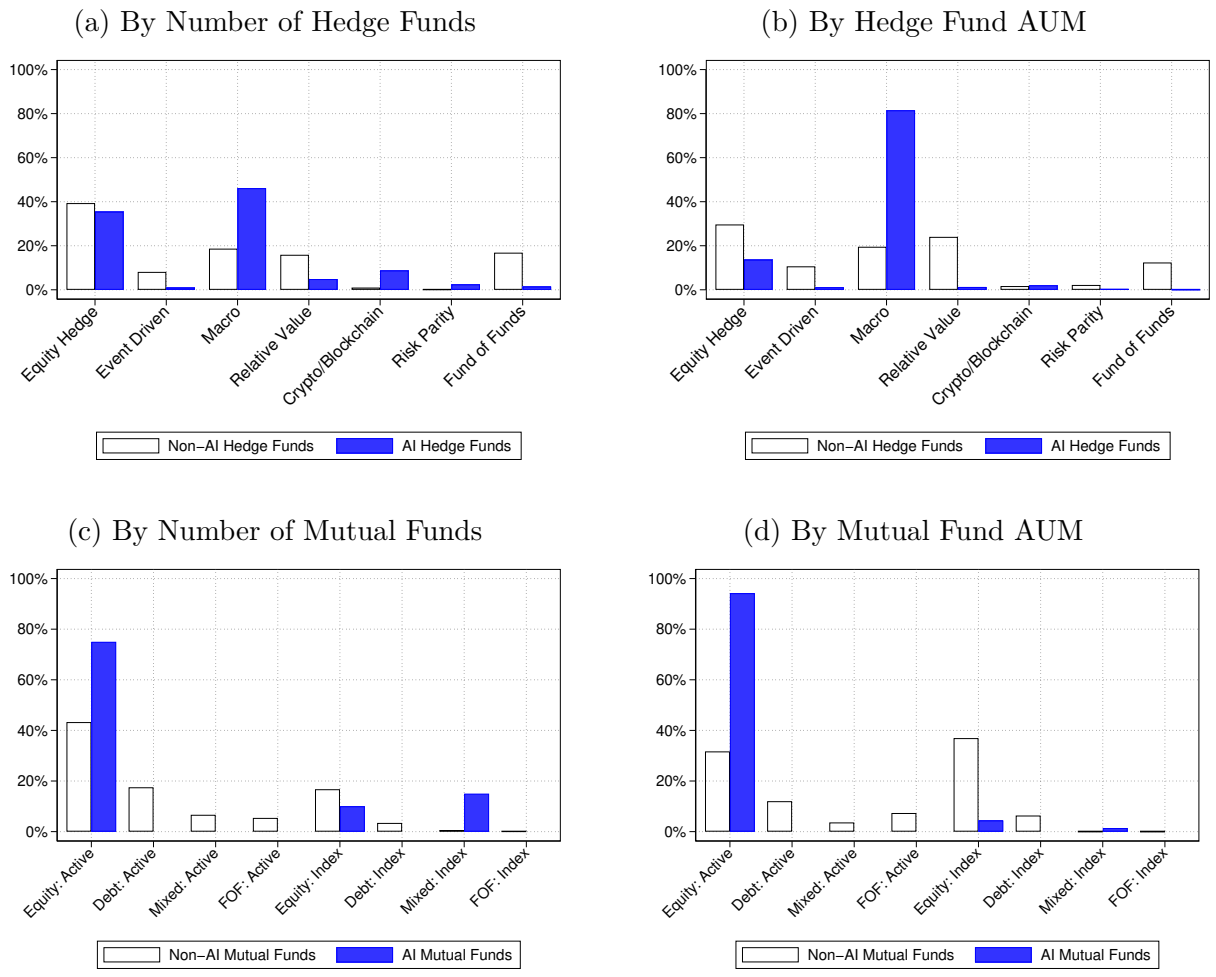
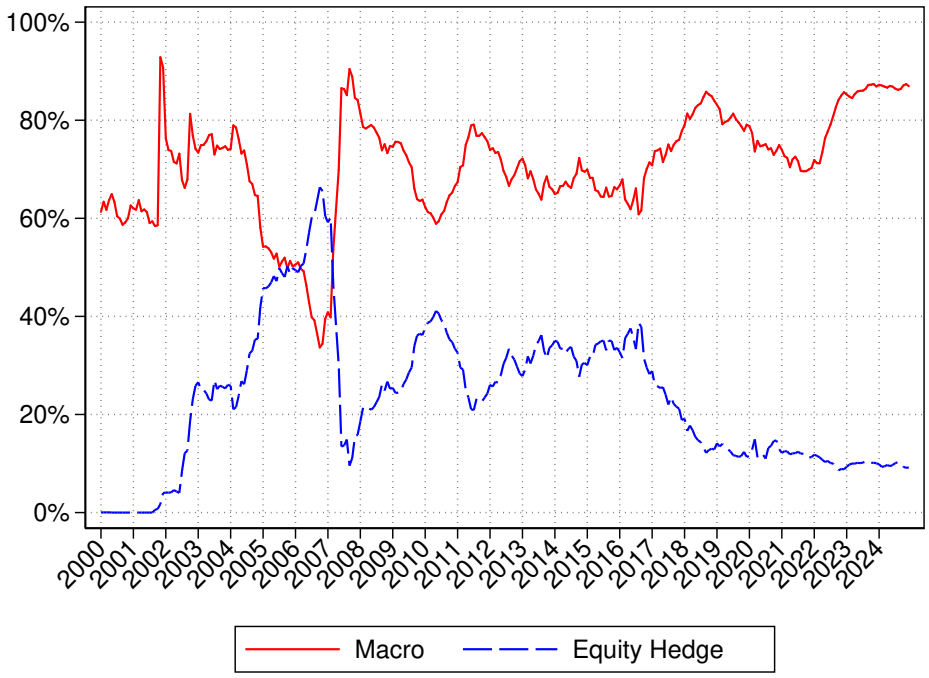


Figure 3: **Distribution of AI-Driven Investment Strategies.**
This figure compares the distribution of investment strategies between AI and non-AI funds. In panels (a) and (b), hedge funds are grouped based on main strategies reported in the last month of a fund in HFR. In panels (c) and (d), open-end mutual funds (including ETFs) are grouped based on CRSP objective code and index fund indicator in the last month a fund is observed.

(a) Monthly AUM Share of AI Hedge Funds



(b) Sub-Strategy Distribution Among Macro Hedge Funds by AUM

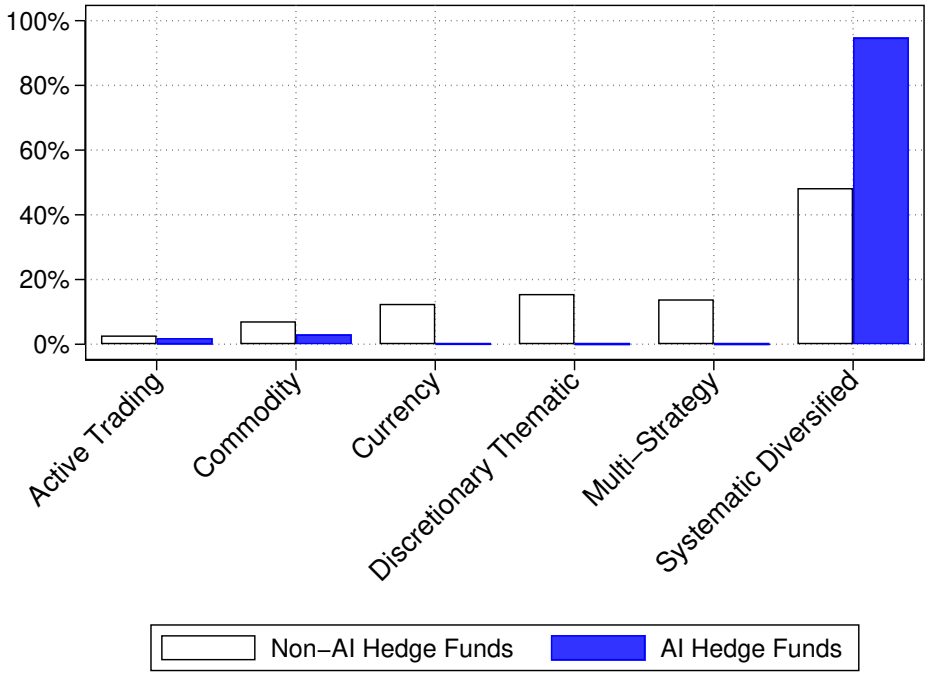
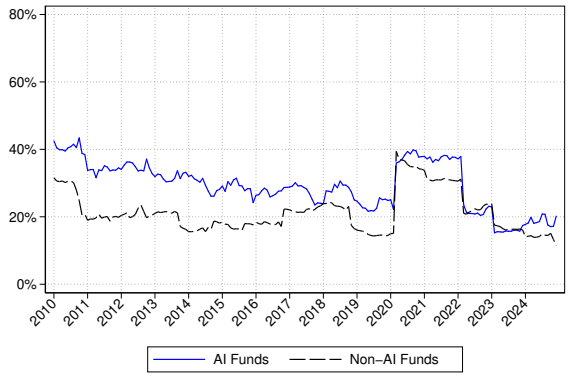
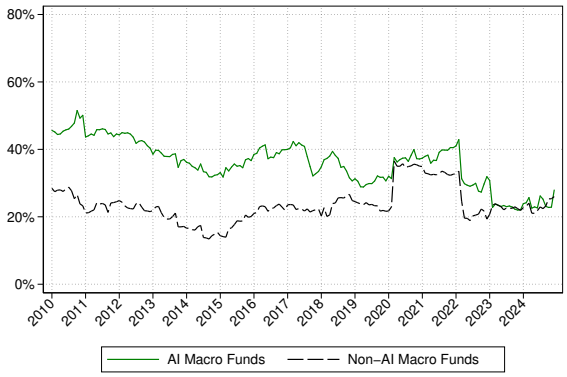


Figure 4: **Distribution of AI Hedge Funds' Investment Strategies.**
Panel (a) of this figure presents monthly shares of three main strategies (Macro, Equity Hedge, and Crypto/Blockchain) among the total AUM of AI hedge funds. Panel (b) presents the distribution of hedge funds whose main strategy is Macro, grouped based on sub-strategies reported in the last month of a fund in HFR.

