The Growth and Performance of Artificial Intelligence in Asset Management†

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Abstract

We examine AI adoption in asset management and its investment implications. We document that AI-driven investing is concentrated among hedge funds, particularly those employing systematic diversified macro strategies. AI funds exhibit greater alpha comovement and are launched by investment advisers facing stronger performance incentives. AI funds significantly outperformed non-AI hedge funds on a risk-adjusted basis in early years, but their outperformance declined over time and mostly disappeared with the growth of AI-driven investing. Our findings highlight both the alpha-generating potential and the 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. In recent decades, Artificial Intelligence (AI) has emerged as a promising avenue in this search. By combining statistical techniques with big data, AI offers strong predictive power and self-adaptive capabilities to guide investment decisions in evolving market conditions. Its potential to generate superior returns has attracted growing interest from both investment advisers and investors. Yet 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 systematically examine AI-driven investing in the U.S. asset management industry. The central challenge of our study is to identify where AI is deployed in investment decisions and to link this usage to fund characteristics and performance. We address this challenge through large-scale textual analyses of SEC-registered investment advisers' job postings and tens of thousands of fund-level strategy descriptions. 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 management. Our novel top-down approach allows us to make some long-awaited progress in understanding the applications and alpha-generating ability of AI technologies in asset management.

Given our focus on AI-driven investment strategies, we consider broadly defined AI technologies, particularly machine learning (ML) techniques that facilitate predictive modeling and trading signal generation. We therefore do not restrict our scope to recent developments in generative AI and large language models (LLMs), such as prompt-based chatbot systems (e.g., OpenAI's ChatGPT), which represent a distinct subset of AI with specialized applications.

[1]Although investment advisers do not disclose their historical internal operations, multiple reports 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."

Our analysis shows that, while AI-related job positions have grown rapidly in the asset management industry, they are positively associated with only one type of fund, namely hedge funds. Moreover, we find that the majority of AI-driven hedge funds ("AI funds") pursue macro strategies concentrated in a narrowly-defined sub-strategy, called Systematic Diversified Macro. As of 2024, 88% of hedge fund assets managed by AI funds in our sample fall into this category, which typically involves short-term trading in liquid instruments such as equity indices, commodities, and currencies. Consistent with these strategies, AI funds exhibit significantly lower exposures to traditional equity risk factors and greater exposures to other asset classes.

Our evidence on the growth of AI funds supports the view that AI is being adopted as a tool to enhance investment performance. We find that hedge fund advisers facing stronger performance incentives are more likely to launch new AI funds and adopt AI in existing funds. Specifically, the number of AI funds managed by an adviser is positively associated with the strength of incentives embedded in the compensation contracts of its existing funds. Among advisers managing AI funds, these contracts feature higher incentive fees and include fewer high water mark and hurdle rate provisions, making the adviser's payoff more sensitive to fund performance. 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).

To investigate whether AI funds deliver superior performance, we analyze a large sample of 6,890 US hedge funds between 2006 and 2024. We find that AI funds significantly outperform non-AI funds by approximately 5% annually on a risk-adjusted basis in earlier years. However, this outperformance gradually decreases and becomes statistically indistinguishable from zero after 2017. The decline in relative performance cannot be explained by differences between early and late AI adopters, because even AI funds launched in the early years have lost most of their outperformance in subsequent years.

We further show that AI funds display stronger comovement than non-AI funds, as their risk-adjusted returns exhibit both higher pairwise correlations and a larger fraction of variation explained by the first principal component. These patterns suggest that the use of similar AI models has led to increased homogeneity among hedge funds.[2] The difference in comovement between AI and non-AI funds gradually decreases over time, potentially reflecting strategic deviations from crowded strategies.

Our findings on AI fund performance align with theoretical discussions on the competitive exploitation of machine learning in non-stationary financial markets (Allen, Kacperczyk, and Kumar, 2025) and more broadly, with decreasing returns to scale in active management. During our sample period, the decline in AI fund performance is accompanied by a rapid expansion in AI funds, with their number quadrupled since 2012. Given that many AI funds pursue similar strategies, invest in overlapping asset classes, and likely trade on correlated signals, the growing scale makes sustaining outperformance increasingly difficult. As such, the future success of AI-driven strategies will depend not only on advances in AI technology, but also on the scale and heterogeneity of its applications within the asset management industry.

The relative performance of AI funds we document may reflect unobserved heterogeneity across hedge fund advisers or the effects of AI adoption on all of an adviser's funds. To distinguish fund-level performance associated with AI-driven investing from these firm-level forces, we further examine how AI funds perform relative to non-AI sibling funds managed by the same adviser. Our estimates show that AI funds consistently outperformed their sibling funds throughout the sample period, with some outperformance persisting even after 2017. This within-adviser comparison suggests that, while AI may provide a meaningful edge over traditional approaches, it is also possible that the diversion of internal resources toward AI

[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).

initiatives is costly to other funds managed by the same advisers.

A driving force behind the growing scale of AI funds is investors' belief in AI's alpha-generating ability. To investigate these beliefs, we apply a revealed preference approach and analyze money flows into hedge funds. Our estimates indicate that AI funds did not receive inflows beyond what would be expected from their realized performance. It also suggests that mentioning AI in strategy descriptions per se does not attract investor flows, whereas the strong historical performance delivered by AI funds does.

Since our study uses fund strategy descriptions to identify and evaluate AI-driven investing, it is critical to address the potential influence of data biases on our inferences. First, hedge fund databases typically report fund contractual terms and investment strategies as of the most recent available date for each fund. Using this information retrospectively over the life of a fund can introduce a look-ahead bias. For example, funds that performed well in the past may be more likely to develop AI-driven strategies subsequently. To avoid this bias, we construct our fund sample from year-by-year archived snapshots of the same database, where each snapshot contains only information available as of that year.[3] Second, we exclude all observations for a given fund that occur before its first recorded snapshot. This ensures that our sample is not affected by a backfilling bias, which is well documented in the hedge fund literature.[4] Third, although the database includes both live and dead funds, the requirement of at least 24 months of returns for alpha estimation could introduce implicit survivorship bias (Baquero, Ter Horst, and Verbeek, 2005). However, this bias is unlikely to drive our results, as AI funds and non-AI funds exhibit similar survival rates, both in terms of liquidations and cessations of reporting to the database.

This paper is closely related to a recent literature on the applications of AI and big data in asset management. Existing studies have developed creative indirect measures of

[3] We find qualitatively similar results on fund performance when using only the 2025 version of the database, though this alternative sample is subject to a look-ahead bias.

[4] See, for example, Ackermann, McEnally, and Ravenscraft (1999), Brown, Goetzmann, and Ibbotson (1999), and Malkiel and Saha (2005).

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 from the association between changes in 13F stock holdings and ChatGPT-generated signals. They show that institutions with a higher reliance on generative AI achieved better performance. In a similar spirit, Hu, Rohrer, and Zhang (2025) infer mutual fund AI adoption from the alignment between portfolio deviations from benchmarks and machine learning-based trading signals, and document outperformance among intensive adopters. Using labor-based, institution-level measures of data science and AI adoption, Cen, Han, Han, and Jo (2024), Zhang (2024), and Kim and Nanda (2025) also find positive impacts of these technologies on investment performance.

We contribute to this literature by providing the first systematic analysis of AI-driven investing in the asset management industry. Unlike prior and contemporaneous studies that rely on indirect proxies within specific fund categories, we examine AI adoption across fund categories and directly identify funds in which AI plays a central role in investment decisions. This approach uncovers AI-driven investing across a broad universe of funds and strategies, offering new insights into the applications and fund-level performance of this technology and informing future research on AI in financial markets.

Our paper also contributes to the hedge fund literature by exploring AI as an understudied source of performance. Prior research has attributed hedge fund performance to managerial incentives and discretion (Agarwal, Daniel, and Naik, 2009; Gupta and Sachdeva, 2025), share liquidity restrictions (Aragon, 2007), hedging choices (Titman and Tiu, 2011), and portfolio disclosure (Shi, 2017). The literature also documents associations between performance and both fund-level and manager-level characteristics.[5] We show that AI has meaningful

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

alpha-generating ability, as evidenced by AI funds' outperformance in earlier years and relative to other funds managed by the same advisers. 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 decay in the alpha of AI hedge funds as their total assets grow extends earlier research on diseconomies of scale in active asset management. The prior literature has focused on decreasing returns to scale at both the fund level (Berk and Green, 2004; Chen, Hong, Huang, and Kubik, 2004; Fung, Hsieh, Naik, and Ramadorai, 2008; Zhu, 2018) and the fund industry level (Pástor and Stambaugh, 2012; Pástor, Stambaugh, and Taylor, 2015). Our findings suggest that the growing use of AI-driven investing among hedge funds has reduced their strategy distinctiveness (Sun, Wang, and Zheng, 2012), leading to diminished performance. 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.

Our findings on AI-driven investing add 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 (Colliard, Foucault, and Lovo, 2022; Dou, Goldstein, and Ji, 2024), 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 documenting AI adoption in the asset management industry and its applications in hedge funds.

More broadly, our paper extends research on AI's impact on firm performance by examining investment advisers. Using US public firms, Babina, Fedyk, He, and Hodson (2024) find that AI-investing firms see increased growth in sales, employment, and market valuations, especially for larger firms. Relatedly, Czarnitzki, Fernández, and Rammer (2023) find a positive relationship between German firms' AI adoption and productivity, and Adams, Fang, Liu, and Wang (2024) find that AI-driven pricing strategies adopted by larger firms accelerate their growth in sales, employment, assets, and markups. Eisfeldt, Schubert, and Zhang (2023) document that firms with greater exposure to generative AI experienced significantly higher firm value growth than less-exposed firms following the release of ChatGPT. Consistent with Babina, Fedyk, He, and Hodson (2024), we find that AI adoption, which is higher for larger advisers, has spurred changes in investment products.

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

This subsection describes the data sources for 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. These annual filings provide comprehensive information about advisers' practices, fees, and business structures. We obtain all Form ADV filings submitted between 2012 and 2024 from the SEC website and extract data from several "Items" and the corresponding "Schedules" in Part 1A of the form. Specifically, Item 1 reports an adviser's identifying information. Item 5 reports an adviser's Regulatory Assets Under Management (RAUM), including decomposed values by type of client.[6] Item 7B indicates whether an

[6]In Form ADV, a client is either a legal entity (e.g., investment fund) or a person (e.g., a retail advisee).

adviser manages private funds. Schedule D of Item 7B further provides detailed fund-level information for private funds, including fund types and gross asset values (GAV).[7]

We use the data from 2012, as 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.[8] 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 5D was revised to report the exact 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

[7] 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.

[8] 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.

dates, sought-after skills, and educational prerequisites.[9] Our data from Lightcast's U.S. job postings are between 2010 and 2024. We focus on entries with available employer names and exclude internships.

Our primary measure of an investment adviser's AI adoption is the fraction of AI-related job postings among its total job postings in a year. Because companies rarely disclose their capital expenditures on AI, the literature typically measures company-level AI intensity using labor market data.[10] We follow the literature by examining each investment adviser's AI labor intensity revealed through their job postings. Specifically, following the methodology in Babina, Fedyk, He, and Hodson (2024), we classify AI-related job postings based on required labor skills. To reduce the influence of outliers, we require each adviser-year observation to include at least five job postings. We also conduct robustness tests using three alternative measures for an investment adviser's job postings related to AI, old technology, and data management, following Abis and Veldkamp (2024). Detailed steps for constructing these labor-based AI adoption measures are 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 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 GAV. We also calculate private fund GAVs separately by fund type: Hedge Funds, Private Equity Funds, Real Estate Funds, Securitized Asset Funds,

[9]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).

[10]See, for example, see Acemoglu, Autor, Hazell, and Restrepo (2022), Babina, Fedyk, He, and Hodson (2023), Eisfeldt, Schubert, and Zhang (2023), and Babina, Fedyk, He, and Hodson (2024).

Venture Capital Funds, and other private funds.[11] We then merge private fund variables with the adviser-year panel using the unique filing identifier.

Third, we construct a linktable 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), headquarters locations, and website URLs. The algorithm also accounts for parent-subsidiary relationships. Figure IA.1 in the Appendix summarizes the annual distribution of linked investment advisers. In terms of total assets under management, almost all Form ADV filers are matched to PitchBook entities, and approximately 70% of those are further linked to job postings in Lightcast.[12]

1.2. Data on hedge funds

We use the Hedge Fund Research (HFR) database for information on fund size, returns, contract terms, and investment strategies. We choose HFR because it offers superior coverage of fund data in recent years, when AI-related activities became especially relevant.[13] More importantly, HFR consistently provides detailed fund-level strategy descriptions, typically with at least 100 words, which we use to identify AI-driven investing through textual analysis.

The standard academic HFR database includes both live and dead funds, but it reports fund characteristics, contractual terms, and investment strategies only as of the last available date of each fund. Using this information retrospectively over the life of a fund would introduce a look-ahead bias. To address this concern, we acquire year-by-year archived snapshots of the

[11] 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.

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

[13] Agarwal, Daniel, and Naik (2004) compare the number of hedge funds covered in three major databases, HFR, ZCM/MAR, and Lipper TASS, during the period 1994–2000, and find that HFR offers the most comprehensive coverage. We also compare HFR and Lipper TASS over the period 2010–2024 and find that HFR offers substantially better fund coverage.

HFR database between 2005-2024, where each snapshot contains only information available as of that year. We then keep data of a fund after the first snapshot in which it appears and merge the fund's monthly observations with its contractual terms and strategy descriptions reported in the corresponding year.

We use OpenAI's latest GPT-5 large language model to analyze fund investment strategy descriptions in each yearly snapshot of the HFR database and evaluate whether the fund employs AI technologies for investment decisions. To ensure the accuracy of this identification and minimize false positives, we design a stringent prompt and refine it through iterative manual inspection and fine-tuning. In this process, we also identify funds that use quantitative strategies and high-frequency trading. The complete AI prompt and classification examples are provided in Internet Appendix IA.1.

