AI Automation and Effort Allocation: Evidence from Sophisticated Investors*

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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 human-interaction-based information acquisition. Using an event study design and an IV approach, I find that hedge funds increase earnings call participation—along 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 AI-productivity mechanism: by *substituting* for human effort at automation-prone tasks, AI *complements* high-skilled workers without directly augmenting them at interaction-based tasks.

JEL Classification: J24, G12, G14, G23

Keywords: AI Automation; Effort Allocation; Hedge Funds; Information Acquisition; Investment Performance; Complement via Substitution

Technological advances in automation, such as artificial intelligence (AI) and robotics, are reshaping the distribution of human effort across job tasks. AI automation, as opposed to robotics automation, is particularly relevant for knowledge workers, as machine algorithms can automate data-intensive tasks that used to be performed by humans (Acemoglu and Restrepo 2020). How does AI affect human-intensive tasks for high-skilled knowledge work? Humans' comparative advantages (e.g., human interactions and judgment) not only make these tasks hard to displace but also underpin human-AI complementarity in different scenarios. For example, institutional knowledge allows human analysts to outperform AI despite AI's disruption of stock analysis, making "man + machine" the likely future of work (Cao, Jiang, Wang, and Yang 2024). AI can also create new tasks that require human skills to accomplish (e.g., Acemoglu and Restrepo 2019). This paper proposes and tests an effort allocation channel underlying human-AI complementarity: high-skilled knowledge workers exert more effort at human-intensive, hard-to-automate tasks, when AI lowers the cost of completing data-intensive, easy-to-automate ones.

In the knowledge economy, big data, information technologies, and labor increasingly interact (Ide and Talamas 2025; Abis and Veldkamp 2024). Previous studies have documented the relevance of big data and AI for the asset management industry that epitomizes such an economy (Bonelli and Foucault 2025; Chen, Sialm, and Xu 2025; Sheng, Sun, Yang, and Zhang 2025). Little is known about how skilled workers in this industry adjust their information acquisition effort in the age of AI. This paper fills the gap by shifting the focus from asset managers' direct use of AI to their complementary use of AI. Specifically, I document hedge funds' productivity gains from AI in the form of both increased use of earnings calls and positive performance effects of post-automation call participation.

The central, broad message of this paper is that artificial intelligence redirects human intelligence toward human-intensive tasks. Hedge funds provide a good empirical setting to give color to this statement. As high-powered information intermediaries and sophisticated investors, hedge funds acquire both standardized, quantifiable information such as regulatory filings and interactive, real-time information such as Q&A during earnings calls. The first type (non-interaction-based) is more prone to algorithmic automation, while the second (human-interaction-based) is not. When AI makes it easier to collect non-interaction-based information, does it shift effort toward tasks that require human interaction? Specifically, I hypothesize that AI leads hedge funds to make greater use of earnings calls and that post-automation call attendance translates into better performance. The call participation hypothesis embeds an implicit assumption that hedge funds are sensitive to effort constraints on actively participating in earnings calls (by asking questions). A priori, hedge funds are privately informed investors, producing two specific priors that could make this assumption debatable: they might have little interest in public calls or they will protect their informational advantages by listening to calls without speaking. This paper challenges these priors regarding hedge funds' earnings call participation incentives and behavior, thus guarding the implicit assumption, while showing support for the hypothesized positive relation between AI automation and call participation.

The first challenge in examining the hypotheses is to identify which hedge funds use AI automation technologies for their information acquisition tasks. Because specific AI usage is not observable, I use machine downloads of SEC filings as a proxy for hedge funds' use of AI (in a similar spirit to the AI readership measure in Cao, Jiang, Yang, and Zhang 2023). The rationale is that one of AI's comparative advantages is scaling up data-intensive tasks beyond what human analysts can do manually: automated downloading typically produces a volume of filings that is only useful when paired with subsequent AI-driven processing and analyzing. [1] Consistent with this logic, I adopt a revealed preference approach: funds that begin machine downloading are classified as AI-adopting hedge funds, and I compare their earnings-call participation to that of non-adopters. Operationally, I define an AI adoption event as a fund's first-time machine downloads, which I identify using SEC EDGAR request patterns that are too fast and too high-volume to be consistent with manual downloading.

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). To the best of my knowledge, this paper is the first to relate hedge funds' EDGAR downloading behavior to their earnings call participation decisions and to show that automated information acquisition increases interactive information acquisition, which in turn improves performance.

[1] This paper does not equate machine downloading alone with AI. Machine downloads signal the use of AI analysis, as the processing of downloaded materials calls for natural language processing, data/text analytics, and image processing, which are algorithms that fall into the AI category defined in the US Census Bureau survey. Also see this blog by V7 Labs (an AI startup). Without AI, analyzing (numerous) SEC filings could be a "Herculean task".

