AI Automation and Effort Allocation: Evidence from Sophisticated Investors

ABSTRACT

Sophisticated investors exert more effort at human-intensive tasks in the age of AI. I hypothesize that AI reduces costs of collecting machine-based information, thereby facilitating the acquisition of human-interaction-based information. Using a stacked difference-in-differences analysis, I find that hedge funds increase earnings call participation—at both the extensive and intensive margins—after adopting machine downloads of SEC filings. Post-automation call attendance is associated with higher fund returns and profitable stock trades. Overall, this study identifies a novel mechanism for productivity effects of AI: by *substituting* for human effort on automation-prone tasks, AI *complements* high-skilled workers without directly augmenting interaction-based tasks.

JEL Classification: J24, G12, G14, G23

Keywords: Artificial Intelligence; Automation; Effort Allocation; Hedge Funds; Information Acquisition; EDGAR Filings; Earnings Conference Calls; Corporate Analyst Meetings; Investment Performance; Labor and Finance; Complement via Substitution

Technological advances in automation are reshaping the distribution of human effort across job tasks. The rapid rise of artificial intelligence (AI) and robotics has sparked debate over whether these automation technologies substitute for or complement labor (e.g., Acemoglu and Autor, 2011; Autor, 2015; Acemoglu and Restrepo, 2018a, 2018b, 2019, 2021). In this knowledge economy where big data, information technologies, and labor increasingly interact (Ide and Talamas 2025; Abis and Veldkamp 2024), it is well recognized that high-skilled knowledge workers in the upper tail of the human effort distribution should be less negatively affected by AI disruption due to humans' comparative advantages over machine.[1] However, it remains underexplored how AI can help humans better exploit the uniqueness of their own intelligence.[2] This study sheds light on how AI enhances high-skilled labor by alleviating the need to rely on human effort for easy-to-automate tasks (such as downloading and processing machine-based information), thereby leading to more productive use of human intelligence in difficult-to-automate activities (such as real-time interpersonal interactions in information gathering).

The delegated asset management industry epitomizes the knowledge economy, relying heavily on vast amounts and various types of data, AI technologies, and skilled human capital (e.g., portfolio managers, investment analysts). Prior work shows the relevance of big data and generative AI for this industry.[3] Relatively little is known about the distinct role of human effort in acquiring information and performance implications of such effort allocation in the age of AI. This paper fills the gap by documenting a change in asset managers' information acquisition behavior following the adoption of AI automation and relating this change to trading behavior and investment performance.

The hedge fund industry offers an ideal setting. As high-powered information intermediaries and sophisticated investors, hedge funds acquire both non-interaction-based information (e.g., regulatory filings) and human-interaction-based information (e.g., Q&A during earnings calls).

[1] For example, Cao, Jiang, Wang, and Yang (2024) find that a human analyst outperforms machine-algorithm-based stock analysis when institutional knowledge like intangible assets and financial distress is involved. They also envision a future with human-machine collaboration in stock analyses based on skill complementarities. However, there is no evidence on how AI changes the use of human intelligence across different tasks or improves human task performance.
[2] Acemoglu and Restrepo (2019) argue that new automation technologies augment human labor by introducing new tasks that better exploit human advantage, counterbalancing labor displacement effects. This paper demonstrates a new mechanism of effort allocation over existing tasks to understand sources of productivity gains from AI automation.
[3] See, for example, Bonelli and Foucault (2025) for evidence on how the use of big/alternative data by active mutual funds changes the value of traditional discretionary expertise and relates to investment performance. See also Sheng, Sun, Yang, and Zhang (2025), who study hedge funds' reliance on ChatGPT-produced information and its implications for portfolio decisions and performance.

The former is standardized and quantifiable, thus prone to automation; the latter is interactive and real-time, thus unique to human processing. With AI reducing the cost of acquiring and processing public filings, funds should reallocate effort toward interaction-intensive activities that AI cannot easily displace. The central message of this paper is that artificial intelligence redirects human intelligence toward human-intensive tasks. Specifically, I hypothesize that AI automation leads hedge funds to make greater use of earnings calls and that the increased earnings call participation translates into better investment performance.

The first empirical challenge is to identify AI automation adoption events that are plausibly exogenous to both hedge funds' information demand and call-hosting firms' information supply. I locate hedge funds' IP addresses in SEC EDGAR (Electronic Data Gathering, Analysis, and Retrieval) Log File data and use the first machine downloading event to isolate staggered AI technological supply shocks.[4] Machine downloads of SEC filings are a relevant proxy for identifying automation-adopting hedge funds because i) they indicate automated retrieval of firms' fundamental data from other sources (e.g., corporate websites and third-party data vendors) or of other types of non-interaction-based information (e.g., satellite imagery, twitter data, air traffic data), ii) they are likely followed by automated processing because of the sheer volume of data. For the same reasons, machine downloads of SEC filings also serve as a proxy with a measurement error that understates the automation adoption intensity, producing an attenuation bias against finding a participation-automation relation. Additionally, relying on SEC footprint only to capture AI technology supply shocks could misclassify some automation-treated funds into the control group.[5] In this case, the estimated treatment effect establishes a lower bound of the true effect.

To study how AI reshapes information acquisition, I construct a comprehensive dataset linking two major data sources: SEC EDGAR search traffic data and earnings conference call transcripts. Prior work on hedge funds' public information acquisition has examined SEC downloading (Crane et al., 2022), earnings call participation (Call et al., 2016), or both without linking them by the same hedge funds (Chen et al., 2020).[6] To my knowledge, this paper is the first to intersect these

[4] I describe how I classify a downloading log entry as a machine-downloading event in the data section (3.2).

[5] In particular, I do not observe any outside-SEC automated information acquisition events that occur earlier than the first-time machine downloads of SEC filings. Any funds that have adopted automation—once included in the control group—will reduce the treatment effect.

[6] In addition to having distinct research focuses, the earnings call transcript data in this paper have a broader coverage in terms of both hosting firms and time periods than that in Call et al. 2016 and Chen et al. 2020. See further details in data section (3.2).

two major datasets on hedge fund appearances to trace the shifts between two types of information—human-interaction-based and non-interaction-based—acquisition activities in response to AI technologies. I focus on traditional, discretionary hedge funds whose expertise rests on fundamental analysis, industry knowledge, and interpersonal interactions. When AI lowers the labor cost of accessing and processing corporate filings, these managers can redirect attention to extracting value-relevant insights from conference interactions with corporate management.

Employing the aforementioned staggered implementation of AI automation under a stacked difference-in-differences design (see, e.g., Cengiz, Dube, Lindner, and Zipperer (2019) and Baker, Larcker, and Wang (2022)), I study the participation effects and performance implications of AI automation adoption by hedge funds in a causal framework. My empirical analysis yields three main sets of results. First, I find that following the adoption of AI automation, hedge funds increase their earnings call participation at both extensive and intensive margins: adopter funds show up in more earnings calls and more call-hosting companies than non-adopters; conditional on participation, they also ask more questions and speak more words during an average call. All the results support the hypothesis that AI automation induces a shift of effort toward human-interaction-based information acquisition. Since AI automation results in more efficient acquisition of non-interaction-based information, the positive participation effect also suggests complementarity between the two types of information—with or without human interactions.

Second, conditional on the adoption of AI automation, funds with greater earnings call participation earn higher returns (both raw returns and abnormal returns), consistent with AI leading to more productive use of human-interaction-based information. Based on a long-short portfolio strategy that buys purchased stocks that are covered in both hedge funds' machine downloads and post-automation earnings call participation and sells sold stocks affected in the same manner, I find that automation-adopting hedge funds (AHFs) earn superior returns from post-call trading of the covered stocks, implying that AHFs elicit more value-relevant information from earnings calls compared to non-adopters. To account for the unobserved heterogeneity in funds' investment ability and time trends that affect both managers' trading decisions and the cross-section of returns, I further use regression analysis to examine the impact of post-automation earnings call participation on trade-adjusted stock performance. I find that funds with greater earnings call participation execute more profitable trades after adopting AI automation, meaning that stock returns evolve in the direction that is favorable to their trading decisions over stocks of the conference-hosting firm post-automation.

Third, both participation effects and performance implications exhibit cross-sectional heterogeneity. In particular, I find that with the advent of AI automation technologies, large funds, old funds, and low-turnover funds all show stronger participation intensity in subsequent earnings calls post-automation. Specifically, my findings first suggest that size still matters—larger funds are more responsive to the alleviation of human effort constraint due in large part to their greater capabilities to redeploy human capital for both automation adoption and earnings call participation compared to small fund firms. In addition to redeployment ability, the diseconomies of scale facing large funds also incentivize them to seek more informational advantages from human-interaction-based activities that small funds may be too constrained to engage in. In terms of older funds, their lower information acquisition cost (due to longer track record or longer relationship with investee companies) and lower career concerns arguably make it easier for them to exert more effort in attending earnings calls after taking up automation. This is indeed what I find in the data. When sorting on portfolio turnover, my results reveal an interesting and intuitive twist: the unconditional effect of portfolio turnover is positive, consistent with more active funds rely more on information acquisition to inform their frequent portfolio adjustment decisions; but the positive conditioning effect comes from funds with low portfolio turnover, plausibly because high-turnover funds are more likely to pursue high-frequency investment strategies for which earnings call participation is unnecessary. In terms of trade performance for stocks covered by automated downloading and earnings call participation, I find that the long-short-portfolio strategy built on hard-to-research stocks delivers higher risk-adjusted returns relative to easy-to-research stocks, consistent with funds earning greater informational rent from informationally-opaque stocks, which are identified following Cao, Gao, and Guo (2025).

This study contributes to several strands of literature. The first strand of literature this paper contributes is on the dynamics between human labor and automation technologies like AI and robotics. It is hotly debated whether new technology displaces or augments labor. For example, Acemoglu and Restrepo (2018b) (Acemoglu and Restrepo 2021) explore how AI (industrial robots) affects labor market outcomes by assuming tasks previously performed by human labor. Other work in the labor economics literature by Webb (2020) and Autor et al. (2024) examines patent data and look for text that indicates worker task automation and augmentation, respectively. The research debate over the Man versus Machine race pays more attention to either the substitutive role or complementary role of AI. This paper uncovers a previously undocumented channel for the complementary aspect of the man-machine relation: AI leads to more productive uses of human intelligence by reducing manual labor exhaustion from repetitive and quantitative tasks.

There is also related literature that explores a similar subject in the financial industry. Cao, Jiang, Wang, and Yang (2024) compare the performance of an AI stock analyst and a human analyst and envisions a future with human-machine collaboration in stock analyses based on skill complementarities. However, there is no evidence on optimized use of human intelligence or improved human task performance due to the presence of AI. Jansen, Nguyen, and Shams (2025) find that automated underwriting outperform human underwriting in loan analysis, plausibly due to the presence of agency conflicts and limited capacity for human analyses.[7] This paper differs from those studies in that I go beyond the conventional substitution-or-complement argument and focus on a new channel of complement-via-substitution, in the sense that AI allows human labor to be more optimally deployed in human-interaction-based tasks that cannot rely on machines to complete. I find that AI automation redirects sophisticated investors' human intelligence to earnings call participation, which in turn translates to better portfolio holding returns.

A nascent but growing literature studies the impact of big data and AI on the skill and performance of professional investment managers. Sheng, Sun, Yang, and Zhang (2025) study the adoption of generative AI by hedge funds and the portfolio performance impact. Their study is based on the hypothesis that ChatGPT is leveraged to analyze earnings conference call texts to enhance their investment decisions. The main hypothesis in my paper is different in the sense that I focus on potentially more productive uses of human intelligence in real-time earnings call participation when AI is available for processing non-interaction-based information, while Sheng et al. (2025) highlight the power of AI in extracting useful information from earnings call transcripts, which would be treated as non-interaction-based information in my study.[8] Crane, Krotty, and Umar (2022) study how hedge funds' public information acquisition via SEC filings is related to both fund-level and stock-level performance. Bonelli and Foucault (2025) study

[7] Various other studies indicate the substitution effect between technology and human labor and an incomplete list includes Ma, Ouimet and Simintzi (2025), Abis and Veldkamp (2024), and Greig et al. (2024).

[8] As described in the former part of introduction, I exclude hedge funds that never participate in an earnings call throughout the sample period. To the extent that these funds are more likely to working on earnings call transcripts that requires machine intelligence, my study and Sheng et al. (2025) complement each other in documenting different channels through which AI technologies benefit sophisticated investors.

whether the use of alternative data devalues traditional fund managers' expertise in the mutual fund industry. Abis (2022) compares how different investment strategies (quantitative versus discretionary) affect mutual fund performance. Zhang (2024) studies how AI labor recruitment affects mutual fund performance. Lyonnet and Stern (2022) and Bonelli (2023) study venture capital investment in the age of AI. Unlike these studies, my paper features the unique role of human intelligence in sophisticated investors' information acquisition and how it further contributes to fund performance when the power of human intelligence can be unleashed from tasks that are displaced by AI.

In addition, this paper also adds to studies of information economics in the financial industry, especially from the information intermediaries' perspectives. Chen, Kelly, and Wu (2020) suggest a substitution effect between sophisticated investors (hedge funds) and public information providers in facilitating market efficiency. Bai and Massa (2025) find that the loss of human-interaction-based informational advantages due to covid lockdown compels mutual fund managers to switch to non-interaction-based information. Cao et al. (2023) find that the adoption of automation by institutional investors in general leads to more human downloads of historical filings, implying the increased need for contextual information and deepening research.[9] Other work also explores how sell-side or buy-side analysts in general acquire information from sources like SEC EDGAR (Gibbons and Iliev, 2021), earnings conference calls (Jung et al., 2018), and financial press (Bradshaw et al., 2020). I make at least two distinctions between this study and the aforementioned line of inquiries. First, this paper is the first study that examines changes in sophisticated investors' information acquisition behavior in response to AI technologies. Second, this paper reveals a novel insight that AI automation raises the degree of complementarity between human-interaction-based information and non-interaction-based information.[10] More human-interaction-based information is produced following the AI-expedited availability of non-interaction-based information.