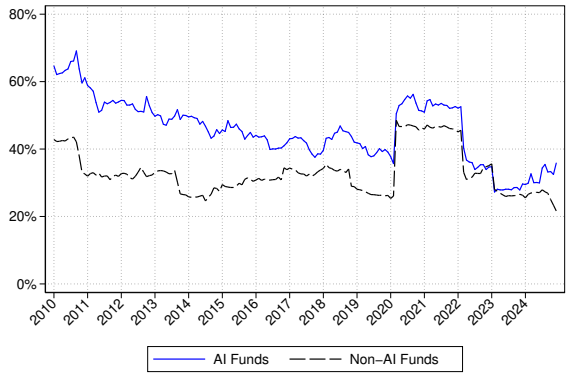
(a) 1st PC: AI Funds vs non-AI Funds



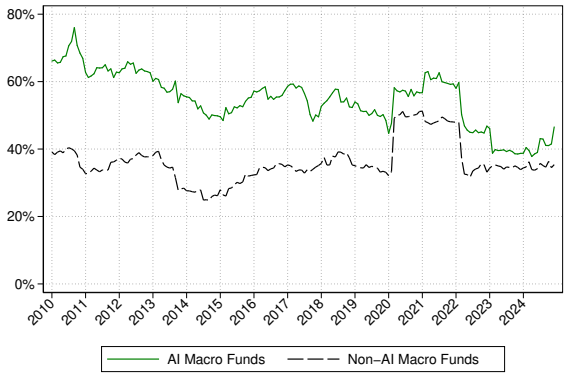
(b) 1st PC: AI vs non-AI Macro Funds



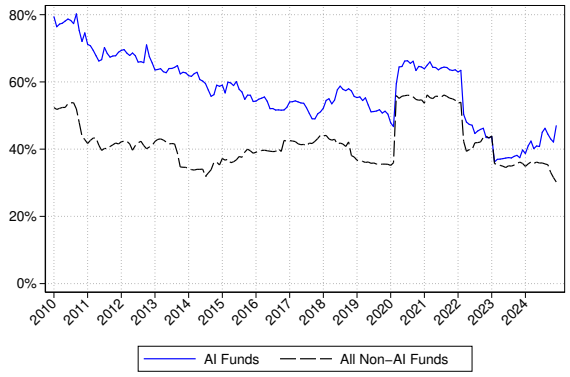
(c) 2 PCs: AI Funds vs non-AI Funds



(d) 2 PCs: AI vs non-AI Macro Funds



(e) 3 PCs: AI Funds vs non-AI Funds



(f) 3 PCs: AI vs non-AI Macro Funds

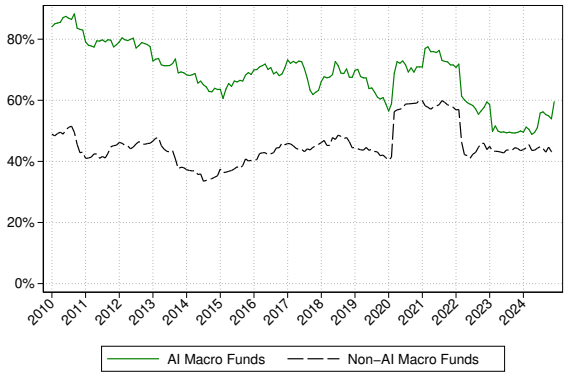


Figure 5: **Comovement of Hedge Fund Performance.**
This figure presents the share of variation in hedge fund monthly alpha explained by their principal components. We conduct a principal component analysis within each 24-month rolling-window, separately for AI and non-AI funds. Panel A compares all AI funds and non-AI funds based on the share of the first eigenvalue among all eigenvalues in the 24-month window ending in the current month. Panel B reports the same comparison within macro funds. Panels C and D replace the comovement measure with the total share of the first two eigenvalues. Panels E and F replace the comovement measure with the total share of the first three eigenvalues.

Table 1: **Summary Statistics: SEC Registered Investment Advisers**

This table presents summary statistics for the sample of investment advisers. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of current AUM and at least 5 job posts in the next year. AI Job Posting is the percentage of AI related jobs among the adviser's job postings in the next year. AUM is the adviser's total regulatory assets under management in billion USD. Client is the adviser's total number of clients in thousands. Advise Private Fund is a dummy that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. GAV is the adviser's total gross net asset values in billion USD. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category.

	N	mean	sd	p10	p25	p50	p75	p90
AI Job Posting	7,646	1.2	4.8	0.00	0.00	0.00	0.45	2.80
AUM	7,646	67.2	267.0	0.3	1.0	5.6	38.3	147.7
Client	7,646	72.6	3,444.8	0.0	0.0	0.2	2.4	23.1
Advise Private Fund	7,646	0.5	0.5	0	0	0	1	1
AUM% Discretionary	7,646	84.9	28.6	33.4	86.2	99.9	100.0	100.0
AUM% Private Fund	7,646	27.6	38.8	0.0	0.0	1.0	62.5	100.0
AUM% Mutual Fund	7,646	15.8	30.7	0.0	0.0	0.0	12.5	87.5
AUM% HighNetWorth	7,646	18.4	27.8	0.0	0.0	0.2	29.9	66.7
AUM% Individual	7,646	15.9	26.8	0.0	0.0	0.0	16.5	62.5
GAV	7,646	7.3	26.1	0.0	0.0	0.0	1.8	15.0
Number of Private Fund	7,646	13.6	41.2	0.0	0.0	0.0	7.0	33.0
GAV% Hedge Fund	3,599	35.0	42.6	0.0	0.0	3.8	87.5	100.0
GAV% Private Equity Fund	3,599	21.9	37.7	0.0	0.0	0.0	29.5	100.0
GAV% Real Estate Fund	3,599	1.2	9.5	0.0	0.0	0.0	0.0	0.0
GAV% Securitized Asset Fund	3,599	12.5	31.1	0.0	0.0	0.0	0.0	90.7
GAV% Venture Capital Fund	3,599	7.1	22.0	0.0	0.0	0.0	0.0	17.2

Table 2: **Summary Statistics: Hedge Funds**

This table presents summary statistics for the hedge fund sample. Every observation is a fund-month between 2001 and 2024. Return is fund net return in percentage points, and Alpha is the fund's out-of-sample alpha based on the seven hedge fund benchmark risk factors from Fung and Hsieh (2004). Flow is net flow into the fund in percentage points. AI Strategy, Quant Strategy, and High Frequency are dummy variables that equal one if the fund is classified as using AI-driven strategy, quantitative strategy, and high-frequency trading strategy, respectively. Incentive Fee and Management Fee are the management and incentive fees charged by the fund adviser. High Water Mark and Hurdle are dummy variables that equal one if the fund's compensation contract includes a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the fund's assets under management in USD million, and Age is its age in months.

	N	mean	sd	p10	p25	p50	p75	p90
Return	708,793	0.51	3.64	-3.27	-0.85	0.55	1.93	4.20
Alpha	708,793	0.17	3.72	-3.59	-1.26	0.20	1.57	3.84
Flow	708,793	0.25	7.94	-4.86	-1.10	0.02	1.24	5.37
AI Strategy	708,793	0.01	0.07	0	0	0	0	0
Quant Strategy	708,793	0.40	0.49	0	0	0	1	1
High Frequency	708,793	0.01	0.10	0	0	0	0	0
Incentive Fee	708,793	15.74	7.59	0	10	20	20	20
High Water Mark	708,793	0.85	0.35	0	1	1	1	1
Hurdle Rate	708,793	0.13	0.33	0	0	0	0	1
Lockup Period	708,793	4.83	7.15	0	0	0	12	12
Restriction Period	708,793	4.35	4.19	1	2	4	5	7
AUM	708,793	324.67	1748.90	5.35	16.83	56.00	195.54	623.14
Age	708,793	96.90	76.07	22	39	75	134	204
Management Fee	708,793	1.36	0.54	1	1	2	2	2

Table 3: **Investment Adviser's Fund Composition and AI Job Postings**

This table reports results from regressing the percentage of the investment adviser's AI-related jobs among its job postings in the next year on the current size and composition of its assets. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of current AUM and at least 5 job posts in the next year. Panel A uses the adviser's total assets under management (AUM), and the sample includes all adviser-years. AUM is the total regulatory assets under management. Client is the adviser's total number of clients. Advise Private Fund is a dummy that equals one if the adviser advises any private funds. AUM% Discretionary is the percentage of AUM that is managed with discretion. AUM% Private Fund, AUM% Mutual Fund, AUM% High Net Worth, and AUM% Individual are the percentages of AUM in private funds ("pooled investment vehicles"), mutual funds including ETFs ("registered investment companies"), high net worth individuals, and other individual clients. Panel B uses the adviser's private fund gross net asset values (GAVs), and the sample includes only adviser-years that manage private funds. GAV% Hedge Fund, GAV% Private Equity Fund, GAV% Real Estate Fund, GAV% Securitized Asset Fund, GAV% Venture Capital Fund are the percentages of total GAV in each private fund category. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Total Assets Under Management

	(1)	(2)	(3)	(4)
log(AUM)	0.253***	0.329***	0.259***	0.236***
	(0.040)	(0.047)	(0.045)	(0.046)
log(Client)		-0.195***	-0.143***	
		(0.038)	(0.033)	
Advise Private Fund			0.739***	
			(0.157)	
AUM% Discretionary				0.006***
				(0.002)
AUM% Private Fund				0.014***
				(0.004)
AUM% Mutual Fund				-0.005*
				(0.003)
AUM% High Net Worth				-0.009***
				(0.002)
AUM% Individual				-0.001
				(0.002)
Year FEs	Y	Y	Y	Y
N	7,646	7,595	7,595	7,646
R^2	0.032	0.050	0.056	0.065

Table 3: **Investment Adviser's Fund Composition and AI Job Postings (Cont'd)**

Panel B: Private Fund Gross Asset Values

	(1)	(2)	(3)	(4)
log(GAV)	0.371***	0.365***	0.596***	0.493***
	(0.092)	(0.097)	(0.136)	(0.116)
log(AUM)		0.014		
		(0.064)		
log(Number of Private Fund)			-0.543***	-0.395**
			(0.176)	(0.165)
GAV% Hedge Fund				0.020***
				(0.007)
GAV% Private Equity Fund				-0.006
				(0.004)
GAV% Real Estate Fund				-0.004
				(0.006)
GAV% Securitized Asset Fund				-0.012***
				(0.004)
GAV% Venture Capital Fund				-0.008
				(0.005)
Year FEs	Y	Y	Y	Y
N	3,599	3,599	3,599	3,599
R^2	0.041	0.041	0.051	0.086

Table 4: **Factor Loadings of AI Fund Returns**

This table reports average estimated factor loadings of monthly fund returns. Panel A reports $\hat{\beta}$s of the seven hedge fund benchmark risk factors from Fung and Hsieh (2004), where SP500$-R_f$ is SP500 index excess return, Russell2000$-$SP500 is Russell 2000 index return less SP500 index return, ΔTreasury is the monthly change in 10-year treasury constant maturity yield, ΔCredit is the monthly change in Moody's Baa yield less 10-year treasury constant maturity yield, and PTFS Bond, PTFS FX, and PTFS Commodity are primitive trend-following strategy returns (Fung and Hsieh, 2001) that capture nonlinear exposures to bonds, foreign currencies, and commodities. Panel B reports $\hat{\beta}$s of mutual fund factor returns, which include SP500$-R_f$, Russell2000$-$SP500, ΔTreasury, ΔCredit, as well as value and momentum factor returns from Ken French's website. Standard errors, two-way clustered at the fund and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Hedge Funds

$\hat{\beta}$	AI	Non-AI	Difference	P-value
SP500$-R_f$	0.258	0.278	-0.021	0.670
Russell2000$-$SP500	0.014	0.105	-0.091***	0.004
ΔTreasury	-0.014	-0.005	-0.009	0.241
ΔCredit	-0.006	-0.020	0.015	0.214
PTFS Bond	0.005	-0.002	0.006	0.245
PTFS FX	0.001	0.007	-0.006	0.395
PTFS Commodity	0.015	0.002	0.013**	0.025
N	3,850	704,943		

Panel B: Mutual Funds

$\hat{\beta}$	AI	Non-AI	Difference	P-value
SP500$-R_f$	0.878	0.604	0.274***	0.000
Russell2000$-$SP500	0.155	-0.046	0.202	0.205
ΔTreasury	-0.010	-0.023	0.013***	0.008
ΔCredit	-0.015	-0.026	0.011	0.254
HML	0.048	-0.019	0.067	0.324
MOM	-0.053	-0.040	-0.013	0.770
N	665	1,426,250		