To examine the automation-participation relation, I employ two empirical strategies. First, I estimate event study specifications that compare AI-adopting hedge funds' earnings call participation to that of non-adopters. Second, to the extent that the initial AI adoption events are still hedge fund firms' endogenous decisions, I further construct a Bartik-style instrument of technology salience induced by local quantitative hedge funds (or quants) to pin down causality. I exploit both the plausibly exogenous time variation from local quants initiating a 13-F filing and the cross-sectional heterogeneity in focal fundamental funds' past reliance on SEC EDGAR. The relevance condition is met because local quant as new 13F filers make automation technology salient to sample fundamental funds, and fundamental funds that were heavy manual SEC EDGAR downloaders pre-adoption benefit the most from automation and thus are more likely to adopt AI technologies. The exclusion restriction condition is also likely satisfied because this technology salience instrument affects how much the fund participates in earnings calls only through shifting the likelihood of adopting automated downloads.

My empirical analysis yields three main sets of results. First, a stacked difference-in-differences design shows 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 59% more earnings calls and interact with 62% more call-hosting companies than non-adopters; conditional on participation, adopters also ask 6 more questions during an average call. Results from IV estimations confirm the positive automation-participation relation in a casual framework, consistent with the hypothesis that AI automation induces a shift of effort toward human-interaction-based information acquisition. Since non-interaction-based information naturally increases with AI adoption, the positive call 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. First, this paper contributes to a nascent and burgeoning literature that studies the impact of big data and AI on the skill and performance of professional investment managers. Two contemporaneous papers study AI adoption among hedge funds. Sheng, Sun, Yang, and Zhang (2025) focus on the use of generative AI for extracting insights from earnings conference call texts and the investment implications of GenAI reliance.[2] Chen, Sialm, and Xu (2025) provide a labor-based approach to measure hedge funds' use of AI and further link it to fund characteristics and performance. For non-hedge-fund asset managers in relation to AI and big data technologies, Bonelli and Foucault (2025) study whether the use of alternative data devalues traditional fund managers' expertise in the mutual fund industry; Zhang (2024) studies how the recruitment of AI talents affects mutual fund performance; Bonelli (2025) examines capital allocation by venture capitalists post the adoption of AI-related data technologies.[3] Unlike these studies, I shift the focus from investors' direct use of AI to their *complementary use* of AI. Specifically, I examine how AI adoption affects hedge funds' earnings call participation and how such a complementary use of AI in turn generates performance impact.

Second, 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 hedge funds and public information providers in facilitating market efficiency. 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. Bai and Massa (2025) find that the loss of human-interaction-based informational advantages due to COVID-19 lockdowns 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, suggesting the increased need for contextual information and deepening research.[4] 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 important 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 relation to AI adoption. Second, this paper reveals a novel insight that AI automation raises the degree of complementarity between human-interaction-based information and non-interaction-

[2] Using AI to analyze earnings call transcripts, just as analyzing SEC filings, is seen as non-interaction-based information acquisition in my study. This process does not render real-time earnings call participation unnecessary.
[3] Also see Hu, Rohrer, and Zhang (2025), Cen, Han, Han, and Jo (2024), and Kim and Nanda (2025), etc.
[4] 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.

based information. More human-interaction-based information is produced following the AI-expedited availability of non-interaction-based information.

More broadly, this paper builds on the literature on the labor impact of automation technologies like AI and robotics. For example, Acemoglu and Restrepo (2018b) (Acemoglu and Restrepo 2021) explore how AI (industrial robots) affects labor market outcomes by taking over tasks previously performed by human labor. Abis and Veldkamp (2024) show that new data management and AI jobs lead to changes in labor shares in the investment management industry. Cao, Jiang, Wang, and Yang (2024) reveal the skill complementarity between humans and machines in the sense that AI-driven stock analyses cannot outperform human analyses when institutional knowledge (e.g., intangible assets, financial distress) is involved. The research debate over the Man versus Machine race tends to be concerned with either the substitutive role or complementary role of AI, with the substitutive role seen as disruptive. This paper uncovers a new angle to interpret the substitutive role: AI replacing labor does not always have to be disruptive; it can be a channel for AI-human complementarity to operate. By replacing effort at repetitive and quantitative tasks, AI enhances labor by facilitating more productive use of human effort.

Lastly, a few studies show that automation technologies affect high-skilled jobs (with human analyses involved) in the financial industry through different dimensions of human decision making, including the presence of agency conflicts and limited cognitive capacity (Jansen, Nguyen, and Shams 2025), algorithm aversion (Greig, Ramadorai, Rossi, Utkus, and Walther 2025), and strategic attention to soft skills (Grennan and Michaely 2020). This paper differs from those studies in that I document a rational effort-allocation channel for the productivity gains from AI automation: AI technologies induce more effort at human-interaction-based tasks by relaxing humans' effort constraint, imparting a new complementarity meaning to AI's substitution effect. By showing that hedge funds' post-automation earnings call participation translates to better investment performance, this paper provides novel evidence on improved task performance due to optimal effort allocation by these high-skilled workers in the age of AI.

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 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.[5] 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 "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

[5] 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.

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.[6] 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.[7] 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 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,

[6] These economic channels are also partly motivated by the empirical facts in my main results contained in Table IV.
[7] 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.

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.[8] 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.*

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[9] and form ADV

[8] 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.
[9] I thank Rick Sias for providing access to 13-F institution taxonomy data sourced from Thomson Reuters.

