Artificial Intelligence Across Asset Management: Evidence from Registered Investment Advisers †

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Abstract

We provide a comprehensive analysis of AI adoption across various aspects of asset management by examining U.S. registered investment advisers. Since 2017, the investment advisory industry has seen significant AI adoption, primarily for investment strategies and IT infrastructure, while generative AI adoption remained minimal until 2023. AI adoption varies substantially across advisers and is related to the size and composition of advisers' assets under management, client base, and workforce. Advisers with greater assets, a higher share of hedge funds, and fewer employees directly interacting with individual clients exhibit higher levels of AI adoption. Moreover, we estimate that AI adoption leads to increased growth of the investment advisory business and a shift toward private funds, with spillover effects extending beyond hedge funds. Our findings underscore the heterogeneity of AI applications across the diverse funds and services in asset management.

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The technological revolution driven by Artificial Intelligence (AI) has transformed various sectors, including financial services.[1] This trend is particularly evident in asset management, where investment advisers actively integrate AI into their operations.[2] Yet, despite rapid AI adoption, specific applications of this technology and its impact on the asset management industry remain largely unclear. A key challenge in analyzing AI applications in this industry is the diverse range of services investment advisers provide, from advising retail financial planning to managing securities portfolios and arranging private capital deals. This diversity complicates the motivations of AI adoption, making it difficult to fully understand the role of AI across different business lines in asset management.

In this paper, we provide a comprehensive analysis of AI adoption across various aspects of the asset management industry. Using a panel of U.S. registered investment advisers with over $80 trillion of total assets under management (AUM) in 2024, we examine the relation between an adviser's firm-level AI adoption and various dimensions of its advisory business. These dimensions, including the size and composition of the AUM, client base, and workforce, as well as the mix of fund types, exhibit significant variations across advisers. By exploring such variations, our examination provides the first evidence on the overarching applications and impacts of AI in asset management.

Following the measurement of firm-level AI investments in Babina, Fedyk, He, and Hodson (2024), we infer an investment adviser's AI adoption using the required AI skills extracted from its job postings. Our measure, the percentage of AI jobs among the adviser's job postings, allows us to quantify its demand for AI-skilled human capital, an essential input of AI adoption. We also construct variants of this measure to capture specific applications of AI technology. For example, these measures include an advisers' adoption of generative AI (GenAI) and the use of AI for specific job roles within the firm.

[1]For example, see Acemoglu, Autor, Hazell, and Restrepo (2022), Babina, Fedyk, He, and Hodson (2024), and Cao, Jiang, Yang, and Zhang (2023).

[2]Bartram, Branke, and Motahari (2020) survey the applications of AI techniques in portfolio management, trading, and risk management, highlighting their role in improving efficiency, accuracy, and compliance.

Aggregate time trends of AI adoption underscore its growing significance in the asset management industry. Prior to 2016, AI adoption by investment advisers was limited and grew slowly, similar to the trends among public firms in Compustat. However, from 2017 onward, the percentage of their AI job postings surged quickly and has since remained at least double that of non-financial firms. This early and elevated rate of AI adoption is notable even when compared to public firms within the financial industry.

Ex ante, it is unclear how investment advisers use AI—whether to automate client communication, reduce operational costs, develop trading strategies, or pursue other purposes. We uncover these use cases by exploring the cross-sectional determinants of AI adoption and document four important facts. First, AI adoption is significantly higher among advisers with greater AUM and, conditional on AUM, with fewer clients.[3] This simple fact suggests that beyond economies of scale, AI is primarily applied in managing large asset portfolios rather than enhancing retail-oriented services. It is also consistent with our finding that the adoption of GenAI is still rare among investment advisers, despite its great potential to enhance retail-oriented services.

Second, controlling for an adviser's AUM and number of clients, AI adoption varies substantially with the composition of its AUM and client base. Among the main types of clients, the fractions of the adviser's AUM and number of clients in "pooled investment vehicles", which are private funds offered to institutional investors, exhibit strong positive correlations with AI adoption. In contrast, AI adoption is negatively related to AUM and clients categorized as registered investment companies (i.e., public funds such as mutual funds and ETFs) as well as individuals. Similar correlations are observed in the adviser's reported advisory services (e.g., whether it manages portfolios for pooled investment vehicles). In addition, AI adoption is higher if the adviser's other businesses involve trading activities, such as advising commodity and swap trading, and it is lower if the adviser engages in retail

[3]In the context of Form ADV, a client refers to either a legal entity (e.g., investment fund) or an individual person (e.g., a retail advisee).

businesses such as real estate or insurance brokerage.

Third, our new fund-level data reveal distinct correlations between an adviser's AI adoption and its weights of advised assets across different types of private funds. Specifically, controlling for the adviser's total gross asset values (GAVs) of private funds, AI adoption is significantly higher if the adviser has a higher percentage of GAVs in hedge funds. This correlation is generally negative for the percentage of GAVs in other fund types, including private equity (PE), venture capital (VC), real estate (RE), and securitized asset (SA) funds.

Fourth, differences in AI adoption between investment advisers are also related to the composition of their workforce. Advisers with a larger proportion of employees who interact directly with individual clients, such as investment adviser representatives (IARs), exhibit lower levels of AI adoption. Furthermore, the fraction of AI-related job postings for investment-specific roles is positively correlated with the percentage of GAVs in hedge funds but does not show a significant relation with other fund types.

Overall, the cross-sectional patterns above reveal a clear association between AI adoption and the advising of private funds, particularly hedge funds, which could benefit from sophisticated trading strategies. This finding suggests that the primary reason for asset managers to adopt AI is likely related to investment strategies rather than operational cost efficiency.

In the second half of this paper, we estimate the impact of the recent AI adoption on the investment advisory business. To address a potential bias from unobserved selection, we exploit a plausibly exogenous variation in investment advisers' AI adoption induced by uneven growth trends in AI technology across geographical locations. Our estimates indicate that AI adoption has a significant effect on the adviser's future AUM growth. On average, a one-percentage-point increase in AI adoption leads to a 3% greater AUM growth. This effect is not uniform across client types, as we find that the fraction of AUM in pooled investment vehicles increases, whereas the fraction of AUM in other client types decreases slightly. Besides AUM growth differences, we also find a shift in the composition of the client

base towards pooled investment vehicles.

Our estimates also indicate that AI adoption positively affects the number of an adviser's employees, suggesting that AI crowds in, rather than crowds out, jobs. Meanwhile, it reduces the fraction of employees directly interacting with retail clients, such as IARs, insurance agents, and broker-dealer representatives, potentially due to diminished needs for multitasking.[4] Finally, we find suggestive evidence that, while AI adoption is motivated by hedge fund strategies, it can generate spillover effects to other fund types and asset classes. Specifically, AI adoption leads to increased private market activities (i.e., PE, VC, and RE deals), a shift toward earlier-staged deal targets, and lower industry concentration among deal targets. Overall, these findings provide corroborative evidence of how AI technology has shaped the evolution of the asset management industry.

This paper contributes to the asset management literature by examining AI adoption among U.S. investment advisers. Existing research on this topic typically focuses on specific investment products or asset classes. For example, recent papers have explored the implications of AI and big data technologies on investment decisions and performance of active equity mutual funds (Bonelli and Foucault, 2023; Zhang, 2024), private equity and venture capital funds (Astebro, 2021; Bonelli, 2022), and institutional investors' stock portfolios (Sheng, Sun, Yang, and Zhang, 2024; Cen, Han, Han, and Jo, 2024). Unlike these papers, we take a holistic approach to examine various aspects of investment advisers' business activities. Our findings provide the first evidence on which aspects of their operations are most closely associated with AI and how AI influences different facets of their business, offering insights to guide future research on AI applications in this industry.

Our paper is also related to research on AI's broader impact on financial industry. Recent research has investigated the benefits and consequences of AI adoption in different financial market settings, including public firm disclosures (Cao, Jiang, Yang, and Zhang, 2023; Cao,

[4]We proxy for multitasking by an adviser's employees using the ratio of the total number of employees engaged in reported activities to the total number of employees.

Jiang, Wang, and Yang, 2024), security trading strategies (Dou, Goldstein, and Ji, 2024; Colliard, Foucault, and Lovo, 2022), credit outcomes in 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 the sales of insurance products (Liu, 2024). Our study adds to this literature by showing that AI adoption improves investment advisers' business growth and has heterogeneous effects across investment advisory services.

More broadly, our paper extends research on AI's impact on firm performance by examining investment advisers as a distinct type of firms. 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.[5] 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 boosted AUM growth and spurred changes in investment products. Our setting also provides a window to study different forms of AI technology applied across business lines within a firm, including the recent development of generative AI.

Finally, our paper contributes to the literature on the substitution between AI and human labor force. Existing studies find mixed evidence. For example, Acemoglu, Autor, Hazell, and Restrepo (2022) show that the substitution towards AI-related jobs have had limited impact on overall employment, whereas Alderucci, Branstetter, Hovy, Runge, and Zolas (2020) find that firms with AI-related innovations experience faster employment growth. Using data on the investment management industry, Abis and Veldkamp (2024) estimate that big data technologies lead to a 5% decline in the labor share of income. By directly

[5]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.

examining different job roles within investment advisers, we provide evidence that AI boosts firm-level employment while disproportionately shifting employment away from client-facing, sales-related roles toward other positions.[6]

1. Data

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

1.1. Registered Investment Advisers

The regulatory framework established by the Investment Advisers Act of 1940 has required investment advisers to register with the U.S. Securities and Exchange Commission (SEC) by filing Form ADV. This annual filing provides comprehensive information about an adviser's practices, fees, and business structure. In 2011, the SEC adopted a Final Rule implementing the Dodd-Frank Act, which brought significant updates to Form ADV. These changes, effective in March 2012, include raising the threshold of registration to $100 million in Regulatory Assets Under Management (RAUM), requiring a decomposition of RAUM by client types, and adding fund-level disclosure for private funds' types, gross asset values, ownership structures, and service providers.[7]

We obtain all Form ADV filings submitted between 2012 and 2024 from the SEC website. Our primary focus are "Items" and the corresponding "Schedules" in the form's Part 1A. Specifically, Item 1 reports the adviser's identifying information, including its name(s), office

[6] Webb (2019) highlights that AI disproportionately affects high-skill occupations, unlike previous automation technologies.

[7] 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, which allows 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.

location(s), and website(s). Item 5 reports details on the adviser's employees, clients, RAUM, including the decomposed values by category, and the types of advisory services. Item 6 reports the adviser's other business activities, such as broker-dealers or banks. Item 7B indicates if the adviser manages private funds. Schedule D of Item 7B provides information on fund type and gross asset value for each of these private funds.