The rest of the paper is structured as follows: Section II outlines the development of my hypotheses; Section III describes the details of data sources, sample construction, and presents

[9] Cao et al. (2023) examine earnings call participation by institutional investor as a whole and do not find an unconditional increase in participation. Additionally, the authors do not investigate the investment performance implications of changes in institutional investors' acquisition behavior.
[10] The reasoning behind this statement is laid out in the Hypothesis Development Section.

summary statistics; Section IV presents and discusses empirical findings in relation to my hypotheses as well as robustness tests. Section V concludes the study.

I. Hypothesis Development

Information plays a crucial part in capital allocation and is at the heart of delegated asset management. Sophisticated investors extract economic rents by incurring information acquisition costs and obtaining informational advantages relative to other traders in the market (Grossman and Stiglitz, 1980). How institutional investors produce or acquire information not only affects their own trade profitability but also influences firm-level decisions through the feedback effect. With AI technologies automating the assembling of information that is applicable to machine algorithms, it is natural to ask whether AI automation will augment high-skilled labor by redirecting human intelligence to information acquisition that is not displaced by AI.

This question is not obvious to answer due partly to the entangled relation between two types of information acquisition activities. Put differently, the relation between human-interactions-based information and non-interaction-based information may be complementary or substitutive. On the one hand, collecting human-interactions-based information usually requires getting prepared with non-interaction-based information.[11] The timing nature of these two different types of information acquisition naturally indicates complementarity. On the other hand, due to limited human information processing capacity, the two types of information acquisition also compete for human effort, thus leading to a potential substitution effect. The complementarity will rise when the effort competition mechanism is less dominating. This is likely the case considering AI relieves the burden of collecting (including accessing and processing) non-interaction-based information, thus freeing up human effort for information acquisition activities that entail human interactions. I hypothesize that AI will optimize human effort allocation by substituting in for humans on automation-prone tasks and freeing up more effort for human-interaction-intensive tasks.

It is important to understand hedge funds' information acquisition behavior in the age of AI for at least three reasons. First, institutional investors have grown into the major stock market player over the last few decades (French, 2008; Lewellen, 2011). Hedge funds, referred to as

[11] AI is hardly a perfect substitute for human intelligence for complex value-relevant human interacting processes. The hard-to-displace and human-interaction-based information acquisition is usually preceded by collecting various non-interaction-based information, which helps to inform further decision making of where to initiate human interactions and to increase the effectiveness of eliciting information during human interactions.

"prototypical sophisticated investors" in Stein (2009), have high-power incentives to constantly expand the information set and increase information precision to maximize their portfolio returns. Aggressive portfolio trading activities further distinguish hedge funds from other information intermediaries like mutual funds, sell-side analysts, broker-dealers, and media. How hedge funds acquire information and incorporate information into their trades is crucial for examining their investment behavior and portfolio performance. Second, the adoption of AI expands the information set and increases the information-processing capacity for hedge funds but potentially at the cost of information precision. For example, the sheer volume of machine downloaded SEC filings implies that subsequent machine processing of those files will be adopted. Machine reading is more error prone than human reading. The need for hedge funds to manually verify some processed information may offset the time freed up from AI automation, thus preventing hedge funds from further incurring the cost of effort to collect information by attending earnings calls. Ex ante, it is not clear whether I will observe the reshaping effect of AI on hedge fund information acquisition activities. Third, hedge funds' active information production also facilitates market efficiency (Chen, Kelly, and Wu, 2020). Accordingly, it is particularly important to study whether AI reshapes information acquisition by hedge funds given their potential implications for market-wide information environment.

I also propose several channels that could be operating behind both the link between the introduction of AI automation technologies and human-interaction-based information acquisition and the link between post-automation earnings call participation and investment performance.[12] The rationale for the automation-participation relation to be mediated by fund firm size is twofold. On the one hand, large fund firms are equipped with better resources and thus are more flexible in adopting new technologies and redeploying human capital away from machine-susceptible tasks to human-interaction-based tasks.[13] On the other hand, large funds are also incentivized to gain an informational edge to offset performance dampening effect from diseconomies of scale. As such, they are likely to seize the automation-induced opportunity to collect more human-interaction-based information that could be relatively costly for small funds. Compared to young funds, old funds have longer track records and relationships with investee firms so that their information

[12] These economic channels are also partly motivated by the empirical facts in my main results contained in table 4.
[13] Despite the fact that the labor scarcity facing small hedge fund companies may create higher levels of incentives for adopting technologies to save labor cost, they are less able to fully embrace the automation technologies due to both labor and capital constraints.

acquisition cost is lower. Managers at older funds are also less likely to be plagued by career concerns that could reduce their activeness in adjusting their effort allocation. Lastly, for funds that rely more on fundamental research and human-interaction-based information acquisition, more frequent portfolio trading activities generate greater information demand and thus lead to higher sensitivity to the automation-induced effort allocation channel. In the cross-section of hedge fund firms, high-turnover funds are more likely to adopt a high-frequency investment approach and shy away from attending earnings calls.[14] Accordingly, conditioning on low portfolio turnover is more likely to identify the treatment effect for fundamental-oriented discretionary managers vis-à-vis non-fundamental groups that make little or no use of earnings calls. Turning to the performance effect, as hard-to-research stocks proxy for higher information costs and thus greater informational advantage for funds that hold them, I expect stock trade performance to be stronger when a long-short strategy is constructed using these stocks.

Based on the institutional background and the rationale set forth above, I formulate two main (alternative) hypotheses with the null hypothesis being that AI automation has no impact on hedge fund information acquisition behavior and investment performance. I also formulate sub-hypotheses under each main hypothesis to test for cross-sectional heterogeneity.

Hypothesis 1 *(Participation hypothesis): Hedge funds engage more in earnings conference calls following the adoption of AI automation, consistent with human effort being shifted toward tasks that require human interactions from ones that do not.*

H1a*: The automation-participation relation is stronger for the group of large funds, old funds, and low-portfolio-turnover funds.*

Hypothesis 2 *(Performance hypothesis): Post-automation earnings call attendance is associated with better investment performance, consistent with human effort being optimized and more valuable information being elicited and assimilated during interactions with firm managers.*

H2a*: Hedge funds, as automation adopters and subsequent earnings call participants, earn higher abnormal returns in hard-to-research stocks.*

[14] Although I require that all funds attend at least one earnings call during the sample period, this does not ensure that all sample funds are fundamental-investing-oriented throughout. Section C.2 presents additional tests related to this.

II. Data sources, Sample Construction, and Summary Statistics

I construct my sample by compiling and merging several data sets. Main data sources include (1) earnings conference call transcripts from LSEG (London Stock Exchange Group) workspace; (2) Classification of hedge funds from proprietary 13-F institution taxonomy data[15] and form ADV filings; (3) SEC filing retrieval footprint from the SEC's EDGAR Server Log File (or SEC EDGAR internet search traffic data); (4) IP registrar from Networksdb.io and American Registry for Internet Numbers (ARIN) WHOIS and WHOWAS database; (5) hedge funds' characteristics and portfolio holdings from LSEG (formerly Thomson Reuters) 13-F filings; (6) stock returns and characteristics from CRSP, Compustat, Russell 2000 index membership, and I/B/E/S.

A. Identifying hedge funds' earnings call participation

I manually collect 130,699 transcripts of earnings-related conference calls—both earnings conference calls and earnings guidance calls (hereafter, earnings calls or virtual conference calls) [16]—from LSEG workspace.[17] In addition to these virtual conference calls, I also collect 3,145 in-person conference calls—annual or bi-annual corporate analyst meetings, also known as analyst/investor days—which has a different focus on a broader range of issues and most importantly, enables face-to-face interactions both in public and in private between investors and corporate management.[18]

The virtual (in-person) conference calls cover the universe of 5,212 (1,165) US firms spanning from 2006 to 2017. I identify hedge funds' appearances in earnings call transcripts in two steps[19]: (1) I use a python script to extract participating analyst information (names and affiliations) from transcript data (.txt files) along with other firm-level and call-level identifiers (e.g., firm names, tickers, timestamp). In this step, I carefully fix missing institution names from either the conference participant list or the entire transcript and rely on extensive internet searches of analyst names (e.g., LinkedIn, Marketscreener, RocketReach, ZoomInfo, firms' official website, and media mentions) to complement the affiliation information; (2) I perform firm-name matching for conference transcript data and 13F institution type classification data compiled by a commercial

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[15] I thank Rick Sias for providing access to 13-F institution taxonomy data sourced from Thomson Reuters.

[16] Firms use earnings guidance calls—either separately or jointly with earnings calls—as bundled financial disclosures in conjuction with earnings releases to comply with Reg FD, as pointed out in Rogers and van Buskrik 2013.

[17] At the time of writing the current draft (August 2025), no API is available for downloading this data.

[18] See the internet appendix for reasons why corporate analyst meetings serve as a viable measure for in-person human-interaction-based information acquisition.

[19] As laid out in the internet appendix, same procedures apply to identifying hedge funds' attendance in corporate analyst meetings.

data vendor. Following the first round of fuzzy name matching, I manually verified the candidates from nearly two-thirds of over 10,000 sample earnings calls at the time of this writing, filtering out false matches and fishing out right matches by considering name variants. When the firm name recorded in the transcript is too brief to pin down an exact match, I turn to corresponding analyst names and conduct the internet searches again to ensure the precision of the firm matches.

To the best of my knowledge, this is the most comprehensive dataset on hedge funds' earnings call participation.[20] This study also provides first evidence on the intensity of hedge funds' in-person information acquisition via their participation in corporate analyst meetings. I include further details on the comparative advantage of my dataset relative to another frequently used commercial dataset on conference calls and elaborate on the name processing and merging steps in the internet appendix.

Table I presents annual counts of earnings calls and call-hosting firms for the full earnings call sample from 2006 to 2017 as well as the number of calls with hedge-fund participation (#Calls), the share of all calls these represent (%Calls), and the number of distinct call-participating hedge funds (#HF)—separately for all 13F-filing hedge funds and the sample hedge funds with no missing IP address and with at least one earnings call appearance during the sample. Overall, with fairly stable call supply from the universe of 5212 US firms across sample years, hedge funds' call participation declines over time—from 27% (16%) to 6% (3%) for 13F-filing hedge funds (sample hedge funds), echoing the rising popularity of high-frequency algorithmic trading. Final sample contains a total of 10,409 calls and 364 unique funds. On average, 13F-filing hedge funds participate in 15% of earnings calls, while sample hedge funds participate in 8% of earnings calls.

[Insert Table 1 about here]

Panel B summarizes the distribution of earnings call participation for 364 sample hedge funds along extensive and intensive margins. On the extensive margin, the median fund appears on 9 calls and engages with 6 distinct hosting firms, with wide dispersion across funds. The extensive-margin distribution is extremely right-skewed. The intensive margin distribution of call participation is tighter. Using the original question count, both the average and median fund asks

[20] See the internet appendix for more details on the construction of conference transcript sample. In two existing studies, hedge funds' earnings call participation, Call et al. (2016) uses a random sample of earnings call transcripts taken from Capital IQ spanning 2007 to 2016, Chen et al. (2020)'s earnings call data are from LexisNexis covering S&P 1500 and Russell 2000 firms from 2001 to 2010. I collect earnings call transcripts for the universe of US firms between 2006 and 2017 from LSEG workspace.

5 questions with an interquartile range of 2 questions. In contrast, the adjusted question count ranges from 3 to 11 from 25th percentile and 75th percentile. The average (median) fund asks 10 (9) questions. Taken together, call-level participation breadth varies substantially across funds, whereas questioning intensity shows relatively limited cross-sectional dispersion.

B. Hedge funds' SEC footprint and AI automation adoption events

I rely on SEC EDGAR log file data to obtain hedge funds' digital footprint of retrieving firms' SEC filings in the EDGAR system from May 15th, 2006, to March 31st, 2017. I choose this sample period because 1) there is about one year of missing SEC log files before May 15th, 2006, which will affect the construction of downloading-related control variables; 2) IP addresses are not available in the log file data after Mar 31st, 2017. The EDGAR log files include IPv4 address with the last three digits masked (e.g., "XXX.XXX.XXX.tqj," where "X" denotes a digit from 0 to 9) along with the unique SEC document accession number, the timestamp of each request, the filer's Central Index Key (CIK). [21]

To enable empirical tests on the impact of AI automation on hedge funds' conference participation, I use the list of conference-participating hedge funds as the starting point and further identify hedge funds with IP information via Networksdb.io and ARIN WHOIS & WHOWAS database, [22] followed by matching with SEC daily log datasets on the first three sections of IP addresses following the practice of existing research (e.g. Crane, Crotty, and Umar 2023).[23] The starting sample of call-participating hedge funds imposes a reasonable assumption that hedge funds that never attend earnings calls tend to be quantitative hedge funds, which do not suit the research purpose of this paper. Prioritizing this sample filter also saves largely unnecessary effort on manually pulling and verifying those non-fundamental-investing hedge funds' IP information.

To implement the stacked DiD empirical design, I use hedge funds' first machine downloading event to capture firm-level AI technological supply shock, because first-time adoption is more likely to be correlated with the advent of new AI technologies. Literature has adopted similar ways

[21] The full variable list in the log file dataset is available at: https://www.sec.gov/data-research/sec-markets-data/edgar-log-file-data-sets.

[22] ARIN WHOWAS provides on-demand searches for historical IP ownership information and I manually verify the IP-institution name matches for a 20% random sample of all 364 sample hedge funds (with IP address information available).