We estimate the monthly hedge fund alpha using the seven hedge fund factors from Fung and Hsieh (2004), which include the following factors: Equity Market, Size Spread, Bond Market, Credit Spread, and Trend-Following Factors for Bonds, Currencies, and Commodities.[14] As an alternative model, we use the six factors developed by AQR, including Global Equity Indices, All Macro Market, and Value, Momentum, Carry, and Defensive factors, which are long-short style premia across all asset classes (Ilmanen, Israel, Moskowitz, Thapar, and Lee, 2021). Moreover, we also consider the Fama-French stock market, size, and value factors. Risk exposures are estimated using a 24-month rolling window, requiring at least 12 observations. We compute the monthly alpha as the out-of-sample residual of the estimated model in the next month.

To be consistent with our analysis of investment advisers, we restrict our sample to USD-nominated US-domiciled hedge funds. We use HFR's classification of hedge fund strategy categories, including Equity Hedge, Event Driven, Macro, Relative Value, Risk Parity, and

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

Crypto/Blockchain.[15] Our fund-month panel sample for regression analysis requires funds to have non-missing size, alpha, and contractual information, and at least \$5 million in AUM. These filters reduce the number of unique hedge funds from 9,626 to 6,890, leaving us with 393,516 fund-month observations. To mitigate the impact of outliers, we winsorize continuous variables at the 1st and 99th percentiles.

1.3. Data on mutual funds

We collect mutual fund investment strategy descriptions from Form 497K filings available on SEC's EDGAR database from 2009 to 2024. Form 497K was introduced following 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 strategy descriptions (see Internet Appendix IA.1) to process the investment strategy text of mutual funds. We then match each fund's extracted strategy features and effective date from Form 497K filings with its monthly data from the CRSP Survivorship Bias-Free Mutual Fund database, using fund ticker, fund name, and company name as common identifiers. Following Kacperczyk, Sialm, and Zheng (2008), we aggregate monthly return and total net asset (TNA) data from the share class level to the fund level.

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

1.4. Summary statistics

Table 1 reports summary statistics for the adviser-year sample between 2012 and 2024. By construction, each adviser in the sample manages at least $100 million in AUM. The median adviser manages $5.4 billion in AUM and approximately 290 accounts. The average adviser has 1.15% of AI-related job postings.

Other variables measure the advisers' AUM composition. First, AUM% Discretionary is the proportion of AUM managed on a discretionary basis, where the adviser makes investment decisions without obtaining client approval for each trade. Advisers mostly operate under discretionary mandates, with a median discretionary AUM share close to 100%. Second, most advisers serve multiple types of clients. Roughly half of the advisers manage private fund(s), which are exempt from registration under the Investment Company Act of 1940, with an average of 28% of AUM in these funds. Public funds refer to investment companies, primarily mutual funds and ETFs, which are governed by the Investment Company Act of 1940. AUM% HighNetWorth is the proportion of AUM managed for high-net-worth individuals.[16] AUM% Individual is the proportion of AUM from retail investors who fall below the high-net-worth threshold. Third, advisers of private funds on average manage 13 private funds, with hedge funds having the largest share of gross asset values.

Table 2 presents summary statistics for our monthly hedge fund sample between 2006 and 2024. The average fund is approximately $420 million in size and 10 years old, with a monthly return of 43 basis points and a monthly alpha of less than 10 basis points. On average, only 1% of fund-month observations are classified as AI funds, which is comparable to the share of AI-related job postings in Table 1. By comparison, 22% of fund-months are classified as quant funds and less than 1% as high-frequency trading funds.

Regarding compensation structure, the average incentive fee among hedge funds in our

[16] High-net-worth individuals are typically defined as clients with at least $1 million in assets with the adviser or a net worth exceeding $2.1 million (excluding their primary residence).

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 less frequently in our sample. Management fee rates are generally between 1% and 2%. Regarding liquidity restrictions on fund shares, the average lock-up and restriction periods are 5.3 months and 4.6 months, respectively.

2. Which Funds Use AI-Driven Investment Strategies?

This section presents a top-down analysis of AI adoption among investment funds, beginning with different legal structures of managed assets, then narrowing to different types of private funds, and finally to different strategies of hedge funds. We then compare hedge fund characteristics and factor exposures between AI funds and non-AI funds.

2.1. The growth of investment advisers' AI job postings

Figure 1 Panel A presents the average time trends in AI-related job postings in SEC-registered 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 persistently 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, Fedyk, He, and Hodson (2024).

To shed light on the roles AI labor plays within investment advisers, we report in Figure

1, Panel B, the average time trends of AI-related job postings across functional areas such as investment, data management, IT, and client communication.[17] By 2024, investment and IT roles together account for over 2% of all job postings, representing more than half of the AI-related positions.

2.2. Investment advisers' fund composition and AI job postings

We next examine the cross-sectional relationship between an investment adviser's AI labor intensity and the composition of the funds it manages.

In Panel A of Table 3, column 1 shows that 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. Column 2 shows that for a given level of AUM, the natural logarithm of the total number of client accounts is negatively associated with AI labor intensity, indicating that advisers managing larger accounts (e.g., investment funds rather than retail accounts) tend to invest more in AI. Figure IA.2 in the Internet Appendix visualizes these two correlations using a heatmap that double-sorts investment advisers by AUM and account count.

Columns 3 and 4 reveal a positive relationship between private funds and AI labor intensity. Column 3 shows that, on average, advisers managing private funds exhibit a 0.72-percentage-point higher AI labor intensity. This effect is economically meaningful, amounting to 63% of the sample mean and 17% of the sample standard deviation of AI labor intensity. Column 4 confirms this relationship using continuous measures of AUM composition. Controlling for the fraction of assets managed under discretionary mandates, a one-standard-deviation increase in the fraction of AUM in private funds (equal to 38.92 percentage points) is associated with a 0.54-percentage-point increase in AI labor intensity in the following year (i.e., 38.92×0.014). This corresponds to around 47% of the sample mean and 13% of the standard deviation. In

[17] We classify AI-related job postings into functional areas by occupation. Internet Appendix Table IA.4 lists the occupations in each area, and Section IA.5 provides illustrative job posting examples.

contrast, the fractions of AUM in mutual funds (including ETFs), high net worth individuals, and other individual clients are all negatively associated with AI labor intensity.[18]

Given the evidence in Panel A that involvement in private fund management is strongly positively associated with future AI labor intensity, we further investigate this relationship by focusing on the subsample of advisers that manage at least one private fund. Specifically, we examine whether the asset concentration of an adviser's private funds in a particular type of target asset predicts its AI labor intensity in the following year.

In column 1 of Panel B, the total GAV of private funds consistently exhibits a statistically significant positive coefficient across all columns. Column 2 shows that, conditional on private fund total GAV, the adviser's total AUM is no longer correlated with AI. This result supports that the size-AI association in Panel A is mainly driven by private funds. In column 3, the number of private funds shows a significant negative association with AI labor intensity, suggesting that AI investments are more concentrated in advisers overseeing fewer, larger private funds. These findings echo the pattern documented in Panel A: given the total AUM, the number of managed accounts is negatively correlated with AI labor intensity.

Column 4 further examines the composition of private fund assets and shows that AI labor intensity is positively associated with only one type of private funds: hedge funds. A one-standard-deviation increase in the fraction of GAV in hedge funds (42.76 percentage points) predicts a 0.86-percentage-point increase in AI labor intensity (i.e., 42.76×0.020), equivalent to 75% of the sample mean and 21% of its standard deviation. In contrast, the fractions of GAV allocated to other types of private funds are all negatively correlated, and this negative correlation is statistically significant among securitized asset funds.[19]

Overall, Table 3 shows that among investment advisers, firm-level AI labor intensity is positively associated with larger total assets and a higher degree of asset concentration in

[18]Figure IA.3 in the Internet Appendix visualizes these relationships with heatmaps.
[19]These relationships are visualized in Figure IA.4 in the Internet Appendix.

their larger funds. Moreover, conditional on asset size, AI labor intensity is further positively related to advising a particular type of private funds: hedge funds.

2.3. The growth of AI funds

This subsection examines AI-driven investing at the individual fund level. In our sample between 2006 and 2024, there are 9,826 unique hedge funds, of which 106 (1.1%) are ever identified as AI funds. This small fraction reflects our strict criteria for identifying AI-driven investing based on fund strategy descriptions. Figure 2 Panel A shows the time-series growth of AI hedge funds, in terms of both total AUM and the number of funds. Panel B scales these two measures by the total AUM and the number of all hedge funds in our sample, which addresses the influence of changes in the coverage of the hedge fund database.

Both the number and percentage of AI hedge funds have increased steadily since 2006. This increase accelerated around 2017, coinciding with the rise in AI labor intensity in Figure 1. The number of AI hedge funds reached its peak in 2021 at 44 funds, accounting for 2.3% of hedge funds. While the number declined slightly after 2021, its percentage remained stable, suggesting that this decline reflects changes in database coverage. In terms of AUM of AI hedge funds, the total amount and percentage remained stable until 2020. It then grew substantially from 2021, reaching approximately USD 12 billion by 2024. These trends underscore the rapid expansion of AI-driven investing among hedge funds.

We further analyze each AI hedge fund's learning paradigms, model approaches, and use cases by manually classifying its historical strategy descriptions. Figure 3 presents the annual frequencies of these classifications. Panel A shows that most funds train their models using supervised learning, which relies on labeled data such as historical returns. Only a few AI funds use unsupervised learning, and even fewer have used reinforcement learning. In panel B, while the majority of funds rely on classical AI model approaches, there has been a rise in the adoption of probabilistic (e.g., Bayesian), deep learning (e.g., neural networks), and evolutionary (e.g., genetic algorithms) models since around 2017. Panel C shows that the use cases of AI are similarly distributed among signal extraction, trade execution, and risk management.

Finally, when we apply the same GPT prompt to mutual fund investment strategy descriptions, we identify very few AI mutual funds. This finding is consistent with Table 3, Panel A, where the variable AUM% Mutual Fund exhibits a weak, negative correlation with future AI labor intensity. We report AI mutual funds' growth in Figure IA.5 in the Internet Appendix. At its peak in 2024, there were only three AI mutual funds. Therefore, we focus on hedge funds in the rest of this paper.

2.4. Investment strategies of AI hedge funds

A hedge fund's investment strategy, such as equity hedge, event-driven, and macro, likely influences the feasibility and effectiveness of AI algorithms. For instance, strategies operating in signal-rich environments, such as global macro or short-horizon equity trading, are particularly suitable for data-intensive AI techniques, whereas illiquid or event-driven strategies rely on low-frequency information that limits the applicability of these models.

Figure 4 shows the distribution of AI and non-AI hedge funds across main strategy categories, using all sample funds as of the last available date of each fund. Each of the four panels compares the share of AI funds (blue bars) and non-AI funds (white bars), where the share is calculated as the number or AUM of funds in a given category divided by the total number or AUM of AI (or non-AI) funds. This comparison reveals which investment strategies have a higher concentration of AI-driven investing.

Panels A and B display the main strategy categories on the horizontal axes. In Panel A, the number of AI hedge funds is disproportionately concentrated in Macro strategies, while being notably underrepresented in Event Driven, Relative Value, and Fund of Funds strategies. Equity Hedge also accounts for a meaningful share of AI funds, but its relative weight is similar to that observed among non-AI hedge funds. When measured by AUM in Panel B, the concentration becomes even more pronounced: roughly 80% of AI hedge fund assets are allocated to Macro strategies, indicating that AI hedge funds in this category are substantially larger than those in other strategies. AI hedge funds continue to be underrepresented in Event Driven, Relative Value, and Fund of Funds, and, in the AUM measure, they are also underrepresented in Equity Hedge. Figure IA.6 in the Internet Appendix further shows that the Macro strategy has been persistently dominant among AI funds over the years.

Panels C and D display the subcategories within Macro on the horizontal axes. Among AI hedge funds in macro strategies, a large majority, over 60% by number of funds and over 90% by AUM, fall into a narrowly-defined sub-strategy called Systematic Diversified Macro. While this sub-strategy also dominates among non-AI macro hedge funds, its dominance is much more pronounced among AI hedge funds.

Overall, the concentration of AI hedge funds in macro strategies provides a new perspective that complements the literature's focus on equities. This pattern likely reflects both economic and technical considerations. Macro assets, such as commodities, fixed income, currencies, and equity indices, tend to exhibit stronger and more persistent predictive structures that can be captured by machine learning models. Their high liquidity also facilitates flexible short-term trading guided by AI signals.

2.5. Characteristics of AI hedge funds

We compare AI funds and non-AI funds through a univariate analysis in Table 4. In both panels, the columns "AI" and "Non-AI" report the between-fund average values for AI funds and non-AI funds, respectively. The "Difference" column shows the average in the AI group minus the average in the non-AI group.

Panel A focuses on fund characteristics and highlights two distinguishing traits of AI hedge funds. First, almost all AI funds use quantitative strategies, whereas only 24.7% of non-AI funds are quant funds. Although AI and non-AI funds also exhibit a statistically significant difference in high-frequency trading, this difference is not economically meaningful due to the rarity of high-frequency strategies. Second, AI funds charge nearly 2 percentage points higher incentive fees and have a 32% lower likelihood of imposing a hurdle rate, meaning that investors pay performance fees more easily and at higher rates. At the same time, they impose around 60% shorter lockup and restriction periods, allowing investors to redeem capital more easily.