In October 2017, the SEC amended Form ADV, which led to changes in the format of a few items. For instance, before 2017Q3, the number of the adviser's employees was reported as a categorical range in Item 5A. After 2017Q3, Item 5A has been revised to a continuous value for the approximate number of employees. To consistently measure various dimensions of the adviser's business across years, we convert the ranges into numerical values by taking the range's midpoint (e.g., "6-10" to 8, "Up to 50%" to 37.5%).[8] Moreover, if the reported percentage of employees, clients, or AUM in a certain category is missing, we fill the percentage with zero.

We create an adviser-year panel as follows. First, we combine all the Form ADV filings in which the adviser's total RAUM is not zero or missing. Then for each adviser (uniquely identified by its SEC file number), we keep the last filing submitted in the year. Next, we clean the private funds data and compute the adviser's total number of and gross asset values (GAVs) in all private funds as well as in each fund type, including hedge funds (HFs), private equity funds (PEFs), real estate funds (REFs), securitized asset funds (SAFs), venture capital funds (VCFs), and other private funds.[9] Finally, we merge variables related to private funds with the adviser-year panel by the unique identifier of the filing.

[8]An exception is Item 5C, which was revised from the number of clients of investment advisory services to the number of clients for whom the adviser has no RAUM. For filings after 2017Q3, we aggregate the number of clients across client types and use the sum as the adviser's total number of clients.

[9]Our data cleaning has three steps. First, for funds reported as "Other Private Funds" along with a specified type description, whenever appropriate, we reclassify the fund as one of five types (i.e., HF, PEF, REF, SAF, VCF) based on the description. Second, if a private fund has a missing type or is reported as a "Liquidity Fund", we reclassify it as "Other Private Fund". Third, we correct any discrepancy by making the indicator for advising private funds in Item 7B consistent with the existence of private funds in Schedule D.

1.2. AI-Related Job Postings

Lightcast (previously known as Burning Glass) aggregates job postings from a variety of online sources, including both job boards and company websites. Through the use of advanced natural language processing techniques and specialized in-house analysts, Lightcast converts these postings into a standardized, machine-readable format, extracting key elements like employer names, job titles, posting dates, sought-after skills, and educational prerequisites. This dataset is widely applied in research across labor economics and finance.[10] In particular, Hershbein and Kahn (2018) find that while Lightcast data focus more on specific occupations and industries, their distribution patterns are relatively consistent over time and align with vacancy trends reported by other major data sources (e.g., Job Openings and Labor Turnover Survey, the Current Population Survey, and Occupational Employment Statistics).

Our data from Lightcast's U.S. job postings are between 2010 and 2024. We focus on entries with available employer names and exclude internships.

1.3. Measuring AI Adoption

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

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

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

where a job is defined as requiring core AI skills if it has at least one of ML, NLP, CV, and

[10] For example, see Acemoglu, Autor, Hazell, and Restrepo (2022), Braxton and Taska (2023), Hershbein and Kahn (2018), Babina, Fedyk, He, and Hodson (2024), Abis and Veldkamp (2024).

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 AV measure results included in the Internet Appendix for robustness.

1.4. Linking Datasets and Sample Construction

We construct a link table between investment advisers in Form ADV and their job postings in Lightcast via Morningstar's PitchBook platform. PitchBook provides a built-in algorithm to identify firms based on their names, headquarter locations, and company websites, which takes into account variations in firm names (e.g., legal names, business names, former names) and parent-subsidiary relations. Figure IA.2 in the appendix summarizes the linked investment advisers by year. Based on total AUM, nearly the entire universe of Form ADV advisers are

linked to PitchBook, with approximately 70% of them also identifiable in Lightcast. [11]

From Pitchbook, we also obtain data on investment advisers' private market deals, including private equity, venture capital, and real estate deals. We construct an adviser-year panel sample for these deals in which we measure the adviser's number of deals, deal stage, deal size, and how concentrated the deals are across industries.

1.5. Summary Statistics

Table 1 presents the summary statistics of our main sample. To be included in our sample, we require an adviser-year to have at least five job postings and $100 million in AUM. Our AI measure shows that, on average, only 1.1% of an investment adviser's job postings are AI-related, with a standard deviation of 3.9%. The average adviser manages $65 billion in AUM, serves 33 thousand clients, and employs around 500 people. There is substantial variation in the AUM, client count, and employee count, along with their respective proportions across different categories (variables starting with AUM%, Client%, and Employee%).

Around half of advisers manage private funds, on average with 13 funds and $7 billion in GAV. The largest fund type is hedge funds, which account, on average, for 35.6% of GAV. Private equity funds, real estate funds, and securitized asset funds also account for substantial shares of GAV, but venture capital funds generally account for a small share.

2. Investment Advisers' AI Adoption

In this section, we discuss the time-series and cross-sectional variations in AI adoption by investment advisers.

[11] Pitchbook's coverage is generally more comprehensive for larger advisers.

2.1. Time-Series Patterns in AI Investment

Examining the trends in measured AI investment intensity reveals two key insights. First, while the percentage of AI-related job postings by registered investment advisers remains low, it rises sharply from 2016 to 2018 before stabilizing. Figure 2 shows that the trend among registered investment advisers closely tracks that of financial firms in Compustat. Registered investment advisers lead in AI investment from 2017 to 2021 but are surpassed by Compustat financial firms in 2022. Compustat firms in other industries also see rapid growth from 2016 to 2018, though at lower levels. In 2024, AI investment intensity declines in these industries, potentially linked to large-scale layoffs in the IT sector, while registered investment advisers and Compustat financial firms remain relatively stable. The annual average time series of AI investment for Compustat firms in our sample aligns with the figure reported by Babina et al. (2024).

Second, AI-related jobs at registered investment advisers span various functional roles, with four key categories: Investment, data management, IT, and client communication. Figure 3 shows that AI-related jobs in investment and IT have been the primary drivers of growth, exhibiting a sharper increase from 2016 to 2018 compared to those in data management and client communication. By 2024, investment and IT roles account for more than half of all AI-related jobs. We also include the average percentage of jobs related to generative AI in the figure. Following the release of ChatGPT in November 2022, which revolutionized generative AI, jobs in this field surged in 2023, rising from negligible levels to numbers comparable to AI-related jobs in client communication.

2.2. Cross-Sectional Determinants of AI Adoption

We then examine which features of registered investment advisers can predict their future AI investment. Identifying these key features allows us to understand the contextual factors influencing advisers' decisions to allocate resources toward AI. We focus on four key aspects:

the sources of assets under management, the types of services offered, involvement in private funds, and the distribution of workforce roles. While most of this information comes from Form ADV filings, we supplement our analysis of workforce roles with job posting data.

2.2.1. Composition of AUM and Clients

An investment adviser's assets under management originate from various investment products tailored to different client types, each subject to distinct regulatory frameworks and investment preferences. Since AI is well-documented for its ability to enhance data processing and decision-making efficiency, we hypothesize that AI adoption is more prevalent among advisers with stronger incentives to improve product performance (i.e., management fees tied to performance) and greater capabilities to do so (i.e., access to extensive data, systematic investment processes, and high trading frequency).

To test this hypothesis, we leverage Form ADV Item 5, which requires investment advisers to disclose the composition of their regulatory AUM and the number of clients in specific categories. These categories include investment companies, pooled investment vehicles (other than investment companies and business development companies), high-net-worth individuals (HNWIs), and other individuals. Advisers also separately report AUM in discretionary and non-discretionary management. We analyze these disclosures to assess the relationship between an adviser's AUM composition and AI investment intensity in the following year in columns 1-3 of Table 2.

The independent variable, "AUM% Discretionary", measures the percentage of AUM under discretionary management, where advisers make investment decisions without clients' prior approval for each transaction. In contrast, non-discretionary management requires client consent before executing trades. Our hypothesis predicts that discretionary management is more likely to adopt AI due to its reliance on fast decision-making and greater benefits from automation.

The independent variable, "AUM% InvtComp", measures the percentage of AUM managed for investment companies, such as mutual funds, ETFs, and closed-end funds, which are governed by the Investment Company Act of 1940. These entities operate under strict regulations and primarily generate revenue through fixed AUM-based fees rather than performance-based incentives. Consequently, their focus is on regulatory compliance, cost efficiency, and AUM growth, rather than aggressively seeking alpha. This makes them less likely to adopt AI compared to advisers managing products with greater flexibility and stronger performance-linked incentives.

The independent variable, "AUM% PooledInvt", measures the percentage of AUM managed for pooled investment vehicles other than investment companies and business development companies, including hedge funds, private equity funds, venture capital funds, and other private investment vehicles. Unlike investment companies, these funds are generally exempt from registration under the Investment Company Act of 1940 (e.g., via Sections 3(c)(1) or 3(c)(7)), allowing them greater flexibility in investment strategies and risk-taking. Their lighter regulatory burden allows them to explore alternative investment approaches, often leveraging AI for complex strategies. Given their emphasis on maximizing returns and their access to extensive proprietary data, these vehicles are well-positioned to integrate AI into investment decision-making.

The independent variable, "AUM% HighNetWorth", measures the percentage of AUM managed for high-net-worth individuals who typically have at least $1 million in AUM with the adviser or a net worth (excluding their primary residence) of $2.1 million or more. These investors are financially sophisticated and capable of bearing higher risk, enabling advisers to offer tailored investment strategies beyond standard retail offerings. This could encourage AI adoption for portfolio optimization, personalized recommendations, and real-time risk assessment. However, AI use in this segment may be constrained by investors' preference for relationship-driven advisory services that emphasize trust, discretion, and

human expertise that AI cannot fully replicate. Moreover, privacy concerns and investor demand for transparent investment strategies may further limit AI integration.

The independent variable, "AUM% Individual", measures the percentage of AUM managed for retail clients who do not meet the SEC's high-net-worth criteria. These clients often seek investment advice for personal financial planning, retirement savings, or education funding. They are offered stronger regulatory protections. Advisers serving retail clients may have fewer incentives to integrate AI, as their primary focus is on compliance, risk minimization, and standardized portfolio management rather than maximizing investment performance.