[23] Further details on obtaining hedge funds' IP addresses and matching them to SEC Edgar log file data are discussed in the internet appendix.

of identifying IP addresses with machines downloading activities using the SEC log file data, imposing a threshold for either the volume of downloaded firms/filings (e.g. 50 unique firms or 1000 filings per day or intervals between two access points (see, e.g., Cao et al. 2023; Crane et al. 2023; Chen et al. 2020). To isolate a technology supply shock plausibly exogenous to transitory shifts in funds' information demand or call-hosting firms' information supply, I impose a tighter filter for machine downloads to purge any idiosyncratic downloading behavior that is driven by changes in portfolios or investment policies of funds or by changes in call-hosting firms' fundamentals. Specifically, I record a fund-date pair as one machine download entry if the fund downloads five filings within a minute and over 1000 filings with the same day, or five filings within one minute and over 50 unique firms that day. For funds with more than one machine download entries during the sample period, I keep the first one only. This process results in 22 adoption events. Unlike most prior work that use one single standard, this identification method highlights the combined importance of speed and volume while maintaining flexibility of using the number of downloaded filings or unique firms. I further exclude those with automated downloading activities prior to the samples start,[24] and I require that the adopters conduct machine downloads at least twice during the sample period so that the implementation of the new automation technology is less likely to be sensitive to employment changes of a specific analyst or fund manager.

Panel C of Table III lists the automation adoption events in the sample. In Section C.3 and Table B.2, I repeat the stacked DiD analysis using an alternative classification method of automation adoption. Figure I plots out the year-to-year evolution of hedge funds as earnings call participants and automation adopters based on the 2007-2016 sample due to truncated SEC IP log data in the year of 2006 and 2017.

[Insert Figure I about here]

To test the performance effect of post-automation earnings call participation by hedge funds predicted in Hypothesis 2, I need to pin down firms covered by EDGAR machine downloads as well as earnings calls with hedge fund participants. I use tickers in the transcript file name (and the conference date information) to link conference call companies to stocks in my sample. The

[24] The earliest SEC log entry was on January 1, 2003. As mentioned above, I set the sample start date on May 15th, 2006, because of missing log files in the previous year that may affect the measuring of the downloading intensity.

EDGAR logs do not include filing type, filing date, or report date. I therefore match each log entry to the SEC master filing index via the accession number to recover filing metadata. For machine downloaded investor-level filings (e.g. 13-F, 13-D, and 13-G), I link the holding firms in the downloading quarter to call-hosting firms in the next quarter. I use the Compustat CIK–GVKEY link to merge filers to CRSP and Compustat so that I can examine the role of certain stock characteristics and stock trading performance.

Apart from these two large-scale datasets above, I also assemble several other data sources including LSEG Data & Analytics (formerly Thomson Reuters/Refinitiv), CRSP, Compustat, Fama-French Portfolios & Factors, and some online databases including EDGAR-Parsing, Blockholder Database based on Jan Philipp (2021), and SEC Insider Trading Data Set.

C. Summary Statistics

Table 2 reports summary statistics of main variables for the full sample (Panel A) and the stacked sample (Panel B), respectively. I provide detailed variable definitions in Appendix A. Panel A summarizes earnings participation outcomes, two EDGAR-based automation adoption variables, as well as fund-level and stock-level characteristics. About 28% of fund-quarters are associated with earnings call participation, which is not surprising. Recall that in Table I, sample hedge funds attend 8% of earnings calls. These statistics suggest that earnings call participation is not a prevalent practice even for a hedge fund sample filtering out some quantitative funds. The conditional participation intensity distribution is less sparse—the average fund-quarter has a total of 16 original questions (33 for the adjusted question count measure). Both call-level and question-level distributions are positively skewed, suggesting that participation intensity has a large cross-sectional variation, with some funds making much more active use of earnings calls than others. In the main test on the fund-quarter panel, I include several fund-level characteristics including return, risk, size, age, and turnover to account for heterogeneity in funds' earnings call participation behavior, and further control for three other self-constructed variables that capture information cost, information demand, and information stickiness to tighten the specification for examining the automation-participation relation. All these control variables' statistics are reported for both the full sample and the stacked sample.

[Insert Table II about here]

In the main test, I use the stacked sample, which increases the fund-quarter observations from 11,594 to 138,954 (±3 year windows around adoption) but preserves the distributional shape. All the means for participation measures are slightly lower in the stacked sample, reflecting the reweighting toward balanced pre/post windows and the inclusion of many non-participation quarters. The adoption indicator's mean falls to 0.002 in the stacked design, as each fund contributes many pre/post quarters but only one adoption quarter. Fund characteristics used as cross-sectional controls are very similar across both samples: quarterly returns (2.7–2.8%), size (log assets ≈ 20.3–20.4), risk (0.10–0.11), turnover (0.10), and age (12–13 years). The share of hard-to-research holdings in the portfolio averages ~0.48–0.49 in both panels. These close moments indicate that stacking does not materially change the composition of funds. Sheng et al. (2025) report a subset of the control variables computed based on 13-F institutional ownership data from 2017 to 2024. Apart from similar means in fund return and portfolio risk, two key characteristics—Size and Turnover—are strikingly different: compared to their sample funds, the typical fund in my sample is much larger and has lower turnover. This difference could be driven by (i) the time-varying fund characteristics: my sample has only one year overlap with theirs; (ii) I restrict the sample to hedge funds attending earnings calls at least once during the period of 2006–2007. It is intuitive that larger companies and low-portfolio turnovers tend to correspond to funds executing a fundamental-research-based investment approach.

In addition, this paper identifies hedge funds in 13-F filing investment companies using a proprietary self-designated institution taxonomy data compiled by Thomson Reuters. When using this data to perform name matches between institution names in earnings calls and manually verifying the matched candidates, I also confirm that the hedge fund institution type in the proprietary data is consistent with other sources including fund companies' official websites, Form ADV filings, and third-party hedge fund data.

Appendix Table C.1 further displays the descriptive statistics of sample hedge fund IP and SEC downloading activities. The distribution of downloading volume per IP is right-skewed: with less than one active date per month, AI IPs (IPs that apply AI automation) account for 95.40% of all sample IP downloads during the sample period from May 15th, 2006, to March 31st, 2017. Even when these IPs accessed the SEC EDGAR server without applying AI automation (i.e., when access requests were sent manually), they still downloaded more files than non-AI IPs (i.e., IPs never used for automated downloading). These IPs were active nearly two days per week and accessed more than 300 files per month, demonstrating both greater total download volume and higher efficiency compared to non-AI IPs. The average number of active days per month per non-

AI IP is 2.07, which is nearly identical to the 2.15 days reported by Aragon, Keen, Tserlukevich, and Wymbs (2024), who examine the full viewership of SEC filings during the period from January 2003 to June 2017. However, the average number of filings viewed per non-AI IP per month (39.6) is approximately 67% lower than the figure reported in their study (98.7).[25]

In Table III, I also report sample hedge funds that are most active in conference call participation and automated downloading. Panel A lists the ten most frequent conference call participants among the sample hedge funds. Panel B reports the ten hedge funds with the highest frequency of automated downloading. Panel C enumerates all adoption events in which sample hedge funds adopted AI automation for SEC file downloading, starting in 2007.

[Insert Table III about here]

III. How does AI Automation Reshape Information Acquisition

A. Earnings call participation around automated downloading

To investigate my first hypothesis that AI optimizes sophisticated investors' effort by tilting information acquisition activities toward those that entail human interactions, I conduct difference-in-differences analysis around hedge funds' staggered implementation of AI automation. The identification of the treatment effect comes from comparing earnings call participation for automation-adopting hedge funds (AHFs) and non-AHFs before and after the staggered automation technological supply shocks as defined in Section III. To account for the possibility of dynamic or heterogeneous treatment effects and to avoid bad comparisons that arise from using earlier-treated units as controls for later-treated units,[26] I conduct a stacked difference-in-differences (henceforth, stacked DiD) design using never-treated firms as controls.[27] In the spirit of Baker et al. (2022) and Cengiz et al. (2019), the main stacked DiD specification is as follows:

[25] In unreported results, when combined the sub-sample of AI IPs – Normal and Non- AI IPs, this summary statistics raise to 94.2, quite similar to the statistics from Aragon, Keen, Tserlukevich, and Wymbs (2024). However, the average active days per month also increases to 3.02 from 2.07.

[26] For details, see the decomposition of the treatment effect in Goodman-Bacon (2021).

[27] There are plenty of never-treated units in my sample, so I do not include not-yet-treated units in the control group to avoid picking up any anticipation effect. Also, given the not-yet-treated funds eventually adopt automation during the sample period, they are more likely to be a contaminated group by adopting automation elsewhere, not being tracked by SEC EDGAR and not being observable, either. To make sure these never-treated units serve as useful counterfactuals, I further include two robustness tests. First, I require that both treatment and control firms participate in at least one earnings call prior to the adoption event. As such, they likely share a similar (fundamental-research-oriented) investment approach, see appendix Table B.2. Second, in the internet appendix I repeated the stacked DiD analysis on a propensity score matched sample to ensure that never treated firms have similar likelihood of adopting AI automation.

$$N^{ECP}_{i,t,s} = \beta \cdot AutoAdoption_{i,t,s} + X'\Gamma + \theta_{i,s} + \delta_{t,s} + \varepsilon_{i,t,s} \quad (1)$$

where i, t, s denote hedge fund company (also referred as fund for brevity), year-quarter time period, and sub-experiment respectively. Each sub-experiment indexes one event stack, which is a three-year period before and after the adoption event. All variables used in this specification are defined in the appendix table A.1.

The dependent variable $N^{ECP}_{i,t,s}$ is the number of earnings calls a fund participated in quarter t. In testing the participation effect, I also replace this LHS variable with other variables include number of unique hosting-firms for calls with fund participation $N^{Host}_{i,t,s}$; number of questions a fund asked in a call $N^{Q}_{i,t,s}$; adjusted number of questions a fund asked in a call $Adjust\_N^{Q}_{i,t,s}$.[28] The first number of questions is to naively count the number of speaking turns associated with a hedge fund during a call. However, this number of question measure could be noisy for at least three reasons i) analysts usually combine several questions in one speaking turn, especially in the first question; ii) first and last questions often include greeting words that are not informative; iii) during some interacting turns, it is also common for analysts to say a word or two simply to facilitate corporate management's responses without putting forward new questions. I also exhibit some sample earnings call Q&A texts in the internet appendix to motivate another question count measure. To reduce the bias introduced by the presence of both multi-question statements and short uninformative statements, I construct this adjusted number of questions in five steps: (i) remove any speaking turn that contains no more than five words; [29] (ii) take the median of the word count; (iii) for a speaking turn with high-above-median word count, divide total word count by the median word count to get the adjusted number of questions in that turn; (iv) for those containing less than or equal to the median word count, count it as one question for each turn; and (v) add up the number of newly estimated questions across all speaking turns in a call.

Since the distribution of number of calls and hosting firms are zero-inflated and right-skewed, the "log1plus" transformations of count-based dependent variables may generate biased or

[28] In the internet appendix, I also show additional extensive-margin and intensive-margin results using the participation indicator $I^{ECP}_{i,t,s}$ and total word count for a call with fund participation L^{Q}_{its}, respectively. Both confirm the positive automation-participation relation with close to marginal significance (with t-stats of 1.64 and 1.51 on the coefficient of interest using participation indicator and question length as a regressor, respectively).

[29] A speaking turn with no more than five words is more likely to be greeting words or other pure conversational words that are not related to direct information acquisition. Examples of removed speaking turns include "Good morning, how are you?" or "Thank you. Great quarter!". The new number of question measure is not sensitive to this threshold.

meaningless estimates (see, Cohn, Liu, and Wardlaw 2022; Chen and Roth 2024), I therefore use Poisson regression model to estimate equation (1) with $N_{i,t,s}^{ECP}$ and $N_{i,t,s}^{Host}$. $AutoAdoption_{i,t,s}$ is a shorthand for the DiD interaction term $Treated_{i,s} \times Post_{t,s}$, where $Treated_{i,s}$ equal to one if a fund becomes an adopter i.e., an automation-adopting fund) in sub-experiment s and zero otherwise, $Post_{t,s}$ equal to one for all post-automation quarters in sub-experiment s and zero otherwise. X represents a vector of control variables with the vector of coefficients Γ. I also include fund-by-stack fixed effects $\theta_{i,s}$ and time-by-stack fixed effects $\delta_{t,s}$ in the model. $\varepsilon_{i,t,s}$ is the error term.

If a fund takes advantage of AI to accelerate the downloading and processing of SEC EDGAR files, thereby spending more time collecting human-interaction-based information, one will expect to see a significantly positive estimated coefficient of β. Results in Table IV confirm this participation hypothesis (H1). I find that the estimations of β are all significant and positive across different specifications with and without control variables, suggesting that hedge funds actively engage in earnings calls. The economic magnitude is also sizable: compared to non-adopters, adopter funds (AHFs) increase quarterly conference call participation by as much as 59.2% $((e^{0.465} - 1) * 100\%)$ after adopting AI automation, compared to the sample mean. This is equivalent to 0.415 (0.592*0.701) more conference participation per quarter. Some control variables also exhibit significant influence on hedge funds' earnings call participation. For example, large hedge funds tend to participate in more conference calls. One log point increase in hedge fund size will increase conference call participation by 6.18% $((e^{0.06} - 1) * 100\%)$, or the hedge fund will show up in 0.043 (0.0618*0.701) more meetings per quarter. Older hedge funds also participate more: a one-year increase in fund age is associated with an increase of calls participation by 73.2% $((e^{0.549} - 1) * 100\%)$, i.e., 0.513 (0.732*0.701) more conference calls to sit in per quarter.