Panel B compares fund risk exposures using factor loadings. First, we consider the Fama–French stock market, size, and value factors. AI funds exhibit significantly lower loadings on all three factors, indicating a lower exposure to traditional risk premia in the US equity market. We next examine Fung–Hsieh seven factors. AI funds display a significantly lower exposure to the small-cap factor, corroborating that they tend not to pick illiquid individual stocks or trade on firm-specific information. They also display nearly zero exposure to the credit spread factor, which is significantly higher than that of non-AI funds, indicating an ability to hedge stress in credit markets. The third set of comparisons uses AQR factors. Again, AI funds load significantly lower on Equity Indices. They also exhibit a higher exposure to the All Macro factor, but the difference is statistically insignificant. In terms of all-asset-class style premia, AI funds have significantly negative loadings on Value, Carry, and Defensive factors but a higher, positive loading on the momentum factor, suggesting their distinctive exposures to global assets.

Taken together, the results in Table 4 show that AI funds exhibit substantially different exposures to asset classes and risk factors. This distinctiveness underscores the importance of adjusting their returns for the relevant risk premia when evaluating the performance of AI-driven investing.

3. Which Hedge Fund Advisers Offer AI Funds?

The distinctiveness of AI hedge funds may reflect characteristics of their managing advisers. To assess the role of advisers in the growth of AI funds, we examine the relationship between adviser characteristics and the creation of AI hedge funds. Specifically, we regress the number of AI funds an adviser manages next year on the characteristics of its existing hedge funds. Because the dependent variable includes a large number of zero-valued observations, we estimate Poisson regressions with year fixed effects. Table 5 shows that, controlling for the size and age of existing funds, advisers facing stronger performance incentives are more likely to launch new AI funds and adopt AI in existing funds.

First, incentive fees are positively and significantly associated with the number of AI funds across all specifications. In Column (3), a one percentage point increase in the average incentive fee is associated with a 13% increase in the expected number of AI funds managed in the following year ($e^{1\times 0.126} - 1 \approx 0.13$). This suggests that greater pay-for-performance sensitivity incentivizes the adviser to improve fund performance by adopting new technologies.

Second, the fractions of funds with high water mark and hurdle rate provisions are negatively associated with the number of AI funds. One potential explanation is that these provisions make the fee structures resemble out-of-the-money options, thereby reducing the sensitivity of manager compensation to performance and discouraging managers from investing in AI technology.

Third, the liquidity an adviser provides to its existing fund investors is also negatively associated with the number of AI funds. Offering shorter lockup and restriction periods imposes implicit incentives to deliver better performance (Agarwal, Daniel, and Naik, 2009). Such investor-friendly contractual terms also require liquidity management skills, suggesting that advisers with such expertise are more likely to manage AI funds.

So far, we have explored adviser-level AI adoption through two measures: AI labor intensity in Section 2 and the number of AI funds in the current section. These two measures, constructed from independent data sources, capture AI adoption from the perspectives of labor input and product output, respectively. We cross-validate the reliability of these measures by regressing the share of AI-related job postings in the subsequent year on an adviser's current number of AI hedge funds. Table IA.2 in the Internet Appendix shows a positive and statistically significant relationship between these two measures. On average, each additional AI fund is associated with a 0.06 percentage point increase in next year's share of AI-related job postings. This pattern suggests that the two measures are consistent and that AI funds are indeed accompanied by firm-level AI labor input.

4. The Performance and Flows of AI Hedge Funds

The performance and flows of AI funds are essential for evaluating AI's alpha-generating potential and for assessing how investors respond to AI-driven investing in their capital allocation decisions. In this section, we use our fund-month sample to examine whether AI funds generate superior risk-adjusted returns and whether they attract additional fund flows.

4.1. Investment performance of AI hedge funds

We test the relative performance of AI funds by regressing fund performance in the next month on current fund characteristics. Our variable of interest is an indicator variable for whether the fund is currently classified as an AI fund. We control for indicator variables capturing whether the fund employs a quantitative strategy or a high-frequency strategy. We also control for fund contractual terms, size, and age, as well as strategy-by-month fixed effects, where strategy refers to HFR's broad fund strategy classification.

Table 6 reports our estimation results. In the first three columns, we measure performance using monthly fund alpha based on the Fung–Hsieh seven factors ("FH Alpha"). The point estimate in column 1 shows that between 2006 and 2024, the difference in monthly performance between AI and non-AI funds is around 10 basis points and is statistically indistinguishable from zero. In column 2, we include an interaction term AI×Year, where Year is the current calendar year minus 2006. Once this interaction term is included, the coefficient of the AI indicator variable. Our estimates indicate that, on average, AI funds outperformed non-AI funds by 85 basis points per month ub 2006 and that this outperformance in monthly alpha declines over time by 6 basis points per year. In column 3, we replace the AI indicator variable and AI×Year interaction effect with two interaction terms that indicate that the observation is an AI fund in a month before and after December 2017, respectively.[20] Our estimates show that AI funds outperform non-AI funds by 45 basis points per month before 2017, and that this outperformance disappears after 2017. In columns 4 to 6, we use alpha based on the AQR six factors as an alternative measure for performance ("AQR Alpha") and find qualitatively similar results with moderately smaller magnitudes.

Our results in Table 6 suggest that, in earlier years, AI funds substantially outperform their non-AI counterparts. Their outperformance is not driven by data outliers, as both performance measures are winsorized at the 1st and 99th percentiles. However, this outperformance diminishes in subsequent years with the growth of AI-driven investing among hedge funds.

A potential explanation for the disappearance of the outperformance is that AI funds launched in earlier years are inherently more skilled than AI funds launched in more recent years. If so, early adopter AI funds may continue to outperform non-AI funds even after 2017. To explore this possibility, we define AI funds as either early or late AI adopters based on whether the first year the fund is classified as an AI fund is before or after 2017. We then estimate regressions of fund performance on interaction terms involving the AI indicator variable, the Early/Late adopter dummies, and the Before/After 2017 dummies. Table 7 reports our estimation results. Similar to the previous table, we find that early-adopter

[20]We use December 2017 as the cutoff because 2017 is the year when the growth of AI funds accelerated, as shown in Figures 2 and 3.

AI funds significantly outperform non-AI funds before 2017. However, after 2017, their performance becomes statistically indistinguishable from that of both later-adopter AI funds and non-AI funds. This result suggests that the disappearance of AI funds' outperformance reflects a general trend among all AI funds rather than a difference between early and late AI adopters.

4.2. Comovement of AI funds

The decline in the outperformance of AI funds is consistent with the challenge of generating profitable investment strategies under the competitive exploitation of machine learning in non-stationary financial markets (Allen, Kacperczyk, and Kumar, 2025). More broadly, it is also consistent with the notion of decreasing returns to scale in active management beyond the fund level (e.g., Pástor and Stambaugh, 2012), whereby the growing scale of AI-driven investing makes sustaining outperformance increasingly difficult.

To shed light on this perspective, we compare the comovement of risk-adjusted returns within AI funds versus within non-AI funds. A higher degree of comovement indicates that the funds pursue more homogeneous, crowded investment strategies. We measure comovement with both pairwise correlations and a principal component analysis (PCA). Specifically, we separately compute the average pairwise correlation among fund alphas (based on the Fung-Hsieh seven factors) and the fraction of fund alphas explained by the first principal component, both over 24-month rolling windows.

Figure 5 presents the monthly comovement measures between 2013 and 2024.[21] Panel A shows that before 2020, the average pairwise correlation among AI funds has been substantially higher than that of non-AI funds. The difference in comovement between AI and non-AI funds might reflect the fact that AI funds have a disproportionately large share in macro strategies. However, Panel B restricts the sample to only macro funds and shows a similar

[21] Our comovement analysis begins in 2013 because we require a sufficient number of AI funds with 24 months of alpha observations, and the estimation of alphas further requires 24 months of past returns.

trend. Within AI macro funds, the difference in comovement before 2020 is even larger, likely reflecting a greater overlap in macro assets and trading signals. Panels C and D repeat the analysis while replacing the average pairwise correlation with the share of the first eigenvalue among all eigenvalues in the PCA. Consistently, we find that the first principal component explains a substantially larger share of fund alphas, especially in the earlier years.

The stronger comovement among AI funds suggests that AI-driven investing has increased similarity across hedge fund strategies. This finding aligns with a widespread concern among regulators that the growth of AI adoption in the asset management industry may amplify strategy homogeneity and herding behavior, thereby posing potential risks to financial market stability (e.g., OECD, 2021; U.S. Senate Committee on Homeland Security and Governmental Affairs, 2024).

In all panels of Figure 5, the elevated level of comovement among AI funds declines over time and becomes similar to non-AI funds after 2021, coinciding with the rapid growth of AI driven investing. There are two potential explanations for the joint decline in AI funds' comovement and performance relative to non-AI funds. First, as competition intensifies and strategies become crowded, advisers may attempt to differentiate their AI funds, even at the cost of deviating from the natural or most effective applications of AI techniques. Second, AI-driven strategies may have become more diverse with recent developments in AI techniques, and this advancement has not yet translated into successful alpha generation. Our evidence in Table 7 aligns better with the first explanation.

4.3. Performance Relative to Sibling Funds

AI funds are managed by a subset of hedge fund advisers. As a result, the difference in performance between AI and non-AI funds may also reflect heterogeneity across hedge fund advisers or firm-level effects of AI adoption that influence all of an adviser's funds. For example, advisers with better firm-level resources might self-select to launch AI funds. If that is the case, our fund-level analysis could have overstated the performance associated with AI-driven investing. Alternatively, after paying fixed costs for AI infrastructure, advisers could share AI-generated signals among all their funds, benefiting funds that do not explicitly follow AI-driven strategies. This within-adviser spillover would imply that our analysis has underestimated the outperformance of AI funds.

To distinguish the performance associated with AI-driven investing from these firm-level confounding forces, we compare fund performance within the same adviser, across its sibling funds. Specifically, we saturate the baseline specifications in Subsection 4.1 with adviser-by-month fixed effects. This stringent specification absorbs any time-varying adviser-level influences on fund performance and restricts the sample to adviser–months with at least two funds. The remaining difference in performance, if any, cannot be attributed to unobserved adviser characteristics or the spillover effects of AI investment on non-AI sibling funds.

Table 8 presents our estimation results. Over the sample period between 2006 and 2024, AI funds outperform sibling funds by 41.1 basis points per month using the FH alpha and by 37.9 basis points using the AQR alpha. This within-adviser difference is economically and statistically significant. The estimated coefficients for our interaction terms AI$\times$Year are no longer significant, which suggests that, relative to sibling funds, the performance of AI funds does not significantly decrease. Moreover, using the FH alpha, our interaction specification with time dummies shows that AI funds continue to outperform sibling funds even after 2017. These results provide additional evidence for AI's alpha-generating ability. However, they may also reflect that the diversion of the adviser's internal resources toward AI initiatives could be costly for its traditional funds.

4.4. Money flows to AI hedge funds

An important driving force behind the rapid growth of AI funds is investors' belief in AI's alpha-generating ability. As highlighted in Pástor and Stambaugh (2012), investors' slow learning about both this ability and returns to scale drives the size of the active management industry. To examine investor beliefs about AI's alpha-generating potential, we apply a revealed preference approach and analyze money flows into hedge funds.

We test whether mentioning AI technologies in strategy descriptions attracts inflows beyond what can be explained by realized performance. Specifically, we regress monthly net fund flow on the AI indicator variable while controlling for fund performance, measured with a lagged 12-month rolling-window average FH alpha. We also control for other fund characteristics and Strategy-by-Month fixed effects.

Table 9 reports our estimation results. Across all specifications, the AI coefficient is positive but statistically insignificant, and it becomes small after controlling for fund performance, size, and age. This result implies that investors do not systematically direct more capital to AI funds once conventional determinants are taken into account. In contrast, past performance strongly predicts flows: column 2 shows that a one percentage point increase in lagged 12-month alpha is associated with a 35.3 basis points higher monthly inflow. Column 3 controls for indicator variables for quant and high-frequency trading strategies, which do not attract extra flows either. In column 4, we further include fund contractual terms and find that lockup and restriction periods are associated with higher inflows, whereas management fees are associated with lower inflows. Overall, we find no evidence that investors hold strong initial beliefs on AI's ability to generate superior performance.

4.5. Survival of AI hedge funds

Although our sample includes both live and dead funds, the requirement of at least 24 months of returns for alpha estimation could introduce implicit survivorship bias (Baquero, Ter Horst, and Verbeek, 2005). To assess whether our findings are influenced by this potential bias, we compare the dropout rates of AI and non-AI hedge funds over different time horizons.

Table 10 presents a summary of dropout rates. A fund may drop out of the database either through liquidation or by stopping to report. Panel A shows the total dropout rates, which reflect both sources of attrition. Across 1-month, 3-month, 6-month, and 1-year horizons, AI funds exhibit slightly higher average dropout rates than non-AI funds. However, these differences are statistically indistinguishable from zero. Panel B focuses on fund liquidation, which primarily drives the differences in the total dropout rates. Again, the difference in liquidation rates between AI and non-AI funds is not statistically significant. Panel C focuses on dropout rates due to ceased reporting and shows that AI and non-AI funds have very similar rates of stopping reporting to the database. Overall, these comparisons show that survivorship bias is unlikely to explain our findings.

5. Conclusion

This paper provides a comprehensive analysis of AI-driven investing in asset management. By combining adviser-level fund composition from regulatory filings, AI labor intensity inferred from job postings, and fund-level investment strategy disclosures, we document a highly uneven pattern of AI adoption across the industry. AI-driven investing is concentrated among hedge funds, especially those employing systematic macro strategies and adopted by large advisers facing stronger incentives to deliver performance.

Our analysis of hedge fund performance reveals evidence consistent with both the market-reflexivity view of AI-driven investing in Allen, Kacperczyk, and Kumar (2025) and the diseconomies-of-scale framework in Pástor and Stambaugh (2012). We find that early AI funds earn significant alphas and that their alphas exhibit stronger comovement than non-AI funds, but this outperformance declines over time, coinciding with the rapid growth of AI funds. In more recent years, no significant difference in performance remains between AI and non-AI funds.