Table 2 Columns 1-3 show that investment advisers with larger total AUM tend to invest more in AI, indicating that scale is a key determinant of AI adoption. Furthermore, the percentage of discretionary AUM is significantly positively associated with AI investment, suggesting that greater autonomy in investment decisions facilitates AI integration. The percentage of AUM in pooled investment vehicles also correlates positively with AI investment, underscoring the critical role of performance-fee-driven products in driving AI adoption. Conversely, AUM percentage from investment companies or high-net-worth individuals is negatively associated with future AI investment, implying that AI adoption is less relevant in contexts where advisers are constrained by regulatory requirements, fee structures, or client preferences for more traditional, relationship-driven advisory services. Figure 5 confirms the correlations between the percentage of AUM in a specific category and future AI investment, with darker colors indicating higher average AI investment levels.

To extend our analysis, we replace AUM-related variables with client count and composition in Columns 4–6 of Table 2 to examine how the number and type of clients relate to future AI investment. Form ADV defines a client as either a managed investment product or a retail customer receiving advisory services. Because Form ADV does not require disclosure of the number of clients under discretionary versus non-discretionary management, we cannot replicate the "AUM% Discretionary" variable using client counts. Instead, we

introduce the total number of clients and the percentage of non-U.S. clients as additional explanatory variables. A higher proportion of non-U.S. clients may reduce regulatory burdens by qualifying the adviser for certain U.S. exemptions, though it also increases complexity related to cross-border tax compliance and local regulations.

The significant negative coefficient on the total client count suggests that, for the same AUM, advisers with more clients (and thus a lower average AUM per client) invest less in AI. Since advisory services for high-net-worth individuals or other individual clients count each person as a separate client, whereas managing an investment company or pooled investment vehicle counts each product as a single client, this finding supports the hypothesis that AI adoption is more prevalent in performance-focused delegated investment portfolios rather than in personalized financial advisory services. Figure 4 supports this finding: areas representing larger AUM and fewer clients show higher AI investment levels.

We also find in Columns 4–6 of Table 2 that the significant positive coefficient of "AUM% PooledInvt" persists for "Client% PooledInvt", reinforcing the role of lightly regulated, performance-driven clients in driving AI adoption. What's more, the significant positive coefficient of the percentage of non-U.S. clients suggests that U.S. regulatory exemptions or the complexity of international operations may further encourage AI adoption.

2.2.2. Types of Advisory Services and Other Business Activities

We further investigate whether the types of advisory services and other business activities an investment adviser provides can predict AI adoption. Form ADV Items 5, 6, and 7 require advisers to disclose their engagement in various predefined services and activities. We convert these disclosures into dummy variables, assigning a value of one if a service is offered and zero otherwise.

Some service categories overlap with client categories, as certain client types (e.g., investment companies and pooled investment vehicles) are defined by the services they receive.

Other service categories provide more insights into specific activities, including whether an adviser advises any private fund, provides financial planning services, manages portfolios for individuals and small businesses, advises selection of other advisers (including private fund managers), actively engages in business as a registered representative of a broker-dealer, commodity pool operator or commodity trading adviser (whether registered or exempt from registration), real estate broker, dealer, or agent, insurance broker or agent, bank (including a separately identifiable department or division of a bank), major security-based swap participant, or other financial product salesperson.

Table 3 reports how AI investment varies with the provision of specific services in the prior year. First, Columns 1 and 2 show a robust, significant positive correlation between future AI investment and acting as an adviser to private funds. In Form ADV, private funds are investment vehicles exempt from registration under the Investment Company Act of 1940, typically offered to accredited investors. By definition, all private funds are pooled investment vehicles (other than investment companies). The positive coefficient of "Advise PrivFund" is consistent with the positive correlation between AUM or client percentage in pooled investment vehicles in Table 2. Due to the collinearity between "Advise PrivFund" and "Service: PooledInvt", we exclude "Advise PrivFund" from Columns 3-5.

Second, consistent with Table 2, portfolio management for pooled investment vehicles has a significantly positive correlation with subsequent AI investment, whereas portfolio management for investment companies (as well as "business development companies" that have elected to be regulated under Section 54 of the Investment Company Act of 1940) has a negative correlation.

Third, portfolio management for retail investors negatively correlates with future AI investment, corroborating the argument that AI adoption is more prevalent in performance-driven delegated investment portfolios rather than in personalized advisory services.

Fourth, offering the selection of other advisers is also associated with lower subsequent AI

investment. This service involves recommending, selecting, or managing the engagement of third-party advisers on behalf of clients. Unlike directly managing a client's portfolio, this activity primarily operates in a consulting or oversight capacity. The negative coefficient suggests that consulting roles have lower AI demand.

Lastly, beyond advisory services, Column 4 shows that business activities related to trading and complex investment strategies, such as commodity pool operation and swap participation, positively predict AI investment. In contrast, activities focused on client communication, including broker-dealer representation, real estate brokerage, and insurance sales, are negatively associated with future AI investment.

2.2.3. Composition of Private funds

Having established the strong positive correlation between advising private funds and future AI investment, we examine how AI investment varies across private fund types within the subsample of investment advisers that manage at least one private fund.

Form ADV Schedule D Section 7B(1) requires private funds to disclose their fund type, specifying whether it is a fund of funds, hedge fund, liquidity fund, private equity fund, real estate fund, securitized asset fund, or venture capital fund. Each private fund also reports its current gross asset value (GAV).[12] Using this information, we calculate the total GAV of all private funds advised by an investment adviser, the number of private funds, and the percentage of GAV attributed to hedge funds, private equity funds, venture capital funds, real estate funds, and securitized asset funds, respectively.[13]

[12]GAV and regulatory AUM often align in value for private funds, but they slightly differ in assets not actively managed by the adviser. GAV includes all assets of the private fund, even if certain assets are not directly under the adviser's active management. For instance, if a fund holds assets managed by a third party, these are still part of GAV. Regulatory AUM only includes assets for which the adviser provides continuous and regular supervisory or management services. If certain assets are outsourced or passively held without ongoing involvement, they are excluded from regulatory AUM. Therefore, GAV focuses on the total value of the private fund's assets to provide a full picture of the fund's size and exposure. Regulatory AUM focuses on the adviser's role and responsibilities, highlighting assets under their direct oversight and decision-making.

[13]Liquidity funds are not separately listed due to their rarity.

Table 4 presents regression results of an adviser's AI investment on its lagged private fund information. Columns 1–3 use all private funds to calculate the explanatory variables, while Columns 4–6 exclude funds of funds to provide a more accurate reflection of the adviser's own fund management activities. This distinction ensures that the results in Columns 4–6 focus on funds directly managed by the adviser, avoiding potential confounding effects from overseeing external managers in fund-of-funds structures.

First, "log(GAV)" consistently exhibits a significant positive coefficient across all columns, indicating that advisers managing larger private fund assets are more likely to invest in AI. "log(N PrivFund)" has a negative coefficient, suggesting that AI adoption is more common when assets are managed within fewer, larger private funds. These correlations are consistent with the coefficients of "log(AUM)" and "log(Client)" in Table 2.

Second, two robust patterns emerge in the composition of private funds. The percentage of GAV in hedge funds is positively associated with future AI investment, regardless of whether the fund of funds subsample is excluded. However, the percentage of GAV in real estate funds shows a significant negative coefficient. This aligns with expectations: hedge funds, characterized by complex, high-frequency, data-intensive investment strategies, drive strong AI demand, whereas real estate funds, relying on traditional valuation methods, have less need for AI tools. Figure 6 confirms these patterns between the percentage of GAV in a specific private fund category and future AI investment, with darker colors indicating higher average AI investment levels.

2.2.4. Composition of Employees and AI Job Roles

The characteristics of investment advisers discussed above focus on how their business models may incentivize AI adoption. This section shifts the focus to the workforce, examining how job composition and organizational readiness relate to AI adoption. The distribution of an investment adviser's workforce across various functions reflects its operational focus

and strategic priorities, which in turn shape its demand for AI tools. For instance, firms with a strong emphasis on research, analytics, and investment advisory functions are more likely to view AI as a valuable asset for enhancing decision-making and operational efficiency. Conversely, firms primarily focused on sales and client solicitation may have a less immediate need for AI-driven automation. We analyze workforce characteristics through two key dimensions: (1) the composition of current employees in different roles, as reported in Form ADV, and (2) the demand for AI-related skills in different roles, inferred from job postings.

Form ADV mandates the disclosure of total employees, including full- and part-time employees but excluding clerical staff, along with the number of employees engaged in specific functions. Key categories include employees who (1) perform investment advisory functions (including research), (2) are registered representatives of a broker-dealer, (3) are registered with one or more state securities authorities as investment adviser representatives, and (4) are licensed as agents of an insurance company or agency. Employees who perform multiple functions are counted in each applicable category.

Table 5 presents the relation between an adviser's workforce composition and its AI investment in the subsequent year. First, the most robust finding is that the proportion of employees registered as investment adviser representatives (scaled by total employees) is negatively correlated with future AI investment. An investment adviser representative, as defined by the U.S. Uniform Securities Act, is an individual employed by or associated with a registered investment adviser who provides securities advice, manages client accounts or portfolios, solicits or negotiates investment advisory services, or supervises others performing these functions. This role is inherently client-facing and demands strong relationship-building skills. On the one hand, AI can enhance these activities by enabling personalized recommendations and improving client engagement through AI-powered chatbots. One the other hand, firms with a high proportion of IARs have traditionally relied on human relationships and may be more resistant to AI tools, prioritizing personal interaction over automation. The

robust negative coefficient of "Employee% IAR" supports this latter interpretation: advisers reliant on adviser-client relationships perceive less immediate value in AI adoption.

Second, the proportion of employees licensed as insurance agents is also negatively associated with AI investment in the following year, consistent with the negative coefficient for "Business: Insurer" in Table 3. Insurance agents primarily sell insurance products, emphasizing personal interaction and relationship building, similar to IARs.

In summary, Table 5 shows that advisers with a higher proportion of client-facing employee roles adopt AI at a slower pace, suggesting AI is not primarily to replace client communication. To understand where AI skills are most applicable, we analyze AI investment across job roles. We focus on four key roles where AI is likely to be relevant: investment, IT, data management, and client communication.

Table 6 presents results of regressing an adviser's AI investment in one specific job role in the following year on its current private fund composition. We focus on private fund composition as the explanatory variable because previous sections have established that investment advisers managing private funds (or pooled investment vehicles) exhibit the strongest association with AI adoption. Specifically, Table 6 extends the analysis from Column 3 of Table 4 by replacing the dependent variable, total $AI\%$, with $AI\%$ in a specific job role.

Table 6 shows that advisers managing larger private fund assets are more likely to adopt AI in all four types of roles, reinforcing findings from Column 3 of Table 4 that larger private funds are at the forefront of AI adoption. However, the negative coefficient for "log(N PrivFund)" is statistically significant only in Column 1 (investment-related roles). This suggests that advisers managing large private fund assets concentrated in fewer funds adopt AI more intensively in investment functions, while AI adoption in other roles is less related to asset concentration.