[Insert Table 4 about here]

To show support of the key identifying assumption that absent the adoption of AI automation, adopter funds and non-adopter funds would have shown the same trend in earnings call participation, I estimate variant of equation (1) to include leads and lags of the AutoAdoption term relative to the event time as in equation (2).

$$N_{i,t,s}^{ECP} = \sum_{\substack{t=-2 \\ t\neq-1}}^{2} \beta \cdot AutoAdoption_{i,t,s} + X'\Gamma + \theta_{i,s} + \delta_{t,s} + \varepsilon_{i,t,s} \quad (2)$$

where i, t, s denotes fund, year-quarter, sub-experiment, respectively, as before; All other variables are the same as in the main stacked DiD model (equation (1)). Base quarter is set as the quarter before the adoption quarter. Figure 2 plots the corresponding quarter-to-quarter estimates from this dynamic model. It shows that AHFs only increase their earnings call participation after the adoption of AI automation, suggesting that there is no pre-trend. All the event lags' coefficients are statistically indistinguishable from zero, lending credibility of causal inference based on the parallel trend assumption. Automation-induced participation increases only concentrate in the first post quarter is not surprising and is in line with the nature of information being timeliness. The non-interaction-based information being processed in the adoption quarter, adopter funds start to collect more human-interaction-based information from earnings calls. Starting the second quarter post the adoption quarter, there is no significant participation effect, consistent with the information collected in the adoption quarter being stale and not useful for guiding earnings call participation in any future quarters that are beyond the immediate next quarter.[30]

[Insert Figure 2 about here]

B. Cross-sectional participation heterogeneity

To further ascertain the economic channels underlying the main results, I sort the automation-participation relation on fund size, fund age, and portfolio turnover by fully interacting with these cross-sectional indicators with the main stacked DiD specification (see equation (1)). As predicted by hypothesis H1a, table V shows that the introduction of AI automation technologies facilitates greater participation increases along all dimensions for funds of larger size, plausibly due to both the ability to redeploy human capital in response to technology shock and the incentive to enhance their informational advantage to compensate for diseconomies of scale compared to smaller funds.

Consistent with hypothesis H1a, table V reports that the participation effect is stronger for old funds across different participation measures, plausibly due to both higher information acquisition skills and greater activeness out of lower career concerns compared to younger funds. Despite the

[30] This finding also provides empirical motivation for the timing assumption of the performance test design in section IV.

presence of the bias that arises from the possibility that large funds and old funds tend to move marginal effort into private interactions instead of earnings calls and have pre-EDGAR AI automation practices, I still find strong conditioning effects of both size and age, which strengthen the unconditional relation between automation and participation.

Table V also lends support to hypothesis H3a, demonstrating that automation adoption leads low-portfolio-turnover funds to participate more in earnings calls. Recall that the main results in table IV show that higher portfolio turnover is associated with higher levels of earnings call participation. Taken together, Table 4 and Table 5 imply that funds with fundamental-research-based investment approaches should be driving the automation-participation relation, consistent with AI automation enabling them to satisfy their trading-induced information demand through more earnings call attendance.

[Insert Table V about here]

A. Robustness Tests

C.1. Controlling for More Variables

In this section, I entertain the possibility of any uncontrolled variables driving the main results. Specifically, I include three extra control variables in the same stacked DiD framework: the percentage of hard-to-research portfolio stocks, the number of abnormal holdings, and greater reliance on earnings calls using the number of call-participating months in the past three years. The inclusion of these three variables is meant to address the concern that funds with any of these pre-shock characteristics will increase their earnings call participation regardless of their adoption of AI automation.

Specifically, with hard-to-research portfolio stocks representing informational opaqueness, the percentage of hard-to-research stocks in any given quarter's fund portfolio could capture both information demand and informational advantage or information acquisition skills. Either way, I expect this measure to be positively associated with automation-adopting hedge funds' subsequent earnings call participation. The evidence on increased earnings call participation outcomes post automation suggests that the human-interaction-related information costs are relatively lower for more informed hedge funds, making it easier for them to exploit the AI-induced shift of human effort. This also alleviates *a priori* concern that informed investors refrain from asking questions during conference calls to avoid revealing valuable information. Asking questions in public incurs a tradeoff between information acquisition and information revelation. The fact that more informed investors actively attend more calls speaks more to the heterogeneity in information acquisition skills. Investors with greater informational advantages are more capable of acquiring value-relevant information from interactions with corporate management. Hedge funds initiating more new positions have greater information demand and thus are more responsive to the AI technological supply shock. Not surprisingly, hedge funds with greater reliance on earnings calls use more of earnings calls for human-interaction-based information when more time and efforts are freed up, implying that the effort-shifting effect is subject to information stickiness. The findings on the participation-automation relation in the context of earnings calls can be a lower bound of the true effect. The evidence is also suggestive of external validity when considering other sources of human-interaction-based information such as corporate visits or private one-on-one meetings with top management under the same setting. For example, hedge funds with greater reliance on corporate visits will pay more on-site visits, when AI reduces machine-based information costs. Table B.1 shows that all three control variables have positive effects on earnings call participation, consistent with the rationale outlined above. More importantly, the coefficient of interest on the diff-in-diffs interaction term remains both quantitatively and qualitatively similar after controlling for more participation determinants including information cost, information demand, and information stickiness.

C.2. Addressing the possibility of potential investment strategy shift

As mentioned in the data section, I construct the hedge fund sample by requiring that a 13-F filing hedge fund with no missing IP information attend earnings calls at least once during the sample period. This partly ensures that quantitative hedge funds throughout the period do not enter the sample, because unlike the "stock prickers", "quants" tend to rely on algorithms and big data only—they may leverage AI to analyze earnings call transcripts but will never attend earnings calls themselves.[31] However, it is still possible that some sample hedge funds shift their investment strategy from quantitative to discretionary or fundamental-oriented, which could coincide with the automation adoption timing. To deal with this confounder to the participation effect of AI automation, I further require that both treated and control groups participate in at least one earnings call in the pre-automation event window. As such, it is less likely to be the case that hedge fund firms that used to execute quantitative strategies either gear into a fundamental-research approach

[31] I thank Ken Kroner, former Blackrock hedge fund manager, for confirming this institutional knowledge.

or add another department in charge of discretionary investment through M&A or other business-expansion-related reasons. From Table B.2, we can see that the DiD estimators for both the extensive-margin participation outcomes and the intensive-margins are still mostly significant at the 1% level (with only one coefficient estimate being marginally significant). With respect to the economic magnitude, the adoption of AI automation exhibits a larger economic impact on earnings call participation compared with full sample, meaning that with more quant funds being excluded prior to the event accentuates the change in the information acquisition behavior of fundamental-investing hedge funds.

C.3. Using Alternative Definitions of Automation Adoption

To conduct stacked DiD analysis, I locate a hedge fund's first automated SEC downloading entry observed in the EDGAR log file data to identify automation adoption. The literature convention on classifying SEC machine downloads is either speed-based or volume-based. In this main test, I take the union on the restriction of five filings in a minute and over 1000 filings and the requirement of five filings in a minute and over 50 unique firms, ending up with 22 first adoption events. In this robustness test, I also use an alternative and an even stricter definition of machine downloads by imposing the requirement that a hedge fund IP address downloaded more than five filings in a minute and over 1000 filings during the same day. I choose to count filings instead of firms because one of the most machine downloaded filing type by hedge funds is 13-F, indicating hedge funds could be interested in learning about other investors' portfolio companies, in which case, one filing leads to subsequent analysis of multiple firms that are more feasible when automation technologies are widely adopted within the fund company. The application of these alternative standard yields 14 adoption events only. Table B.3 represents the robustness test results, which are consistent with the main results and provide further supporting evidence for my main hypothesis.

C.4. Using Alternative Event Windows and Event Groups

In the main Stacked DiD test, I estimate equation (1) and impose an event window of three years before and after the automation adoption event. Ex-ante, it is unclear whether automation induced participation increase is instantaneous or not: On the one hand, it takes time to fully adopt automated downloading so that it becomes a firm-wide new information acquisition practice. In addition, it is costly for funds to comb through the sheer volume of downloaded files even with

AI's further help in processing the information, and to decide which firm interests or concerns them enough for them to allocate effort in interacting with corporate management during earnings calls. So, it could take at least longer than one quarter to reflect the effort-allocation channel in earnings call participation behavior. On the other hand, the timeliness of the information makes it less likely for firms to wait a few more years to act on the information acquired via SEC downloads. However, considering the adoption timing plausibly captures an automation technology shock, it is likely to induce a change in funds' long-term information acquisition strategy: with the effort constraints on human-interaction-based information acquisition alleviated by the introduction of automation, funds tend to make more uses of earnings calls that is not necessarily related to the specific information acquired from the adoption event. As argued in the previous sections, the first machine downloading event on SEC is just a proxy for automation adoption. Any changes in the participation outcomes are still relevant for this study's purpose as it reflects how funds change their information acquisition behavior in response to technological shock.

Choosing this event window (i.e.,−12 to +12 quarters) generally reflects a balance between capturing clean effects of automation and preserving test power in the stacked design. In particular, I avoid using a wider window because i) for a fund-quarter-level regression, even considering the infrequent hedge funds earnings call appearances over just one quarter, three years pre and post the event is a relatively long horizon to estimate the average treatment effect. Expanding the window will also shrink the estimation sample to a great extent as I only have 12 years of data, ii) when going farther away from the event time, noisy confounder events will be added—such as strategy shifts, personnel changes, or macro conditions that affect both investors' information demand and call-hosting investee firms' information supply. I also refrain from using a window too narrow to maintain test power as the most obvious reason.[32] A narrower window would understate these adjustments and limit our ability to detect meaningful changes in participation.

As I point out in this section, the use of a stacked sample imposing a fixed window could largely reduce sample size and test power: for a three-year pre- and post-adoption window, events that occur before 2009 or after 2014, either pre-shock or post-shock window is truncated. To this end, I conduct two more robustness tests by i) dropping either too-early or too-late events (see

[32] In the dynamic model, I test for the parallel trend using a short event window because the seasonality of earnings call hosting makes quarter -1 an inadequate baseline if the quarter contains three low-data-point months (June, September, and December).

Panel A of Table B.4),[33] ii) imposing a shorter event window of -8 to +8 quarters and use events only between 2008 and 2015 (see Panel B of Table B.4). The results in table B.4 suggest that my main findings still hold with a shorter event window and after excluding some adoption events due to truncated event windows.

In addition to robustness tests presented in the subsection III.C, I also include two more robustness tests on the automation-participation relation in the internet appendix, including i) confirming that the stacked DiD results are robust to using a propensity-score matched sample, ii) showing suggestive evidence of external validity on in-person human-interaction-based information acquisition. Since I used never-treated units as controls in the main tests, I conduct propensity score matching between treated and controls to ensure that the matched controls are more likely to represent a valid counterfactual. As mentioned in the data section, I collect the corporate analyst meeting sample during the same sample period to capture in-person human-interaction-based information acquisition. This alternative sample size is much smaller, but I still show that test results about in-person conference call participation outcomes are all in the same direction as the main results and mostly statistically significant as well despite the reduced test power. These results alleviate the concerns that the results have limited external validity on other types of human-interaction-based information acquisition activities.

For completeness of results, I also present in the internet appendix the two-way fixed effects DiD results based on the staggered sample, which still confirm my hypothesis, but should be interpreted with caution. As I point out, in motivating the use of stacked DiD analysis to present my main results, the naïve staggered DiD analysis involves inadequate controls (i.e., already-treated units) and is not sufficient to produce the desired average treatment effect.

IV. Does Post-Automation Call Participation Affect Investment Performance?

A. Fund-level performance implications

A.1. Participation-performance relation

Consistent with the participation hypothesis (H1), prior tests show that AI automation enables hedge funds to reallocate effort toward acquiring more human-interaction-based information. This

[33] The earnings call sample ends in 2017 at the time of this writing. Given the last adoption event in 2016, more robustness tests can be shown by appending two more years of earnings call and make the extended sample period end in 2019. However, it is not advisable to change the start of the sample to add in more earlier years because there is about one year of missing SEC log data that will introduce misclassification of treated and control groups for automation adoption.

naturally raises the question of whether fund-level performance improves when automation-adopting hedge funds (AHFs) obtain more of such information. To address this, we test whether AHFs deliver superior performance following automated downloading and subsequent earnings-call participation.

To evaluate the performance impact of post-automation call participation, I relate hedge fund performance in quarter t+1 to earnings call participation decisions in quarter t-1 and automation adoption decisions in quarters covering from t-4 and t-2. More specifically, the timeline in this test design consists of a sequence of four events at different time points including that 1) AI automation becomes in place in the quarterly window [t-4, t-2] when funds automate the collecting and processing of machine-based information,[34] 2) earnings call participation begins in quarter t-1, when funds engage in human-interaction-based information acquisition, 3) portfolio adjustment and investment decisions are made in quarter t, 4) investment outcomes are evaluated in quarter t+1 by computing portfolio-holding-based returns. With this timing assumption, I estimate the participation-performance relation based on the specification below:

$$\begin{aligned} \mathrm{Ret}_{i,t+1} &= \beta \cdot \mathrm{I}_{i,t-1}^{\mathrm{ECP}} \cdot \mathrm{HasAuto}_{i,(t-4,t-2)} + \gamma \cdot \mathrm{I}_{i,t-1}^{\mathrm{ECP}} + \delta \cdot \mathrm{HasAuto}_{i,(t-4,t-2)} \\ &+ X_1'\Gamma + \theta_i + \delta_t + \varepsilon_{i,t} \qquad (4) \end{aligned}$$

where i and t indexes hedge fund company (or fund for brevity) and quarter, respectively; $\mathrm{Ret}_{i,t+1}$ denotes fund holding-based turns adjusted using Fama-French-Carhart four-factor model; $\mathrm{I}_{i,t-1}^{\mathrm{ECP}}$ equals 1 if a hedge fund participated in at least one conference call in quarter t-1, and 0 otherwise, as defined in appendix A; HasAuto equals 1 if a hedge fund has automated its downloading by quarter t-2 (at least one quarter prior to attending earnings calls), and 0 otherwise; X_1 represents a vector of equation (1) control variables interacted with the automation adopting indicator. θ_i is fund (hedge fund company) fixed effect and δ_t is time (year-quarter) fixed effect. $\varepsilon_{i,t}$ is the error term. Control variables and fixed effects are fully interacted with HasAuto.