Our findings have important implications for both practitioners and researchers. First, investment professionals and investors should recognize that the future success of AI-driven strategies will depend not only on advances in AI technology but also on the scale and heterogeneity of its applications within the asset management industry. Second, the popularity of AI-driven investing in macro asset classes complements the literature's traditional focus on equities and bonds, opening new questions about how AI affects pricing efficiency and stability in global commodity and currency markets. Finally, the patterns AI fund performance we document highlight the role of scale constraints in asset management and the broader interplay between technological innovation and industry competition. As AI continues to evolve, its deployment offers a valuable lens for studying these questions.

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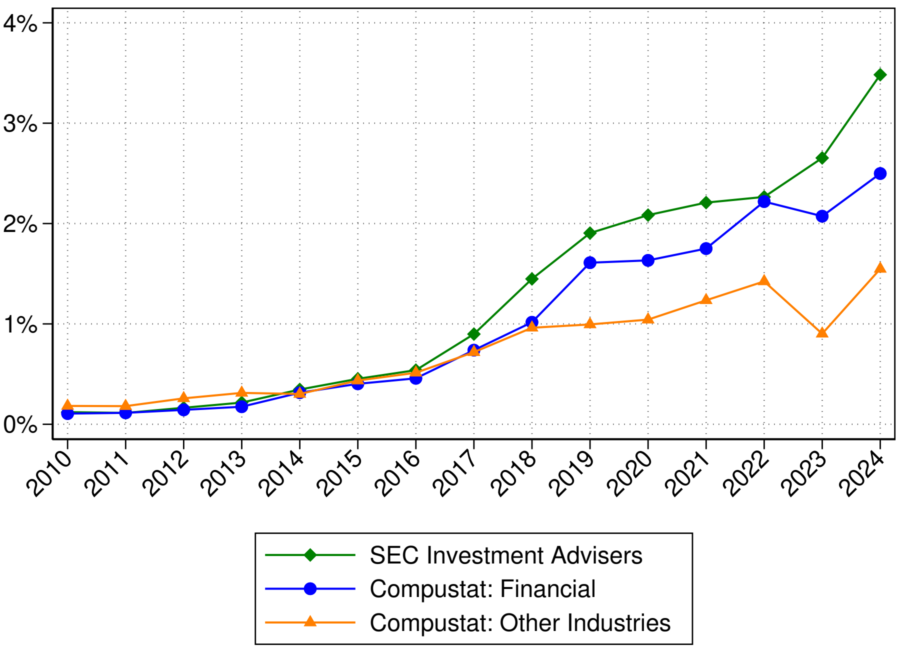
(a) AI Job Postings by Investment Advisers and Compustat Firms



(b) Investment Advisers' AI Jobs for Specific Roles

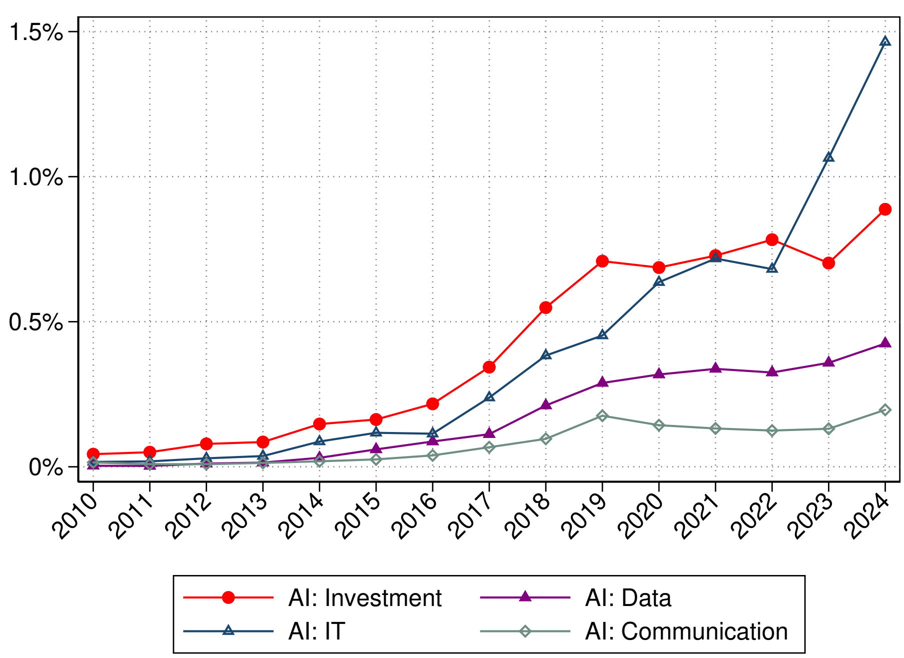
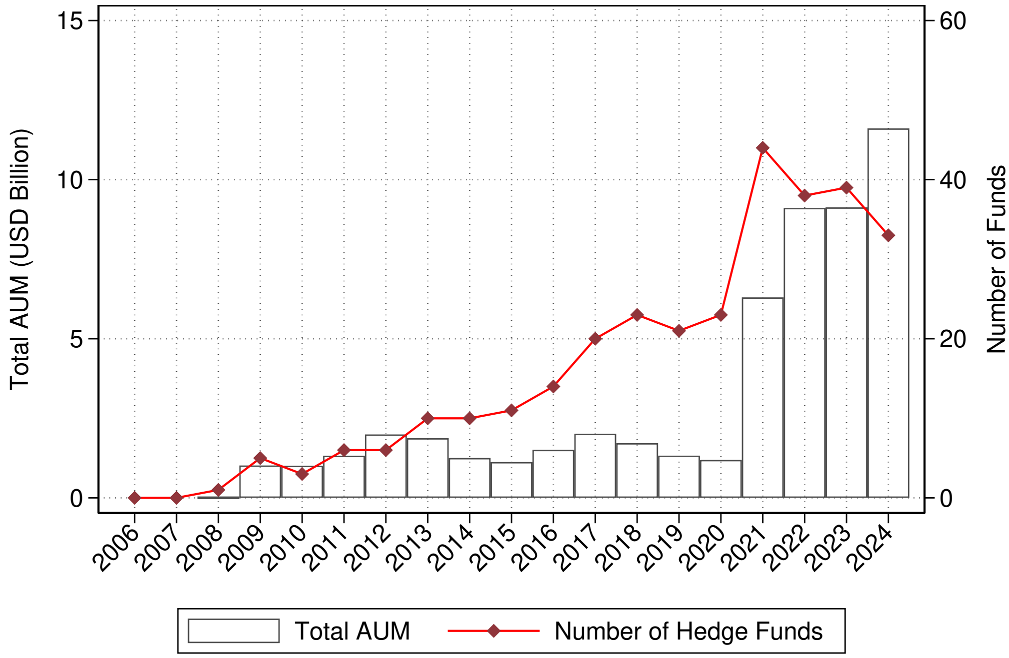


Figure 1: **AI Job Postings by Registered Investment Advisers.**
This figure summarizes AI-related job postings. Panel A shows the annual percentages of AI jobs among total job postings by each of three groups of firms: SEC registered investment advisers, financial industry firms in Compustat, and non-financial firms in Compustat. Panel B shows annual percentages of AI jobs for specific functional areas among total job postings by investment advisers. Internet Appendix Table IA.4 and Section IA.5 provide the categorization method and examples.

(a) Number and AUM of Hedge Funds



(b) Percentage of Hedge Funds

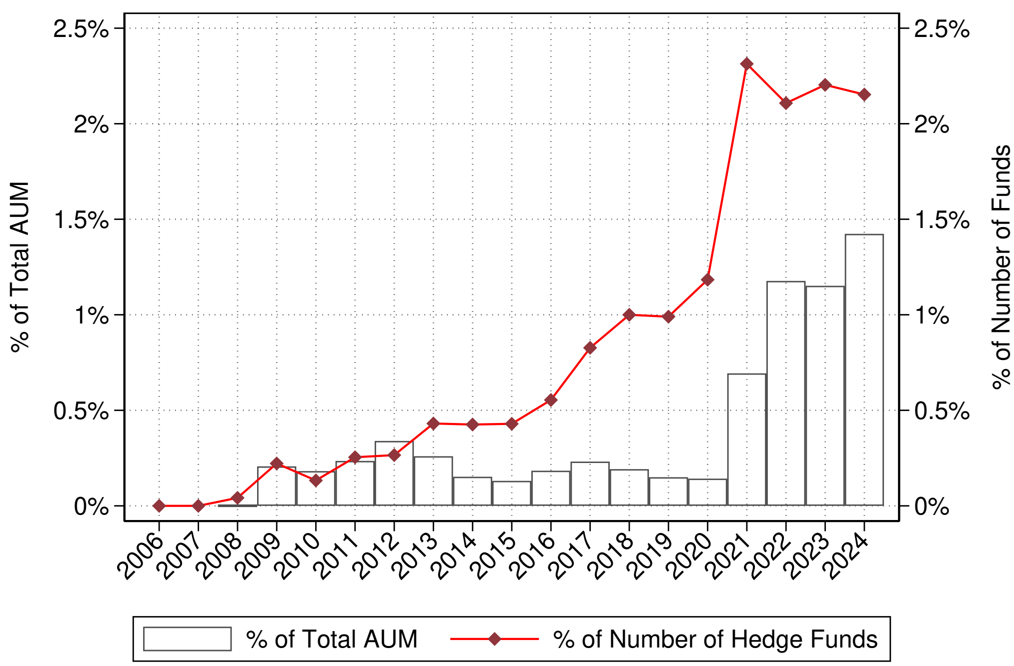


Figure 2: **The Growth of AI Hedge Funds.**
This figure presents the growth of AI hedge funds between 2006 and 2024. Panel A shows the number and total AUM of AI hedge funds by year. Panel B shows their number and total AUM as percentages of USD-denominated U.S. hedge funds in the HFR database.

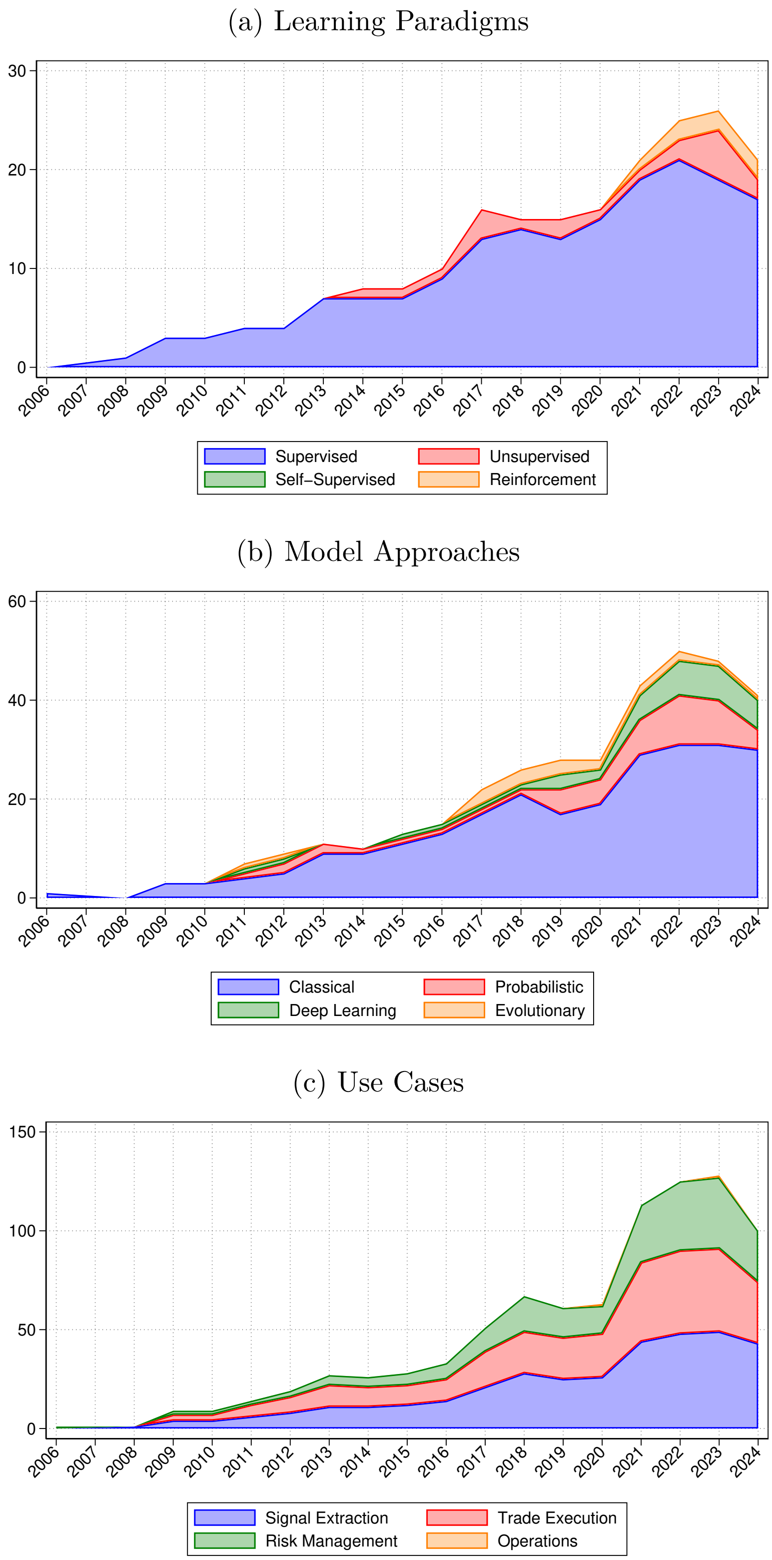


Figure 3: **AI Techniques of Hedge Funds.**
This figure presents AI learning paradigms, model approaches, and use cases among U.S. hedge funds. Stacked areas represent the number of funds by year. Classifications are not mutually exclusive.