Table 5: **Which Hedge Fund Advisers Use AI Strategies?**

This table reports Poisson regressions of a hedge fund adviser's number of AI funds in the next year on its current fund characteristics. Every observation is a hedge fund adviser-year between 2001 and 2024. Incentive Fee and Management Fee are the average management and incentive fees charged by the adviser's hedge funds. High Water Mark and Hurdle Rate are the fractions of the adviser's hedge funds whose compensation contracts include a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the adviser's total hedge fund assets. Age is the adviser's maximum fund age. Return is the average annual net return of the adviser's funds during the current year. In columns (1)-(3), all funds are included, and independent variables are equally weighted across the adviser's funds. In columns (4)-(6), only funds that consistently report monthly AUM are included, and independent variables are weighted by fund assets. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Number of AI Hedge Funds

	Equally-Weighted			Asset-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive Fee	0.082***	0.089***	0.103***	0.088***	0.096***	0.114***
	(0.029)	(0.031)	(0.027)	(0.030)	(0.029)	(0.025)
High Water Mark	-1.519***	-0.806**	-0.585	-1.418***	-0.700*	-0.491
	(0.393)	(0.374)	(0.427)	(0.420)	(0.383)	(0.425)
Hurdle Rate	-3.949***	-3.337***	-3.800***	-3.496***	-2.793***	-3.182***
	(0.922)	(0.913)	(1.307)	(1.016)	(0.923)	(1.180)
Lockup Period		-0.101*	-0.097*		-0.095*	-0.092**
		(0.057)	(0.054)		(0.049)	(0.045)
Restriction Period		-0.409***	-0.468***		-0.501***	-0.555***
		(0.115)	(0.109)		(0.111)	(0.095)
Log(AUM)			0.319***			0.367***
			(0.090)			(0.084)
Log(Age)			-0.352			-0.443
			(0.331)			(0.333)
Management Fee			-0.163			-0.116
			(0.357)			(0.227)
Return			0.000			-0.005
			(0.004)			(0.004)
Year FEs	Y	Y	Y	Y	Y	Y
N	29,276	29,276	29,276	28,662	28,662	28,662

Table 6: **Performance of AI Hedge Funds**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Every observation is a fund-month between 2001 and 2024. AI Strategy, Quant Strategy, and High Frequency are dummy variables that equal one if the fund is classified as using AI-driven strategy, quantitative strategy, and high-frequency trading strategy, respectively. Incentive Fee and Management Fee are the management and incentive fees charged by the fund adviser. High Water Mark and Hurdle are dummy variables that equal one if the fund's compensation contract includes a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the fund's assets, and Age is its age. In columns (1)-(3), performance is measured as fund monthly net return. In columns (4)-(6), performance is measured as out-of-sample alpha based on the seven hedge fund benchmark risk factors from Fung and Hsieh (2004). Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Performance

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy	0.012	0.045	0.188**	0.070	0.122	0.248***
	(0.065)	(0.070)	(0.089)	(0.096)	(0.103)	(0.075)
Quant Strategy	-0.073	-0.062*	-0.055**	0.016	-0.004	0.001
	(0.051)	(0.034)	(0.025)	(0.031)	(0.025)	(0.018)
High Frequency	-0.140*	-0.104	-0.133**	-0.096	-0.105	-0.069
	(0.073)	(0.065)	(0.062)	(0.067)	(0.073)	(0.065)
Incentive Fee	0.005***	-0.001	-0.004**	0.005***	0.004**	-0.001
	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
High Water Mark	-0.011	0.025	-0.011	0.007	0.021	0.003
	(0.027)	(0.024)	(0.022)	(0.027)	(0.024)	(0.018)
Hurdle Rate	-0.003	0.022	0.041	-0.024	-0.025	0.008
	(0.025)	(0.026)	(0.025)	(0.025)	(0.025)	(0.021)
Lockup Period	0.003*	0.002*	-0.001	0.002	0.002	0.000
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)
Restriction Period	0.006**	0.008***	0.002	0.005*	0.006***	0.003
	(0.003)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
Log(AUM)	-0.013	-0.009	-0.007	0.003	-0.000	-0.011**
	(0.009)	(0.007)	(0.005)	(0.006)	(0.006)	(0.005)
Log(Age)	-0.058***	-0.054***	-0.005	-0.079***	-0.075***	-0.027**
	(0.018)	(0.016)	(0.011)	(0.016)	(0.015)	(0.013)
Management Fee	0.038	0.030	0.003	0.064**	0.052**	0.004
	(0.029)	(0.022)	(0.021)	(0.025)	(0.022)	(0.020)
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	708,793	708,644	498,984	708,793	708,644	498,984
R^2	0.191	0.271	0.779	0.057	0.102	0.709

Table 7: **Performance of AI Hedge Funds By Time Period**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Every observation is a fund-month between 2001 and 2024. AI Strategy×2001-2014, AI Strategy×2015-2019, and AI Strategy×2020-2024 are dummy variables that equal one if the fund is classified as using AI-driven strategy, and the current month is in 2001-2014, 2015-2019, and 2020-2024, respectively. Control variables are the same as in Table 6. In columns (1)-(3), performance is measured as fund monthly net return. In columns (4)-(6), performance is measured as out-of-sample alpha based on the seven hedge fund benchmark risk factors from Fung and Hsieh (2004). Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Performance

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy×2001-2014	0.133	0.157*	0.256**	0.444***	0.421**	0.389***
	(0.099)	(0.087)	(0.113)	(0.147)	(0.170)	(0.145)
AI Strategy×2015-2019	0.012	0.078	0.147	0.204	0.250*	0.139
	(0.153)	(0.139)	(0.182)	(0.147)	(0.142)	(0.417)
AI Strategy×2020-2024	-0.038	-0.019	0.166	-0.150	-0.068	0.220
	(0.124)	(0.116)	(0.176)	(0.145)	(0.162)	(0.235)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	708,793	708,644	498,984	708,793	708,644	498,984
R^2	0.191	0.271	0.779	0.057	0.102	0.709

Table 8: **Money Flows to AI Hedge Funds**

This table reports estimation results of regressing hedge fund flow in the next month on current fund characteristics. Every observation is a fund-month between 2001 and 2024. AI Strategy, Quant Strategy, and High Frequency are dummy variables that equal one if the fund is classified as using AI-driven strategy, quantitative strategy, and high-frequency trading strategy, respectively. Incentive Fee and Management Fee are the management and incentive fees charged by the fund adviser. High Water Mark and Hurdle are dummy variables that equal one if the fund's compensation contract includes a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the fund's assets, and Age is its age. In columns (1)-(3), performance is measured with 12-month rolling average fund monthly net return. In columns (4)-(6), performance is measured with 12-month rolling average out-of-sample monthly alpha based on the seven hedge fund benchmark risk factors from Fung and Hsieh (2004). Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Flow

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy	0.655***	0.627***	0.981***	0.654***	0.600***	0.984***
	(0.241)	(0.229)	(0.221)	(0.228)	(0.226)	(0.200)
Performance	0.469***	0.514***	0.526***	0.286***	0.304***	0.273***
	(0.045)	(0.040)	(0.088)	(0.034)	(0.033)	(0.075)
Quant Strategy	0.059	0.022	0.160***	0.017	-0.014	0.129**
	(0.042)	(0.040)	(0.056)	(0.043)	(0.040)	(0.056)
High Frequency	0.034	0.053	-0.237	-0.002	0.031	-0.306
	(0.204)	(0.198)	(0.284)	(0.207)	(0.202)	(0.292)
Incentive Fee	-0.006	-0.011***	-0.009	-0.004	-0.012***	-0.010
	(0.004)	(0.004)	(0.007)	(0.004)	(0.004)	(0.007)
High Water Mark	0.041	0.043	-0.020	0.023	0.041	-0.033
	(0.077)	(0.074)	(0.099)	(0.077)	(0.075)	(0.100)
Hurdle Rate	0.011	0.023	-0.064	0.011	0.037	-0.054
	(0.056)	(0.055)	(0.090)	(0.057)	(0.056)	(0.091)
Lockup Period	0.001	0.003	-0.004	0.002	0.003	-0.004
	(0.003)	(0.003)	(0.005)	(0.003)	(0.003)	(0.005)
Restriction Period	0.013**	0.018***	-0.000	0.014***	0.021***	0.000
	(0.005)	(0.005)	(0.008)	(0.005)	(0.005)	(0.008)
Log(AUM)	-0.011	-0.017	-0.063***	-0.010	-0.012	-0.053**
	(0.016)	(0.015)	(0.021)	(0.015)	(0.015)	(0.021)
Log(Age)	-0.856***	-0.843***	-0.766***	-0.875***	-0.859***	-0.774***
	(0.037)	(0.037)	(0.046)	(0.037)	(0.037)	(0.046)
Management Fee	-0.042	-0.084*	-0.102	-0.021	-0.071	-0.099
	(0.050)	(0.050)	(0.083)	(0.052)	(0.052)	(0.084)
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	666,219	666,070	466,348	666,219	666,070	466,348
R^2	0.028	0.034	0.429	0.024	0.031	0.428

Table 9: **Money Flows to AI Hedge Funds By Time Period**

This table reports estimation results of regressing hedge fund flow in the next month on current fund characteristics. Every observation is a fund-month between 2001 and 2024. AI Strategy×2001-2014, AI Strategy×2015-2019, and AI Strategy×2020-2024 are dummy variables that equal one if the fund is classified as using AI-driven strategy, and the current month is in 2001-2014, 2015-2019, and 2020-2024, respectively. Control variables are the same as in Table 8. In columns (1)-(3), performance is measured with 12-month rolling average fund monthly net return. In columns (4)-(6), performance is measured with 12-month rolling average out-of-sample monthly alpha based on the seven hedge fund benchmark risk factors from Fung and Hsieh (2004). Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Flow

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy×2001-2014	1.281***	1.235***	0.767	1.207***	1.165**	0.764
	(0.443)	(0.457)	(0.536)	(0.465)	(0.491)	(0.521)
AI Strategy×2015-2019	1.430***	1.415***	0.825	1.382***	1.382***	0.850
	(0.483)	(0.476)	(0.825)	(0.496)	(0.496)	(0.823)
AI Strategy×2020-2024	0.036	-0.001	1.204**	0.086	-0.007	1.200*
	(0.281)	(0.252)	(0.601)	(0.258)	(0.245)	(0.647)
Performance	0.469***	0.514***	0.526***	0.286***	0.304***	0.273***
	(0.045)	(0.040)	(0.088)	(0.034)	(0.033)	(0.075)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	666,219	666,070	466,348	666,219	666,070	466,348
R^2	0.028	0.034	0.429	0.025	0.031	0.428

Table 10: **Robustness: Survivorship of AI Hedge Funds**

This table reports average dropout rates of AI and Non-AI hedge funds over 1-month, 3-month, 6-month, and 1-year time horizons. The sample period is between 2001 and 2024. Panel A presents dropout rates related to both fund liquidations and stopped reportings. Panels B and C separately present the rates of liquidations and stopped reportings, respectively. T-statistics from testing the the difference between AI funds and non-AI funds are based on Newey-West standard errors with 12 monthly lags. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Dropout Rate (%)

	1m	3m	6m	1y
AI Funds	0.86	1.87	3.13	5.44
Non-AI Funds	0.76	1.41	2.36	4.19
Difference	0.10	0.47	0.77	1.26
t-statistics	0.50	1.07	1.09	1.11

Panel B: Liquidation Rate (%)

	1m	3m	6m	1y
AI Funds	0.35	1.05	2.04	3.57
Non-AI Funds	0.43	1.29	2.56	5.01
Difference	-0.08	-0.24	-0.52	-1.44*
t-statistics	-0.68	-0.73	-0.90	-1.86

Panel C: Stop Reporting Rate (%)

	1m	3m	6m	1y
AI Funds	0.51	1.52	2.78	5.09
Non-AI Funds	0.33	0.98	1.93	3.75
Difference	0.18	0.55	0.85	1.34
t-statistics	1.31	1.38	1.28	1.21