[34] In this fund-quarter-level performance specification, I relate hedge funds' quarterly portfolio returns to automation adoption in a quarterly window of t-4 to t-2 to accommodate the start-of-quarter adoption timing versus end-of-quarter adoption timing based on calendar-quarter timeline. Also, there could be heterogeneous timing for intra-quarter earnings call participation, too. In other words, the firm a fund develop further research interest in may not hold quarterly earnings call in the same calendar quarter or even in the next two quarters, consistent with some sample call-hosting firms hold fewer than four calls a year and very often, for four-call-per-year firm, there could be four months apart be between two calls (e.g., one in November and one in March). So, I allow for the adoption quarter to extend into previous two quarters.

If the increased conference call appearances by AHFs results from their redirected efforts to human-interaction-based information acquisition, we should expect to see a positive estimate of δ, which means that AHFs gain better human-interaction-based information during the conference call when automation downloading had been done in past quarters. The estimation results in Table VI confirm this performance hypothesis (H2). Panel A results are based on raw returns and Panel B results are based on Fama-French-Carhart four-factor alphas. Along with the effort-redirection hypothesis, the interaction item, $\mathrm{HasAutoI}_{i,t-1}^{ECP}$, has positive and significant parameter estimations, and the estimation results are stable across different measures of return. The economic magnitudes of these effects are also significant: when automation downloading is followed by one conference call participation, the next quarter fund raw (risk-adjusted) return can increase by as much as 1.5% (2.5%) in terms of holding stocks' value-weighted average return (Fama-French-Carhart four-factor alpha).

[Insert Table VI about here]

B. Stock-level Trade Performance

To link fund-level performance improvements to hedge funds' trading, I conduct additional tests in this section on whether automation-adopting hedge funds (AHFs) make profitable trades after participating in earnings calls that follow automated downloads of firms' SEC filings.

B.1 Returns on a long-short portfolio strategy

I start by testing whether funds earn abnormal returns by making trades in a stock that is covered by both automated downloads and conference-participating hedge funds. The test sample only includes stocks whose owner hedge funds trade them in quarter t, and participate in at least one conference meeting in quarter t-1. Among the sample stocks, the treated stocks are those whose owner hedge funds accessed SEC files covered the stocks through machine downloading at least once in the quarterly window [t-4, t-2]. Direct coverage refers to downloads of a firm's own filings (e.g., 10-K). Indirect coverage refers to downloads of other entities' filings that reference the firm (e.g., a manager's Form 13F listing the firm's shares; Form 4), from which AHFs may do further research on these portfolio companies of their peers by attending earnings calls.

Because AI automation shifts information acquisition effort toward call participation, stocks that are both automation-covered and then discussed on a call attended by the fund should confer information advantage that accounts for funds' superior returns from post-automation call participation. To test if increased human-interaction-based information is value-relevant, AHFs' buys (sells) of those stocks should be followed by positive (negative) future returns. Accordingly, trade profitability should increase with conference call participation for AHFs, consistent with redirected effort yielding more valuable interaction-based information after automation.

To see whether AHFs' trades are more informative of stock returns, I form two long–short portfolios following Cao, Gao, and Guo (2025) and Pool, Stoffman, and Yonker (2015): a treated portfolio (automation-covered, call-attended stocks) and a control portfolio (non-automation-covered, non-call-attended stocks). Within each group and quarter, I go long stocks with increased shares and short those with decreased shares, then compare one-quarter (three-month) performance of the two long–short portfolios. Table VII reports results from t-tests. Trades are more informative when AHFs attend earnings calls after adopting automation for a given firm: the treated long–short portfolio delivers a significantly positive three-month Fama–French–Carhart four-factor alpha and outperforms its control group. Consistent with the reduced information acquisition costs mechanism, the performance is largely driven by stronger subsequent performance of the long leg in the treated group.

[Insert Table VII about here]

B.2. Assessing trade performance via regression analysis

The long-short portfolio strategy helps isolate the information content of AHFs' trades from factor- or market-wide movements. Stock trade performance results could be driven by differences in fund ability or some time-varying market conditions like financial crisis that affect both managers' trading decisions and stock returns at the same time. To control for these possibilities, I regress trade-sign-adjusted stock performance on post-automation earnings-call participation with both fund fixed effects and time fixed effects added and based on the identifications of covered stocks described in section B.1. After adopting AI automation, funds with greater call participation execute more profitable trades: for conference-hosting firms, subsequent returns move in the direction of the funds' trades.

The model specification for the quarterly hedge-fund-stock panel is as follows:

$$\begin{aligned}\mathrm{Ret}_{i,j,t+1}^{\mathrm{Trade}} = \beta \cdot \mathrm{I}_{i,j,t-1}^{\mathrm{ECP}} \cdot \mathrm{HasAuto}_{i,j,(t-4,t-2)} + \gamma \cdot \mathrm{I}_{i,j,t-1}^{\mathrm{ECP}} + \delta \cdot \mathrm{HasAuto}_{i,j,(t-4,t-2)} \\ + \mathrm{X}_2{}'\Gamma + \theta_{i,t} + \delta_{j,t} + \varepsilon_{i,j,t} \qquad (5)\end{aligned}$$

where i, j, t denotes hedge fund, stock, and quarter, respectively; $\mathrm{Ret}^{\mathrm{Trade}}$ is trade-sign-adjusted stock performance defined as the product between traded stock's Fama-French-Carhart four-factor alpha in quarter t+1 and the indicator of its share change in quarter t (1 if increases or remains; -1 if decreases), as in Section 3.2; HasAuto is the indicator function of a treated stock, which equals one if a stock was covered by a hedge fund's access of EDGAR data in the quarterly window [t-4, t-2] through automation downloading; $\mathrm{I}^{\mathrm{ECP}}$ is the indicator of whether the trading hedge fund appeared in the public company's earnings calls in the quarter before the trading; X_2 are controls with interaction with HasAuto; $\theta_{i,t}$ represent the hedge-fund-quarter fixed effects, $\delta_{j,t}$ represent stock-quarter fixed effects.

Table VIII reports regression estimates from specification (5). The results are consistent with the univariate t-tests, though the implied economic magnitudes are smaller than in the corresponding same-identification comparisons. The estimated coefficient on the variable of interest, δ, is positive and statistically significant whether performance is measured by cumulative monthly returns or by risk-adjusted returns (Fama–French–Carhart four-factor alpha), suggesting that trades by these hedge funds are more informative than trades by funds that only participate in earnings calls.

[Insert Table VIII about here]

B.3. Stronger Trade performance using hard-to-research stocks

I further conduct subsample tests to unpack the economic channels for the performance effects documented in the main results. The sub-hypothesis is that performance effects will be stronger for hard-to-research stocks, consistent with AI reducing the average information acquisition costs for hedge funds. I follow Cao, Gao, and Guo (2025) and identify hard-to-research stocks as those of smaller size, lower analyst coverage, and higher intangible assets in the year prior to the conference participation date. The treated-control stocks are formed by the same process as in tests of Table VIII and Table IX: the treated stocks have both AI automation coverage and conference participation coverage; and the control stocks have neither conference participation coverage nor AI automation coverage, as defined previously in Section 5.2.

The subsample results in Panel A and Panel B of Table IX show that the long–short portfolio consisting of hard-to-research stocks delivers risk-adjusted performance similar to the full sample

(Table VII, Panel A). This suggests that the previous performance result is driven by hard-to-research stocks, for which reductions in information-acquisition costs are more binding.

[Insert Table IX about here]

In Panel C, only the coefficient on $\mathrm{HasAuto} * \mathrm{I}^{\mathrm{ECP}} * \mathrm{Is\_H2R}$ is positive and significant, with magnitudes similar to Panel A of Table VIII. This indicates that automated downloading benefits conference-call–participating hedge funds only when they trade hard-to-research stocks, consistent with an information-cost-reduction mechanism.

V. Concluding Remarks

How does AI unleash the power of human intelligence in this knowledge economy? By zooming in on high-skilled knowledge workers like sophisticated investors, I shed light on a new "complement-via-substitution" channel through which AI automation affects hedge fund information acquisition behavior and fund performance. This speaks to two statements in labor economics and information economics, respectively: first, AI augments high-skilled labor by freeing up human intelligence for engaging in human-interactions and facilitating the extraction of economic rents that are not exploitable due to limited human capacity; second, human-interaction-based information exhibits high complementarity with non-interaction-based information. Furthermore, this study reveals a previously undocumented mechanism of how information elicited from earnings calls can influence fund investment behavior and predict fund performance.

The hedge fund setting presents two unique edges. First, as sophisticated investors, hedge funds exert great efforts to obtain their informational advantage in both non-interaction-based information and human-interaction-based information. Hedge fund analysts are deployed to collect information and provide investment recommendations for managers to make final investment decisions. Automation increases the efficiency of collecting non-interaction-based information. However, machine algorithms cannot easily and completely supersede human labor due to human's comparative advantage in collecting and processing information from human interactions. Consistent with my hypothesis that automating machine algorithms make it easier for hedge funds to exert more effort to collect information that requires human interactions, I find hedge funds increase their earnings call participation both at the extensive margin and at the intensive margin following the implementation of automated information acquisition: both the likelihood of earnings call participation and the participation intensity increase post automation. Second, hedge fund portfolio trading and performance measures are well documented in the literature, allowing me to further speak to the productivity aspect of this AI-labor relation in the context of hedge funds. Consistent with high-skilled labor redeploying human intelligence to their advantage, I find that hedge funds make more profitable trades after exerting more effort in attending post-automation earnings calls, plausibly due to their comparative advantage in human-interaction-based information acquisition.

This study focuses on hedge funds' public information acquisition for fundamental investing in the age of AI. As mentioned in previous sections of this paper, one limitation of this paper is that a lot of other human-interaction-based information is not observable. As with investors' public interactions with corporate managers, their private interactions are also sensitive to the time and effort constraints alleviated by AI. Since the same effort reallocation channel will still be operating when other types of human-interaction-based information acquisition is taken into consideration, the findings in this paper have external validity and set a lower bound for how AI improves investment decisions and performance by facilitating the shift of effort from automation-prone to automation-resistant (or human-intensive) information acquisition activities.

This paper documents the complementarity between two types of traditional public information. To the extent that the automating capacity of AI is applicable to alternative data such as social media and satellite image data, one interesting direction to pursue might be examining whether the relationship between alternative data and human-interaction-based information is substitutive or complementary following the adoption of AI technologies. Such research can be enabled if investors' footprints like IP addresses can be tracked from some other web traffic data related to websites that are sources of alternative data. Bonelli and Foucault (2024) find that traditional fund managers lack the expertise required to exploit alternative data. With the growing application of AI automation technologies to fundamental-oriented funds beyond quant funds, I would expect to see the increasing use of alternative data in fundamental research. It would be interesting to explore how the use of alternative data interacts with traditional human-interaction-based information acquisition.

This paper documents how AI automation optimizes the use of human intelligence in the asset management industry. It is natural to apply this insight in a corporate setting. For example, one question yet to explore is the relationship between robotics automation technologies and human intelligence in the context of product pricing by industrial firms. On the one hand, robots can perform tasks with precision and consistency, thereby reducing product prices from the cost side. On the other hand, human intelligence can be redirected to more creative uses such as product variety and more tailored product market strategies. As such, firms may enjoy monopoly pricing benefit as a result of robotics automation-induced human effort reallocation. The net effect of changes in product prices would be unclear and is eventually an empirical question.

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Figure 1. Hedge Funds as Conference Participants and Automation Adopters

This figure plots out the year-to-year evolution of hedge funds as earnings call participants and automation adopters. Each whole bar indicates the number of sample hedge funds existing in the referenced year. The light blue top bar indicates the number of sample hedge funds that attend at least one call in that year. The grey bottom bar refers to the number of sample hedge funds without earnings call participation in that year. Each dot on the purple line denotes the percentage of hedge funds that have implemented automated downloading by that year among call-participating hedge funds in that year. The earnings call sample spans from 2006 to 2017. This figure is based on the 2007-2016 sample due to truncated SEC IP log data in the year of 2006 and 2017.

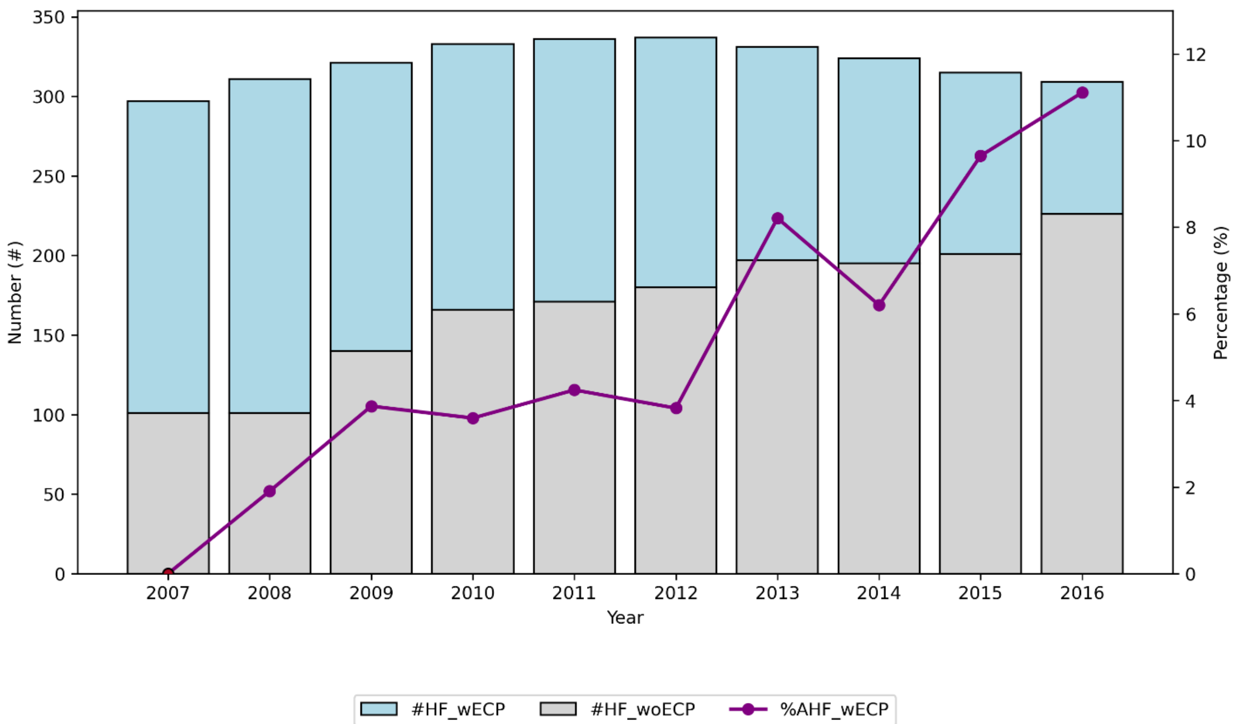

Figure 2. Earnings Call Participation around Automation Adoption

This figure plots the coefficient estimates of β in the dynamic model below. The x-axis shows two quarters before and after the automation adoption quarter 0. The error bars correspond to the 90% confidence intervals, which are computed based on standard errors clustered by fund company and event-time.