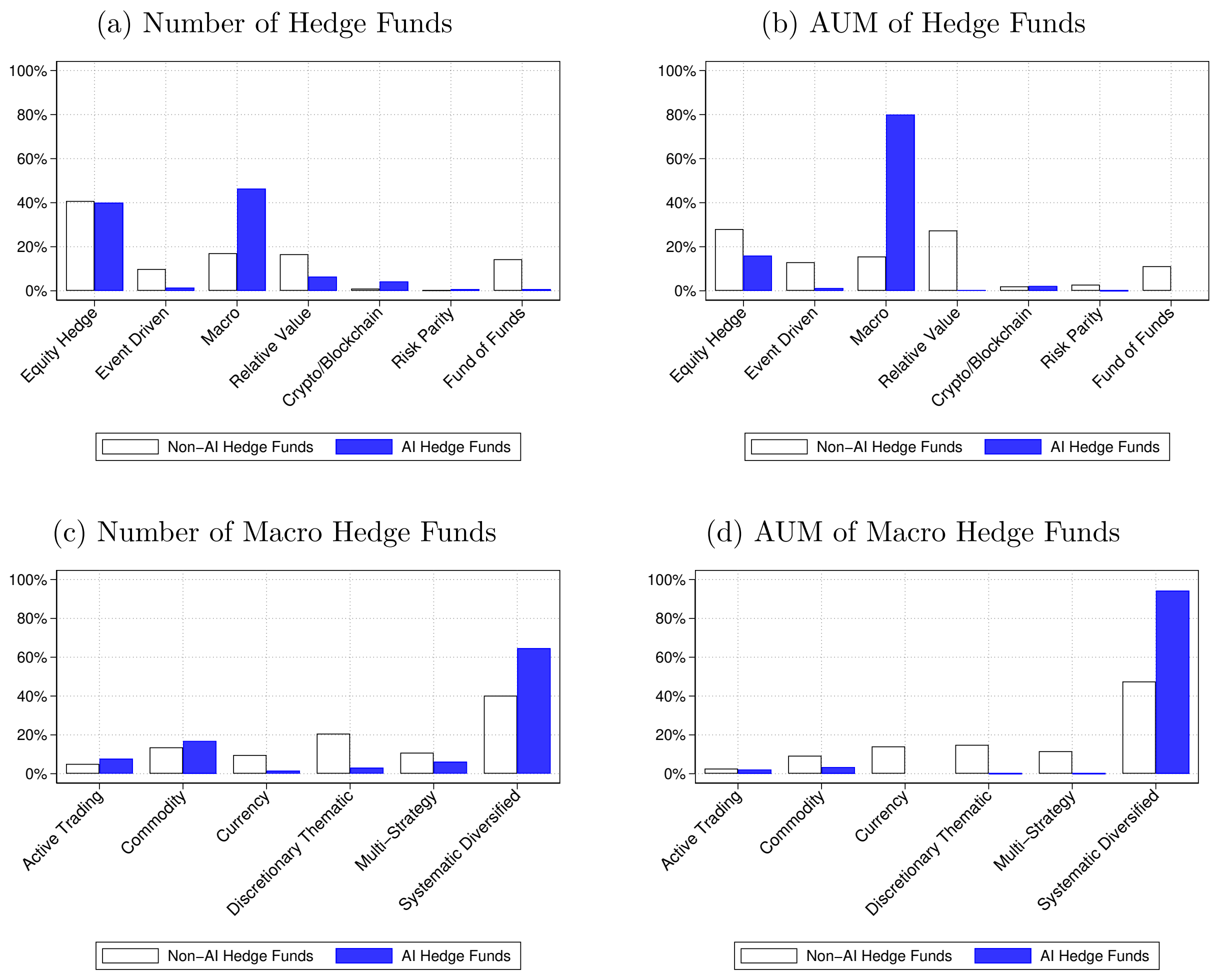


Figure 4: **Distribution of AI Hedge Funds By Strategy Categories.**
This figure compares the distribution of investment strategies between AI and non-AI funds. The sample includes all USD-denominated U.S. funds ever included in HFR as of the last available date of each fund. Panels A and B show the distributions of the number and total AUM of hedge funds across main strategy categories, respectively. Panels C and D restrict to macro strategy hedge funds and show the distributions across sub-strategy categories in HFR.

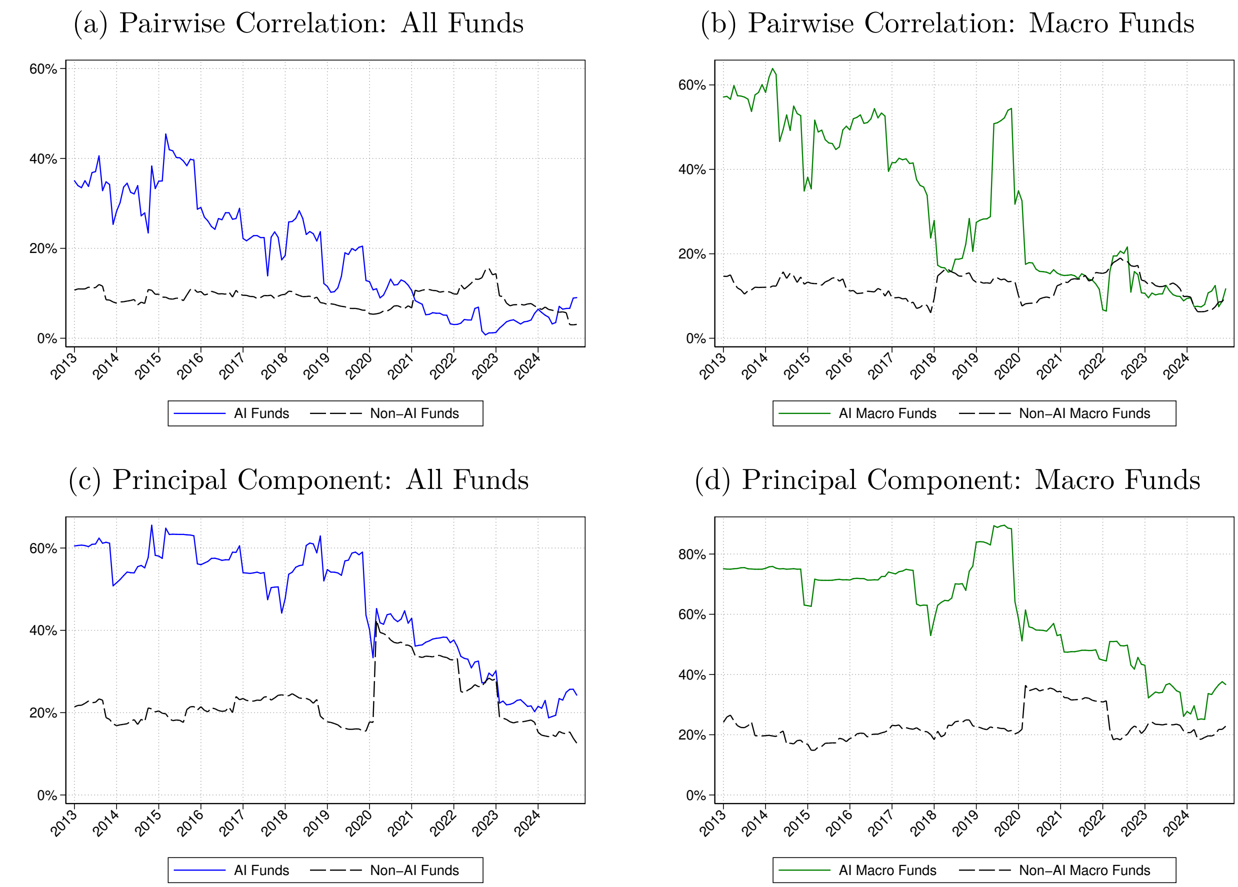


Figure 5: **Comovement of Hedge Fund Performance.**
This figure compares the comovement of hedge fund performance between AI and non-AI hedge funds. Panel A shows the average pairwise correlation of monthly alphas among hedge funds over 24-month rolling windows, separately for AI and non-AI funds. Panel B shows the average pairwise correlation among macro strategy hedge funds. Panel C shows the share of variation in hedge fund monthly alpha explained by the first principal component within each 24-month rolling window, separately for AI and non-AI funds. Panel D shows the share of variation in hedge fund monthly alpha explained by the first principal component among macro strategy hedge funds. Alpha is estimated based on Fung-Hsieh seven hedge fund risk factors.

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 2024 with at least $100 million of current AUM and at least 5 job posts. AI Job Posting is the percentage of AI-related jobs among the adviser's job postings. AUM is the adviser's total regulatory assets under management in billion USD. Account is the adviser's total number of managed accounts in thousands. Advise Private Fund is an indicator variable 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 private fund gross 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	7,898	1.15	4.16	0.00	0.00	0.00	0.45	2.92
AUM	7,898	65.59	263.04	0.26	0.95	5.40	36.58	145.40
Account	7,898	29.06	263.06	0.00	0.02	0.29	3.99	28.56
Advise Private Fund	7,898	0.47	0.50	0.00	0.00	0.00	1.00	1.00
AUM% Discretionary	7,898	84.91	28.67	32.93	86.59	99.95	100.00	100.00
AUM% Private Fund	7,898	27.65	38.92	0.00	0.00	0.79	62.50	100.00
AUM% Public Fund	7,898	15.63	30.55	0.00	0.00	0.00	12.50	87.50
AUM% HighNetWorth	7,898	18.63	27.91	0.00	0.00	0.15	31.27	67.41
AUM% Individual	7,898	16.01	26.91	0.00	0.00	0.00	17.33	62.50
GAV	7,898	7.07	25.66	0.00	0.00	0.00	1.67	14.23
Number of Private Fund	7,898	13.16	39.99	0.00	0.00	0.00	7.00	32.00
GAV% Hedge Fund	3,703	35.40	42.76	0.00	0.00	4.17	89.09	100.00
GAV% Private Equity Fund	3,703	21.76	37.62	0.00	0.00	0.00	28.89	100.00
GAV% Real Estate Fund	3,703	12.71	31.34	0.00	0.00	0.00	0.00	91.88
GAV% Securitized Asset Fund	3,703	6.79	21.53	0.00	0.00	0.00	0.00	16.18
GAV% Venture Capital Fund	3,703	1.27	9.94	0.00	0.00	0.00	0.00	0.00

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

This table presents summary statistics for the hedge fund sample. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. Return is the fund's net return in percentage points. Alpha is the fund's monthly out-of-sample alpha based on Fama-French three equity factors, Fung-Hsieh seven hedge fund factors, and six AQR multi asset class factors. Flow is the net flow into the fund in percentage points. AI, Quant, and High Frequency are indicator variables that equal one if the fund is classified as an AI fund, a quant fund, and a high-frequency trading fund, respectively. Incentive Fee and Management Fee are the management and incentive fees charged by the fund adviser. High Water Mark and Hurdle are indicator 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	393,488	0.43	3.57	-3.33	-0.91	0.51	1.85	4.04
Alpha: FF3	393,488	0.01	3.11	-3.27	-1.24	0.10	1.25	3.10
Alpha: FH	393,488	0.08	3.52	-3.55	-1.31	0.16	1.47	3.59
Alpha: AQR	393,488	0.06	4.03	-4.07	-1.49	0.10	1.59	4.08
Flow	393,488	-0.26	6.63	-4.99	-1.22	0.00	0.90	3.99
AI	393,488	0.01	0.08	0.00	0.00	0.00	0.00	0.00
Quant	393,488	0.22	0.42	0.00	0.00	0.00	0.00	1.00
High Frequency	393,488	0.00	0.02	0.00	0.00	0.00	0.00	0.00
Incentive Fee	393,488	15.73	7.53	0.00	10.00	20.00	20.00	20.00
High Water Mark	393,488	0.85	0.35	0.00	1.00	1.00	1.00	1.00
Hurdle Rate	393,488	0.28	0.45	0.00	0.00	0.00	1.00	1.00
Lockup Period	393,488	5.32	7.43	0.00	0.00	0.00	12.00	12.00
Restriction Period	393,488	4.62	4.19	1.10	2.00	4.00	5.17	8.00
AUM	393,488	418.19	2151.00	11.90	26.70	75.00	250.00	785.00
Age	393,488	119.98	81.28	33.00	57.00	101.00	164.00	235.00
Management Fee	393,488	1.40	0.61	1.00	1.00	1.50	1.88	2.00

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 represents an adviser-by-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. Account is the adviser's total number of managed accounts. Advise Private Fund is an indicator variable 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 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: AI% Job Postings, All Investment Advisers

	(1)	(2)	(3)	(4)
log(AUM)	0.253***	0.327***	0.260***	0.236***
	(0.040)	(0.047)	(0.045)	(0.046)
log(Account)		-0.192***	-0.144***	
		(0.035)	(0.031)	
Advise Private Fund			0.723***	
			(0.159)	
AUM% Discretionary				0.006***
				(0.002)
AUM% Private Fund				0.014***
				(0.004)
AUM% Mutual Fund				-0.005*
				(0.003)
AUM% HighNetWorth				-0.009***
				(0.002)
AUM% Individual				-0.001
				(0.002)
Year FEs	Y	Y	Y	Y
N	7,646	7,646	7,646	7,646
R^2	0.032	0.052	0.057	0.065

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

Panel B: AI% Job Postings, Advisers of Private Funds

	(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: **Univariate Analysis of AI Hedge Funds**

This table reports univariate analysis that compares AI and non-AI hedge funds. Panel A shows average fund characteristics. Panel B shows average fund factor loadings. Fama-French factors are MKT, SMB, and HML for U.S. stock market, size, and value factors. Fung-Hsieh seven factors include SP500$-R_f$, SP500 index excess return, Russell2000$-$SP500, Russell 2000 index return less SP500 index return, Treasury Yield, the monthly change in 10-year treasury constant maturity yield, Credit Spread, the monthly change in Moody's Baa yield less 10-year treasury constant maturity yield, and PTFS Bond, PTFS FX, and PTFS Commodity, which are primitive trend-following factors that capture nonlinear exposures to bonds, foreign currencies, and commodities. AQR factors include Equity Indices, excess returns of global equity indices, All Macro, excess returns across global fixed income, currency, and commodity markets, and Value, Momentum, Carry, and Defensive, which are long-short style premia across all asset classes. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Panel A: Fund Characteristics