Table 6 also shows that the percentage of GAV in hedge funds is positively associated

with future AI adoption, particularly in investment-related job roles. This suggests that hedge funds' AI demand, observed in Table 4 Column 3, is primarily driven by investment applications such as algorithmic trading and quantitative analysis.

Conversely, Column 2 of Table 6 indicates that venture capital, real estate, and securitized asset funds exhibit significantly negative coefficients for AI adoption in IT-related roles. This suggests that advisers managing these funds have relatively lower AI demand in IT functions compared to the unspecified baseline benchmark that includes liquidity funds and other types of private funds.

Overall, Table 6 highlights that AI adoption among investment advisers is closely tied to private fund composition and job roles. Advisers managing larger private fund assets, especially those concentrated in fewer funds, integrate AI more extensively, with hedge fund managers showing the strongest adoption in investment functions.

3. How Does AI Adoption Shape Asset Management?

In this section, we explore how investment advisers' adoption of AI technology shapes their advisory business. An empirical challenge to estimating the effects of AI on adviser-level outcomes is that AI adoption is the adviser's endogenous choice. This choice might be driven by unobserved adviser characteristics, e.g., shocks to demand for specific advisory services, which confounds the interpretation of our estimated effects.

To address this endogeneity concern, we apply an instrumental variable approach that exploits differential trends in the employment of AI talents across geographical locations. Consistent with recent research (e.g., Hunt, Cockburn, and Bessen, 2024), in our sample, U.S. companies' AI job postings exhibit large and persistent differences across US communing zones (CZs). To illustrate these differential trends, Figure IA.3 compares the percentage of AI jobs among all job positions posted for a location, between commuting zones that already

had AI jobs in 2010 and those that had zero AI jobs in 2010. Clearly, AI jobs in the latter CZs grew slowly and never reached the level in 2010 of the former CZs. We exploit these geographical differences to isolate plausibly exogenous variation in the local supply of AI talent that shifts investment advisers' AI adoption.

Specifically, we construct an instrumental variable $CZAI\%$ at the adviser-year level, calculated as the weighted average percentage of AI jobs among all job postings in a CZ-year, where the weights are the shares of an adviser's job postings in a CZ in the previous year.[14] As these adviser-CZ level job shares are highly persistent over time, our instrument captures an adviser's exposures to local trends in AI adoption that are unlikely to be driven by unobserved determinants of investment advisers' business activities.

3.1. Growth of Business

Using the above instrumental variable approach, we first examine the impact of instrumented AI investment on the annual changes in an investment adviser's AUM, client count, employee count, and the respective compositions of these variables in the subsequent year. Tables 7, 8, 9, and 10 present results from two-stage least squares regressions. The first-stage regression using $CZAI\%$ as an instrument for current-year AI investment is included as Column 1 in each of these tables. The Kleibergen-Paap F statistic of 24.34 exceeds the commonly used rule-of-thumb threshold of ten, suggesting that the instrument is not weak and provides substantial explanatory power for the current year's AI investment $AI\%$.

Table 7 focuses on the annual growth rate in overall AUM, client count, and employee count. Controlling for the current year's AUM, client count, employee count, and year fixed effects, the results show that instrumented AI investment is significantly positively associated with next year's growth rate in AUM, client count, and employee count, implying that increased AI investment fosters business growth by accelerating the expansion of assets under

[14]We map county FIPS to 2000 commuting zones using the crosswalk provided by the USDA website.

management and client numbers, while also driving an increase in employee count.

Table 8 examines how the composition of an investment adviser's AUM in the following year changes with its instrumented AI investment in the current year. Controlling for year fixed effects and other relevant adviser characteristics, we find no significant relationship between instrumented AI investment and the annual change in AUM percentage invested by high-net-worth individuals or other individuals. However, the annual change in the AUM percentage in pooled investment vehicles, such as hedge funds, private equity funds, and venture capital funds, is higher with greater exogenously induced AI investment. In contrast, the annual change in the AUM percentage in investment companies, such as mutual funds, ETFs, and closed-end funds, is significantly lower under the same conditions.

This contrast reveals that advisers investing more heavily in AI tend to further shift their focus toward products where they have both stronger incentives to enhance product performance (i.e., management fees tied to performance) and greater capabilities to do so (i.e., access to extensive data, systematic investment processes, and high trading frequency). Recalling the positive correlation between "AUM% PooledInvt" and next year's AI% and the negative correlation between "AUM% InvtComp" and next year's AI% observed in Table 2, these findings imply a positive feedback loop in which AI investment reinforces a strategic shift toward performance-based fee structures, more sophisticated investment strategies, and less regulated asset management practices.

Table 9 replaces the composition of an investment adviser's AUM in Table 8 with the composition of an investment adviser's client count, serving as a robustness check. Consistent with the findings in Table 8, the annual change in the client count percentage in pooled investment vehicles is significantly higher with greater exogenously induced AI investment. For the annual change in the client count percentage in investment companies (Column 3), while the coefficient of instrumented AI investment remains negative, as in Column 3 of Table 8, it is not statistically significant.

Table 10 investigates how AI investment affects the composition of an investment adviser's workforce in the subsequent year. Consistent with the findings in Table 5, we categorize employees into four functional groups. The results reveal that instrumented AI investment is significantly negatively associated with the annual change in employee numbers in three out of four categories: investment adviser representatives, insurance agents, and broker-dealer representatives. This suggests that employees in client-facing, sales-related, and relationship-driven roles grow more slowly (or decline more rapidly) than other positions within an investment adviser as AI investment increases.

This slower growth in client-facing job roles contrasts with the positive overall employee growth associated with AI investment (Column 4 of Table 7). Taken together, these findings suggest that while AI investment supports the expansion of the total workforce size to accommodate faster business growth, it reshapes the functional distribution of employees. In particular, client-facing roles exhibit slower growth compared to other functions, potentially reflecting a shift in workforce priorities.

Moreover, Form ADV's requirement to count employees performing multiple roles in each job category may offer additional insight. The slower growth in client-facing roles could indicate increased workforce specialization, with employees focusing on fewer responsibilities and reducing their involvement in client-facing tasks. This trend suggests that AI investment not only drives business growth but also reshapes organizational structures by redefining workforce roles and focus areas.

3.2. Private Market Deals

Finally, we test how AI investment influences investment advisers' private market deals in the following year, analyzing four dimensions: deal count, stage, size, and industry concentration. Each year, an adviser's private market deals include all investments recorded in PitchBook. We classify deals into four stages:

- Stage 0: if the deal type is among accelerator/incubator, angel (individual), platform creation, seed round, or Grant
- Stage 1: if the deal type is among early stage VC, equity crowdfunding, or project financing
- Stage 2: if the deal type is among later stage VC, restart - later VC, project financing, joint venture
- Stage 3: if the deal type is among buyout/LBO, capital spending, convertible debt, corporate, corporate asset purchase, debt - acquisition, IPO, debt - general, debt - PPP, debt conversion, debt refinancing, dividend, dividend recapitalization, general corporate purpose, leveraged recapitalization, merger/acquisition, PE growth/expansion, merger of equals, mezzanine, PIPE, public investment second offering, reverse merger, secondary transaction - open market, secondary transaction - private, secondary transaction - stock distribution, share repurchase, spin-off, bankruptcy: admin/reorg

Industry concentration is measured using the Herfindahl-Hirschman Index (HHI), where higher values indicate specialization and lower values reflect diversification.

As shown in Table 11, exogenously induced AI investment is associated with a significant increase in deals closed in the subsequent year. These deals tend to occur at earlier stages and are more diversified across industries. These findings support the hypothesis that AI enhances an adviser's ability to process complex information, leading to greater deal activity, increased engagement in early-stage investments (where information asymmetry is high), and broader industry expansion.

4. Conclusion

Our study provides a comprehensive analysis of AI adoption across various aspects of asset management, focusing on its uneven distribution, the business characteristics associated with adoption speed, and its consequences. Although overall adoption rates remain relatively low, the rapid growth since 2017 and sustained levels thereafter suggest a structural transformation within the industry. We find that AI adoption is most pronounced among advisers managing pooled investment vehicles, which benefit from greater regulatory flexibility and performance-based incentives. These advisers are well-positioned to leverage AI's ability to process large datasets, enhance decision-making, and automate complex tasks, making it a valuable tool in their investment approach.

Beyond descriptive patterns, our analysis provides causal evidence that AI investment drives business expansion. Advisers investing more in AI experience faster AUM and client growth, along with shifts in workforce composition, particularly a declining share of employees in client-facing, sales-related, and relationship-driven roles. These findings suggest that AI adoption is not merely a technological upgrade but a strategic shift reshaping competition in investment advisory services. However, while AI is clearly transforming industry operations, its long-term effects and equilibrium outcomes remain an open question.

Our study lays the groundwork for future research on the broader implications of AI across the asset management industry. Key areas for further exploration include whether the short-term growth in AUM and client base driven by AI investment can be sustained long-term and whether such expansion comes at the cost of extra risk and regulatory considerations, such as transparency, compliance, and cybersecurity. For practitioners, our findings highlight the importance of aligning AI adoption with business models that capitalize on AI's strengths while preserving human's competitive advantages. Striking the right balance between technological efficiencies and human expertise will be critical to ensuring that AI enhances rather than disrupts the fundamental functions of the asset management industry.



Figure 1: **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.