$$\mathrm{N}_{\mathrm{i,t,s}}^{\mathrm{ECP}} = \sum_{\substack{\mathrm{t}=-2 \\ \mathrm{t}\neq-1}}^{2} \beta \cdot \mathrm{AutoAdoption}_{\mathrm{i,t,s}} + \mathrm{X}'\Gamma + \theta_{\mathrm{i,s}} + \delta_{\mathrm{t,s}} + \varepsilon_{\mathrm{i,t,s}}$$

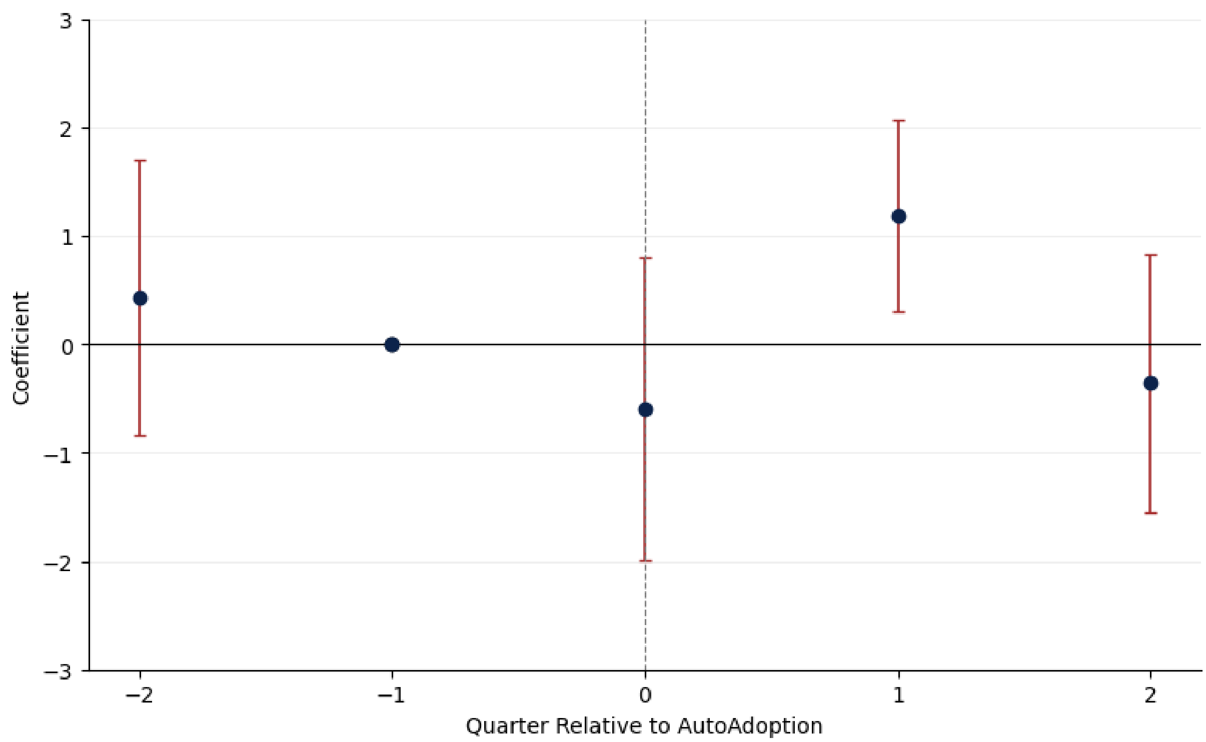

Table I. Sample descriptive statistics

This table reports the sample of earnings calls and call participation by all 13F-filing hedge funds and those without missing IP addresses during the period of 2006-2017. IP addresses are collected for hedge funds that attend earnings calls at least once during the sample period. Panel A summarizes the overall number of conferences and hosts, the number and percentage of calls covered by hedge funds, and the number of hedge funds by year. Panel B reports the extensive-margin and intensive-margin distribution of earnings call participation for the sample hedge funds.

Panel A. Earnings Calls and Hedge Fund Participation

			All 13F-filing Hedge Funds			Hedge Funds w/ no missing IPs		
Year	#Calls	#Host	#Calls	%Calls	#HF	#Calls	%Calls	#HF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2006	9,830	2,864	2,637	27%	512	1,568	16%	197
2007	10,231	3,046	2,585	25%	533	1,449	14%	203
2008	10,930	3,021	2,482	23%	541	1,375	13%	216
2009	10,782	2,988	2,056	19%	468	1,193	11%	187
2010	10,938	2,999	1,853	17%	410	1,059	10%	172
2011	11,183	3,050	1,572	14%	368	872	8%	170
2012	11,166	3,079	1,382	12%	342	753	7%	161
2013	10,348	2,848	1,094	11%	314	581	6%	137
2014	11,358	3,148	955	8%	290	486	4%	132
2015	11,500	3,248	901	8%	259	461	4%	116
2016	10,973	3,080	682	6%	216	312	3%	86
2017	11,460	3,143	714	6%	230	300	3%	93
Full	130,699	5,212	18,913	15%	1,031	10,409	8%	364

Panel B. Distribution of Earnings Call Participation by Sample Hedge Funds

Variable	N	Mean	25th pctl	Median	75th pctl
Extensive Margins					
#Conference Appearances	364	31.604	3	9	27
#Interacting Hosting Firms	364	15.294	2	6	17
Intensive Margins					
#Questions	364	4.961	4	5	6
#Questions adjusted	364	9.643	3	9	11

Table II. Summary Statistics

This table reports the variable summary statistics of this research. Panel A reports the summary statistics of the full sample covering all the 13F-filing hedge funds that participate in earnings conference calls during the period of 2006–2017. Panel B reports the summary statistics for the stacked sample, which consists of the automation adoption events by hedge funds during the sample period. Hedge funds remaining non-adopters throughout the sample period serve as controls. All continuous variables are winsorized at the 1st and 99th percentiles. Variable definitions are provided in Appendix A.

Panel A: Full Sample						
Variables	Obs	Mean	SD	P25	P50	P75
Hedge Funds' Quarterly Conference Participation						
N^{ECP}	11,594	0.765	1.958	0	0	1
N^{Host}	11,594	0.737	1.854	0	0	1
N^{Q}	3,197	16.043	25.255	4	7	17
Adjusted_N^{Q}	3,197	33.31	51.694	8	16	36
Hedge Funds' SEC Downloads						
AutoAdoption	11,594	0.019	0.137	0	0	0
HasAuto	11,594	0.007	0.083	0	0	0
Fund-level Characteristics						
Alpha	11,594	0.023	0.101	-0.023	0.031	0.081
Return	11,594	0.027	0.108	-0.025	0.036	0.088
Size	11,594	20.426	1.904	19.186	20.395	21.613
Risk	11,594	0.101	0.057	0.058	0.089	0.13
Turnover	11,594	0.099	0.075	0.044	0.084	0.14
Age (in years)	11,594	12.619	8.827	6	11	18
High_PastECP	11,594	0.098	0.298	0	0	0
Abnormal_Hld	11,594	1.720	60.933	-10.585	-0.809	9.333
H2R_PortPct	11,594	0.487	0.200	0.346	0.471	0.621
Stock-level Characteristics						
Is_H2R	2,726,524	0.504	0.500	0	1	1
Return_Trade	2,726,524	0.004	0.193	-0.101	0.003	0.106
Alpha_Trade	2,726,524	0.002	0.267	-0.132	0.002	0.136
Quarterly Raw Returns	2,726,524	0.024	0.193	-0.078	0.024	0.124
Quarterly Abnormal Returns	2,726,524	0.010	0.267	-0.123	0.011	0.143

Panel B: Stacked Sample						
Variable	Obs	Mean	SD	P25	P50	P75
Hedge Fund Conference Call Participation						
N^{ECP}	138,954	0.701	1.853	0	0	1
N^{Host}	138,954	0.674	1.853	0	0	1
N^{Q}	36,331	15.492	24.652	3	7	16
Adjusted_N^{Q}	36,331	32.06	50.63	7	15	34
Hedge Funds' SEC Downloads						
AutoAdoption	138,954	0.002	0.042	0	0	0
Fund-level Characteristics						
Return	138,954	0.028	0.112	-0.026	0.038	0.094
Size	138,954	20.319	1.843	19.116	20.312	21.498
Risk	138,954	0.107	0.058	0.061	0.096	0.136
Turnover	138,954	0.099	0.075	0.043	0.084	0.14
Age	138,954	12.147	8.689	5	10	17
High_PastECP	138,954	0.089	0.285	0	0	0
Abnormal_Hld	138,954	1.073	56.48	-10.08	-0.917	8.167
H2R_PortPct	138,954	0.484	0.201	0.344	0.467	0.619

Table III. Top Hedge Fund Call Participants, Machine Downloaders, and Adoption Events

This table reports sample hedge funds that are most active in conference call participation and automated downloading. Panel A lists the ten most frequent conference call participants among the sample hedge funds. Panel B reports the ten hedge funds with the highest frequency of automated downloading. Panel C lists all automation adoption events for sample hedge funds.

Panel A Top 10 Earnings Call Participants

Hedge Fund Company	#Earnings calls attended
Philadelphia Financial Management of San Francisco	628
Heartland Advisors Inc.	510
Ingalls & Snyder L.L.C. (Asset Management)	453
Zimmer Lucas Capital, L.L.C.	392
Citadel Investment Group, L.L.C.	343
Cardinal Capital Management L.L.C.	315
Gates Capital Management	262
Visium Asset Management, L.P.	255
Sage Asset Management, L.L.C.	245
First Wilshire Securities Management, Inc.	230

Panel B Top 10 Machine downloaders

Hedge Fund Company	#Months with Machine Downloads
Forest Investment Management, L.L.C.	44
FBR Fund Advisers, Inc	30
Marathon Capital Management	25
Ridgecrest Investment Management, L.L.C.	24
Apollo Advisors, L.P.	22
Heartland Advisors, Inc	19
DW Investment Management, L.P.	17
Aristeia Capital, L.L.C.	12
Sir Capital Management, L.P.	10
Eos Partners, L.P.	10

Panel C Automation Adoption Events	
Hedge Fund Company	Adoption Date
FBR Fund Advisers, Inc	2007-05-18
Forest Investment Management, L.L.C.	2007-06-27
Fiduciary Asset Management, Inc	2007-08-27
Voya Investment Management, L.L.C.	2008-04-04
Marathon Capital Management	2008-09-19
Heartland Advisors, Inc	2009-02-11
TPG Axon Capital	2009-07-21
Ridgecrest Investment Management, L.L.C.	2009-12-11
Palisade Capital Management, L.L.C.	2010-06-16
Stevens Capital Management, L.P.	2010-09-15
Brown Advisory	2011-05-19
Iridian Asset Management, L.L.C.	2012-09-07
Visium Asset Management, L.P.	2012-11-06
Eos Partners, L.P.	2013-06-27
Sir Capital Management, L.P.	2013-11-21
Solus Alternative Asset Management, L.P.	2014-08-15
Beacon Light Capital, L.L.C.	2014-12-30
Apollo Advisors, L.P.	2015-02-05
Glenview Capital Management, L.L.C.	2015-06-11
Aristeia Capital, L.L.C.	2015-09-28
Davidson Kempner Advisers, Inc.	2015-11-09
DW Investment Management, L.P.	2016-03-14

Table IV. Hedge Fund Earnings Call Participation: Stacked DiD Analysis

This table reports the average treatment effect of AI automation adoption on hedge funds' conference calls participation. Panel A reports the extensive margin participation effect with two dependent variables: column (1)–(2) show the results for the number of earnings calls attended by hedge funds ($\mathrm{N}^{\mathrm{ECP}}$) and column (3)–(4) for the number of distinct host firms associated with those calls in that quarter ($\mathrm{N}^{\mathrm{Host}}$). AutoAdoption, equals 1 if a hedge fund adopted AI automation in any previous quarter and 0 otherwise. Estimates are based on the stacked DiD specification in equation (1). The stacked events are funds' first-time adoptions, and controls are never-adopters. Panel B estimates the same regression model and reports the intensive margin participation effect with two dependent variables: column (1)–(2) show the results for the original question count for a given hedge fund in a call (N^{Q}) and column (3)–(4) the adjusted question count (Adjusted_N^{Q}). All dependent variables at quarter t are related to independent variables at quarter (t-1). The standard errors are clustered by fund company and event. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

Panel A: Extensive Margin Participation				
	$\mathrm{N}^{\mathrm{ECP}}$		$\mathrm{N}^{\mathrm{Host}}$	
	(1)	(2)	(3)	(4)
AutoAdoption	0.465***	0.441***	0.482***	0.459***
	[5.42]	[5.49]	[5.41]	[5.49]
Returns		-0.003		0.020
		[-0.04]		[0.34]
Size		0.066***		0.062***
		[4.34]		[4.22]
Risk		-0.890***		-0.973***
		[-3.14]		[-3.54]
Turnover		0.493***		0.502***
		[7.09]		[7.39]
Age		0.549***		0.638***
		[4.56]		[5.06]
Model	Poisson	Poisson	Poisson	Poisson
Observations	113,957	113,957	113,957	113,957
Pseudo R-square	0.505	0.506	0.496	0.496
Year-Quarter X Stack FEs	Yes	Yes	Yes	Yes
Fund X Stack FEs	Yes	Yes	Yes	Yes