Characteristic	AI	Non-AI	Difference	P-value
Quant	0.980	0.247	0.733***	0.000
High Frequency	0.000	0.001	-0.001***	0.001
Incentive Fee	17.999	16.042	1.957**	0.048
High Water Mark	0.862	0.858	0.005	0.914
Hurdle Rate	0.066	0.387	-0.321***	0.000
Lockup Period	2.129	5.078	-2.949***	0.000
Restriction Period	1.753	4.297	-2.544***	0.000
AUM	184.382	252.839	-68.456	0.496
Age	77.577	84.735	-7.158	0.575
Management Fee	1.422	1.413	0.009	0.894

Panel B: Fund Return Factor Loadings

$\hat{\beta}$	AI	Non-AI	Difference	P-value
		Fama-French Factors		
MKT	0.175	0.336	-0.161***	0.000
SMB	-0.023	0.075	-0.099**	0.011
HML	-0.066	0.006	-0.072**	0.028
		Fung-Hsieh Factors		
SP500 - r_f	0.231	0.256	-0.025	0.565
Russell2000 - SP500	-0.003	0.093	-0.096**	0.017
Treasury Yield	-0.004	-0.002	-0.002	0.771
Credit Spread	0.004	-0.023	0.026***	0.000
PTFS Bond	0.006	-0.002	0.008	0.188
PTFS FX	0.006	0.006	0.000	0.945
PTFS Commodity	0.002	0.001	0.001	0.908
		AQR Factors		
Equity Indices	0.149	0.305	-0.155***	0.005
All Macro	0.282	0.214	0.068	0.580
Value	-0.518	-0.275	-0.243*	0.076
Momentum	0.162	-0.121	0.282***	0.005
Carry	-0.297	0.052	-0.349***	0.002
Defensive	-0.030	0.371	-0.401***	0.002

Table 5: **The Growth of AI Hedge Funds at the Adviser Level**

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 2006 and 2024 with at least \$5 million of hedge fund AUM. Incentive Fee and Management Fee are the average incentive and management fee rates 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 high water mark and hurdle rate provisions, respectively. Lockup Period is the minimum number of months that investors must 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 under management. Age is the adviser's maximum fund age. Return is the average annual 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 AUM. 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

	Equal-Weighted			AUM-Weighted		
	(1)	(2)	(3)	(4)	(5)	(6)
Incentive Fee	0.094***	0.102***	0.126***	0.085**	0.094**	0.134***
	(0.035)	(0.036)	(0.023)	(0.039)	(0.038)	(0.032)
High Water Mark	-1.939***	-0.915**	-0.011	-1.815***	-0.787**	-0.620
	(0.375)	(0.422)	(0.531)	(0.362)	(0.397)	(0.465)
Hurdle Rate	-2.953***	-2.251**	-3.020*	-2.380***	-1.575**	-2.236*
	(0.865)	(0.977)	(1.715)	(0.817)	(0.788)	(1.185)
Lockup Period		-0.044	-0.026		-0.039	-0.025
		(0.045)	(0.049)		(0.043)	(0.045)
Restriction Period		-0.687***	-0.689***		-0.806***	-0.798***
		(0.140)	(0.154)		(0.162)	(0.156)
Log(Number of Funds)			1.448***			1.217***
			(0.189)			(0.203)
Log(Age)			-1.028**			-1.090***
			(0.432)			(0.358)
Management Fee			-0.119			0.254
			(0.443)			(0.369)
Return			0.003			-0.003
			(0.006)			(0.007)
Log(AUM)						0.201*
						(0.115)
Year FEs	Y	Y	Y	Y	Y	Y
N	13,809	13,809	13,809	12,793	12,793	12,793

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

This table reports estimation results from regressing next-month hedge fund performance on current fund characteristics. The sample consists of fund-month observations between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI, Quant, and High Frequency are indicator variables that equal one if the fund is classified as an AI fund, a quant fund, and a high-frequency trading fund in the current year, respectively. Year is the value of the current year minus 2006. Before 2017 and After 2017 are indicator variables that capture whether the current month is after December 2017. Incentive Fee and Management Fee are the incentive and management fees charged by the fund adviser. High Water Mark and Hurdle are indicator 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. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh seven hedge fund factors in columns 1-3 and based on AQR six multi asset class factors in columns 4-6. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Table 6: **Performance of AI Hedge Funds (Cont'd)**

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH			AQR		
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.102	0.847***		0.005	0.685***	
	(0.123)	(0.211)		(0.105)	(0.251)	
AI × Year		-0.056***			-0.051**	
		(0.019)			(0.023)	
AI × Before 2017			0.449***			0.349**
			(0.155)			(0.163)
AI × After 2017			-0.035			-0.131
			(0.128)			(0.144)
Quant	0.027	0.027	0.027	0.028	0.028	0.028
	(0.040)	(0.040)	(0.040)	(0.044)	(0.044)	(0.044)
High Frequency	-0.000	0.001	0.001	0.068	0.069	0.069
	(0.381)	(0.381)	(0.381)	(0.408)	(0.408)	(0.408)
Incentive Fee	0.007***	0.007***	0.007***	0.007***	0.007***	0.007***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
High Water Mark	-0.057*	-0.056*	-0.056*	-0.046	-0.045	-0.045
	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)
Hurdle Rate	-0.011	-0.011	-0.011	-0.014	-0.014	-0.014
	(0.032)	(0.032)	(0.032)	(0.034)	(0.034)	(0.034)
Lockup Period	0.003*	0.003*	0.003*	0.001	0.001	0.001
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Restriction Period	0.000	0.000	0.000	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(AUM)	0.024***	0.023***	0.023***	0.019**	0.018*	0.018*
	(0.007)	(0.007)	(0.007)	(0.009)	(0.010)	(0.009)
Log(Age)	-0.024	-0.023	-0.024	-0.013	-0.013	-0.013
	(0.017)	(0.017)	(0.017)	(0.023)	(0.023)	(0.023)
Management Fee	0.039*	0.040*	0.039*	-0.013	-0.012	-0.013
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Strategy-Month FEs	Y	Y	Y	Y	Y	Y
N	393,516	393,516	393,516	393,516	393,516	393,516
R^2	0.117	0.117	0.117	0.135	0.135	0.135

Table 7: **Performance of Early and Late AI Adopters**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI is an indicator variable that equals one if the fund is classified as an AI fund in the current year. Early Adopter and Late Adopter are indicator variables that equal one if the fund's first year of using an AI-driven strategy is before 2017 and after 2017, respectively. Before 2017 and After 2017 are indicator variables that capture whether the current month is after December 2017. Control variables are the same as in Table 6. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh seven hedge fund factors in columns 1-3 and based on AQR six multi asset class factors in columns 4-6. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH	AQR
	(1)	(2)
AI × Early Adopter × Before 2017	0.558***	0.284**
	(0.140)	(0.142)
AI × Early Adopter × After 2017	0.169	-0.276
	(0.383)	(0.263)
AI × Late Adopter × After 2017	-0.061	-0.039
	(0.117)	(0.135)
Controls	Y	Y
Strategy-Month FEs	Y	Y
N	393,516	393,516
R^2	0.117	0.135

Table 8: **Performance of AI Hedge Funds Relative to Sibling Funds**

This table reports estimation results of regressing hedge fund performance in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. The sample includes funds of hedge fund advisers with at least two funds in the month. AI is an indicator variable that equals one if the fund is classified as an AI fund in the current year. Year is the value of the current year minus 2006. Before 2017 and After 2017 are indicator variables that capture whether the current month is after December 2017. Control variables are the same as in Table 6. Fund performance is measured with out-of-sample alpha based on Fung-Hsieh seven hedge fund factors in columns 1-3 and based on AQR six multi asset class factors in columns 4-6. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Performance

Factor Model:	FH			AQR		
	(1)	(2)	(3)	(4)	(5)	(6)
AI	0.411***	0.321		0.379**	0.916***	
	(0.056)	(0.451)		(0.179)	(0.145)	
AI × Year		0.008			-0.046	
		(0.042)			(0.028)	
AI × Before 2017			0.380***			0.694***
			(0.122)			(0.100)
AI × After 2017			0.437***			0.105
			(0.134)			(0.336)
Controls	Y	Y	Y	Y	Y	Y
Strategy-Month FEs	Y	Y	Y	Y	Y	Y
Adviser-Month FEs	Y	Y	Y	Y	Y	Y
N	274,397	274,397	274,397	274,397	274,397	274,397
R^2	0.733	0.733	0.733	0.736	0.736	0.736

Table 9: **Money Flows to AI Hedge Funds**

This table reports estimation results of regressing hedge fund flow in the next month on current fund characteristics. Each observation represents a fund-by-month between 2006 and 2024 for USD-denominated U.S. hedge funds with at least $5 million in assets. AI, Quant, and High Frequency are indicator variables that equal one if the fund is classified as an AI fund, a quant fund, and a high-frequency trading fund in the current year, respectively. Performance is lagged 12-month rolling-window cumulative alpha based on Fung-Hsieh seven hedge fund factors. AUM is the fund's assets, and Age is its age. 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. Management Fee is the management fee rate charged by the fund adviser. Standard errors, two-way clustered at the adviser and year-month levels, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Hedge Fund Monthly Flow

	(1)	(2)	(3)	(4)
AI	0.347	0.064	0.078	0.109
	(0.222)	(0.235)	(0.238)	(0.246)
Performance		0.353***	0.353***	0.354***
		(0.041)	(0.041)	(0.042)
Log(AUM)		0.049***	0.049***	0.045***
		(0.016)	(0.016)	(0.016)
Log(Age)		-0.531***	-0.531***	-0.540***
		(0.047)	(0.046)	(0.044)
Quant			-0.024	0.030
			(0.056)	(0.054)
High Frequency			-1.084	-0.990
			(0.801)	(0.815)
Incentive Fee				-0.003
				(0.005)
High Water Mark				-0.053
				(0.089)
Hurdle Rate				0.070
				(0.073)
Lockup Period				0.009**
				(0.004)
Restriction Period				0.027***
				(0.006)
Management Fee				-0.124**
				(0.050)
Strategy-Month FEs	Y	Y	Y	Y
N	387,134	387,134	387,134	387,134
R^2	0.024	0.033	0.033	0.033

Table 10: **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 2006 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 difference between AI funds and non-AI funds are based on Newey-West standard errors with 12 monthly lags. All differences are statistically insignificant at the 10% level.

Panel A: Dropout Rate (%)

	1m	3m	6m	1y
AI Funds	1.65	4.83	9.44	18.00
Non-AI Funds	1.45	4.26	8.26	15.34
Difference	0.20	0.56	1.18	2.66
t-statistics	0.66	0.66	0.75	1.01

Panel B: Liquidation Rate (%)

	1m	3m	6m	1y
AI Funds	1.04	3.12	6.14	11.78
Non-AI Funds	0.89	2.62	5.08	9.47
Difference	0.14	0.50	1.06	2.31
t-statistics	0.66	0.78	0.90	1.13

Panel C: Stop Reporting Rate (%)

	1m	3m	6m	1y
AI Funds	0.62	1.71	3.30	6.22
Non-AI Funds	0.56	1.64	3.18	5.87
Difference	0.06	0.07	0.12	0.35
t-statistics	0.38	0.16	0.15	0.25

Internet Appendix

“The Growth and Performance of AI in Asset Management”

IA.1. AI prompt for processing fund strategy descriptions

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 the description explicitly mentions AI technologies terms such as machine learning, deep learning, neural network, natural language processing, genetic algorithm, evolutionary computation, or reinforcement learning, or directly states that models self-learn or adapt automatically over time from big data. Do not infer AI usage from general terms like quantitative, systematic, algorithmic, predictive models, technical analysis, or statistical models unless paired with one of the AI terms above. Answer **N** for general quantitative, systematic, or algorithmic strategies, statistical objectives, proprietary formulas, or technical indicators that do not learn from data, or rules-based systems without adaptation. Answer N for pattern recognition not explicitly linked to machine learning, neural networks, or other adaptive AI methods. Answer only **Y**, **N**, or Borderline.

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

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

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. Alternative measure of investment adviser's AI adoption

Although Babina, Fedyk, He, and Hodson (2024) document a strong positive correlation between the share of AI-related roles among new hires (based on job postings) and that among existing employees (based on resumes), we further construct an alternative measure of investment adviser's AI adoption using existing employees' LinkedIn profiles to test the robustness of the job-posting–based results in Table 3.

We obtain investment advisers' employee LinkedIn profiles from Revelio Labs. Unlike job postings, which are designed to attract candidates for specific tasks and therefore provide detailed descriptions of responsibilities and required skills, LinkedIn profiles primarily highlight past experiences in a way that showcases a user's capabilities rather than precisely documenting job tasks. As a result, LinkedIn entries tend to be brief, and phrases that clearly signal AI adoption appear only rarely in job titles or descriptions. This makes it difficult to apply the AI-skill or AI-keyword approaches commonly used for job-posting data in the literature.

To address this challenge, we follow the method in Cen, Han, Han, and Jo (2024) and use the share of employees in data-related occupations[1] as a proxy for the share of AI-related employees. Table IA.1 reports the relation between an investment adviser's fund composition and its share of data-related employees in the following year. Consistent with Table 3, the data-related employee share is positively associated with only one category of private funds: hedge funds.

[1]Cen, Han, Han, and Jo (2024) consider three groups of data-related roles: data collection, data analytics, and data maintenance. The specific occupations include Data Scientists, Statisticians, Digital Forensics Analysts, Business Intelligence Analysts, Clinical Data Managers, Database Administrators, Database Architects, Information Security Analysts, Data Warehousing Specialists, Information Security Engineers, Penetration Testers.