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) [10]—from LSEG workspace.[11] 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.[12]

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[13]: (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 data vendor. Following the first round of fuzzy name matching, I have 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

[10] 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.
[11] At the time of writing the current draft (August 2025), no API is available for downloading this data.
[12] See the internet appendix for reasons why corporate analyst meetings serve as a viable measure for in-person human-interaction-based information acquisition.
[13] As laid out in the internet appendix, same procedures apply to identifying hedge funds' attendance in corporate analyst meetings.

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.[14] This study also provides the 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 5,212 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 I 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 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

[14] 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.

(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). [15]

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, [16] 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).[17] 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 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

[15] 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.

[16] 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).

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

1000 filings per day) or the velocity of downloading (e.g. 5 filings per minute).[18] 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,[19] 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 plot 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 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

[18] See, e.g., Cao et al. 2023, Crane et al. 2023, and Chen et al. 2020.
[19] 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.

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 II 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).[20]

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: DiD analysis

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. By construction, AI adoption in this paper is based on first-time machine downloads, which are flagged by the standard of being faster and bulkier than human downloads (see section II.B for details). 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,[21] I conduct a stacked difference-in-differences (henceforth, stacked DiD) design using never-treated firms as controls.[22] In the

[20] In unpresented summary statistics, when combined the sub-sample of AI IPs and Non-AI IPs, the average number of filings viewed per non-AI IP per month becomes 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.

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

[22] 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.

spirit of Baker et al. (2022) and Cengiz et al. (2019), the main stacked DiD specification is as follows:

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

where i, t, s denotes 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 $\mathrm{N}^{\mathrm{ECP}}_{\mathrm{i,t,s}}$ 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 $\mathrm{N}^{\mathrm{Host}}_{\mathrm{i,t,s}}$; number of questions a fund asked in a call $\mathrm{N}^{\mathrm{Q}}_{\mathrm{i,t,s}}$; adjusted number of questions a fund asked in a call $\mathrm{Adjust\_N}^{\mathrm{Q}}_{\mathrm{i,t,s}}$.[23] The first variable on the number of questions is to naively count the number of speaking turns associated with a hedge fund during a call. However, this question count 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 three Q&A interaction examples in the internet appendix (see IA-6) 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; [24] (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.

[23] In the internet appendix, I also show additional extensive-margin and intensive-margin results using the participation indicator $\mathrm{I}^{\mathrm{ECP}}_{\mathrm{i,t,s}}$ and total word count for a call with fund participation $\mathrm{L}^{\mathrm{Q}}_{\mathrm{its}}$, 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).

[24] 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.

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 meaningless estimates (see, Cohn, Liu, and Wardlaw 2022; Chen and Roth 2024), I therefore use Poisson regression model to estimate equation (1) with $\mathrm{N}_{\mathrm{i,t,s}}^{\mathrm{ECP}}$ and $\mathrm{N}_{\mathrm{i,t,s}}^{\mathrm{Host}}$. $\mathrm{AutoAdoption}_{\mathrm{i,t,s}}$ is a shorthand for the DiD interaction term $\mathrm{Treated}_{i,s} \times \mathrm{Post}_{t,s}$, where $\mathrm{Treated}_{i,s}$ equal to one if a fund becomes an adopter i.e., an automation-adopting fund) in sub-experiment s and zero otherwise, $\mathrm{Post}_{t,s}$ 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 $\theta_{\mathrm{i,s}}$ and time-by-stack fixed effects $\delta_{\mathrm{t,s}}$ in the model. $\varepsilon_{\mathrm{i,t,s}}$ 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 IV 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).

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

where i, t, s, n denotes fund, quarter, sub-experiment, the length of the quarterly event window, respectively; All other variables are the same as in the main stacked DiD model (equation (1)). Base quarter is set as the quarter/year before the adoption quarter. Figure II 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.[25]

[Insert Figure II (a) about here]

$$N^{ECP}_{i,\bar{t},s} = \sum_{\substack{\bar{t}=-\bar{n} \\ \bar{t}\neq -1}}^{\bar{n}} \beta \cdot AutoAdoption_{i,\bar{t},s} + X'\Gamma + \theta_{i,s} + \delta_{\bar{t},s} + \varepsilon_{i,\bar{t},s} \tag{3}$$

where i, $\bar{t}$, s, n denotes fund, year, sub-experiment, the length of the yearly event window, respectively; All other variables are the same as in the main stacked DiD model (equation (1)). Base year is set as the year before the adoption year. Figure IIb plots the corresponding year-to-year estimates from this dynamic model. Once again, this figure provides supporting evidence for the parallel trend assumption that without AI adoption, the adopter funds and non-adopters would have evolved similarly in terms of earnings call participation. An interesting long-run dynamic presented itself when focusing on yearly window around the adoption event: Automation-induced

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

call participation lasts for at least three years, which does not contract with the results on the quarterly dynamic model because of the dual role of the adoption events. On the one hand, the primary purpose of the adoption event is to proxy for technological supply shocks (assuming that the time lag from the unobserved supply shocks to the firm's adoption decisions is similar across 13-F filing hedge funds). As such, once fund firms adopt AI automation, they achieve greater efficiency levels in terms of acquiring non-interaction-based information, thus facilitating redeploying human capital to the collection of interaction-based information. On the other hand, the empirical nature of the adoption event has an informational role embedded in the sense that machine downloads of SEC filings naturally serve as an informational supply shock (in addition to a technological supply shock). Hedge funds make investment decisions based on an information set that is as complete as possible. It is necessary that the downloaded and processed information from the SEC EDGAR system be used in a timely manner to guide the decisions of whether to attend earnings call or not and what to ask during calls. Hence, in the short run, the participation effect appears in the ensuing quarter $t + 1$ but disappears in the subsequent quarters (from $t + 2$ onwards).