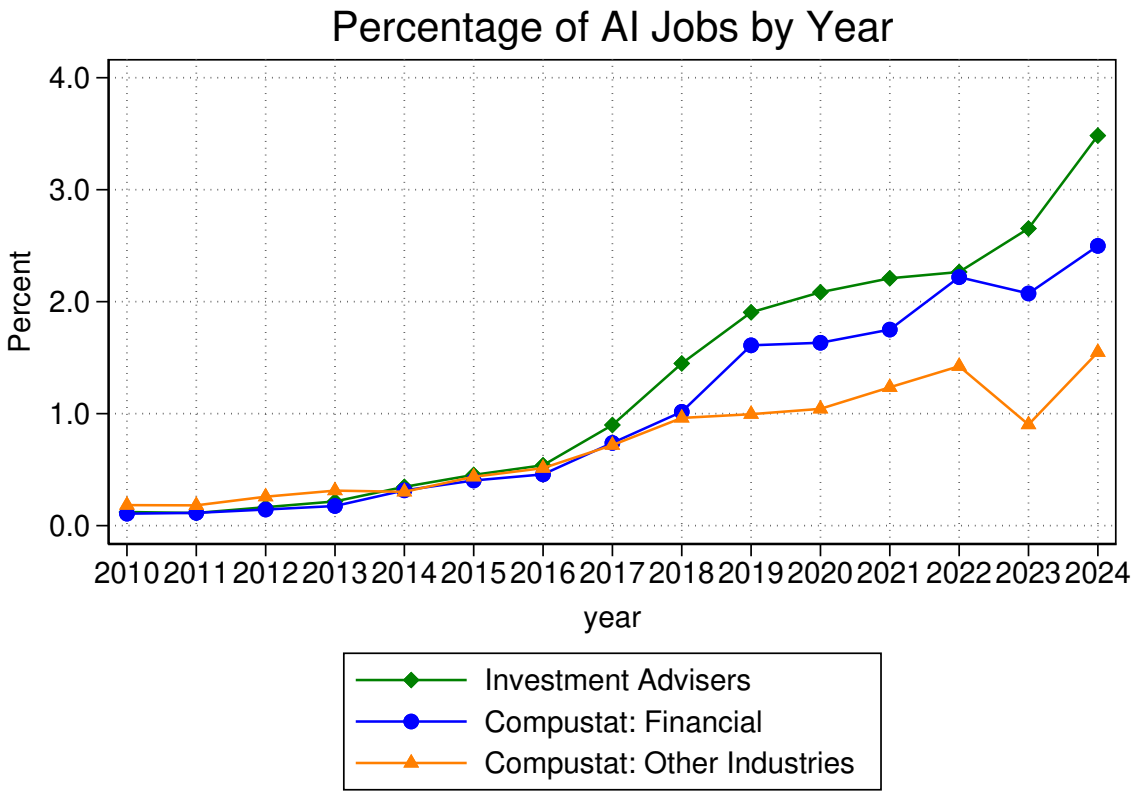


Figure 2: **AI Job Postings by Investment Advisers and Compustat Firms.**
This figure presents the annual percentages of AI-related jobs among total job postings by each of three groups of firms: registered investment advisers, financial industry firms in Compustat, and non-financial firms in Compustat.

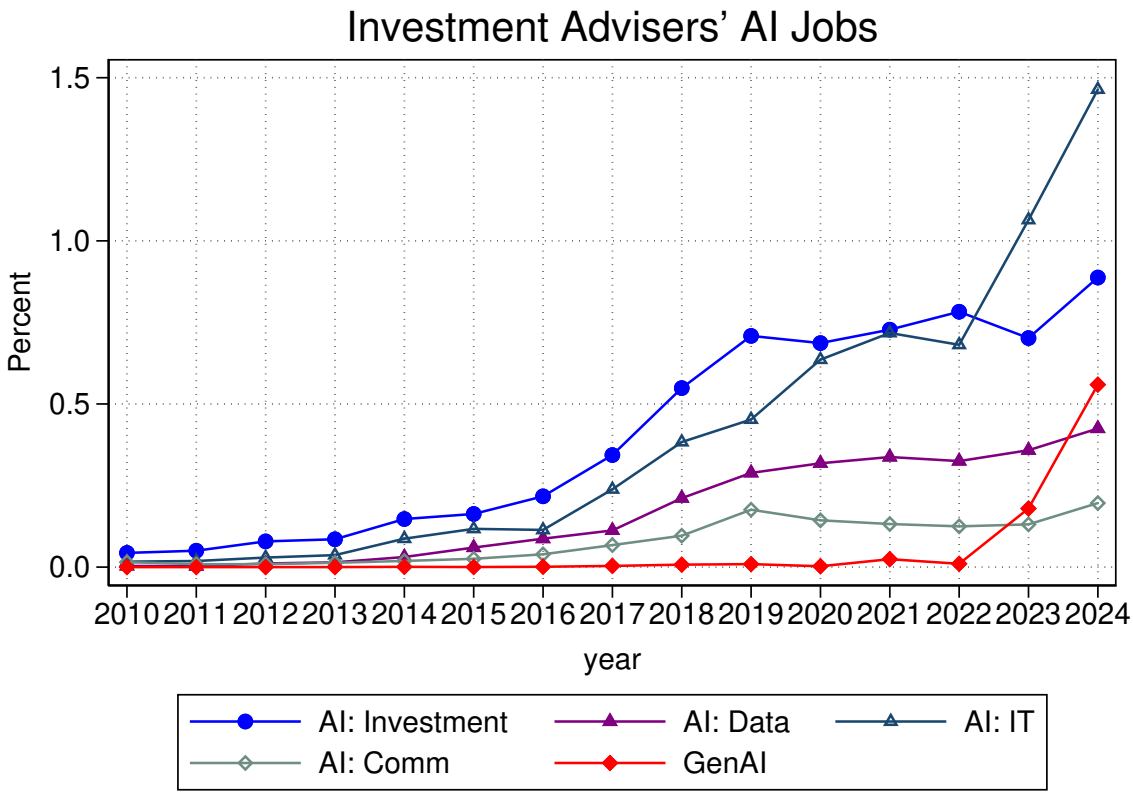


Figure 3: **Investment Advisers' AI Jobs for Specific Roles and Generative AI.** This figure presents annual percentages of AI-related job postings for specific roles and generative AI among total job postings by registered investment advisers.

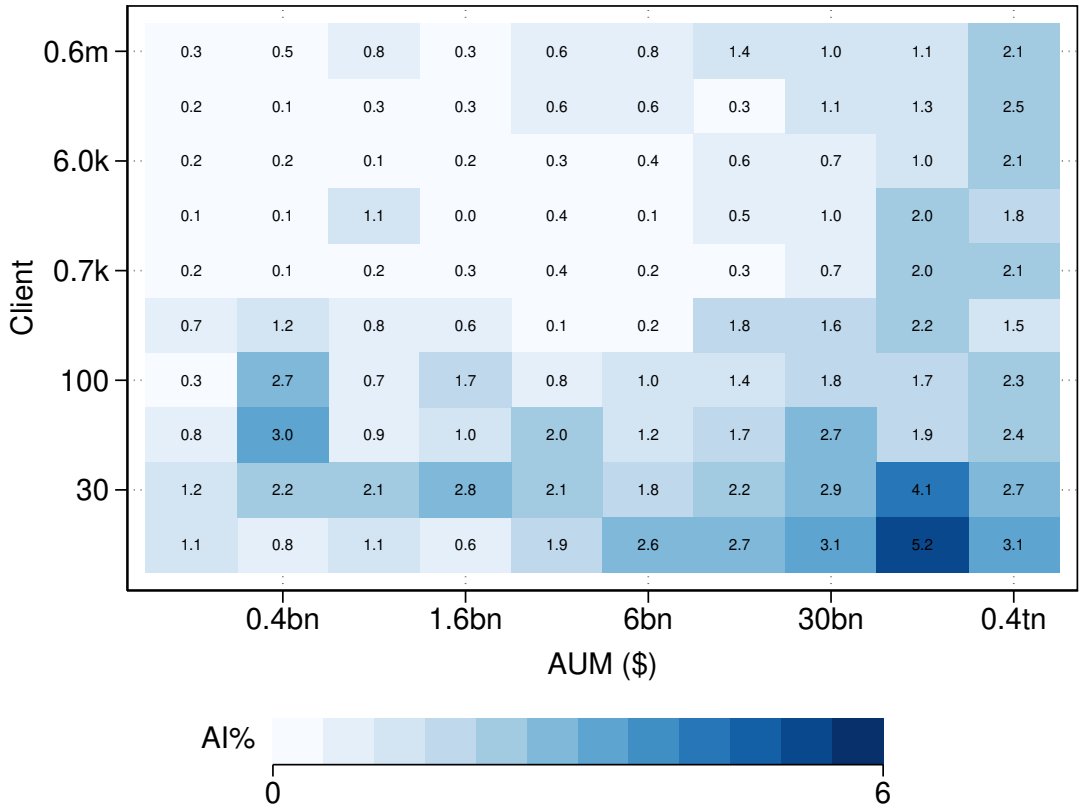


Figure 4: **Investment Adviser's AUM, Number of Clients, and AI Investment.** This figure presents the relationship between an investment adviser's current total AUM, the current total number of clients, and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. In each year, 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.