Table IA.1: **Investment Adviser's Fund Composition and Data-related Employees**

This table reports results from regressing the percentage of the investment adviser's data-related employees among all its employees in the next year on the current size and composition of its assets. Every observation represents an adviser-by-year between 2012 and 2023 with at least \$100 million of current AUM and at least 5 employees 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. Account is the adviser's total number of managed accounts. Advise Private Fund is an indicator variable 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 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: Data% Employees, All Investment Advisers

	(1)	(2)	(3)	(4)
log(AUM)	0.693***	0.789***	0.740***	0.511***
	(0.053)	(0.046)	(0.046)	(0.062)
log(Account)		-0.339***	-0.275***	
		(0.035)	(0.036)	
Advise Private Fund			0.569***	
			(0.138)	
AUM% Discretionary				0.003
				(0.002)
AUM% Private Fund				0.002
				(0.002)
AUM% Mutual Fund				0.006
				(0.004)
AUM% HighNetWorth				-0.021***
				(0.002)
AUM% Individual				-0.021***
				(0.004)
Year FEs	Y	Y	Y	Y
N	78,214	78,214	78,214	78,214
R^2	0.074	0.109	0.110	0.110

Table IA.1: **Investment Adviser's Fund Composition and Data-related Employees (Cont'd)**

Panel B: Data% Employees, Advisers of Private Funds

	(1)	(2)	(3)	(4)
log(GAV)	0.286***	0.081**	0.482***	0.365***
	(0.042)	(0.040)	(0.060)	(0.049)
log(AUM)		0.448***		
		(0.069)		
log(Number of Private Fund)			-0.579***	-0.144
			(0.147)	(0.116)
GAV% Hedge Fund				0.008***
				(0.003)
GAV% Private Equity Fund				-0.028***
				(0.003)
GAV% Real Estate Fund				-0.011
				(0.010)
GAV% Securitized Asset Fund				-0.002
				(0.006)
GAV% Venture Capital Fund				-0.017***
				(0.005)
Year FEs	Y	Y	Y	Y
N	35,116	35,116	35,116	35,116
R^2	0.017	0.036	0.025	0.089

IA.4. Supplementary Results

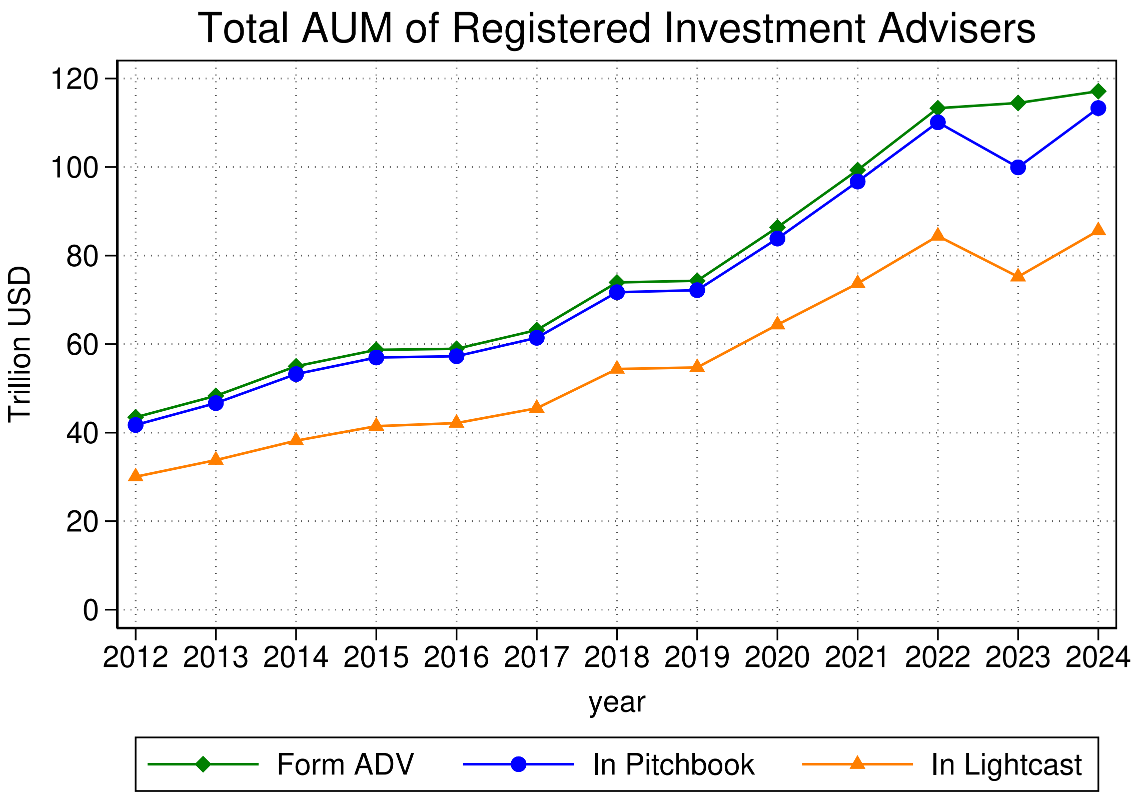


Figure IA.1: **Total AUM of Investment Advisers.**
This figure presents the total assets under management (AUM) of three sets of registered investment advisers. The green line indicates all investment advisers that file Form ADV. The blue line indicates the subset of investment advisers that are matched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

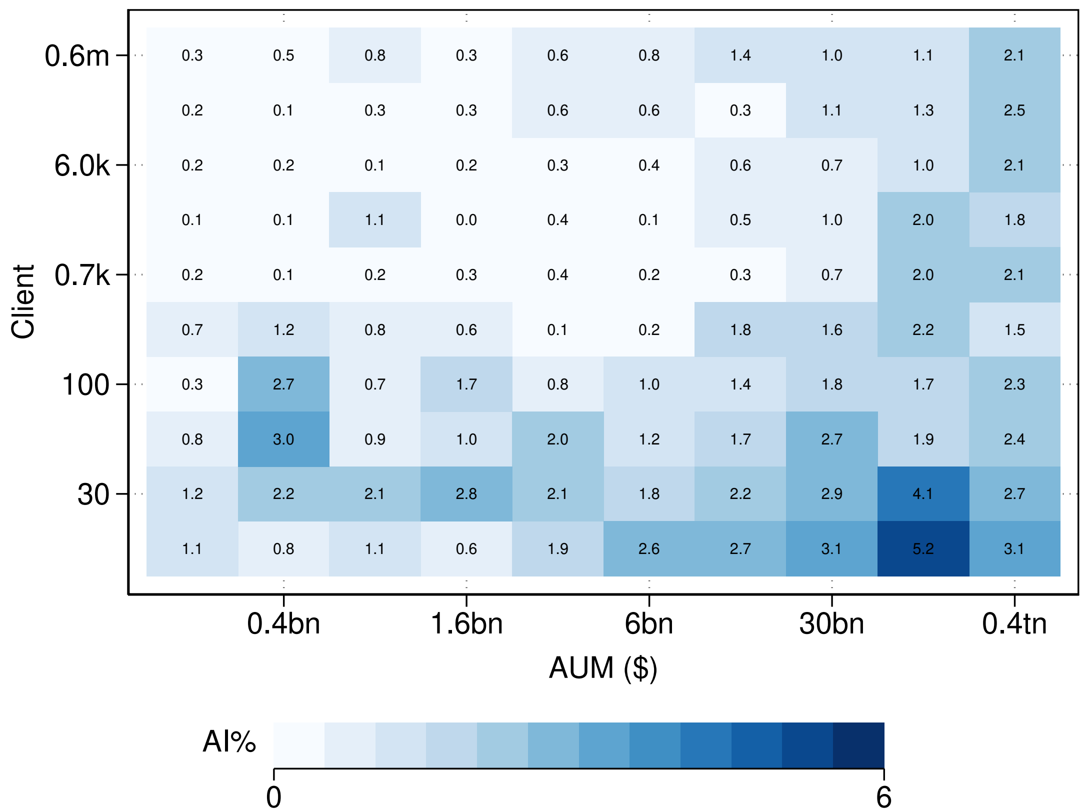


Figure IA.2: **Investment Adviser's AUM, Number of Clients, and AI Investment.** This figure presents the relationship between an investment adviser's current total AUM, the current total number of clients, and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. In each year, 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.

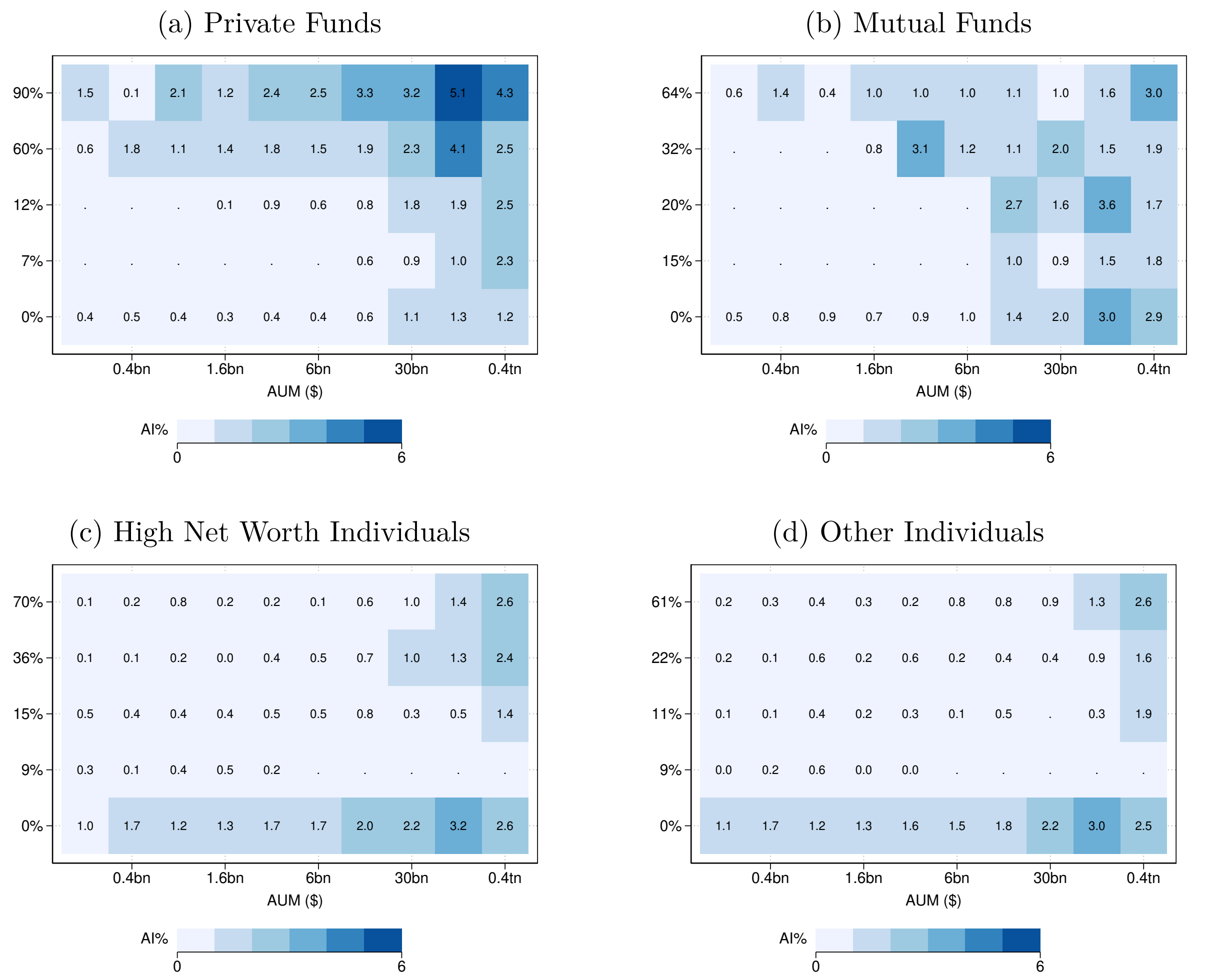


Figure IA.3: **Investment Adviser's AUM Composition and AI Investment.**
This figure presents the relationship between the composition of an investment adviser's current AUM and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels A-D focus on the fraction of AUM in 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 bins.