Taken together, the short-run and long-run dynamic models not only cross-validate the absence of pre-trend in the diagnostic test for the parallel trend assumption but also reveal an interesting dual role of the SEC-download-based automation adoption events in capturing both the technological supply and informational supply.

[Insert Figure II (b) about here]

B. Earnings call participation around automated downloading: IV estimation

The event study design demonstrates a positive association between funds' AI adoption and earnings call participation. However, it may fail to capture causal effects due to either the omitted variable bias or reverse causality. On the one hand, one may argue that some strategic motive may lead a fund company to adopt AI and to deploy human capital for attending earnings calls as well. For example, implementing a new investment strategy firmwide can increase the demand for both non-interaction-based information and interaction-based information.[26] On the other hand, if

[26] Being the closest observable event to a costly technology adoption decision, initiating machine downloads of SEC files is likely uncorrelated with transitory information demand but may still capture long-run strategic information demand that also raises earnings call participation.

increased earnings call participation is driven by the greater availability of human capital due to fund firms' phasal upsizing strategy, such an increase in labor demand could lead to an AI adoption decision. Specifically, during workforce expansion, a firm could spot data experts in the labor market and hire them to design and execute machine algorithms for retrieving and processing SEC filings. Even if the variable timing in the main results is conceived as automation followed by participation, given that the hiring process could start in the preceding quarters relative to the current quarter with increased earnings call participation, hiring could be contemporaneous with or even prior to automation adoption. As such, the observed automation-participation relation could still be spurious due to a reverse causality possibility.

B.1. Constructing the instrumental variable

To deal with these endogeneity concerns that plague causal identification, I devise an instrumental variable that exploits plausibly exogenous variation in fundamental funds' technology salience. Specifically, I hypothesize focal fundamental hedge funds are more likely to adopt AI automation when 1) local quant hedge funds newly become their 13-F peers (filing for 13-F for the first time), making AI-related technologies more salient to the fundamental ones, and 2) they themselves had been more active SEC EDGAR downloaders and thus are more exposed to such technology salience shocks. To operationalize this idea, I construct the instrument variable for the adoption indicator as the product of the number of 13-F filings initiated by local quant hedge funds during quarter $t-1$ and quarter $t-4$ and the number of unique firms manually downloaded via SEC EDGAR during quarter $t-8$ and quarter $t-5$. In this Bartik-style shift-share instrument variable, all time variation comes from the shocks of new 13-F entries by local quants, and the cross-sectional heterogeneity in terms of fundamental funds' exposure to technology salience is linked to their pre-treatment reliance on SEC EDGAR. It is a valid IV because both the relevance condition and the exclusion restriction condition are met. First, local quant as new 13F filers make technology salient to focal fundamental funds, and even more so when fundamental funds were already heavy users of SEC EDGAR pre-adoption. The combination of quant-induced technology salience and firms' pre-treatment adoption incentives makes it more likely for treated focal funds to adopt machine downloads of SEC filings. Second, this technology salience instrument affects how much the fund participates in earnings calls only through the shift in the likelihood of adopting automated downloads, justifying the exclusion restriction.

B.2. Data sources and empirical models

My identification of quant funds is based on 13-F institution taxonomy data sourced from Thomson Reuters and Internet Search.[27] There is a total of 59 new 13-F quant hedge fund filing events during the period between 2007 and 2016. I obtain each hedge fund's ZIP code from the SEC and define 'local' ZIP codes as those within a 100-mile radius of the fund's ZIP, using the NBER ZIP Code Distance Database.

First-stage model:

$$\mathrm{AutoAdoption}_{i,t} = \beta Z_{i,t-1} + X'\Gamma + \theta_i + \delta_t + \varepsilon_{i,t} \tag{4}$$

where i, t, denote fund and year-quarter time period, respectively, and

$$Z_{i,t-1} = \mathrm{Downloads}^{FM}_{i,t-8,t-5} \times N^{NewQuant}_{i,t-4,t-1} \tag{5}$$

where $\mathrm{Downloads}^{FM}_{i,t-8,t-5}$ represents the number of unique firms covered by the focal hedge fund through manual EDGAR filing downloading in quarters $t-8$ to $t-5$, $N^{NewQuant}_{i,t-4,t-1}$ denotes the number of new 13-F filing events of local quant hedge funds for the focal hedge fund in quarters $t-1$ to $t-4$. All variables used in this specification are defined in the appendix table A.1. The estimation method is linear probability model.

Second-stage model:

$$N^{ECP}_{i,t} = \beta \cdot \widehat{\mathrm{AutoAdoption}}_{i,t} + X'\Gamma + \theta_i + \delta_t + \varepsilon_{i,t} \tag{6}$$

where i, t, denote fund and year-quarter time period, respectively, and $\widehat{\mathrm{AutoAdoption}}_{i,t}$ is the estimated $\mathrm{AutoAdoption}_{i,t}$ in the first stage. The IV Poisson estimation is based on a Two-Stage Residual Inclusion (2SRI) model (see Schwarz et al. 2024 and Basu et al. 2017), where a control function approach is adopted in the IV estimation process. All variables used in this specification are defined in the appendix table A.1.