Table 11: **Robustness: Backfill Bias**

This table reports the results of re-estimating regressions in Tables 7 and 9 using a sample that excludes fund-month observations before the fund was added to the HFR database. Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Hedge Fund Performance

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy×2001-2014	0.116	0.147***	0.226	0.483**	0.467**	0.360**
	(0.084)	(0.049)	(0.141)	(0.197)	(0.214)	(0.169)
AI Strategy×2015-2019	0.012	0.100	0.090	0.183	0.216	0.043
	(0.167)	(0.135)	(0.206)	(0.164)	(0.149)	(0.512)
AI Strategy×2020-2024	-0.045	-0.041	0.106	-0.219	-0.144	0.282
	(0.127)	(0.118)	(0.207)	(0.156)	(0.173)	(0.322)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	542,236	542,063	380,211	542,236	542,063	380,211
R^2	0.193	0.272	0.783	0.059	0.107	0.716

Panel B: Hedge Fund Flow

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy×2001-2014	1.213**	1.184**	0.703	1.127*	1.105*	0.684
	(0.564)	(0.571)	(0.602)	(0.593)	(0.613)	(0.577)
AI Strategy×2015-2019	1.352***	1.349***	0.328	1.321**	1.353**	0.362
	(0.514)	(0.510)	(0.872)	(0.524)	(0.527)	(0.877)
AI Strategy×2020-2024	0.204	0.174	1.308**	0.279	0.187	1.245*
	(0.298)	(0.258)	(0.627)	(0.275)	(0.251)	(0.686)
Performance	0.449***	0.500***	0.504***	0.290***	0.319***	0.259***
	(0.047)	(0.042)	(0.102)	(0.038)	(0.036)	(0.087)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	521,217	521,049	363,338	521,217	521,049	363,338
R^2	0.025	0.032	0.432	0.022	0.030	0.431

Table 12: **Robustness: Linear Time Trends**

This table reports the results of re-estimating regressions in Tables 7 and 9 using interaction specifications. Year is a discrete variable that equals the current year minus 2000. Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Hedge Fund Performance

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy	0.239	0.176	0.167*	0.839***	0.653***	0.285**
	(0.188)	(0.158)	(0.099)	(0.198)	(0.226)	(0.144)
AI Strategy×Year	-0.012	-0.007	0.001	-0.042***	-0.029**	-0.002
	(0.012)	(0.010)	(0.009)	(0.012)	(0.014)	(0.011)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	708,793	708,644	498,984	708,793	708,644	498,984
R^2	0.191	0.271	0.779	0.057	0.102	0.709

Panel B: Hedge Fund Flow

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy	2.822***	2.671**	1.326*	2.692***	2.563**	1.309*
	(0.995)	(1.040)	(0.699)	(0.955)	(1.041)	(0.693)
AI Strategy×Year	-0.118**	-0.112**	-0.021	-0.111**	-0.107*	-0.019
	(0.055)	(0.056)	(0.037)	(0.052)	(0.056)	(0.039)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	666,219	666,070	466,348	666,219	666,070	466,348
R^2	0.028	0.034	0.429	0.025	0.031	0.428

Table 13: **Robustness: Flow-Performance Sensitivity**

This table reports the results of re-estimating regressions in Table 8 using interaction specifications. Standard errors, two-way clustered at the adviser and month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Flow

	Return			Alpha		
	(1)	(2)	(3)	(4)	(5)	(6)
AI Strategy	0.713***	0.589**	0.895***	0.680***	0.596***	0.972***
	(0.229)	(0.231)	(0.210)	(0.224)	(0.225)	(0.189)
Performance	0.470***	0.514***	0.525***	0.287***	0.304***	0.273***
	(0.044)	(0.040)	(0.088)	(0.034)	(0.033)	(0.076)
AI Strategy×Performance	-0.104	0.069	0.123	-0.076	0.013	0.019
	(0.162)	(0.132)	(0.096)	(0.090)	(0.085)	(0.047)
Controls	Y	Y	Y	Y	Y	Y
Month FEs	Y	N	N	Y	N	N
Strategy-Month FEs	N	Y	Y	N	Y	Y
Adviser-Month FEs	N	N	Y	N	N	Y
N	666,219	666,070	466,348	666,219	666,070	466,348
R^2	0.028	0.034	0.429	0.025	0.031	0.428

References

Abis, S. (2020). Man vs. machine: Quantitative and discretionary equity management. *Working Paper*.

Abis, S. and L. Veldkamp (2024). The changing economics of knowledge production. *Review of Financial Studies 37*(1), 89–118.

Acemoglu, D., D. Autor, J. Hazell, and P. Restrepo (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics 40*(S1), S293–S340.

Agarwal, V., N. D. Daniel, and N. Y. Naik (2004). Flows, performance, and managerial incentives in hedge funds. *Working Paper*.

Agarwal, V., N. D. Daniel, and N. Y. Naik (2009). Role of managerial incentives and discretion in hedge fund performance. *The Journal of Finance 64*(5), 2221–2256.

Agarwal, V., N. D. Daniel, and N. Y. Naik (2011). Do hedge funds manage their reported returns? *The Review of Financial Studies 24*(10), 3281–3320.

Aggarwal, R. and N. M. Boyson (2016). The performance of female hedge fund managers. *Review of Financial Economics 29*, 23–36.

Aggarwal, R. K. and P. Jorion (2010). The performance of emerging hedge funds and managers. *Journal of financial economics 96*(2), 238–256.

Aragon, G. O. (2007). Share restrictions and asset pricing: Evidence from the hedge fund industry. *Journal of financial economics 83*(1), 33–58.

Arya, A. and B. Mittendorf (2005). Offering stock options to gauge managerial talent. *Journal of Accounting and Economics 40*(1-3), 189–210.

Babina, T., A. Fedyk, A. He, and J. Hodson (2024). Artificial intelligence, firm growth, and product innovation. *Journal of Financial Economics 151*, 103745.

Babina, T., A. Fedyk, A. X. He, and J. Hodson (2023). Artificial intelligence and firms' systematic risk. *Working Paper*.

Berk, J. B. and R. C. Green (2004). Mutual fund flows and performance in rational markets. *Journal of political economy 112*(6), 1269–1295.

Bollen, N. P., J. Joenväärä, and M. Kauppila (2021). Hedge fund performance: End of an era? *Financial Analysts Journal 77*(3), 109–132.

Bonelli, M. and T. Foucault (2023). Displaced by big data: Evidence from active fund managers. *Working Paper*.

Brown, S., Y. Lu, S. Ray, and M. Teo (2018). Sensation seeking and hedge funds. *The Journal of Finance 73*(6), 2871–2914.

Cao, S., W. Jiang, J. Wang, and B. Yang (2024). From man vs. machine to man+machine: The art and AI of stock analyses. *Journal of Financial Economics 160*, 103910.

Cao, S., W. Jiang, B. Yang, and A. L. Zhang (2023). How to talk when a machine is listening: Corporate disclosure in the age of ai. *The Review of Financial Studies 36*(9), 3603–3642.

Cen, L., B. Han, Y. Han, and C. Jo (2024). Data scientists on wall street. *Working Paper*.

Chen, J., H. Hong, M. Huang, and J. D. Kubik (2004). Does fund size erode mutual fund performance? the role of liquidity and organization. *American Economic Review 94*(5), 1276–1302.

Choi, J. J., D. Huang, Z. Yang, and Q. Zhang (2024). Better than human? experiments with AI debt collectors. *Working Paper*.

Colliard, J.-E., T. Foucault, and S. Lovo (2022). Algorithmic pricing and liquidity in securities markets. *HEC Paris Research Paper No. FIN-2022-1459*.

Dou, W. W., I. Goldstein, and Y. Ji (2024). Ai-powered trading, algorithmic collusion, and price efficiency. *Jacobs Levy Equity Management Center for Quantitative Financial Research Paper*.

Eisfeldt, A. L., G. Schubert, and M. B. Zhang (2023). Generative AI and firm values. Technical report, National Bureau of Economic Research.

Franzoni, F. and M. Giannetti (2019). Costs and benefits of financial conglomerate affiliation: Evidence from hedge funds. *Journal of Financial Economics 134*(2), 355–380.

Fung, W. and D. A. Hsieh (2001). The risk in hedge fund strategies: Theory and evidence from trend followers. *The review of financial studies 14*(2), 313–341.

Fung, W. and D. A. Hsieh (2004). Hedge fund benchmarks: A risk-based approach. *Financial Analysts Journal 60*(5), 65–80.

Fuster, A., P. Goldsmith-Pinkham, T. Ramadorai, and A. Walther (2022). Predictably unequal? the effects of machine learning on credit markets. *The Journal of Finance 77*(1), 5–47.

Gambacorta, L., F. Sabatini, and S. Schiaffi (2024). Artificial intelligence and relationship lending. *Working Paper*.

Gupta, A. and K. Sachdeva (2025). Skin or skim? inside investment and hedge fund performance. *Management Science 71*(4), 3357–3383.

Hershbein, B. and L. B. Kahn (2018). Do recessions accelerate routine-biased technological change? evidence from vacancy postings. *American Economic Review 108*(7), 1737–1772.

Joenväärä, J., J. Karppinen, M. Teo, and C. I. Tiu (2019). The vocabulary of hedge funds. *Working Paper*.

Kacperczyk, M., C. Sialm, and L. Zheng (2008). Unobserved actions of mutual funds. *The Review of Financial Studies 21*(6), 2379–2416.

Li, H., X. Zhang, and R. Zhao (2011). Investing in talents: Manager characteristics and hedge fund performances. *Journal of Financial and Quantitative Analysis 46*(1), 59–82.

Liu, X. (2024). Artificial intelligence and customer acquisition in retail financial services: Experimental evidence from insurance distribution. *Working Paper*.

Lu, Y., N. Y. Naik, and M. Teo (2024). Diverse hedge funds. *The Review of Financial Studies 37*(2), 639–683.

Lu, Y., S. Ray, and M. Teo (2016). Limited attention, marital events and hedge funds. *Journal of Financial Economics 122*(3), 607–624.

Lu, Y. and M. Teo (2022). Do alpha males deliver alpha? facial width-to-height ratio and hedge funds. *Journal of Financial and Quantitative Analysis 57*(5), 1727–1770.

Lynch, A. W. and D. K. Musto (2003). How investors interpret past fund returns. *The Journal of Finance 58*(5), 2033–2058.

OECD (2021). *OECD Business and Finance Outlook 2021: AI in Business and Finance*. Paris: OECD Publishing.

Panageas, S. and M. M. Westerfield (2009). High-water marks: High risk appetites? convex compensation, long horizons, and portfolio choice. *The Journal of Finance 64*(1), 1–36.

Pástor, L. and R. F. Stambaugh (2012). On the size of the active management industry. *Journal of Political Economy 120*(4), 740–781.

Pástor, L., R. F. Stambaugh, and L. A. Taylor (2015). Scale and skill in active management. *Journal of financial economics 116*(1), 23–45.

Piao, J., K. P. Wang, and D. Weng (2024). US banks' artificial intelligence and small business lending: Evidence from the census bureau's technology survey. *Working Paper*.

Sheng, J., Z. Sun, B. Yang, and A. L. Zhang (2024). Generative AI and asset management. *Working Paper*.

Shi, Z. (2017). The impact of portfolio disclosure on hedge fund performance. *Journal of Financial Economics 126*(1), 36–53.

Sun, Z., A. Wang, and L. Zheng (2012). The road less traveled: Strategy distinctiveness and hedge fund performance. *The Review of Financial Studies 25*(1), 96–143.

U.S. Senate Committee on Homeland Security and Governmental Affairs (2024, June). AI in the Real World: Hedge Funds' Use of AI in Trading. Technical report, U.S. Senate Committee on Homeland Security and Governmental Affairs.