Table IV—Continued

Panel B: Intensive Margin Participation				
	N^Q		$Adjusted\_N^Q$	
	(1)	(2)	(3)	(4)
AutoAdoption	0.334***	0.314***	0.303***	0.287***
	[3.08]	[3.01]	[2.70]	[2.68]
Return		0.425***		0.451***
		[6.14]		[6.60]
Size		0.057***		0.048***
		[3.92]		[3.32]
Risk		-0.201		-0.178
		[-0.79]		[-0.66]
Turnover		-0.048		-0.068
		[-0.56]		[-0.78]
Age		0.364***		0.323***
		[6.79]		[5.39]
Model	Poisson	Poisson	Poisson	Poisson
Observations	35,175	35,175	35,175	35,175
Pseudo R-squared	0.641	0.642	0.676	0.677
Year-Quarter X Stack FEs	Yes	Yes	Yes	Yes
Fund X Stack FEs	Yes	Yes	Yes	Yes

Table V. Cross-sectional Heterogeneity

This table reports how the cross-sectional differences in hedge fund characteristics influence the treatment effect of automation adoption on conference call participation. Is_large and Is_old are indicator variables equal to one for hedge funds with above-median fund size and fund age, respectively. Low_Turnover is an indicator variable equal to one for hedge funds with below-median fund turnover. All dependent variables at quarter t are related to independent variables at quarter (t-1). The standard errors are clustered by fund company and event. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

		N^{ECP}	
	(1)	(2)	(3)
Is_large X AutoAdoption	2.469***		
	[3.93]		
Is_large	5.000***		
	[5.87]		
Is_old X AutoAdoption		1.680**	
		[2.27]	
Is_old		1.469***	
		[3.26]	
Low_Turnover X AutoAdoption			2.051***
			[2.85]
Low_Turnover			0.113
			[0.59]
AutoAdoption	-1.235**	-1.103***	-1.269***
	[-2.47]	[-7.83]	[-7.92]
Controls & Interactions	Yes	Yes	Yes
Model	Poisson	Poisson	Poisson
Observations	113,957	113,957	113,957
Adj. R-squared	0.507	0.507	0.506
HasAuto X Year-Quarter FEs	Yes	Yes	Yes
HasAuto X Fund FEs	Yes	Yes	Yes

Table VI. Fund Performance and Post-Automation Earnings Call Participation

This table reports the fund-level performance effects of post-automation earnings-call participation. Return is the hedge fund's cumulative monthly raw return in the current quarter, and Alpha is the Fama–French–Carhart four-factor adjusted return in the same period. All dependent variables at quarter t+1 are related to HasAuto in quarter (t-4, t-2) and I^{ECP} at quarter (t-1). Standard errors are clustered at the fund company level. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

	Return	Alpha
I^{ECP}	-0.002	-0.002
	[-0.59]	[-1.21]
HasAuto X I^{ECP}	0.006***	0.003**
	[2.79]	[2.13]
Model	OLS	OLS
Controls & Interactions	Yes	Yes
Observations	11,594	11,594
Adj. R-squared	0.695	0.073
HasAuto X Year-Quarter FEs	Yes	Yes
HasAuto X Fund FEs	Yes	Yes

Table VII. Stock Trade Performance: Portfolio Analysis

This table reports results from the long–short portfolio analysis. Columns (1)–(3) present portfolios of stocks traded by hedge funds that participated in at least one conference call in the previous quarter and engaged in automated downloading at least once in the quarterly window [t-4, t-2]. Columns (4)–(6) present portfolios of stocks traded by hedge funds that neither participated in any conference call in the previous quarter nor engaged in automated downloading in the quarterly window [t-4, t-2]. All portfolios are equal-weighted and rebalanced every three months. Returns are measured as quarterly abnormal returns (Fama-French-Carhart four-factor alphas) in Panel A and cumulative monthly returns in Panel B, respectively. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively.

Panel A. Quarterly Abnormal Returns (%)

	Buy (1)	Sell (2)	Diff. (3)	Buy (4)	Sell (5)	Diff. (6)	Diff.-Diff. (7)
Full	2.17***	0.80	1.37**	1.05***	0.81***	0.25***	1.12
	[5.02]	[1.45]	[1.98]	[38.13]	[29.65]	[6.36]	[1.58]
Intensive margin trades	2.34***	0.95*	1.40**	0.93***	0.77***	0.16***	1.24*
	[5.25]	[1.73]	[2.00]	[27.52]	[23.96]	[3.54]	[1.76]
Extensive margin trades	0.78	-0.56	1.34	1.25***	0.88***	0.37***	0.97
	[0.51]	[-0.22]	[0.48]	[26.46]	[17.54]	[5.38]	[0.35]

Panel B. Quarterly Raw Returns (%)

	Buy (1)	Sell (2)	Diff. (3)	Buy (4)	Sell (5)	Diff. (6)	Diff.-Diff. (7)
Full	5.28***	4.06***	1.22**	2.49***	2.23***	0.26***	0.96***
	[17.33]	[10.79]	[2.53]	[124.38]	[113.56]	[9.39]	[1.99]
Intensive margin trades	5.53***	4.05	1.48***	2.61***	2.47***	0.13***	1.35***
	[17.39]	[10.78]	[3.01]	[106.10]	[107.08]	[3.99]	[2.73]
Extensive margin trades	3.34***	4.21**	-0.87	2.30***	1.76***	0.54***	-1.41
	[3.26]	[2.44]	[-0.46]	[48.72]	[67.20]	[10.78]	[0.70]

Table VIII. Stock Trade Performance: Regression Analysis

This table reports the empirical results testing whether automation-adopting hedge funds benefit more from conference-call participation by applying AI automation. Return_Trade denotes the trade-sign-adjusted cumulative monthly stock return three months after the trade, and Alpha_Trade denotes the trade-sign-adjusted Fama–French–Carhart four-factor alpha over the same horizon. Standard errors are clustered at the fund company level. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

	Return_Trade	Alpha_Trade
I^{ECP}	-0.000	-0.001
	[-0.27]	[-1.24]
HasAuto X I^{ECP}	0.018**	0.016**
	[2.25]	[1.98]
Model	OLS	OLS
Observations	2,726,524	2,726,524
Adj. R-squared	0.003	0.000
HasAuto X Year-Quarter FEs	Yes	Yes
HasAuto X Fund FEs	Yes	Yes

Table IX. Hard-to-Research Stocks and Trade Performance

This table examines whether hedge funds that adopt AI automation will show stronger informational advantage when trading hard-to-research stocks. Panel A reports the long-short portfolio performance based on hard-to-research stocks traded by hedge funds. Panel B reports the long-short portfolio performance based on easy-to-research stocks traded by hedge funds. Panel C reports the regression analysis results. Portfolio formation follows the procedure in Table VII. Returns are measured as quarterly abnormal returns (Fama-French-Carhart four-factor alphas). Standard errors are clustered at the hedge-fund level. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

Panel A. Long-short portfolio analysis using hard-to-research stocks

	Buy	Sell	Diff.	Buy	Sell	Diff.	Diff.-Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full	2.13***	0.26	1.87*	1.50***	1.21***	0.29***	1.58
	[3.38]	[0.30]	[1.81]	[34.57]	[27.73]	[4.77]	[1.53]
Intensive margin trades	2.64***	0.42	2.22**	1.34***	1.08***	0.26***	1.96*
	[3.97]	[0.50]	[2.10]	[24.90]	[20.68]	[3.45]	[1.81]
Extensive margin trades	-0.92	-0.93	0.01	1.75***	1.43***	0.32***	-0.31
	[-0.49]	[-0.27]	[0.00]	[24.09]	[18.05]	[3.05]	[0.09]

Panel B. Long-short portfolio analysis using easy-to-research stocks

	Buy	Sell	Diff.	Buy	Sell	Diff.	Diff.-Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Full	2.22***	1.43**	0.79	0.61***	0.43***	0.17***	0.62
	[3.94]	[2.11]	[0.90]	[11.74]	[12.98]	[3.62]	[0.70]
Intensive margin trades	2.00***	1.53**	0.46	0.53***	0.49***	0.05	0.41
	[3.47]	[2.25]	[0.52]	[12.85]	[12.59]	[0.81]	[0.47]
Extensive margin trades	5.19**	0.16	5.04	0.73***	0.33***	0.40***	4.64
	[2.06]	[0.04]	[1.20]	[12.75]	[5.20]	[4.58]	[1.10]

Panel C Regression analysis using hard-to-research stocks

	Return_trade	Alpha_trade
HasAuto X I^{ECP}	0.021	0.017
	[1.35]	[0.82]
HasAuto X I^{ECP} X Is_H2R	0.021**	0.026**
	[2.48]	[2.02]
Model	OLS	OLS
Observations	2,726,524	2,726,524
Adj. R-squared	0.003	0.000
HasAuto X Year-Quarter FEs	Yes	Yes
HasAuto X Fund FEs	Yes	Yes

Appendix A

Table A.1 Variable Definitions

Variables	Definition
Hedge Funds' Conference Participation	
N^{ECP}	Number of earnings calls a hedge fund participated in the given quarter. Source: London Stock Exchange Group (LSEG) Workspace; LSEG 13-F; Form ADV; Internet Searches.
I^{ECP}	Indicator equal to one if N^{ECP} is positive, and zero otherwise. Source: LSEG WS; LSEG 13-F; Form ADV; Internet Searches.
N_Conf^{M}	Number of conference analyst meetings a hedge fund participated in the given quarter. Source: LSEG WS; LSEG 13-F; Form ADV; Internet Searches.
I_Conf^{M}	Indicator equal to one if N_Conf^{M} is positive, and zero otherwise. Source: LSEG WS; LSEG 13-F; Form ADV; Internet Searches.
N^{Q}	Number of questions averaged across all earnings calls a hedge fund participated in the given quarter. Source: LSEG WS; LSEG 13-F; Form ADV; Internet Searches.
$Adjusted\_N^{Q}$	Adjusted number of questions computed based on the following steps: 1) remove any speaking turn that contains no more than five words; 2) take the median of the word count; 3) for a speaking turn with high-above-median word count, divide total word count by the median word count to get the adjusted number of questions in that turn; 4) for those containing less than or equal to the median word count, count it as one question for each turn; 5) add up the number of newly estimated questions across all speaking turns in a call. Source: Self-constructed.
N^{Words}	Length of questions in terms of total word count averaged across all earnings calls a hedge fund participated in the given quarter. Source: LSEG WS; LSEG 13-F; Form ADV; Internet Searches.
N^{Host}	Number of call-hosting firms a hedge fund interacted with in the given quarter. Source: London Stock Exchange Group (LSEG) Workspace; LSEG 13-F; Form ADV; Internet Searches.
Hedge Funds' SEC Downloads	
AutoAdoption	Indicator equal to one if a hedge fund has adopted AI automation in the given quarter. Adoption events are identified using hedge funds' first-time machine downloads of SEC filings. Source: SEC EDGAR server log files (EDGAR logs); LSEG 13-F; IP Registras [including Networksdb.io; American Registry for Internet Numbers (ARIN) WHOIS and WHOWAS]; Internet Searches.
HasAuto	Indicator equal to one if a hedge fund automated its downloading at least once in three quarters prior to its conference participation.
#IP	Number of IP addresses for sample hedge funds. Sources: IP Registras.
#AI-IP	Number of IP addresses using machine downloads at least once during the sample period. Sources: EDGAR logs; IP Registras.
Downloads^FL	Natural Logarithm of one plus the total number of filings downloaded in the previous 36 months. Sources: EDGAR logs.
Downloads^FM	Natural Logarithm of one plus the total number of unique firms downloaded in the previous 36 months. Sources: EDGAR logs.

Fund-level Characteristics	
Return	Value-weighted average buy-and-hold quarterly returns across all previous-quarter stocks held by a hedge fund. The value weight of each stock is taken at the end of previous quarter, dividing its market cap by the hedge fund's total stock holding value. Sources: LSEG 13-F; CRSP.
Alpha	Value-weighted average quarterly returns adjusted using Fama-French four-factor model. At the end of each month of a quarter t, I use daily stock returns to estimate each of a hedge fund's last-quarter 13F holding stock's daily risk-adjusted return using the Fama-French-Carhart four-factor model. I further multiply the daily alpha by 30 to get the monthly alpha and sum the monthly alphas within a quarter to get the quarterly alpha. Lastly, I compute the value-weighted quarterly alpha of the holding stocks as the hedge fund's current quarter's risk-adjusted returns. Sources: LSEG 13-F; CRSP.
Risk	Standard deviation of the hedge fund's holding-based returns in the past 24 months. Sources: LSEG 13-F; CRSP.
Size	Natural logarithm of the total market value of a hedge fund's quarterly 13F stock holdings. Sources: LSEG 13-F; CRSP.
Age	Number of months since the hedge fund's first 13F filing date. Sources: LSEG 13-F.
Turnover	Minimum of purchases and sales divided by the average total holding values of the current and the previous quarter. Sources: LSEG 13-F; CRSP.
H2R_PortPct	Percentage of hard-to-research stocks in a 13-F portfolio in any given quarter. Sources: LSEG 13-F; Compustat; Russell 2000 index; I/B/E/S.
High_PastECP	Indicator equal to one if the number of earnings calls a hedge fund participated in the past eight quarters is higher than the median. Sources: LSEG WS; LSEG 13-F; Form ADV; Internet Searches.
Abnormal_Hld	Difference between hedge fund holdings in the current quarter and the average hedge fund holdings over the previous eight quarters. Sources: LSEG 13-F
Stock-level characteristics	
Return_trade	Quarterly stock raw returns by taking the cumulative monthly raw returns at the end of any given quarter multiplied by the trade direction indicator that is equal to 1 if a hedge fund buys shares of the given stock in the previous quarter and -1 if a hedge fund sells shares of the given stock in the previous quarter. Sources: CRSP.
Alpha_trade	Quarterly stock abnormal returns using Fama-French-Carhart four-factor models at the end of any given quarter multiplied by the trade direction indicator that equal to 1 if a hedge fund buy shares of the given stock in the previous quarter. Sources: CRSP.
Is_H2R	Indicator equal to one if the stock belongs to the union of small-size stocks and low-analyst-coverage stocks in a given year as defined in Cao, Gao, and Guo (2025). Sources: Compustat; Russell 2000 index; I/B/E/S.