[27] I obtain a list of quant hedge funds from partow.net and perform name matching between this internet-sourced quant list and the 13-F filing hedge fund names. https://www.partow.net/miscellaneous/quantfirms.html.

B.3. IV estimation results and magnitude interpretation

This technology salience instrument strongly predicts the adoption of AI automation (AutoAdoption). At the median SEC-filing reliance, a one–standard-deviation increase in first-time local quantitative 13F filers raises the probability of AutoAdoption by 4.88% of the sample mean. First-stage strength is above the threshold of 10 (Kleibergen–Paap F-stat = 54.6), alleviating weak-instrument concerns. The second-stage Poisson regression estimate suggests automation-adopting hedge funds attend 5.57 more earnings calls per quarter compared to non-adopters following AI adoption. Figure III shows a binscatter representation of instrumental variable estimation, directly visualizing the positive relation between the number of earnings conference calls and the predicted values of adoption likelihood.

[Insert Table V about here]

[Insert Figure III about here]

Taking stock of the results from both the Stack DiD analysis and IV estimation, the relation between hedge funds' adoption of AI automation and their earnings call participation behavior is likely to be causal and is positive and significant. The 2SLS estimate implies an economic effect that is about five times the DiD estimator (see Table IV). This magnitude differentials could be attributed to three reasons:

First, as discussed earlier in the stacked DiD setting, machine downloads only serve as a noisy measure for AI adoption (by not capturing other automation-related activities such as using AI to automate the processing of the downloaded files and accessing other corporate disclosure files including earnings call transcripts). Such measurement errors could lead to the presence of attenuation bias that understate the true effect of adopting AI technologies on earnings call participation. In the IV setting, fund companies' AI adoption decisions induced by their technology salience could be a more precise proxy to the actual adoption events, thus reducing the measurement errors in the first-time adoption proxy.

Second, there could be some unmeasured, time-varying confounders in the error terms that bias DiD estimates downwards. For example, machine downloads could be correlated with the shortage of human capital in a company, which is negatively correlated with earnings call participation.[28] In this case, the estimated automation-participation relation is closer to a lower bound of the true relation. A discrepancy in the magnitude between the IV test and the DiD test could imply that such unobservable confounders that are difficult to measure do exist but they are less of an impact in the IV analysis, because the instrumental variable more precisely projects the exogenous variation onto the endogenous variables. Specifically, AI adoption instrumented by technology salience is more likely to be out of efficiency reasons and less likely to be plagued by factors that could drive down earnings call participation.

Lastly, the IV estimator essentially measures the local average treatment effect (LATE), i.e., the effect of treatment on compliers (not including always-takers) whose treatment status is turned on by the instrument. The stacked DiD estimator reflects the average treatment effect on the treated (ATT). LATE does not have to be greater than ATT, but in this context, the bigger LATE indicates that marginal adopters—those induced by the technology shock—realize larger productivity gains from adoption than the average adopter. This is consistent with the construction of the Bartik-style IV, the essential part of which is the pre-determined fund-level SEC reliance. Due to the inclusion of such cross-sectional heterogeneity in the instrumental variable, some complier funds reap more productivity benefits from adopting AI, in terms of making time and efforts for attending earnings calls and asking questions. On a related note, due to this average treatment effect being "local" under the IV setup, we should exercise usual caution when interpreting its bigger economic magnitude due to potential loss of external validity.[29]

C. 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

[28] In Section D.1., I further construct three time-varying control variables that could lead to greater levels of earnings call participation anyways regardless of automation adoption. Table B.1 shows that after controlling for funds' time-varying information demand, informational advantages, and information stickiness, the results still remain significant and strong. However, there are still other unobserved variables that cannot be explicitly controlled for in the stacked DiD setting. The short-staffed scenario is a case in point.

[29] I use the sample of corporate analyst meeting (in-person conference calls) to address potential external validity concerns. The sample description, summary statistics, and results are included in the internet appendix.

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 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 IV and Table V 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]

D. Robustness Tests

D.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.

D.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.[30] 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 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.

D.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,

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

which are consistent with the main results and provide further supporting evidence for my main hypothesis.

D.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.[31] 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 Panel A of Table B.4),[32] 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

[31] 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).

[32] 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.

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.

D.5. Robustness tests for IV estimation

I further conduct several robustness tests for the IV model and lay out the rationale and results (see Table B.5) in this section. The first sensitivity check is on the definition of "local". The main IV test results require a local quant to be based within 100 miles for a focal given fundamental fund. I use an alternative definition of "local", which is within a focal fund's 100 km/62 miles area. The regression estimates remain almost the same. The Kleibergen Paap F-statistic is 40, which suggests a similarly high first-stage strength.