Zhang, Y. (2024). Do mutual funds benefit from the adoption of AI technology? *Working Paper*.

Zheng, L. and X. Yan (2021). Financial industry affiliation and hedge fund performance. *Management Science 67*(12), 7844–7865.

Zhu, M. (2018). Informative fund size, managerial skill, and investor rationality. *Journal of Financial Economics 130*(1), 114–134.

Internet Appendix

"The Growth and Performance of AI in Asset Management"

IA.1. AI prompt for extracting fund investment strategy

Please read the following text from a fund strategy description. Extract the following details, each on a new line:

1. Does the fund use **Artificial Intelligence (AI)**? Answer **Y** only if there is evidence of AI technologies such as machine learning, natural language processing, or other advanced AI methods. General algorithmic or quantitative strategies do *not* count as AI. Answer **Y** or **N**.
2. Original sentence(s) that led to the conclusion in 1. If none, answer **NA**.
3. Does the fund use a **quantitative strategy** (regardless of AI)? Answer **Y** only if there is evidence of mathematical models, statistical techniques, algorithmic trading, or systematic approaches used in investment decisions. Discretionary, fundamental, or human-driven strategies should be marked **N**. Answer **Y** or **N**.
4. Original sentence(s) that led to the conclusion in 3. If none, answer **NA**.
5. Does the fund's strategy require **high-frequency trading**? Answer **Y** or **N**.
6. Original sentence(s) that led to the conclusion in 5. If none, answer **NA**.

Example of a hedge fund investment strategy description:

Millburn Multi-Markets Program's ('MMM') core focus is to seek to provide investors with positive absolute returns through a variety of market cycles and environments, through diversified exposure to a range of liquid global markets and with an emphasis on rigorous risk

management. MMM implements a group of models that collectively trade more than 100 futures, forward and spot contracts on currencies, interest rate instruments, stock indices, metals, energy and agricultural commodities, targeting opportunities in a wide range of global markets under a variety of conditions. Trade implementation takes place on U.S. and international exchanges and in the interbank currency market. Positions in each instrument traded can be either long or short, providing opportunities in both rising or falling markets.

MMM's trading strategies are based on the implementation of a multi-data-input, statistical/machine learning framework, and are 100% systematic and quantitative in nature. This framework utilizes price, price-derivative, and non-price data sources or 'features' in an attempt to provide an informed, context-specific and continuous view of portfolio positioning (long or short, and to what extent) in a particular market. Features/data inputs utilized in the construction of these trading models are generally intuitive, understandable and observable. MMM's statistical/machine learning approaches can enable the models to adapt over time, with the goal of reflecting underlying structural properties of markets and the importance of particular features during a range of market conditions.

Strategies are intended to be able to detect and take advantage of longer-term, persistent trending activity (up or down), but also short-term or idiosyncratic market behavior. Risks of over-fitting to recent data are reduced through the careful application of techniques, a focus on diversification and the use of often decades of historic data in the construction of the models. MMM covers themes that Millburn believes are capable of generating positive absolute returns including: the strength or weakness of global economies, changing currency values, rising or falling global interest rates and equities, and the changing prices of many essential commodities.

AI returns the following answers:

1. Y

2. MMM's trading strategies are based on the implementation of a multi-data-input, statistical/machine learning framework...

3. Y

4. ...and are 100% systematic and quantitative in nature.

5. N

6. NA

Example of a mutual fund investment strategy description:

The Fund is actively managed and invests primarily in equity securities listed on a U.S. exchange, based on the results of a proprietary quantitative model (the "EquBot Model") developed by EquBot LLC ("EquBot") that runs on the IBM Watson™ platform. EquBot, the Fund's sub-adviser, is a technology-based company focused on applying artificial intelligence ("AI") solutions to investment analysis.

As an IBM Global Entrepreneur company, EquBot leverages IBM's Watson AI to conduct objective, fundamental analysis of U.S.-listed common stocks and real estate investment trusts ("REITs") using up to ten years of historical data. It integrates this analysis with recent economic and news data. Each day, the EquBot Model ranks companies based on the probability that they will benefit from current economic conditions, trends, and world events. It then identifies approximately 30 to 125 companies with the greatest potential for appreciation over the next twelve months, assigning corresponding portfolio weights while maintaining a volatility level comparable to the broader U.S. equity market.

The Fund may invest in companies of any market capitalization. The EquBot Model recommends a weight for each company based on its appreciation potential and correlation with other holdings in the portfolio. The model limits the weight of any single company to 10%. At times, a significant portion of the Fund's assets may be held in cash or cash

equivalents.

IBM Watson AI is a computing platform capable of answering natural language questions by connecting large amounts of structured data (e.g., spreadsheets) and unstructured data (e.g., news articles). It continuously learns from the analyses it conducts—recognizing patterns and producing more accurate results over time.

The Fund's investment adviser uses the EquBot Model's recommendations to determine which securities to buy and sell, in compliance with the Investment Company Act of 1940 (the "1940 Act") and its regulations. The adviser anticipates basing most trading decisions on EquBot Model outputs. The Fund may frequently and actively trade securities.

Additionally, the Fund may lend its portfolio securities to brokers, dealers, and other financial institutions. These loans, if made, may not exceed 33 1/3% of the Fund's total asset value (including collateral). Securities lending may increase the Fund's income through borrower payments.

AI returns the following answers:

1. Y

2. EquBot, the Fund's sub-adviser, is a technology based company focused on applying artificial intelligence ("AI") based solutions to investment analyses.

3. Y

4. The Fund is actively managed and invests primarily in equity securities listed on a U.S. exchange based on the results of a proprietary, quantitative model (the 'EquBot Model') developed by EquBot LLC.

5. Y

6. The Fund may frequently and actively purchase and sell securities.

IA.2. Measure of investment adviser's AI adoption

Our key measure of an investment adviser's AI adoption is constructed using the skills required for job positions, following the methodology in Babina, Fedyk, He, and Hodson (2024) ("BFHH" henceforth). Specifically, we evaluate each job posting's relevance to AI and its core fields machine learning (ML), natural language processing (NLP), and computer vision (CV)—based on the skills extracted from online job postings.

For each skill s required in job postings, we calculate its relevance to AI as

$$w_s^{\text{AI}} = \frac{\text{number of jobs requiring both core AI skills and skill } s}{\text{number of jobs requiring skill } s}, \tag{IA.1}$$

where a job is defined as requiring core AI skills if it has at least one of ML, NLP, CV, and AI in its required skills or job title.

Next, we calculate the AI-relevance of a job posting j, w_j^{AI}, as the average of w_s^{AI} across all skills s required by the job posting j. Following BFHH, we define job posting j as AI-related if w_j^{AI} exceeds 0.1, a threshold chosen based on manual inspection of the data.

Finally, we calculate $AI\%$, the fraction of AI-related job postings by investment adviser i in year t. This fraction measures the intensity of the adviser's annual AI investment.

In addition to the BFHH measure, we also construct three measures for an investment adviser's job postings related to AI, old technology (OT), and data management (DM), following Abis and Veldkamp (2024). Collectively, we refer to these three as "AV" measures. Unlike the BFHH measure, which relies on the frequency of co-occurrence between a job posting's required skills and core AI skills, the AV measure classifies job postings into one of four categories—AI, OT, DM, or none—based on the relative frequency of keywords associated with AI, OT, or DM in the job description. For example, if a job posting contains nine AI-related phrases and ten DM-related phrases, the AV measure categorizes it as a DM post rather than an AI post. Given the highly symbiotic relationship between big data and

AI models, we view the AV measure as applying a narrow definition of AI. This paper focuses on results from the broader BFHH measure, with consistent results from AV measure for robustness.

IA.3. Supplementary Results

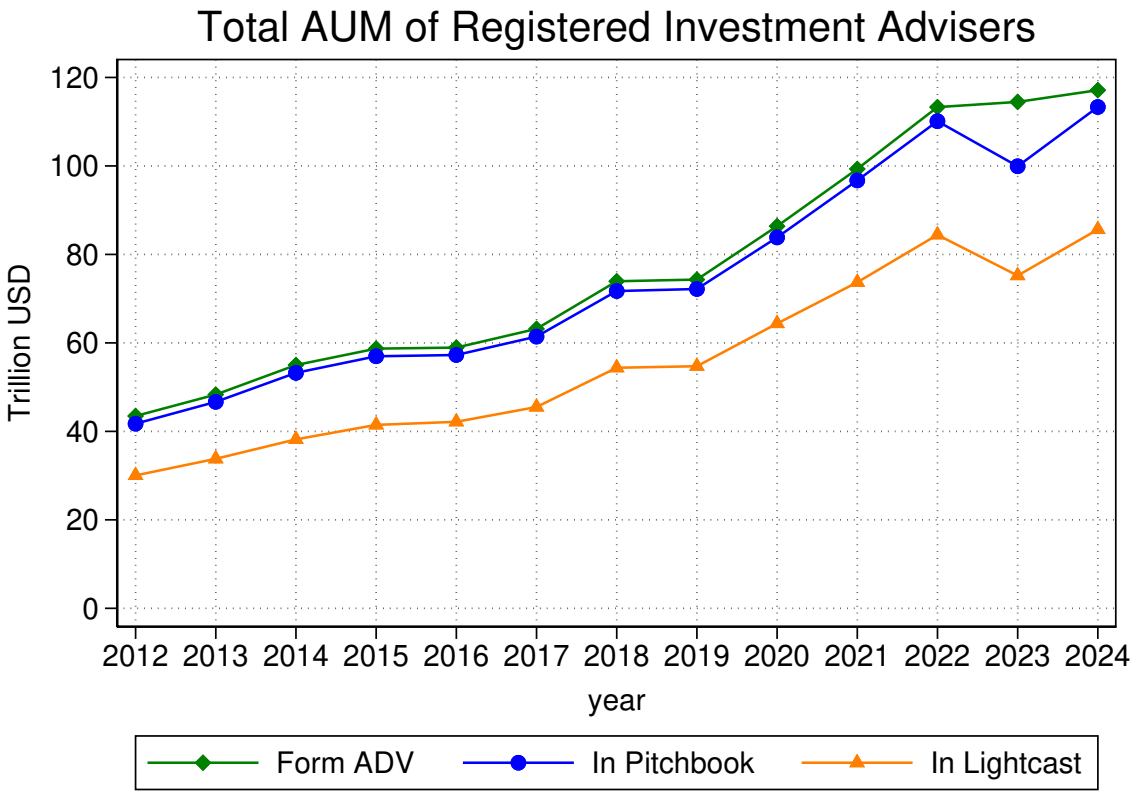


Figure IA.1: **Total AUM of Investment Advisers.**
This figure presents the total assets under management (AUM) of three sets of registered investment advisers. The green line indicates all investment advisers that file Form ADV. The blue line indicates the subset of investment advisers that are matched with companies in Pitchbook. The orange line indicates investment advisers matched to job postings in Lightcast.