Appendix B Robustness Tests

Table B.1 Adding More Control Variables

This table reports the average treatment effect of AI automation adoption on hedge funds' conference-call participation after adding additional controls that proxy for information frictions and demand. Panel A reports the extensive-margin effects with two dependent variables: columns (1)–(2) show results for the number of earnings calls attended by hedge funds (N^{ECP}), and columns (3)–(4) for the number of distinct host firms in that quarter (N^{Host}). AutoAdoption equals 1 if a hedge fund adopted AI automation in any previous quarter and 0 otherwise. Estimates are based on the stacked DiD specification in equation (1). The stacked events are funds' first-time adoptions, and controls are never-adopters. Panel B estimates the same model for the intensive margin with two dependent variables: columns (1)–(2) use the original question count in a call (N^{Q}) and columns (3)–(4) the adjusted question count (Adjusted_N^{Q}). All dependent variables at quarter t are related to independent variables at quarter t-1. Standard errors are clustered by fund company and event. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

	N^{ECP}	N^{Host}	N^{Q}	Adjust_N^{Q}
AutoAdoption	0.254**	0.277***	0.240**	0.213*
	[2.22]	[2.71]	[1.99]	[1.77]
Return	-0.022	0.007	0.522***	0.550***
	[-0.35]	[0.11]	[7.04]	[7.55]
Size	0.081***	0.079***	0.070***	0.055***
	[6.09]	[6.06]	[5.76]	[4.43]
Risk	-1.359***	-1.420***	-1.033***	-0.991***
	[-5.27]	[-5.66]	[-3.77]	[-3.45]
Turnover	0.478***	0.486***	-0.068	-0.099
	[6.95]	[7.23]	[-0.87]	[-1.25]
Age	0.748***	0.830***	0.527***	0.473***
	[6.93]	[7.30]	[10.02]	[8.06]
H2R_PortPct	0.956***	0.932***	1.165***	1.108***
	[14.92]	[14.70]	[15.45]	[13.67]
Abnormal_Hld	0.001***	0.001***	0.001***	0.001***
	[7.48]	[6.45]	[6.12]	[7.32]
High_PastECP	0.568***	0.562***	0.312***	0.306***
	[22.20]	[22.41]	[11.14]	[11.34]
Model	Poisson	Poisson	Poisson	Poisson
Observations	113,957	113,957	35,175	35,175
Pseudo R-squared	0.513	0.504	0.650	0.685
Year-Quarter X Stack FEs	Yes	Yes	Yes	Yes
Fund X Stack FEs	Yes	Yes	Yes	Yes

Table B.2 Requiring at least One Pre-Automation Earnings Call Appearance

This table re-estimates the average treatment effect of AI automation adoption in a sample restricted to funds that made at least one earnings-call appearance prior to adoption. Panel A reports extensive-margin effects for the number of calls attended (N^{ECP}, columns (1)–(2)) and the number of distinct host firms (N^Host, columns (3)–(4)). AutoAdoption equals 1 if a hedge fund adopted AI automation in any previous quarter and 0 otherwise. Estimates are based on the stacked DiD specification in equation (1). The stacked events are funds' first-time adoptions, and controls are never-adopters. Panel B repeats the model for the intensive margin (N^Q in columns (1)–(2) and Adjusted_N^Q in columns (3)–(4)). This restriction addresses the concern that results could reflect a contemporaneous shift into an interaction-intensive style rather than reallocation within an existing fundamentals-oriented approach. All dependent variables at quarter t are related to independent variables at quarter t-1. Standard errors are clustered by fund company and event. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

Panel A. Extensive Margins						
		N^{ECP}			N^{Host}	
	(1)	(2)	(3)	(4)	(5)	(6)
AutoAdoption	0.486***	0.459***	0.286***	0.502***	0.477***	0.307***
	[5.25]	[5.32]	[2.73]	[5.17]	[5.25]	[3.23]
Return		0.055	0.042		0.083	0.074
		[0.94]	[0.69]		[1.43]	[1.23]
Size		0.072***	0.091***		0.067***	0.085***
		[4.72]	[6.92]		[4.39]	[6.56]
Risk		-0.737***	-1.335***		-0.821***	-1.389***
		[-2.67]	[-5.25]		[-3.08]	[-5.64]
Turnover		0.525***	0.521***		0.535***	0.528***
		[7.32]	[7.35]		[7.62]	[7.62]
Age		0.509***	0.714***		0.591***	0.789***
		[4.24]	[6.62]		[4.70]	[6.93]
H2R_PortPct			1.083***			1.043***
			[15.63]			[15.14]
Abnormal_Hld			0.001***			0.001***
			[6.08]			[5.18]
High_PastECP			0.521***			0.515***
			[19.48]			[19.60]
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Observations	86,525	86,525	86,525	86,525	86,525	86,525
Pseudo R-squared	0.486	0.486	0.494	0.476	0.476	0.484
Year-Quarter X Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund X Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table B.2—Continued

Panel B. Intensive Margins						
		N^Q			$Adjust\_N^Q$	
	(1)	(2)	(3)	(4)	(5)	(6)
AutoAdoption	0.347***	0.327***	0.247**	0.311***	0.295***	0.214*
	[3.15]	[3.09]	[1.98]	[2.70]	[2.68]	[1.68]
Return		0.367***	0.449***		0.380***	0.461***
		[5.24]	[5.97]		[5.49]	[6.26]
Size		0.056***	0.069***		0.049***	0.057***
		[3.82]	[5.70]		[3.44]	[4.59]
Risk		-0.220	-1.095***		-0.213	-1.062***
		[-0.85]	[-3.94]		[-0.78]	[-3.66]
Turnover		-0.020	-0.033		-0.018	-0.040
		[-0.23]	[-0.43]		[-0.20]	[-0.51]
Age		0.357***	0.519***		0.310***	0.460***
		[6.29]	[9.44]		[5.05]	[7.67]
H2R_PortPct			1.183***			1.114***
			[15.83]			[13.94]
Abnormal_Hld			0.001***			0.001***
			[7.72]			[10.11]
High_PastECP			0.313***			0.309***
			[10.99]			[11.33]
Model	Poisson	Poisson	Poisson	Poisson	Poisson	Poisson
Observations	32,979	32,979	32,979	32,979	32,979	32,979
Pseudo R-squared	0.639	0.640	0.649	0.674	0.675	0.684
Year-Quarter X Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes
Fund X Stack FEs	Yes	Yes	Yes	Yes	Yes	Yes

Table B.3 Using Alternative Definitions of Automation Adoption

This table examines robustness to alternative definitions of automation adoption based on SEC EDGAR machine-download activity. Panel A presents extensive-margin effects for N^{ECP} (columns (1)–(2)) and N^Host (columns (3)–(4)); Panel B presents intensive-margin effects for N^{Q} (columns (1)–(2)) and Adjusted_N^{Q} (columns (3)–(4)). The stacked difference-in-differences specification (equation (1)) is unchanged. The stacked events are funds' first-time adoptions, and controls are never-adopters. AutoAdoption is re-defined using alternative download thresholds from the EDGAR logs (e.g., 1000 filings per day and 5 filings per minute). All dependent variables at quarter t are related to independent variables at quarter (t-1). Standard errors are clustered by fund company and event. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

	N^{ECP}		N^{Host}	
	(1)	(2)	(3)	(4)
AutoAdoption	0.489***	0.512***	0.494***	0.518***
	[3.18]	[3.50]	[3.00]	[3.33]
Return		-0.065		-0.032
		[-0.65]		[-0.33]
Size		0.085***		0.081***
		[4.48]		[4.37]
Risk		-0.500		-0.564
		[-1.38]		[-1.60]
Turnover		0.736***		0.734***
		[5.57]		[5.60]
Age		0.622***		0.712***
		[4.07]		[4.39]
Model	Poisson	Poisson	Poisson	Poisson
Observations	57,779	57,779	57,779	57,779
Pseudo R-square	0.496	0.497	0.488	0.489
Year-Quarter X Stack FE	Yes	Yes	Yes	Yes
Fund X Stack FE	Yes	Yes	Yes	Yes

Table B.4 Using Alternative Event Windows and Event Groups

This table assesses robustness to alternative event-time constructions in the stacked design. Panel A (Shorter Event Windows) reports the extensive-margin effects for $\mathrm{N}^{\mathrm{ECP}}$ (columns (1)–(2)) and $\mathrm{N}^{\mathrm{Host}}$ (columns (3)–(4)) when the event window around adoption is shortened relative to the main ±3-year window. Panel B (Alternative Event Groups) reports the intensive-margin effects for N^{Q} (columns (1)–(2)) and Adjusted_N^{Q} (columns (3)–(4)) when event groups are redefined to ensure complete pre/post coverage and to vary cohort construction. The stacked difference-in-differences specification (equation (1)) is unchanged. The stacked events are funds' first-time adoptions, and controls are never-adopters. AutoAdoption equals 1 if a hedge fund adopted AI automation in any previous quarter and 0 otherwise. All dependent variables at quarter t are related to independent variables at quarter (t-1). Standard errors are clustered by fund company and event. t-statistics are reported in brackets, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% level, respectively. Variable definitions are provided in Appendix A.

Panel A. Events from 09-14 w/ full 3-yr pre & post window		
	$\mathrm{N}^{\mathrm{ECP}}$	$\mathrm{N}^{\mathrm{ECP}}$
AutoAdoption	0.505***	0.481***
	[5.92]	[5.82]
Return		-0.021
		[-0.24]
Size		0.051**
		[2.55]
Risk		-0.703*
		[-1.85]
Turnover		0.586***
		[6.19]
Age		0.362*
		[1.75]
Model	Poisson	Poisson
Observations	67,242	67,242
Pseudo R-square	0.502	0.502
Year-Quarter FEs	Yes	Yes
Fund FEs	Yes	Yes

Table B.4—Continued

Panel B. Events from 08-15 w/ full 2-yr pre & post window		
	N^{ECP}	N^{ECP}
AutoAdoption	0.249**	0.236**
	[2.37]	[2.34]
Return		0.022
		[0.32]
Size		0.055***
		[3.22]
Risk		-0.926***
		[-2.79]
Turnover		0.657***
		[7.91]
Age		0.539***
		[3.39]
Model	Poisson	Poisson
Observations	65,726	65,726
Pseudo R-square	0.510	0.511
Year-Quarter FEs	Yes	Yes
Fund FEs	Yes	Yes

Appendix C Additional Descriptive Statistics

Table C.1 Descriptive Statistics of Sample Hedge Fund IP and SEC Downloading Activities

This table reports the summary statistics of sample hedge fund IPs and their daily SEC footprints, with classification of IP type (AI or Non-AI) and IP status (Machine or Human). The sample period is from May 15th, 2006, to March 31st, 2017. An AI IP is an IP that adopts AI automation, and a non-AI IP is a non-adopter IP. AI automation refers to the downloading activity that covers files from more than 50 unique firms in a day. The activities of AI IP are further classified into two statuses: "Machine", when an AI IP conducts AI automation, and "Human", otherwise. N is the number of IP-day observations. DL_MeanDays is the sample mean of an IP's monthly visiting days. DL_MeanFirms is the average number of unique firms covered by an IP's monthly downloading. DL_MeanFiles is the average number of files downloaded by an IP in a month. DL_TotalFiles and DL_Ratio refers to the total downloading volume of an IP category during the sample period, and its proportion of the full downloading volume, respectively.

Sample	N	DL_ MeanDays	DL_ MeanFirms	DL_ MeanFiles	DL_ TotalFiles	DL_ Ratio
AI IP (Machine uses)	1,867,757	0.43	1623.15	25,481.64	121,088,768	95.40%
AI IP (Human uses)	1,867,757	7.42	1.91	11.76	3,819,278	3.01%
Non-AI IP	1,867,757	2.07	0.22	1.32	2,024,195	1.59%
Full	1,867,757	3.09	4.64	67.95	126,932,241	100%

Table C.2 Descriptive Statistics of in-person Conferences and Hedge Fund Participation

This table reports the sample of corporate analyst meetings (in-person conferences) and conference participation by all 13F-filing hedge funds and those without missing IP addresses during the period of 2006-2017. IP addresses are collected for hedge funds that attend earnings calls at least once during the sample period. Panel A summarizes the overall number of conferences and hosts, the number and percentage of calls covered by hedge funds, and the number of hedge funds by year.

			All 13F-filing Hedge Funds			Hedge Funds w/ no missing IPs		
Year	#Calls	#Host	#Calls	%Calls	#HF	#Calls	%Calls	#HF
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
2006	167	141	27	16.17%	32	16	9.58%	19
2007	171	145	44	25.73%	35	17	9.94%	14
2008	203	172	57	28.08%	42	22	10.84%	22
2009	168	148	48	28.57%	39	22	13.10%	24
2010	225	196	61	27.11%	37	33	14.67%	21
2011	209	176	64	30.62%	34	41	19.62%	19
2012	210	188	51	24.29%	33	31	14.76%	20
2013	264	232	65	24.62%	31	35	13.26%	16
2014	373	329	106	28.42%	47	51	13.67%	26
2015	362	313	117	32.32%	50	66	18.23%	27
2016	335	300	125	37.31%	34	66	19.70%	16
2017	458	413	100	21.83%	27	65	14.19%	15
Full	3,145	1,165	865	27.09%	204	465	14.30%	111