Second, hedge funds may be more likely to adopt AI technology when the local new 13-F quant filers are comparable to them portfolio-wise. If local quant funds hold far more stocks than the focal fund, the 13-F entry event is less relevant and thus less salient because the information acquisition and investment strategies adopted by technology-savvy quants may not be scalable and well applied to a fundamental portfolio. To capture this intuition, I redefine the instrumental variable by restricting first-time local quant 13F filers to have their portfolio size in terms of the number of holdings smaller (or twice, three times smaller) than that of a focal fundamental fund. Consistent with this comparability hypothesis, the first-stage coefficients increase: at the median level of SEC-filing reliance, a one–standard-deviation increase in first-time local quantitative 13F filers raises the probability of AutoAdoption by 9.00% of the sample mean, nearly twice the previous effect. The corresponding Kleibergen–Paap F-statistics range from 12 to 19, which are lower due to the tighter instrument but still indicate adequate first-stage strength.

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

A. Fund-level performance implications

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 naturally raises the question of whether fund-level performance improves when automation-adopting hedge funds (AHFs) obtain more of such information. To address this, I 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 automated downloading activities from quarter t-4 to quarter 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,[33] 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:

$$\begin{aligned}\mathrm{Ret}_{i,t+1} = {} & \beta \cdot \mathrm{I}^{\mathrm{ECP}}_{i,t-1} \cdot \mathrm{HasAuto}_{i,(t-4,t-2)} + \gamma \cdot \mathrm{I}^{\mathrm{ECP}}_{i,t-1} + \delta \cdot \mathrm{HasAuto}_{i,(t-4,t-2)} \\ & + X_1'\Gamma + \theta_i + \delta_t + \varepsilon_{i,t} \qquad (7)\end{aligned}$$

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; $\mathrm{I}^{\mathrm{ECP}}_{i,t-1}$ 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.

If the increased conference call appearances by AHFs result 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 automated downloading had been done in past quarters. The estimation results in Table

[33] 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. 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.

VII confirm this performance hypothesis (H2). Consistent with the performance hypothesis, the interaction item, $\mathrm{HasAuto} \cdot \mathrm{I}_{i,t-1}^{\mathrm{ECP}}$, has positive and significant coefficient estimates that are consistent across different return measures. The economic magnitudes of these effects are also significant: when automated downloading is followed by one time of conference call participation, the fund's next-quarter annualized returns increase by up to 2.4% (raw) and 1.2% (risk-adjusted using Fama–French–Carhart four factors), measured as the value-weighted average return of its equity holdings.

[Insert Table VII 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 with owner hedge funds implementing automated downloading of one of their SEC filings 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): 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 VIII 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 VIII 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:

$$\begin{aligned}\mathrm{Ret}^{\mathrm{Trade}}_{\mathrm{i,j,t+1}} = {} & \beta \cdot \mathrm{I}^{\mathrm{ECP}}_{\mathrm{i,j,t-1}} \cdot \mathrm{HasAuto}_{\mathrm{i,j,(t-4,t-2)}} + \gamma \cdot \mathrm{I}^{\mathrm{ECP}}_{\mathrm{i,j,t-1}} + \delta \cdot \mathrm{HasAuto}_{\mathrm{i,j,(t-4,t-2)}} \\ & + \mathrm{X_2}'\Gamma + \theta_{\mathrm{i,t}} + \delta_{\mathrm{j,t}} + \varepsilon_{\mathrm{i,j,t}} \end{aligned} \tag{8}$$

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; I^{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 IX 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 IX 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 X show that the long–short portfolio consisting of hard-to-research stocks delivers risk-adjusted performance similar to the full sample (Table VIII, 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 X about here]

In Panel C, only the coefficient on $\text{HasAuto} * I^{ECP} * \text{Is\_H2R}$ is positive and significant, with magnitudes similar to Table IX. 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 show that AI results in productivity gains by redirecting human intelligence toward human-intensive tasks. First, I provide novel stylized facts on hedge funds' direct use and complementary use of AI (earnings call participation in the age of AI). Not all hedge funds adopt AI automation; but for those who do, they increase earnings call participation along both the extensive and the intensive margins. Second, I show that AI-powered non-interaction-based information acquisition is followed by human-interaction-based information acquisition, suggesting high degrees of information complementarity between the two types, when AI alleviates the constraint of human effort making. Last but not least, this paper sheds light on a new "*complement-via-substitution*" channel through which AI automation affects hedge fund information acquisition behavior and fund performance. AI *complements* high-skilled labor *via* its *substitution* effects on easy-to-automate tasks, thus allowing for more effort at hard-to-automate tasks that require human interactions and judgment.

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. In particular, it reveals the interactive dynamics between two different types of hedge funds' public information acquisition behavior with and without human-interactions, represented by SEC filing retrieval and earnings call participation. 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 (2025) 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 also shows 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 I. 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.