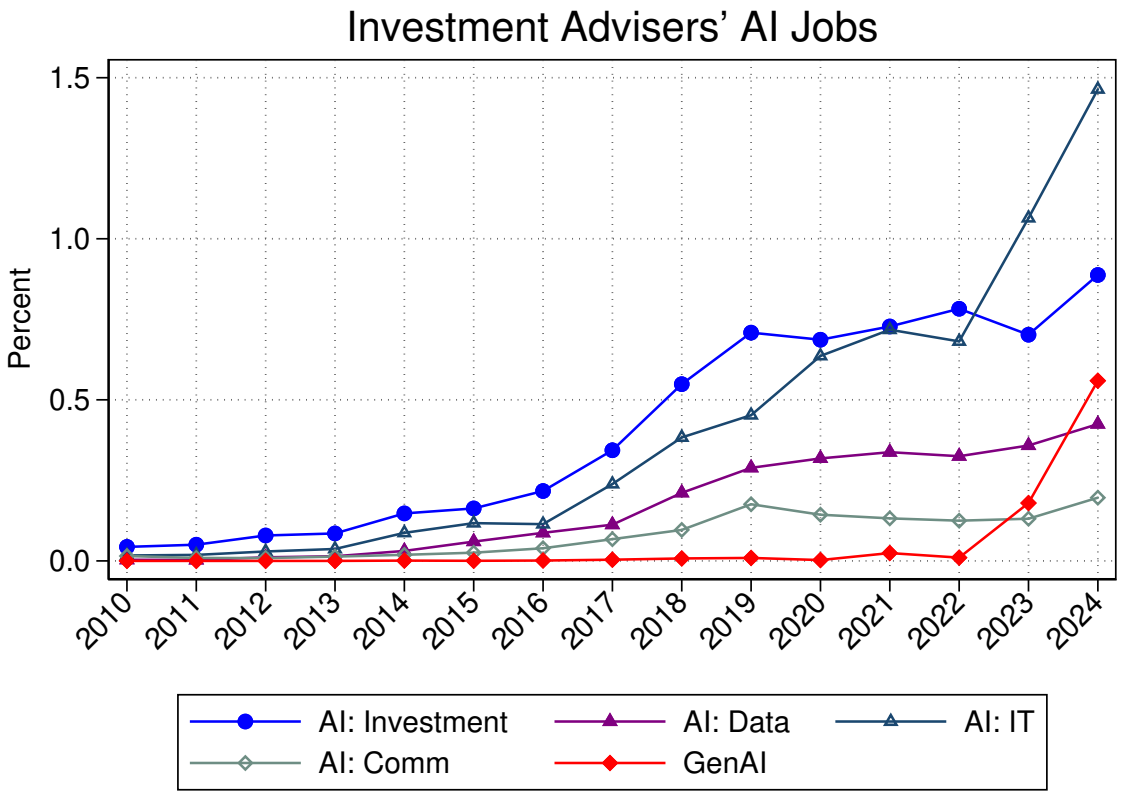


Figure IA.2: **Investment Advisers' AI Jobs for Specific Roles and Generative AI.** This figure presents annual percentages of AI-related job postings for specific roles and generative AI among total job postings by registered investment advisers. Examples of AI-related job postings in each specific role, keywords indicating the use of Generative AI, and occupations indicating each specific role are attached at the end of this Internet Appendix.

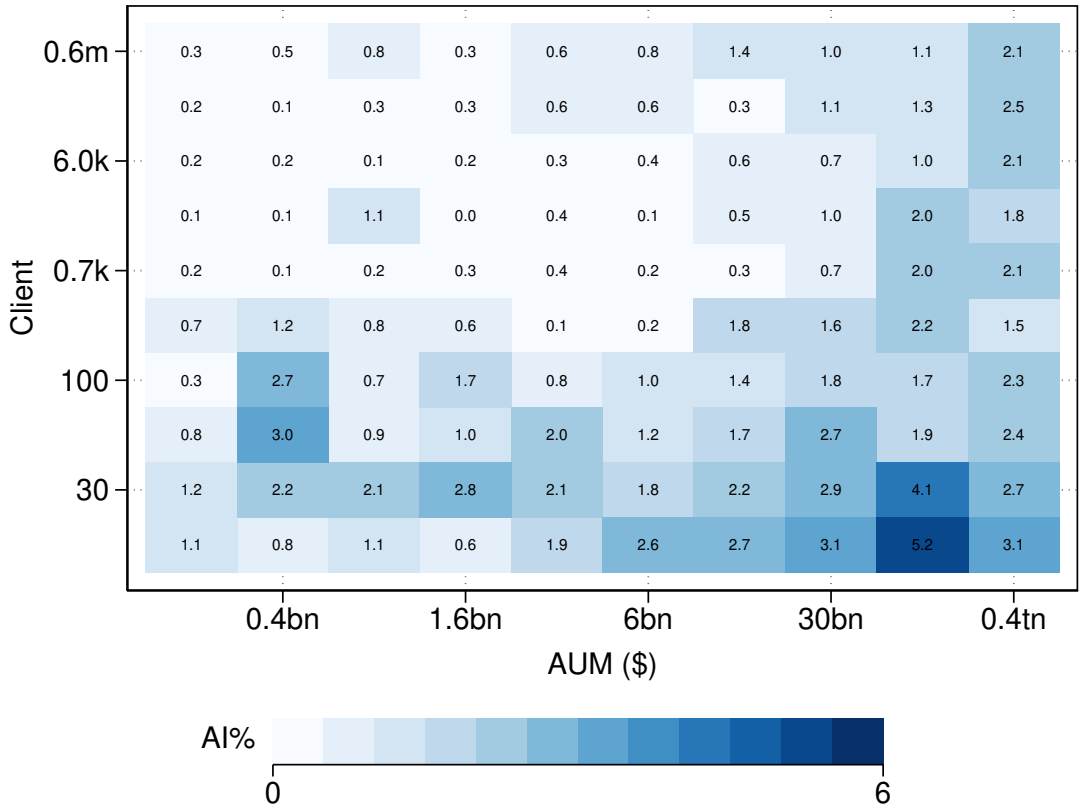


Figure IA.3: **Investment Adviser's AUM, Number of Clients, and AI Investment.** This figure presents the relationship between an investment adviser's current total AUM, the current total number of clients, and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. In each year, advisers are grouped into 10×10 bins sequentially by AUM and by the number of clients. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in the horizontal axis indicate the approximate average AUM in each of the ten AUM group bins, and labels in the vertical axis indicate the approximate average number of clients in each of the ten client number bins.

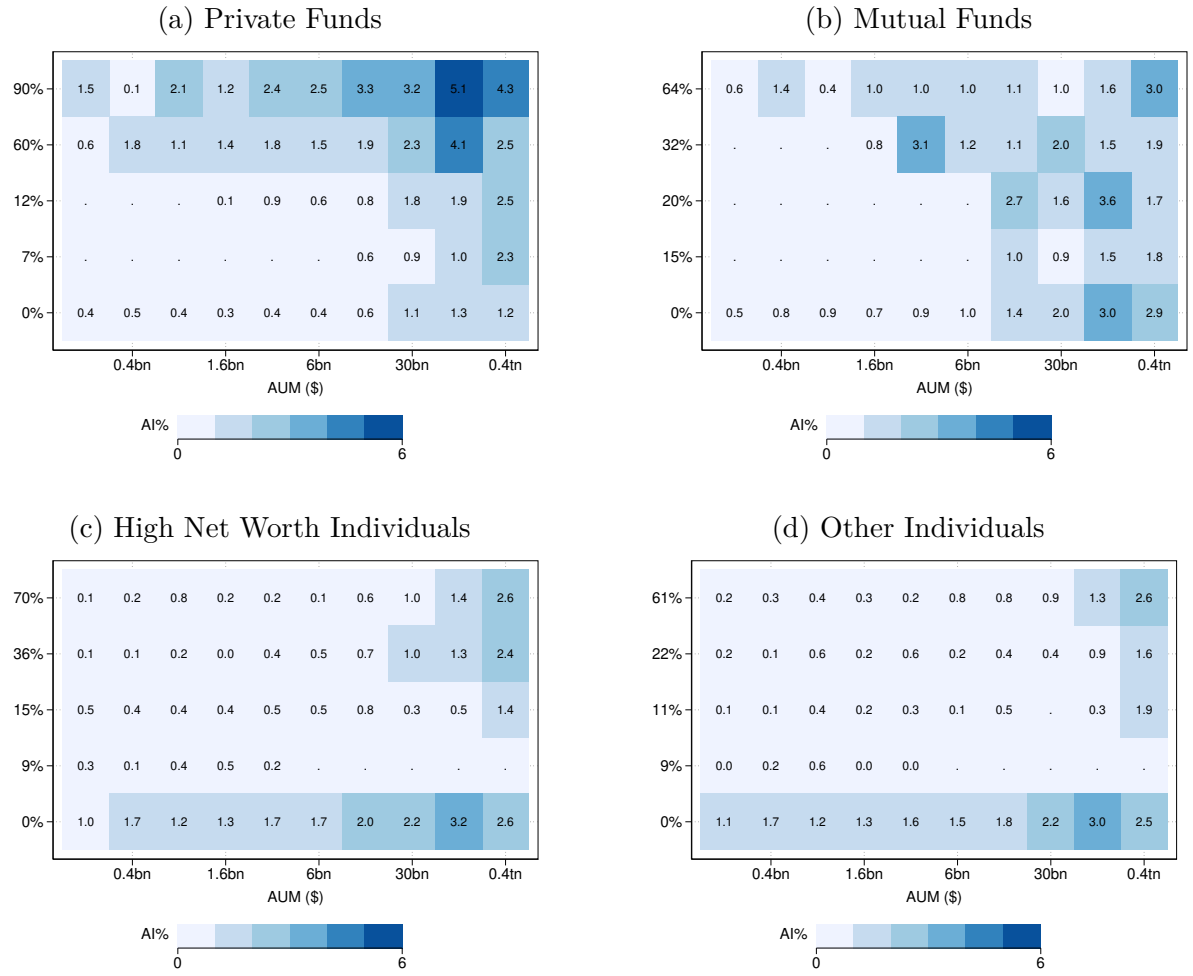


Figure IA.4: **Investment Adviser's AUM Composition and AI Investment.** This figure presents the relationship between the composition of an investment adviser's current AUM and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels (a)-(d) focus on the fraction of AUM in the four largest groups of clients: private funds (i.e., pooled investment vehicles), public funds (i.e., registered investment companies), high-net-worth individuals, and other individuals, respectively. In each year, advisers are grouped into 10×5 bins sequentially by AUM and by the percentage of AUM in a client type. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in horizontal axes indicate the approximate average AUM in each of the ten AUM group bin, and labels in vertical axes indicate the approximate average percentage of AUM in each of the five client type bin.