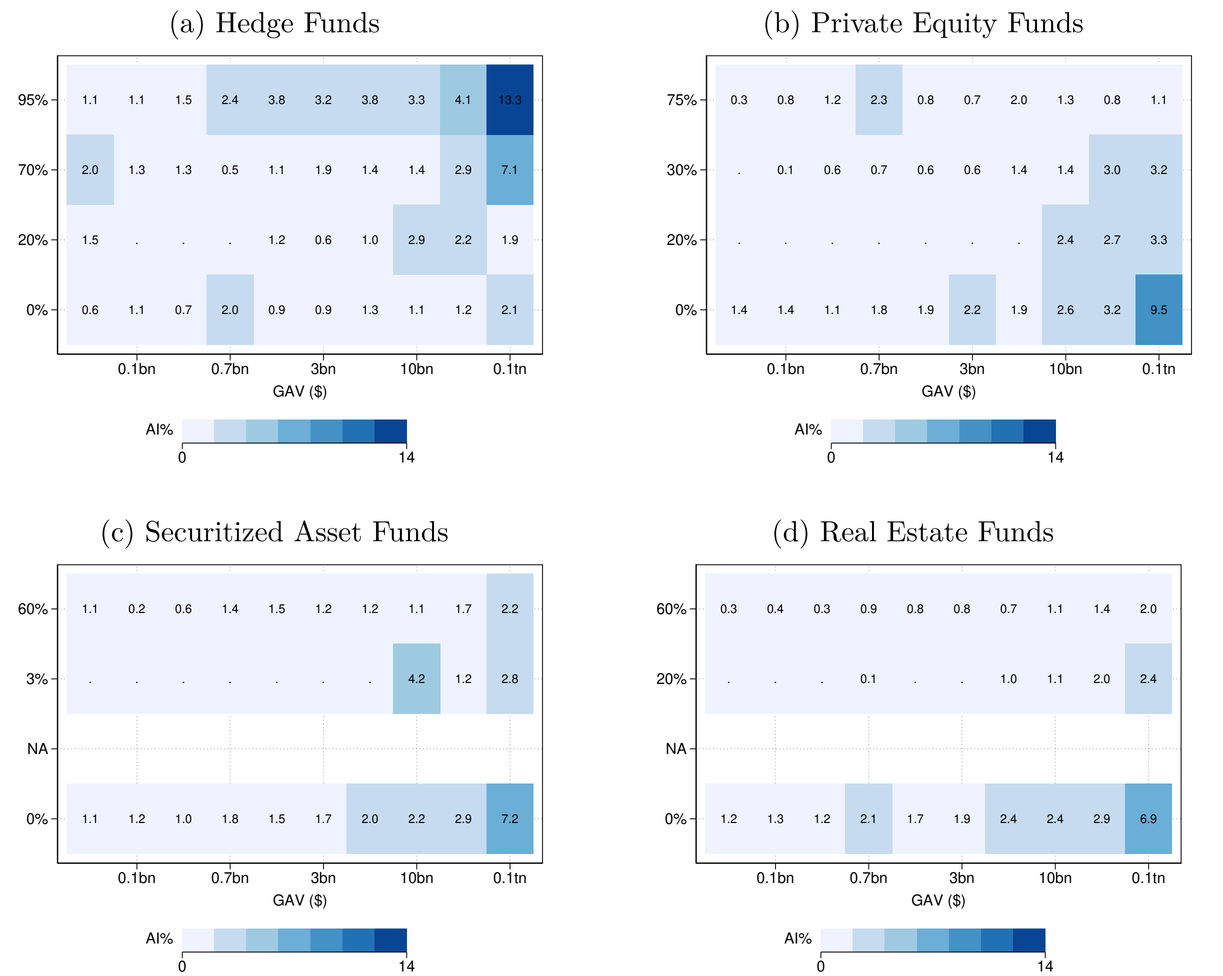
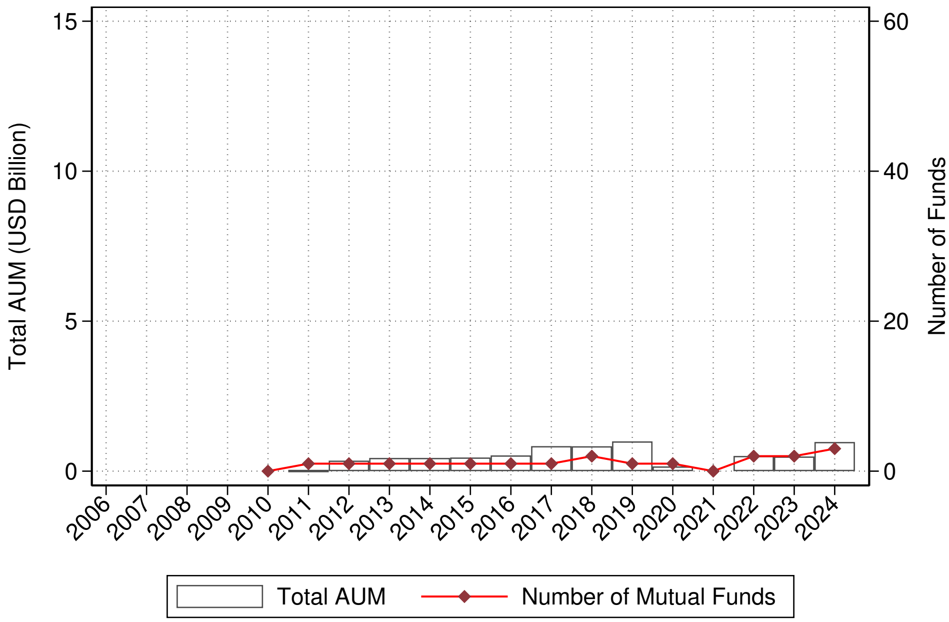


Figure IA.4: **Investment Adviser's Private Funds Composition and AI Investment.** This figure presents the relationship between the composition of an investment adviser's current private fund gross asset value (GAV) and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. 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 bins, and labels in vertical axes indicate the approximate average percentage of GAV in each of the four fund group bins.

(a) Number and AUM of Mutual Funds



(b) Percentage of Mutual Funds

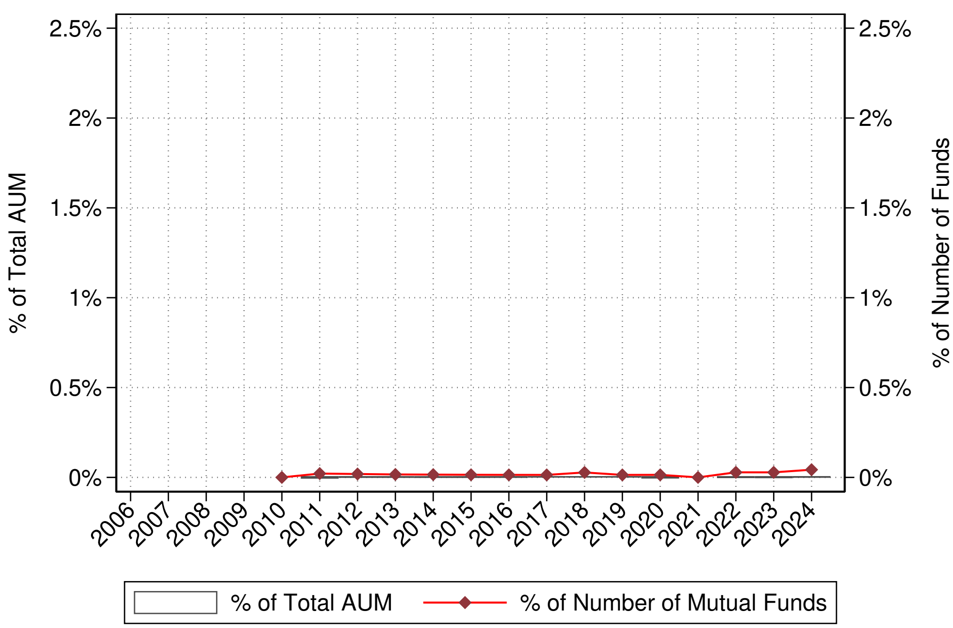


Figure IA.5: **The Growth of AI Mutual Funds.**
This figure presents the growth of AI mutual funds. We identify AI mutual funds by processing investment strategy descriptions in Form 497K with the same GPT-5 model and prompt. Panel A shows the number and total AUM of AI mutual funds by year. Panel B shows their number and total AUM as percentages of all open-ended mutual funds in the SEC Form 497K and CRSP database. The horizontal and vertical axes are kept the same as in Figure 2.

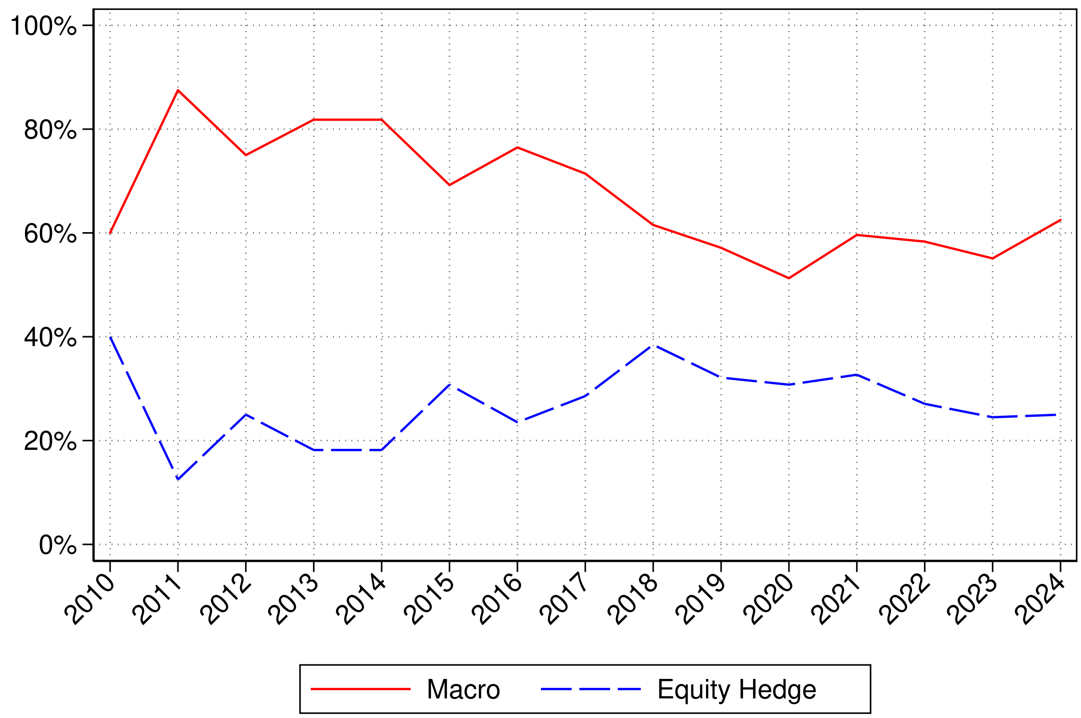


Figure IA.6: **Fractions of Main Strategies Among AI Hedge Funds Over Time.** This figure presents the fractions of funds, measured by the number of funds, classified as macro strategy and equity hedge strategy among AI hedge funds between 2010 and 2024.

Table IA.2: **AI Hedge Funds and Investment Advisers' 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 hedge funds. Every observation is an adviser-year between 2012 and 2024 with at least $5 million of current hedge fund assets and at least 5 job posts in the next year. Incentive Fee and Management Fee are the average incentive and management 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	0.056***	0.055***	0.053***	0.050***
	(0.003)	(0.003)	(0.003)	(0.004)
Incentive Fee		0.001	0.001	0.001
		(0.001)	(0.001)	(0.001)
High Water Mark		0.002	0.007	0.003
		(0.019)	(0.019)	(0.018)
Hurdle Rate		-0.019**	-0.019**	-0.019**
		(0.009)	(0.008)	(0.008)
Lockup Period			-0.001*	-0.001*
			(0.000)	(0.000)
Restriction Period			-0.001**	-0.001
			(0.001)	(0.001)
Log(AUM)				0.005
				(0.004)
Log(Age)				-0.012**
				(0.006)
Management Fee				-0.000
				(0.011)
Performance				-0.000
				(0.000)
Year FEs	Y	Y	Y	Y
N	593	593	593	593
R^2	0.057	0.075	0.100	0.115

IA.5. AI-related Job Examples

IA.5.1. 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.5.2. 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.5.3. 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.5.4. 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.6. Skills, Generative AI keywords, and roles in job postings

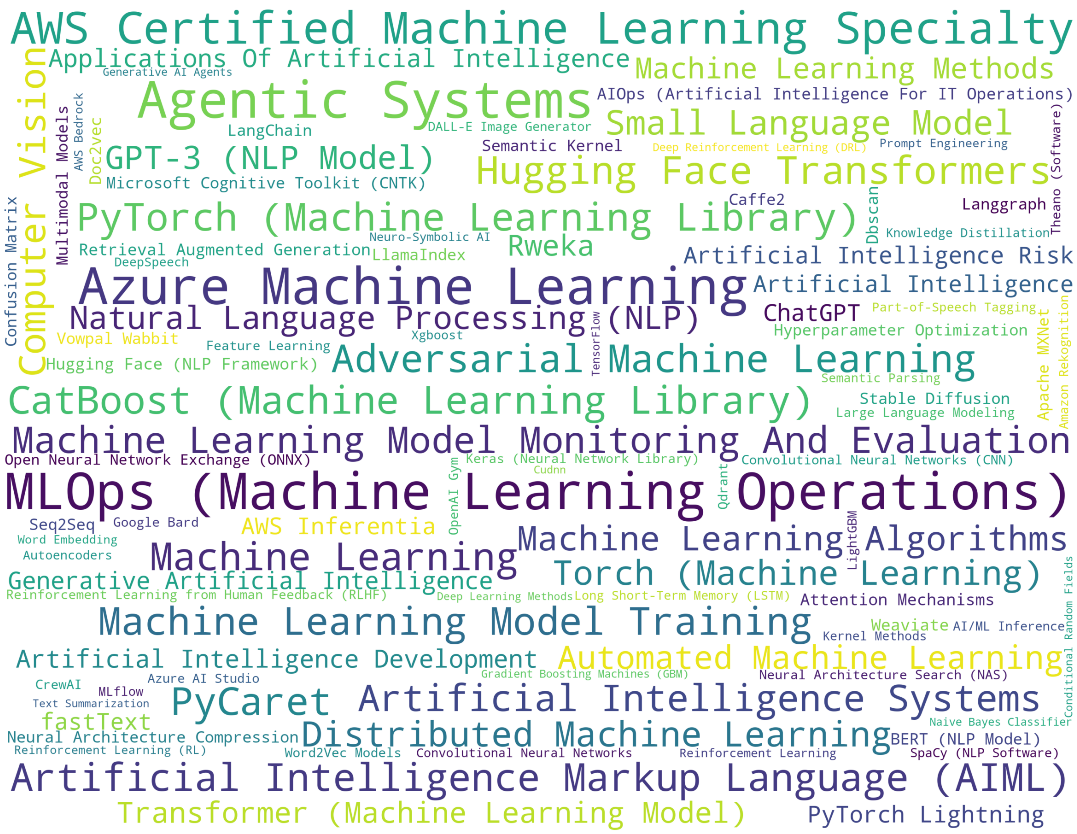


Figure IA.7: **Top 100 Skills with the Highest $w_s^{\mathbf{AI}}$.**

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.8: **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.3: **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.4: **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.4: 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