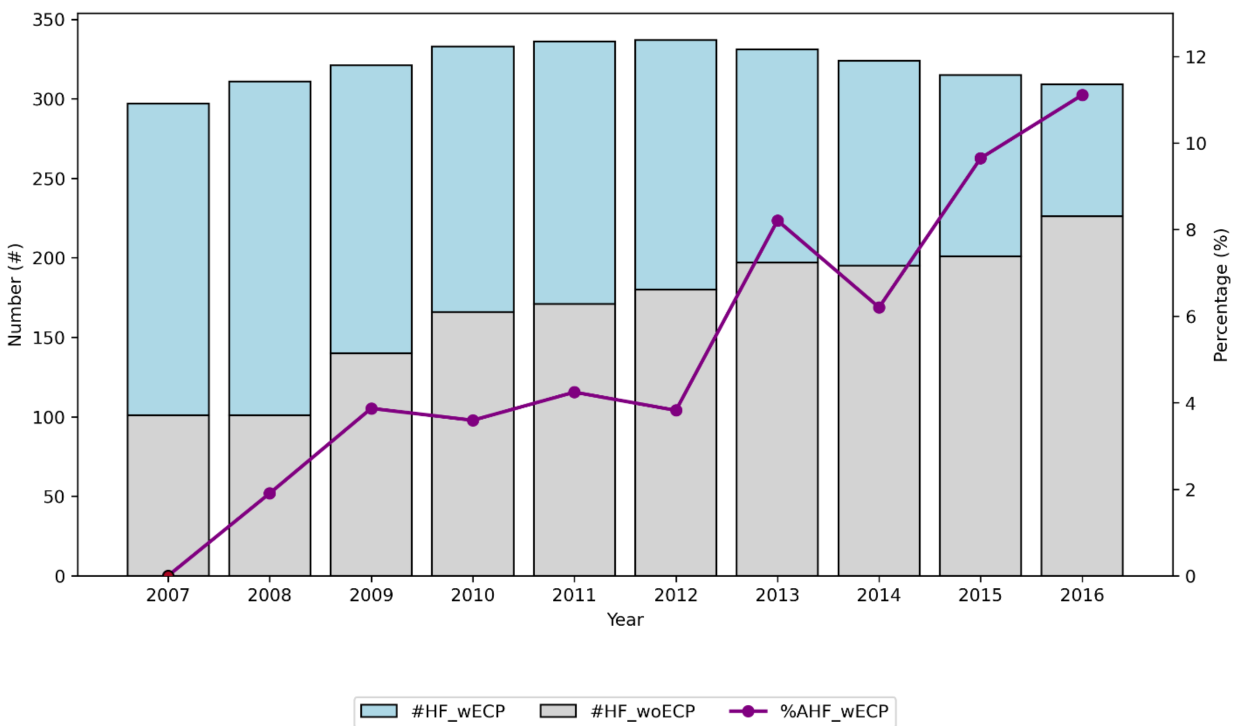

Figure II. Earnings Call Participation around Automation Adoption

The two figures plot out the coefficient estimates of β in the dynamic model of Equation (2) and Equation (3). Figure II (a) plots the dynamic effects for a quarterly event window. The x-axis shows two quarters before and after the automation adoption quarter 0. Figure II (b) plots the dynamic effects for a yearly event window. The x-axis shows three years before and after the automation adoption year 0. The error bars correspond to the 90% confidence intervals, which are computed based on standard errors clustered by fund company and event-time.