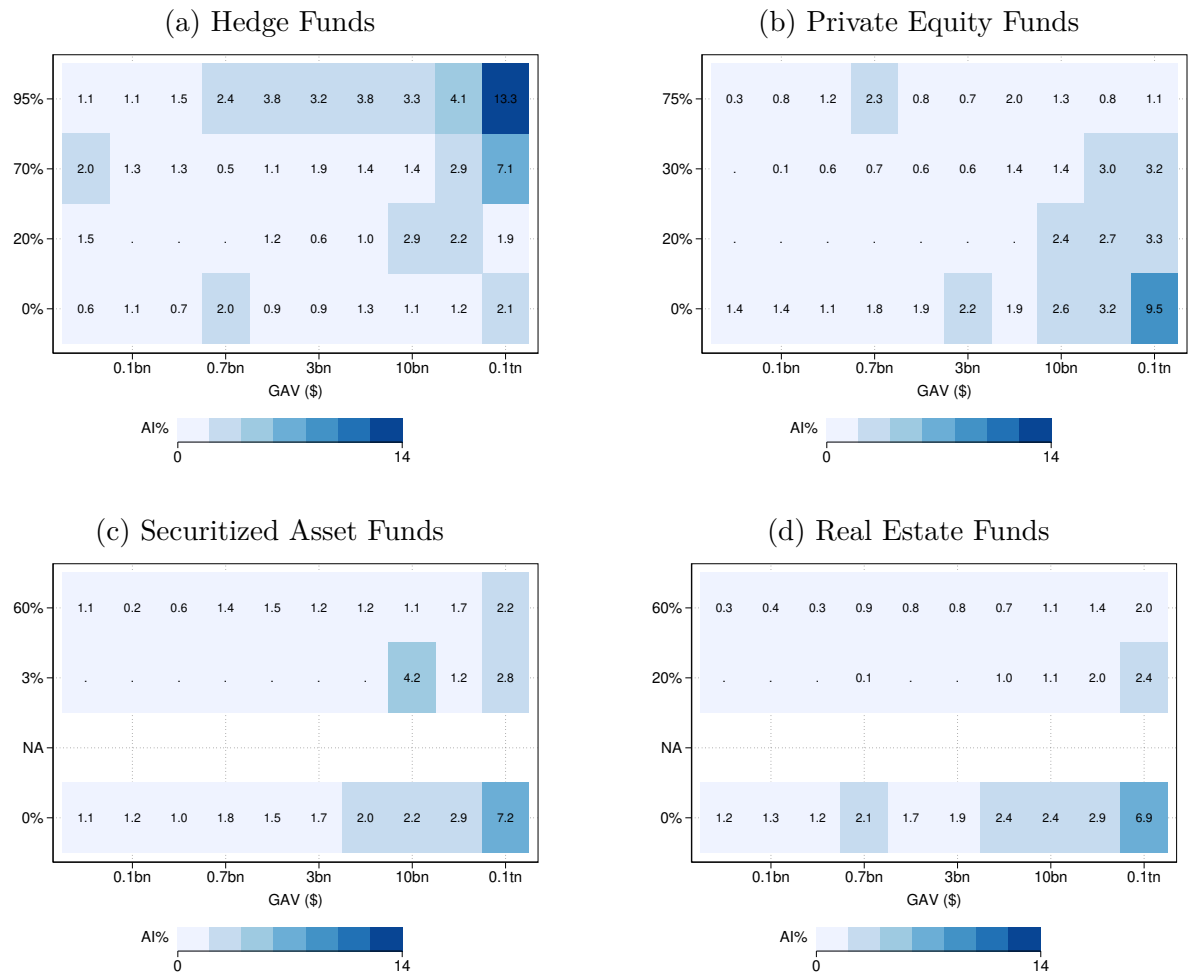


Figure IA.5: **Investment Adviser's Private Funds Composition and AI Investment.** This figure presents the relationship between the composition of an investment adviser's current private fund gross asset value (GAV) and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels (a)-(d) focus on the fraction of GAV in the four largest groups of private funds: hedge funds, private equity funds, securitized asset funds, and real estate funds, respectively. In each year, advisers are grouped into 10×4 bins sequentially by total GAV and by the percentage of GAV in a private fund group. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in horizontal axes indicate the approximate average GAV in each of the ten GAV group bin, and labels in vertical axes indicate the approximate average percentage of GAV in each of the four fund group bin.

Table IA.1: **Investment Adviser's AI Hedge Funds and AI Job Postings**

This table reports results from regressing the investment adviser's AI% job postings in the next year on its current number of AI strategy hedge funds. Every observation is a hedge fund adviser-year between 2012 and 2024 with at least $5 million of hedge fund assets and at least 5 job posts in the next year. Incentive Fee and Management Fee are the average management and incentive fees charged by the adviser's hedge funds. High Water Mark and Hurdle Rate are the fractions of the adviser's hedge funds whose compensation contracts include a high water mark provision and a hurdle rate provision, respectively. Lockup Period is the minimum number of months that an investor has to wait before withdrawing invested money. Restriction Period is the number of months the fund takes to return the money to a withdrawing investor. AUM is the adviser's total hedge fund assets. Age is the adviser's maximum fund age. Return is the average annual return of the adviser's funds during the current year. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: AI% Job Postings				
	(1)	(2)	(3)	(4)
Number of AI Funds	0.080***	0.074***	0.011***	0.012**
	(0.007)	(0.008)	(0.004)	(0.005)
Incentive Fee		0.001		-0.003**
		(0.001)		(0.001)
High Water Mark		0.013		0.085***
		(0.018)		(0.026)
Hurdle Rate		-0.013		-0.006
		(0.010)		(0.013)
Lockup Period		-0.001		0.000
		(0.000)		(0.000)
Restriction Period		-0.000***		-0.001**
		(0.000)		(0.000)
Log(AUM)		0.003*		0.005*
		(0.002)		(0.003)
Log(Age)		-0.014**		-0.003
		(0.006)		(0.005)
Management Fee		0.002		0.006
		(0.010)		(0.017)
Return		-0.000		-0.000
		(0.000)		(0.000)
Year FEs	Y	Y	Y	Y
Adviser FEs	N	N	Y	Y
N	739	721	715	696
R^2	0.149	0.200	0.577	0.594

IA.4. AI-related job examples

IA.4.1. An example in the Investment role

This excerpt comes from a job advertisement posted by Fidelity Investments on May 12, 2024, under the job title "Director of Data Science," categorized by the data vendor Lightcast as "Data Scientists" according to standard O*NET occupation categories.

Job Description

The Asset Management Technology, Quant Development Data Science Team is seeking a highly motivated and technically proficient Director of Data Science who is passionate about applying new AI technologies in the finance domain. This individual will act as the technical lead, collaborating with investment professionals (such as quants and portfolio managers) as well as engineers to prototype, develop, and deliver cutting edge investment solutions.

The role is available in Boston, MA;

The Expertise and Skills You Bring

- Minimum Master's Degree in Engineering, Computer Science, Mathematics, Computational Statistics, Operations Research, Machine Learning, or related technical fields.
- An advanced degree or equivalent experience in Engineering, Computer Science, Mathematics, Computational Statistics, Operations Research, Machine Learning or related technical fields.
- 6+ years of prior work experience with text data and advanced natural language processing (NLP).
- Hands-on experience in most of the following: Knowledge Graphs, Graph Learning, Generative AI, Large Language Models (LLMs) applications, and Information Retrieval.
- Experience in Deep Learning engineering.
- Proficiency in agile coding principles and expertise in writing high-quality Python

modules.

- Proficiency in developing supervised and unsupervised machine learning algorithms.
- Knowledge of model evaluation, tuning, performance, operationalization, scalability of scientific techniques, and establishing decision strategies.
- Experience in evaluating and deciding on the use of new or existing tools for a project.
- Experience in projects with large-scale, multi-dimensional databases, business infrastructure, and multi-functional teams.
- Proficient programming skills in Python and SQL.
- Ability to translate technical topics to non-technical audiences.
- Passionate about staying ahead of the industry with the latest advancements in AI and machine learning and eager to drive innovation.

The Team

The Quant technology team is at the frontier of Fidelity Technology and delivers scalable, innovative, industry-leading investment tools that enable Asset Management to achieve a global advantage. Our work in this groundbreaking initiative will contribute significantly to Asset Management's investment performance and scale and efficiency objectives.

Company Overview

At Fidelity, we are passionate about making our financial expertise broadly accessible and effective in helping people live the lives they want! We are a privately held company that places a high degree of value in creating and nurturing a work environment that attracts the best talent and reflects our commitment to our associates. We are proud of our diverse and inclusive workplace where we respect and value our associates for their unique perspectives and experiences. For information about working at Fidelity, visit FidelityCareers.com. Fidelity Investments is an equal opportunity employer.

IA.4.2. An example in the IT role

This excerpt comes from a job advertisement posted by Fidelity Investments on Oct 29, 2024, under the job title "Principal Full Stack Engineer - Emerging Technologies," categorized by the data vendor Lightcast as "Software Developers" according to standard O*NET occupation categories.

Job Description

We are seeking a Principal Full Stack Engineer to join a team focused on research and development activities. We will explore groundbreaking technologies like AI/ML and develop innovative proofs of concepts for financial solutions using these technologies. The team uses new technologies or existing technologies in new ways to solve complex future or existing problems. This role is approximately half development & half researching and documenting new solutions and technologies. The successful candidate will have the opportunity to work on high value products that support our customers in providing excellent financial solutions. Must be a self-starter, able to work in teams, and communicate software changes to business partners and system partners.

The Expertise and Skills You Bring

- Bachelor's degree in computer science, Information Systems, or related field 8+ years of development experience
- Solid foundation in Computer Science, with competencies in data structures, algorithms, and software design
- Experience in research theories, principles, and models to perform variety of experiments and activities.
- Experience in crafting a variety of products/future products, drawing product sketches, resolving product dimensions and build mockups of proposed products.
- Experience with several of the following technologies (or similar): Strong working knowledge of at least one major programming language Java, .Net., Strong experience

with web services (JSON, XML, REST, SOAP, etc.) Continuous Integration - Jenkins, Stash, Git Test Automation (JUnit, Cucumber, Mockito, EasyMock or any other mocking framework) Experience Technologies - Angular, Angular.js, Spring, React.js, Node.js Strong experience with database technologies such as Snowflake, Apache Spark, Oracle, AWS/Azure database technologies. Experience of Agile development practices Cloud - AWS or Azure

- Experience with one or more groundbreaking technologies such as AI/ML is a plus
- Passion for staying ahead of on technology trends to shift direction and get results. Willingness to learn and experiment new technology, innovate and seek resources to learn, grow and find solutions Working alongside other specialists and developers to mockup product designs.
- Being highly self-motivated & Strong work-ethic is a must.
- Financial experience is a plus

The Team

Fidelity Investments is a privately held company with a mission to strengthen the financial well-being of our clients. We help people invest and plan for their future. We assist companies and non-profit organizations in delivering benefits to their employees. And we provide institutions and independent advisors with investment and technology solutions to help invest their own clients' money. Join Us At Fidelity, you'll find endless opportunities to build a meaningful career that positively impacts peoples' lives, including yours. You can take advantage of flexible benefits that support you through every stage of your career, empowering you to thrive at work and at home. Honored with a Glassdoor Employees' Choice Award , we have been recognized by our employees as a top 10 Best Place to Work in 2024. And you don't need a finance background to succeed at Fidelity-we offer a range of opportunities for learning so you can build the career you've always imagined.

IA.4.3. An example in the Data role

This excerpt comes from a job advertisement posted by Fidelity Investments on Dec 29, 2024, under the job title "Director, Data Architect," categorized by the data vendor Lightcast as "Database Architects" according to standard O*NET occupation categories.

Job Description

Fidelity Workplace Investing(WI) is seeking an experienced architect in Data & AI/ML Architecture group to support Personalization and Experimentation product area. Personalization, a key pillar of our Digital Strategy uses industry leading platforms to deliver experiment-based, algorithm and AI/ML driven experiences to customers to help achieve their financial and health wellness objectives. You will be working across business units and Enterprise Technology teams partnering with business leaders, architecture, and engineering to influence our core and common strategy and deliver these foundational capabilities.

The Expertise and Skills You Bring

- Education - Bachelors or Masters degree required.
- 10+ years of professional technology experience with a minimum 5+ years of architecture experience in Data, Analytics and AI/ML space.
- Ability to formulate Data & AI/ML Strategy, Conceptual Architecture and work with development teams to execute the strategy.
- Good understanding of Data Modeling concepts including 3rd normal form and dimensional modeling
- Experience with data management practice including data integration, data security, data warehousing, data analytics, metadata management and data quality
- Experience in building prototypes, driving Pilot and PoCs, and exploring new solutions
- Experience working on low latency NoSql databases such as DynamoDB, Aerospike, Redis and Cloud databases such as Snowflake
- Experience developing enterprise solutions using Spark (AWS EMR, Azure Synapse,

DataBricks)

- Experience in designing, testing and deploying machine learning frameworks to rapidly iterate on model development & deployment
- Experience developing enterprise applications and data solutions in the cloud - Azure/AWS
- Experience working with data engineers and data scientists to implement AI/ML models and deploying them on ML platform AWS Sagemaker
- Excellent communication and facilitation skills with ability to communicate complex designs and solutions to non-technical and highly technical audiences alike.