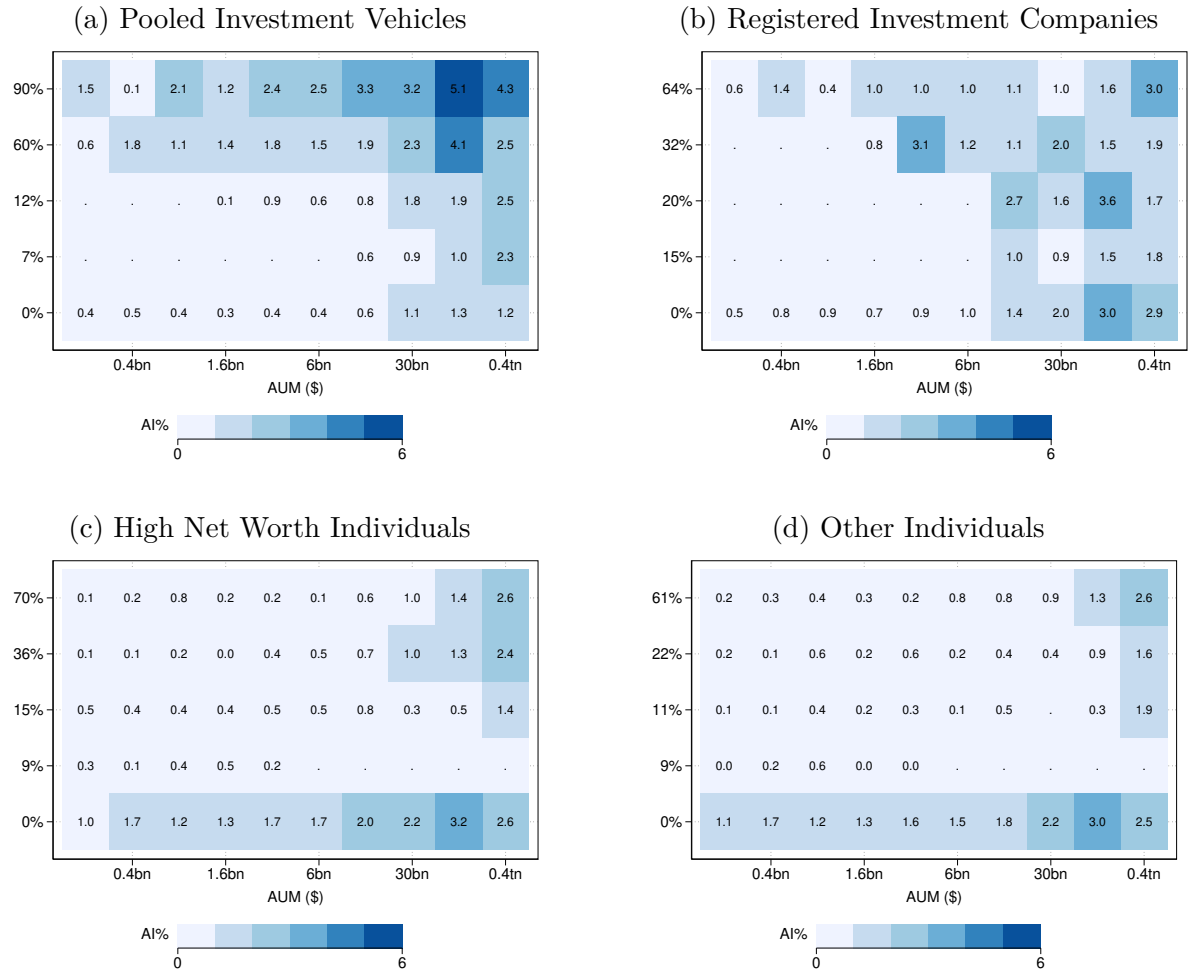


Figure 5: **Investment Adviser's AUM Composition and AI Investment.**
This figure presents the relationship between the composition of an investment adviser's current AUM and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels (a)-(d) focus on the fraction of AUM in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

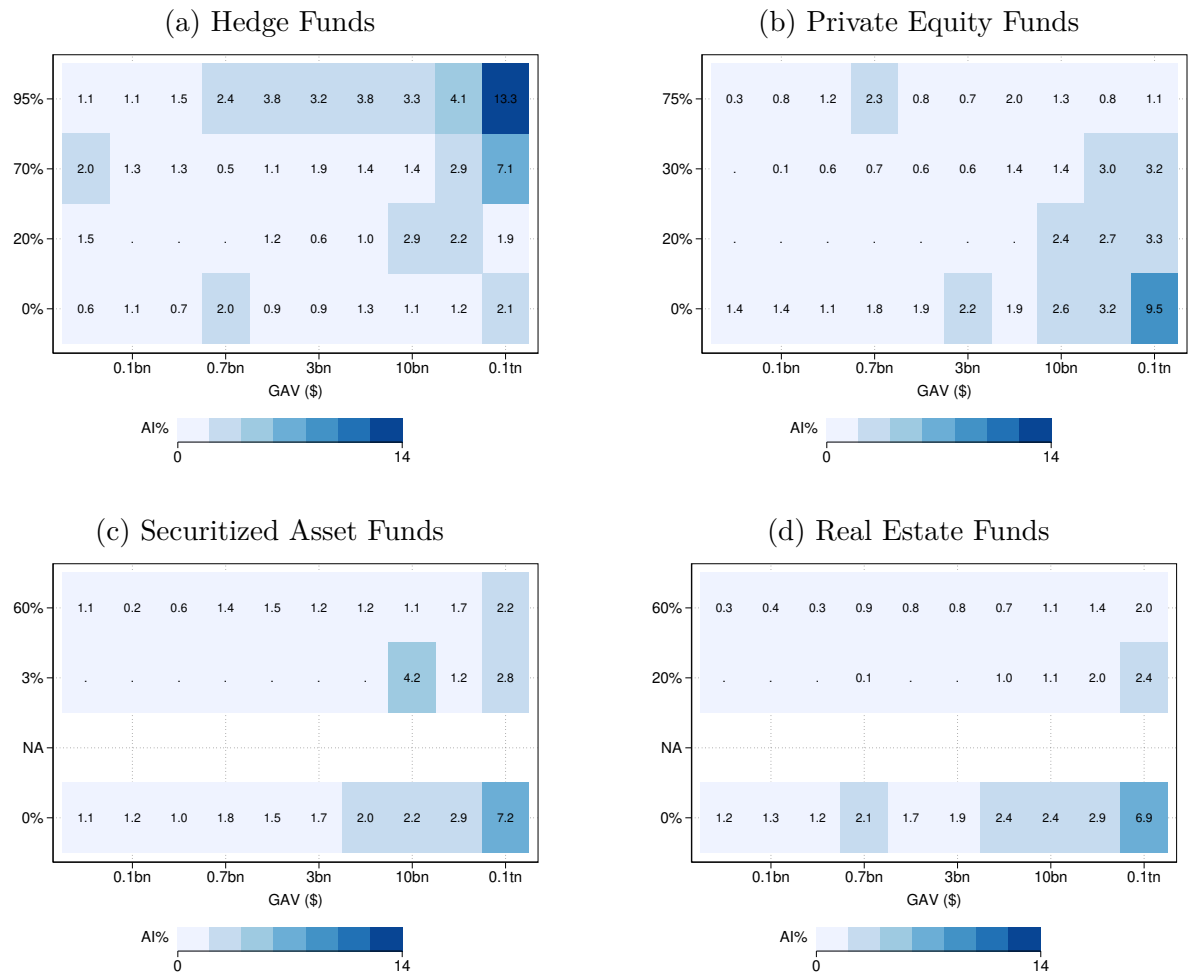


Figure 6: **Investment Adviser's Private Funds Composition and AI Investment.** This figure presents the relationship between the composition of an investment adviser's current private fund gross asset value (GAV) and the percentage of AI-related jobs among its jobs posted (AI%) in the next year. Panels (a)-(d) focus on the fraction of GAV in the four largest groups of private funds: hedge funds, private equity funds, securitized asset funds, and real estate funds, respectively. In each year, advisers are grouped into 10×4 bins sequentially by total GAV and by the percentage of GAV in a private fund group. The average AI% across adviser-year observations within a bin is reported in the figure. Labels in horizontal axes indicate the approximate average GAV in each of the ten GAV group bin, and labels in vertical axes indicate the approximate average percentage of GAV in each of the four fund group bin.

Table 1: **Summary Statistics**

This table presents summary statistics for our main sample, with each observation representing an investment adviser-year from 2012 to 2023.

	N	mean	sd	p25	p50	p75
AI(%)	6,929	1.1	3.9	0.0	0.0	0.6
AUM and Clients						
AUM ($bn)	6,929	65.0	257.2	1.0	5.4	36.9
AUM% PooledInvt	6,929	27.2	38.4	0	1	63
AUM% InvtComp	6,929	16.1	30.8	0	0	13
AUM% HighNetWorth	6,929	18.2	27.5	0	0	28
AUM% Individual	6,929	16.2	27.1	0	0	17
Client	6,929	33,023	321,838	26	221	2,312
Client% PooledInvt	6,929	25.2	37.9	0	0	42
Client% InvtComp	6,929	10.4	26.0	0	0	5
Client% HighNetWorth	6,929	13.4	22.4	0	1	18
Client% Individual	6,929	28.1	36.0	0	0	63
Employees						
Employee	6,929	501	1,842	25	91	300
Employee% Investment	6,929	53.0	28.0	33	50	75
Employee% IAR	6,929	25.1	33.3	0	2	50
Employee% Insurer	6,929	12.9	26.4	0	0	4
Employee% BDealer	6,929	27.5	34.2	0	10	49
Advisory Services and Other Business						
Service: PooledInvt	6,929	0.3	0.5	0	0	1
Service: InvtComp	6,929	0.6	0.5	0	1	1
Service: Retail	6,929	0.5	0.5	0	0	1
Service: OtherRIA	6,929	0.3	0.5	0	0	1
Service: Planning	6,929	0.3	0.5	0	0	1
Business: Commodity	6,929	0.1	0.2	0	0	0
Business: Swap	6,929	0.0	0.2	0	0	0
Business: Bank	6,929	0.0	0.2	0	0	0
Business: BDealer	6,929	0.0	0.1	0	0	0
Business: RealEstate	6,929	0.1	0.3	0	0	0
Business: Insurer	6,929	0.0	0.2	0	0	0
Business: Sales	6,929	6.9	24.5	0	0	2
Private Funds						
Advise PrivFund	6,929	0.5	0.5	0	1	1
GAV ($bn)	6,929	6.9	24.5	0	0	2
N PrivFund	6,929	12.9	38.2	0	0	7
GAV% HF	3,237	35.6	42.8	0	5	90
GAV% PEF	3,237	21.1	37.2	0	0	22
GAV% REF	3,237	12.6	31.2	0	0	0
GAV% SAF	3,237	7.3	22.4	0	0	0
GAV% VCF	3,237	1.1	9.4	0	0	0

Table 2: **Investment Adviser's Client Composition and AI Adoption**

This table reports results from regressing investment adviser's AI adoption in the next year on the composition of its AUM and clients in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: AI% next year

	AUM			Client		
	(1)	(2)	(3)	(4)	(5)	(6)
log(AUM)	0.198***	0.180***	0.184***	0.266***	0.204***	0.205***
	(0.032)	(0.032)	(0.037)	(0.036)	(0.033)	(0.045)
AUM% Discretionary		0.010***	0.006***			
		(0.002)	(0.001)			
AUM% PooledInvt			0.012***			
			(0.004)			
AUM% InvtComp			-0.005**			
			(0.002)			
AUM% HighNetWorth			-0.009***			
			(0.002)			
AUM% Individual			-0.001			
			(0.002)			
log(Client)				-0.178***	-0.111***	-0.069
				(0.033)	(0.026)	(0.042)
Client% nonUS					0.020***	0.014***
					(0.005)	(0.004)
Client% PooledInvt						0.011***
						(0.004)
Client% InvtComp						-0.002
						(0.002)
Client% HighNetWorth						-0.003
						(0.003)
Client% Individual						0.002
						(0.003)
Year FEs	Y	Y	Y	Y	Y	Y
N	6,929	6,929	6,929	6,878	6,878	6,878
R^2	0.025	0.030	0.058	0.042	0.056	0.063