IA.4.4. An example in the Communication role

This excerpt comes from a job advertisement posted by Fidelity Investments on Oct 23, 2024, under the job title "Senior Manager, Digital Marketing," categorized by the data vendor Lightcast as "Marketing Managers" according to standard O*NET occupation categories.

Position Description

- Creates engaging conversational content for a customer self- service virtual assistant (chatbot) to enhance user interaction and satisfaction.
- Analyzes performance data, identifies gaps in the virtual assistant's functionality, and uncovers opportunities for User Experience (UX) improvements using Tableau.
- Designs digital content, conducts UX writing, and prepares content strategy while balancing multiple workstreams.
- Defines, tests, and delivers best digital experiences using Natural Language Processing (NLP), chatbot architecture, Artificial Intelligence (AI), and Machine Learning (ML).
- Gathers requirements, creates dialogues and flows, and builds prototypes to create scalable and intuitive conversational experiences.
- Crafts compelling language and dialogue flows, facilitating customers in completing tasks and retrieving information seamlessly through the virtual assistant.

Education and Experience

Bachelor's degree (or foreign education equivalent) in Computer Science, Engineering, Information Technology, Information Systems, Mathematics, Physics, Strategic Design and Management or a closely related field and five (5) years of experience as a Senior Manager, Digital Marketing (or related occupation) leveraging expertise in conversation design, natural language processing, content strategy, user research, and data analysis to architect and iterate exceptional chatbot experiences within an agile development framework.

Or, alternatively, Master's degree (or foreign education equivalent) in Computer Science, Engineering, Information Technology, Information Systems, Mathematics, Physics, Strategic Design and Management or a closely related field and three (3) years of experience as a Senior Manager, Digital Marketing (or related occupation) leveraging expertise in conversation design, natural language processing, content strategy, user research, and data analysis to architect and iterate exceptional chatbot experiences within an agile development framework.

IA.5. Skills, Generative AI keywords, and roles in job postings

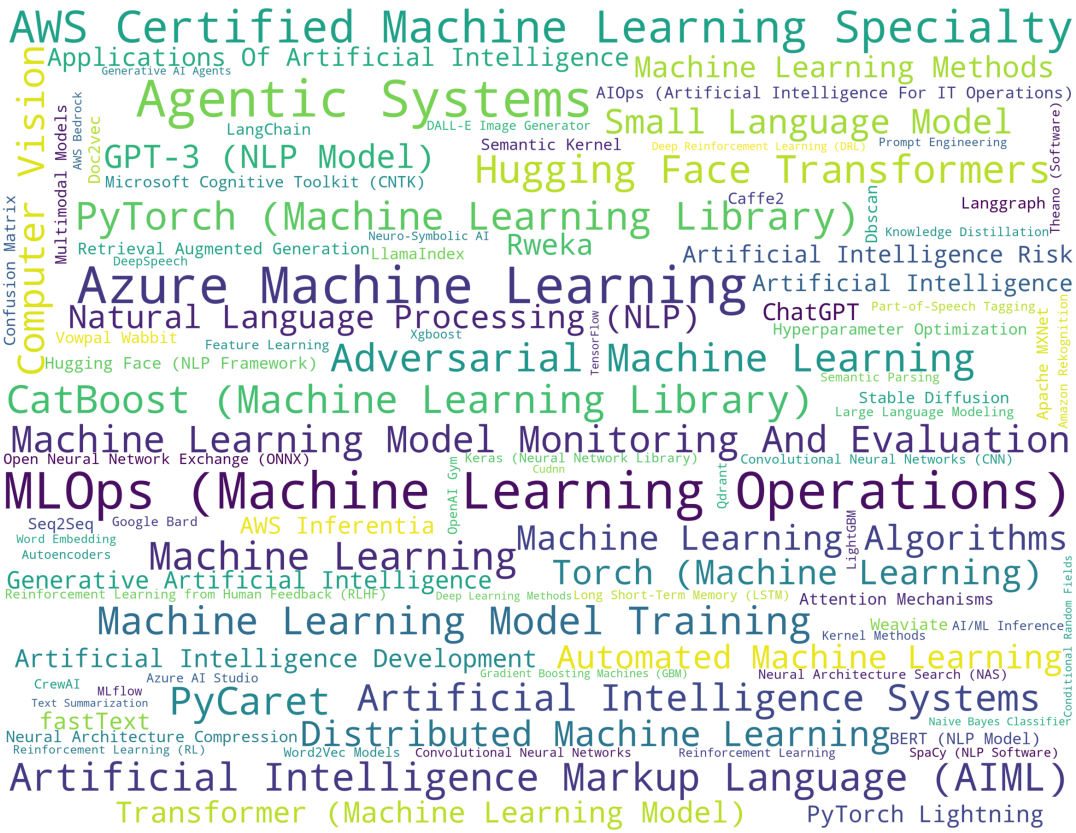


Figure IA.6: **Top 100 Skills with the Highest $w_s^{\mathbf{AI}}$.**
This figure shows the top 100 skills from job postings ranked by their AI relevance score, w_s^{AI}. The AI relevance score for a given skill (w_s^{AI}) measures how frequently this skill co-occurs with core AI skills. Specifically, it is calculated as: $w_s^{\text{AI}} = \frac{\text{Number of job postings requiring both core AI skills and skill } s}{\text{Number of job postings requiring skill } s}$.
A job posting is considered to require core AI skills if it explicitly mentions at least one of the following terms: machine learning (ML), natural language processing (NLP), computer vision (CV), or artificial intelligence (AI), either among its required skills or in the job title. In this figure, skills with higher values of w_s^{AI} appear in larger fonts.



Figure IA.7: **Top 100 Most Frequent Skills in AI Job Postings by Investment Advisers.**

This figure presents the 100 most frequently required skills in AI-related job postings by registered investment advisers. A job posting j is classified as AI-related if the average AI relevance score (w_j^{AI}) across its required skills exceeds 0.1. Skills that occur more frequently are displayed in larger fonts.

Table IA.2: **Frequency of Generative AI Keywords in AI Job Postings by Investment Advisers.**

This table reports the frequency of Generative AI Keywords in AI-related job postings by registered investment advisers. A job posting j is classified as AI-related if the average AI relevance score (w_j^{AI}) across its required skills exceeds 0.1.

keyword	frequency
generative ai	8110
large language model	2890
prompt engineering	668
natural language generation	501
openai	302
generative artificial intelligence	122
chatgpt	112
llama	104
gpt 3	36
gpt 4	36
gemini	27
large language modeling	22
microsoft copilot	11
claude	8
gpt 3 5	2

Table IA.3: **Frequency of Occupations by Role Type (Investment, IT, Data, Communication) in AI Job Postings by Investment Advisers.**

This table reports the frequency of occupations across four role categories (Investment, IT, Data, and Communication) in AI-related job postings by registered investment advisers. A job posting j is classified as AI-related if the average AI relevance score (w_j^{AI}) across its required skills exceeds 0.1.

O*NET Title	O*NET code	Role	Frequency
Software Developers	15-1252.00	IT	25266
Data Scientists	15-2051.00	Investment	25213
Database Administrators	15-1242.00	Data	10187
Database Architects	15-1243.00	Data	7304
Business Intelligence Analysts	15-2051.01	Investment	6973
Computer Systems Engineers/Architects	15-1299.08	IT	5351
Financial Risk Specialists	13-2054.00	Investment	3828
Web Developers	15-1254.00	IT	3741
Marketing Managers	11-2021.00	Comm	3142
Information Technology Project Managers	15-1299.09	IT	2025
Financial Quantitative Analysts	13-2099.01	Investment	1893
Market Research Analysts and Marketing Specialists	13-1161.00	Comm	1631
Financial and Investment Analysts	13-2051.00	Investment	1425
Statisticians	15-2041.00	Investment	1043
Information Security Engineers	15-1299.05	IT	1000
Operations Research Analysts	15-2031.00	Investment	864
Computer Occupations, All Other	15-1299.00	IT	846
Personal Financial Advisors	13-2052.00	Comm	629
Computer and Information Research Scientists	15-1221.00	IT	526
Sales Managers	11-2022.00	Comm	524
Data Warehousing Specialists	15-1243.01	Data	501
Web and Digital Interface Designers	15-1255.00	IT	501
Computer Network Architects	15-1241.00	IT	429
Securities, Commodities, and Financial Services Sales Agents	41-3031.00	Comm	366
Compliance Officers	13-1041.00	Comm	365
Computer Systems Analysts	15-1211.00	IT	335
Computer Programmers	15-1251.00	IT	320
Computer User Support Specialists	15-1232.00	IT	261
Software Quality Assurance Analysts and Testers	15-1253.00	IT	258
Computer and Information Systems Managers	11-3021.00	IT	242
Information Security Analysts	15-1212.00	IT	238
Actuaries	15-2011.00	Investment	221
Network and Computer Systems Administrators	15-1244.00	IT	218
Search Marketing Strategists	13-1161.01	Comm	202
Compliance Managers	11-9199.02	Comm	192
Credit Analysts	13-2041.00	Investment	187
Economists	19-3011.00	Investment	161

Table IA.3: Frequency of Occupations by Role Type (Investment, IT, Data, Communication) in AI Job Postings by Investment Advisers (continued).

O*NET Title	O*NET code	Role	Frequency
Customer Service Representatives	43-4051.00	Comm	155
Sales Representatives of Services, Except Advertising, Insurance, Financial Services, and Travel	41-3091.00	Comm	147
Retail Salespersons	41-2031.00	Comm	119
Public Relations Managers	11-2032.00	Comm	99
Loan Interviewers and Clerks	43-4131.00	Comm	77
First-Line Supervisors of Retail Sales Workers	41-1011.00	Comm	58
Brokerage Clerks	43-4011.00	Comm	57
Blockchain Engineers	15-1299.07	IT	54
Sales Engineers	41-9031.00	Comm	32
First-Line Supervisors of Non-Retail Sales Workers	41-1012.00	Comm	32
Investment Fund Managers	11-3031.03	Investment	30
Data Entry Keyers	43-9021.00	Data	27
Bill and Account Collectors	43-3011.00	Comm	24
Public Relations Specialists	27-3031.00	Comm	24
Insurance Sales Agents	41-3021.00	Comm	20
Regulatory Affairs Specialists	13-1041.07	Comm	20
Appraisers and Assessors of Real Estate	13-2023.00	Investment	17
Tellers	43-3071.00	Comm	14
Regulatory Affairs Managers	11-9199.01	Comm	13
Document Management Specialists	15-1299.03	IT	12
Fundraising Managers	11-2033.00	Comm	11
Digital Forensics Analysts	15-1299.06	IT	11
Geographic Information Systems Technologists and Technicians	15-1299.02	IT	8
Billing and Posting Clerks	43-3021.00	Comm	7
Administrative Services Managers	11-3012.00	Comm	6
Advertising and Promotions Managers	11-2011.00	Comm	5
Credit Counselors	13-2071.00	Comm	5
Clinical Data Managers	15-2051.02	Data	5
Real Estate Brokers	41-9021.00	Comm	4
Penetration Testers	15-1299.04	IT	4
Telecommunications Engineering Specialists	15-1241.01	IT	3
Advertising Sales Agents	41-3011.00	Comm	3
New Accounts Clerks	43-4141.00	Comm	3
Real Estate Sales Agents	41-9022.00	Comm	2
Statistical Assistants	43-9111.00	Investment	1
Door-to-Door Sales Workers, News and Street Vendors, and Related Workers	41-9091.00	Comm	1
Sales and Related Workers, All Other	41-9099.00	Comm	1