Table 3: **Investment Advisory Services, Other Businesses, and AI Adoption**

This table reports results from regressing investment adviser's AI adoption in the next year on its services and businesses in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: AI% next year					
	(1)	(2)	(3)	(4)	(5)
Advise PrivFund	1.231***	1.047***			
	(0.182)	(0.186)			
log(AUM)		0.128***	0.184***	0.053	0.121***
		(0.032)	(0.042)	(0.040)	(0.041)
Service: PooledInvt			0.505***		0.223*
			(0.133)		(0.125)
Service: InvtComp			-0.446*		-0.719***
			(0.228)		(0.269)
Service: Retail			-0.789***		-0.694***
			(0.168)		(0.162)
Service: OtherRIA			-0.395***		-0.448***
			(0.142)		(0.146)
Service: Planning			-0.207		-0.065
			(0.146)		(0.146)
Business: Commodity				1.254***	1.111***
				(0.258)	(0.277)
Business: Swap				1.774***	1.560***
				(0.462)	(0.467)
Business: Bank				-0.159	-0.144
				(0.319)	(0.315)
Business: BDealer				-0.324*	-0.136
				(0.185)	(0.193)
Business: RealEstate				-0.520**	-0.749***
				(0.236)	(0.274)
Business: Insurer				-0.344***	0.033
				(0.079)	(0.087)
Business: Sales				-0.270**	-0.063
				(0.113)	(0.132)
Year FEs	Y	Y	Y	Y	Y
N	6,929	6,929	6,929	6,929	6,929
R^2	0.036	0.041	0.056	0.049	0.070

Table 4: **Investment Adviser's Private Funds Composition and AI Adoption**

This table reports results from regressing investment adviser's AI adoption in the next year on the composition of its private funds in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: AI% next year						
	All PrivFund			Excluding FOF		
	(1)	(2)	(3)	(4)	(5)	(6)
log(GAV)	0.288***	0.485***	0.404***	0.328***	0.463***	0.377***
	(0.071)	(0.112)	(0.098)	(0.080)	(0.116)	(0.101)
log(N PrivFund)		-0.481***	-0.376**		-0.360*	-0.247
		(0.171)	(0.160)		(0.187)	(0.179)
GAV% HF			0.018***			0.018***
			(0.006)			(0.006)
GAV% PEF			-0.003			-0.002
			(0.004)			(0.004)
GAV% REF			-0.009***			-0.010***
			(0.003)			(0.003)
GAV% SAF			-0.005			-0.006
			(0.004)			(0.004)
GAV% VCF			-0.008*			-0.004
			(0.004)			(0.005)
Year FEs	Y	Y	Y	Y	Y	Y
N	3,237	3,237	3,237	2,946	2,946	2,946
R^2	0.033	0.041	0.072	0.038	0.042	0.072

Table 5: **Investment Adviser's Employee Composition and AI Adoption**

This table reports results from regressing investment adviser's AI adoption in the next year on the composition of its employees in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: AI% next year				
	(1)	(2)	(3)	(4)
log(Employee)	0.155***	-0.021	0.168***	0.084
	(0.040)	(0.048)	(0.047)	(0.063)
log(AUM)		0.209***		0.089*
		(0.039)		(0.046)
Employee% Investment			0.002	0.001
			(0.003)	(0.003)
Employee% IAR			-0.013***	-0.013***
			(0.002)	(0.002)
Employee% Insurer			-0.007**	-0.004
			(0.003)	(0.003)
Employee% BDealer			-0.001	-0.001
			(0.002)	(0.002)
Year FEs	Y	Y	Y	Y
N	6,870	6,870	6,870	6,870
R^2	0.016	0.025	0.038	0.039

Table 6: **Private Funds Composition and Job Role-Specific AI Adoption**

This table reports results from regressing investment adviser's AI adoption by job roles in the next year on the composition of its private funds in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: AI% by Job Roles next year				
	Investment	IT	Data	Comm
	(1)	(2)	(3)	(4)
log(GAV)	0.179***	0.103***	0.024**	0.019**
	(0.049)	(0.038)	(0.010)	(0.009)
log(N PrivFund)	-0.233***	-0.028	-0.021	-0.018
	(0.077)	(0.047)	(0.016)	(0.015)
GAV% HF	0.011***	0.003	0.000	0.001
	(0.003)	(0.003)	(0.001)	(0.000)
GAV% PEF	-0.000	-0.003	-0.000	0.000
	(0.001)	(0.002)	(0.000)	(0.000)
GAV% VCF	-0.001	-0.005**	-0.001**	-0.000
	(0.002)	(0.002)	(0.001)	(0.000)
GAV% REF	-0.002*	-0.005***	-0.001	-0.000
	(0.001)	(0.002)	(0.000)	(0.000)
GAV% SAF	0.000	-0.004**	0.000	-0.000
	(0.002)	(0.002)	(0.001)	(0.000)
Year FEs	Y	Y	Y	Y
N	3,237	3,237	3,237	3,237
R^2	0.055	0.026	0.021	0.008

Table 7: **Effects of AI Adoption on Investment Adviser's Growth**

This table reports results from two-stage least squares regressions of annual changes in investment adviser's AUM, Clients, and Employees next year on its AI adoption in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Column (1) reports Kleibergen-Paap F statistic of weak identification test. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variables: Growth next year				
	First Stage	Second Stage		
	AI%	ΔAUM	ΔClient	ΔEmployee
	(1)	(2)	(3)	(4)
CZAI%	1.332***			
	(0.270)			
AI%		3.176***	2.295*	2.022***
		(1.163)	(1.219)	(0.685)
log(AUM)	0.123***	-3.570***	-2.374***	0.035
	(0.039)	(0.405)	(0.436)	(0.221)
log(Client)	-0.159***	0.634**	-0.305	0.444**
	(0.035)	(0.281)	(0.339)	(0.176)
log(Employee)	0.141**	1.816***	2.249***	-1.523***
	(0.064)	(0.492)	(0.533)	(0.296)
Year FEs	Y	Y	Y	Y
N	6,336	6,336	6,336	6,336
R^2	0.066			
F statistic	24.34			

Table 8: **Effects of AI Adoption on Adviser's AUM Composition**

This table reports results from two-stage least squares regressions of annual changes in investment adviser's composition of AUM next year on its AI adoption in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Column (1) reports Kleibergen-Paap F statistic of weak identification test. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variables: ΔAUM% next year

	First Stage	Second Stage			
	AI%	PooledInvt	InvtComp	HighNetWorth	Individual
	(1)	(2)	(3)	(4)	(5)
CZAI%	1.332***				
	(0.270)				
AI%		0.448*	-0.286*	-0.276	-0.190
		(0.261)	(0.149)	(0.171)	(0.181)
log(AUM)	0.123***	-0.188**	0.235***	-0.241***	-0.605***
	(0.039)	(0.074)	(0.081)	(0.047)	(0.090)
log(Client)	-0.159***	-0.386***	-0.089**	0.319***	0.459***
	(0.035)	(0.065)	(0.045)	(0.051)	(0.082)
log(Employee)	0.141**	0.332***	-0.090	-0.133	0.353***
	(0.064)	(0.094)	(0.079)	(0.086)	(0.109)
AUM% PooledInvt		-0.045***			
		(0.007)			
AUM% InvtComp			-0.029***		
			(0.006)		
AUM% HighNetWorth				-0.061***	
				(0.007)	
AUM% Individual					-0.121***
					(0.013)
Year FEs	Y	Y	Y	Y	Y
N	6,336	6,336	6,336	6,336	6,336
R^2	0.066				
F statistic	24.34				

Table 9: **Effects of AI Adoption on Adviser's Client Composition**

This table reports results from two-stage least squares regressions of annual changes in investment adviser's composition of clients next year on its AI adoption in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Column (1) reports Kleibergen-Paap F statistic of weak identification test. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variables: ΔClient% next year

	First Stage	Second Stage			
	AI%	PooledInvt	InvtComp	HighNetWorth	Individual
	(1)	(2)	(3)	(4)	(5)
CZAI%	1.332***				
	(0.270)				
AI%		0.526**	-0.219	0.088	-0.594**
		(0.232)	(0.164)	(0.159)	(0.284)
log(AUM)	0.123***	-0.043	0.132	-0.035	-0.680***
	(0.039)	(0.066)	(0.089)	(0.056)	(0.114)
log(Client)	-0.159***	-0.432***	-0.124**	0.232***	1.073***
	(0.035)	(0.062)	(0.052)	(0.046)	(0.147)
log(Employee)	0.141**	0.298***	-0.033	-0.284***	0.032
	(0.064)	(0.090)	(0.090)	(0.079)	(0.134)
Client% PooledInvt		-0.059***			
		(0.007)			
Client% InvtComp			-0.057***		
			(0.009)		
Client% HighNetWorth				-0.084***	
				(0.009)	
Client% Individual					-0.139***
					(0.012)
Year FEs	Y	Y	Y	Y	Y
N	6,336	6,336	6,336	6,336	6,336
R^2	0.066				
F statistic	24.34				

Table 10: **Effects of AI Adoption on Adviser's Employee Composition**

This table reports results from two-stage least squares regressions of annual changes in investment adviser's composition of employees next year on its AI adoption in the current year. Every observation is an adviser-year between 2012 and 2023 with at least $100 million of AUM and at least 5 job posts in the year. Column (1) reports Kleibergen-Paap F statistic of weak identification test. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variables: ΔEmployee% next year

	First Stage	Second Stage			
	AI%	Investment	IAR	Insurer	BDealer
	(1)	(2)	(3)	(4)	(5)
CZAI%	1.332***				
	(0.270)				
AI%		-0.411	-1.089***	-0.346***	-0.469**
		(0.326)	(0.344)	(0.132)	(0.201)
log(AUM)	0.123***	-0.306**	-1.002***	-0.268***	-0.427***
	(0.039)	(0.128)	(0.137)	(0.050)	(0.086)
log(Client)	-0.159***	-0.025	0.771***	0.094***	0.167***
	(0.035)	(0.101)	(0.118)	(0.033)	(0.060)
log(Employee)	0.141**	0.252	0.443**	0.443***	0.873***
	(0.064)	(0.182)	(0.183)	(0.083)	(0.139)
Employee% Investment		-0.143***			
		(0.009)			
Employee% IAR			-0.133***		
			(0.011)		
Employee% Insurance				-0.052***	
				(0.007)	
Employee% BrokerDealer					-0.071***
					(0.006)
Year FEs	Y	Y	Y	Y	Y
N	6,336	6,336	6,336	6,336	6,336
R^2	0.066				
F statistic	24.34				

Table 11: **Effects of AI Adoption on Adviser's Private Market Deals**

This table reports results from two-stage least squares regressions of investment adviser's private market deals next year on its AI adoption in the current year. Every observation is an adviser-year between 2012 and 2023 with at least 1 deal in Pitchbook and at least 5 job posts in the year. Column (1) reports Kleibergen-Paap F statistic of weak identification test. Standard errors, clustered at the adviser level, are reported in parentheses. *, **, *** represent 10%, 5%, and 1% levels of statistical significance.

Dependent Variable: Private Market Deals next year

	First Stage	Second Stage			
	AI%	N Deal	Deal Stage	Deal Size	Industry HHI
	(1)	(2)	(3)	(4)	(5)
CZAI%	1.908***				
	(0.547)				
AI%		0.246**	-0.094**	0.261	-0.080**
		(0.112)	(0.041)	(0.169)	(0.037)
Year FEs	Y	Y	Y	Y	Y
N	2,092	2,092	2,092	1,467	1,467
F statistics	12.16				

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Internet Appendix

"AI Across the Landscape of Asset Management"

IA.1. AI-related job examples

IA.1.1. 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.1.2. 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.1.3. 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.1.4. 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.2. AI Relevance Score of Skills in Job Postings

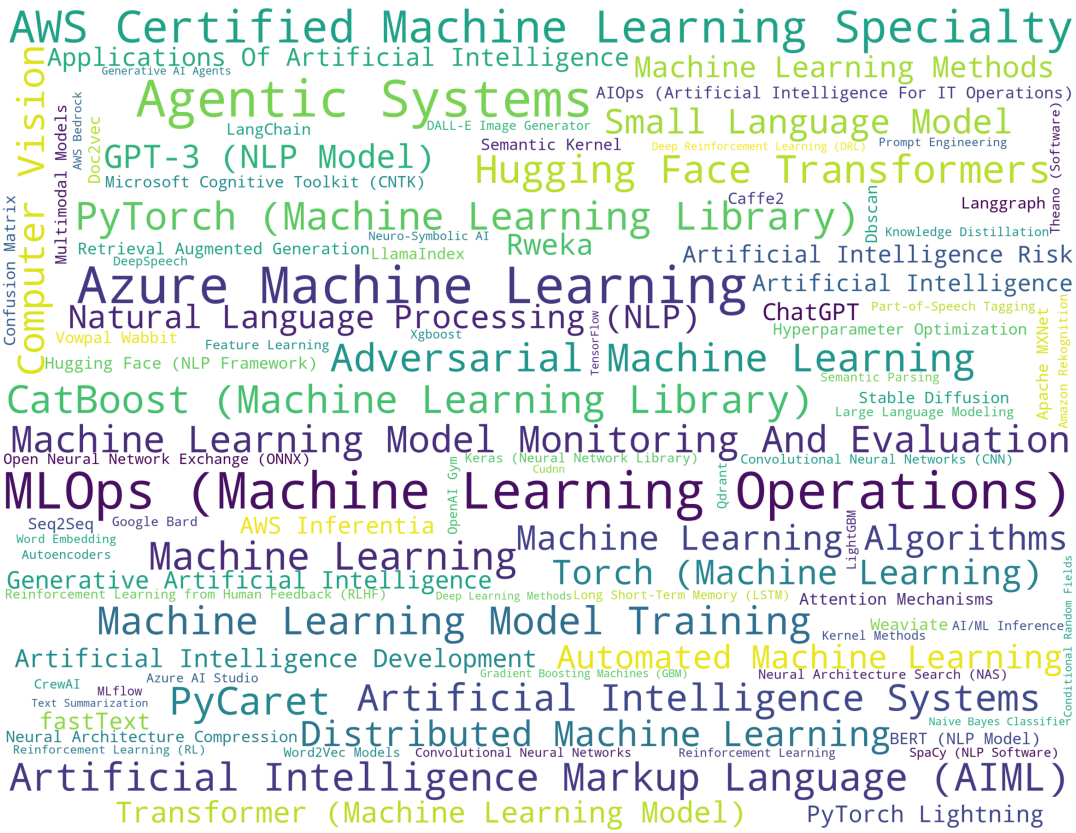


Figure IA.1: **Top 100 Skills with the Highest $w_s^{\mathbf{AI}}$.**
This figure shows the top 100 skills from job postings ranked by their AI relevance score, w_s^{AI}. The AI relevance score for a given skill (w_s^{AI}) measures how frequently this skill co-occurs with core AI skills. Specifically, 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.

IA.3. Supplementary Results

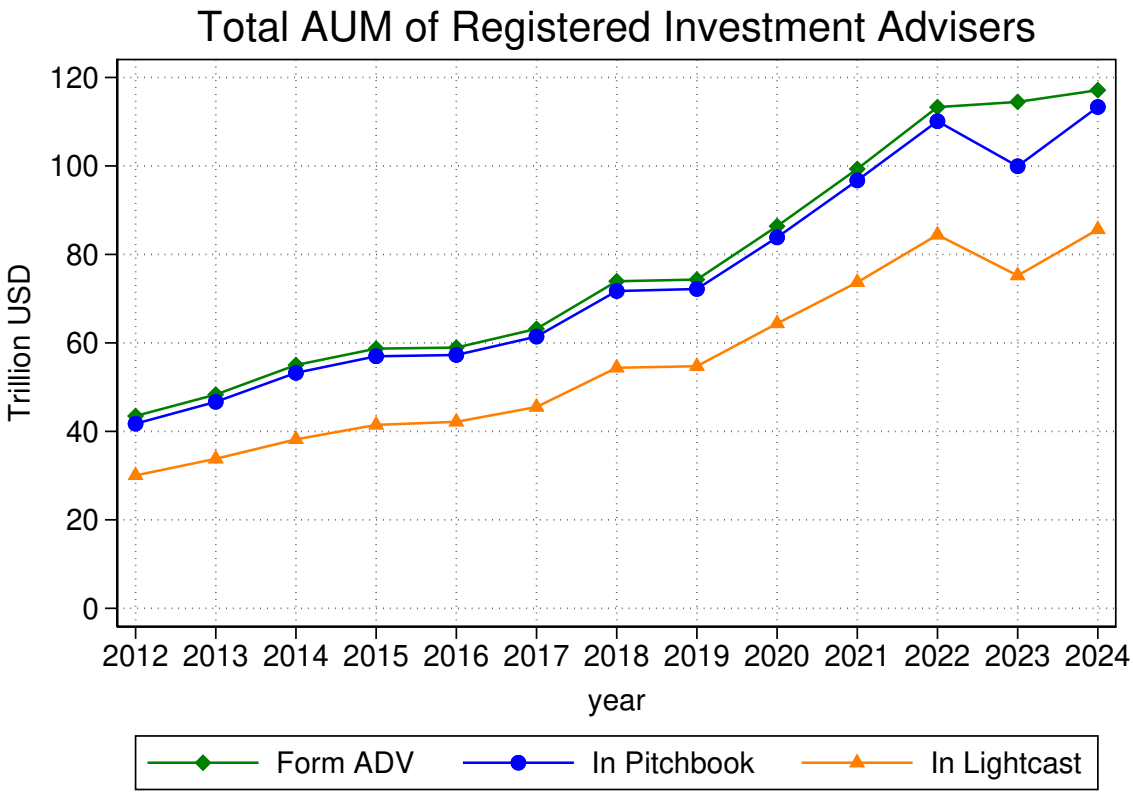


Figure IA.2: **Total AUM of Investment Advisers.**
This figure presents the total assets under management (AUM) of three sets of registered investment advisers. The green line indicates all investment advisers that file Form ADV. The blue line indicates the subset of investment advisers that are matched with companies in Pitchbook. The orange line indicates investment advisers matched to job postings in Lightcast.

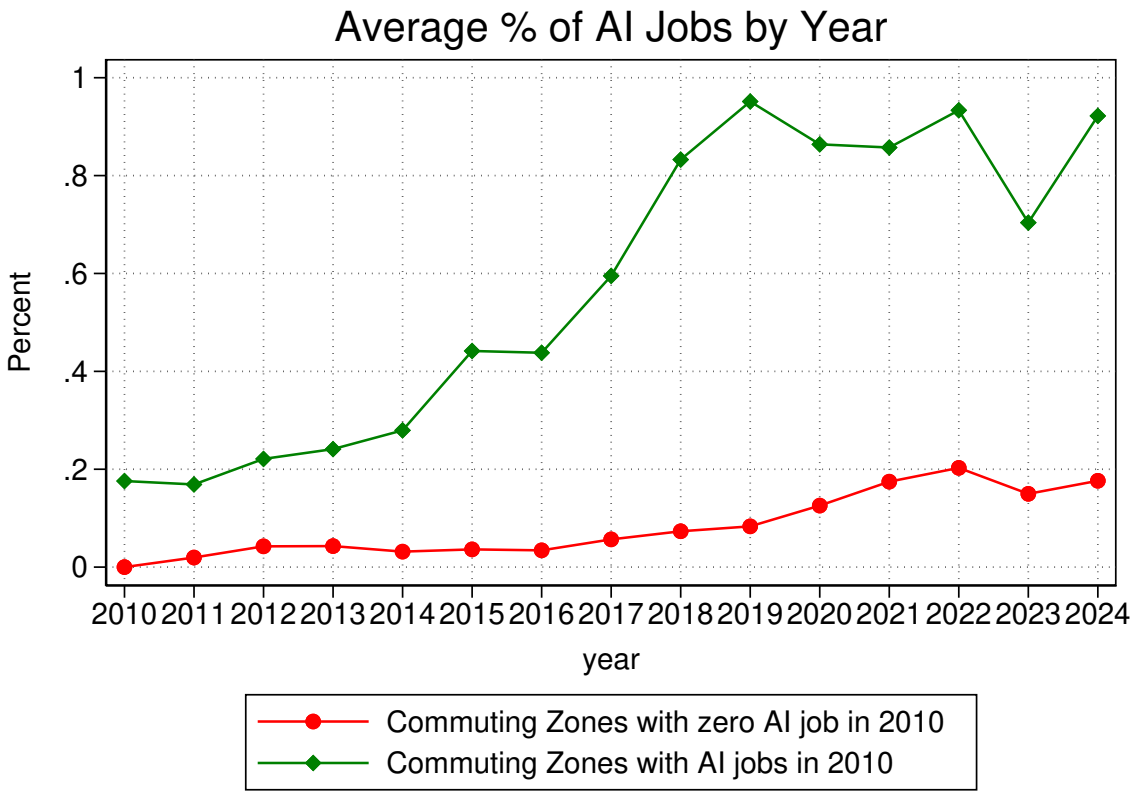


Figure IA.3: **US Commuting Zones With and Without AI Job Posts in 2010.** This figure presents the percentage of AI jobs among all jobs posted in a commuting zone-year. US commuting zones are divided into two groups based on whether there is any AI job(s) in 2010. There are 319 and 225 commuting zones in the two groups, respectively.

Table IA.1: **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.2: **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.2: 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