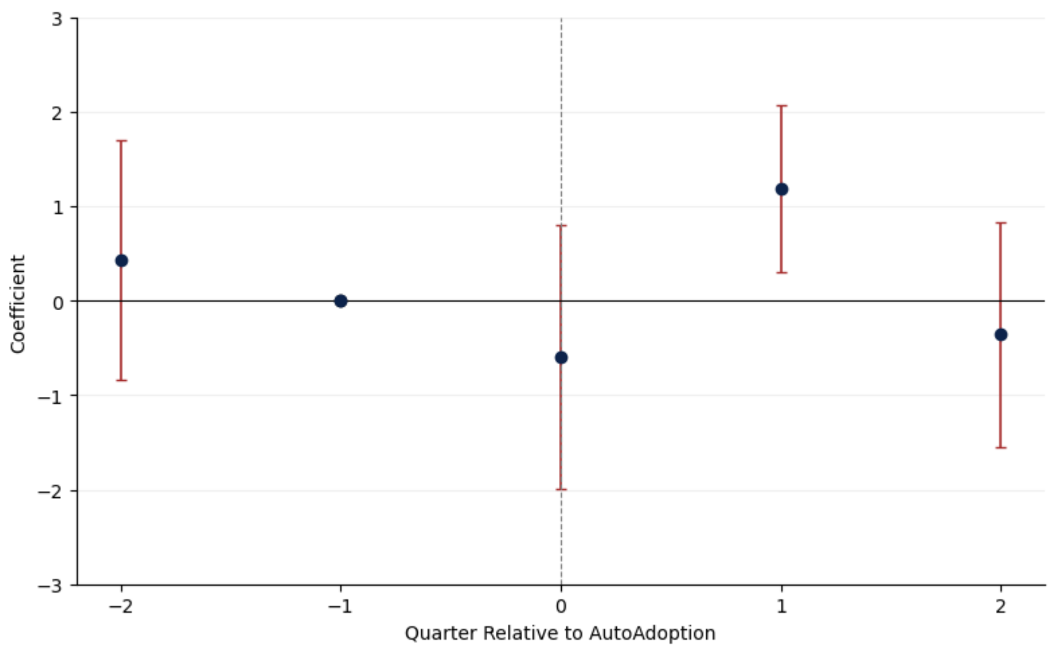

Figure II (a) Quarterly Earnings Call Participation around Automation Adoption

Figure II—Continued

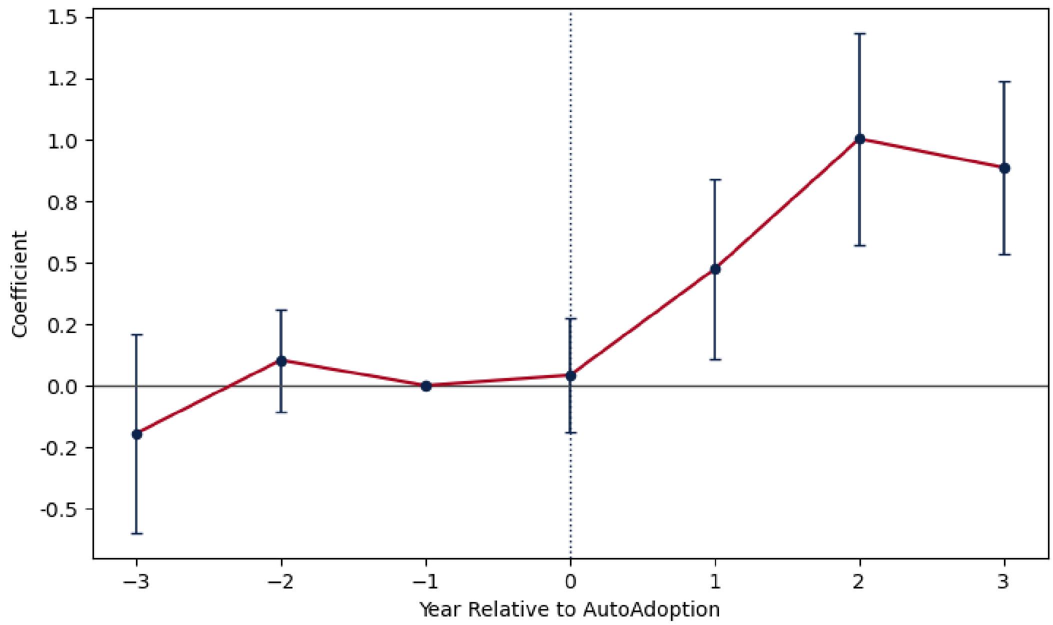

Figure II (b) Quarterly Earnings Call Participation around Automation Adoption

Figure III. Bin-Scattered Representation of Automation-Participation Relation

This figure shows the binned scattered plot of the automation-participation relation. The number of earnings calls attended by a sample hedge fund in a given quarter is plotted against the predicted likelihood of Automation Adoption in the previous quarter. Predicted adoption of AI is the predicted adoption likelihood from regressing the indicator of AI adoption against the technology salience IV along with fund company and year-quarter fixed effects. The technology salience IV is the interaction of local quants' 13-F entries in the past four quarters and focal fundamental funds' SEC downloading intensity in the four quarters prior to any new 13-F filing of local quants.

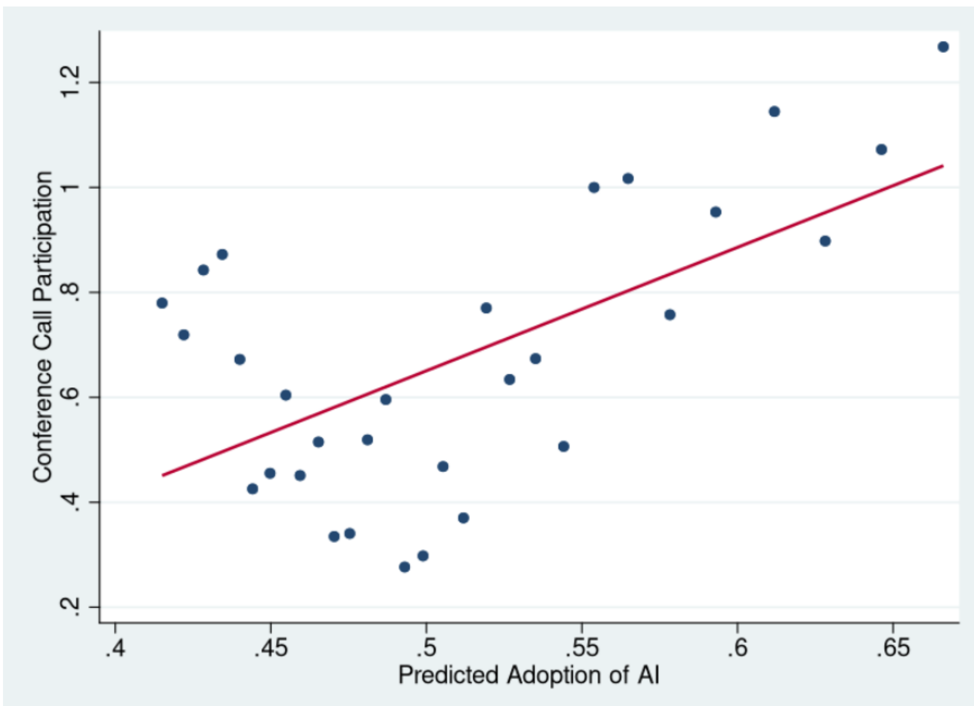

Table I. Sample Descriptive Statistics

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
$Downloads^{FM}$	11,594	755.715	2717.883	0	5	176
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
$N^{NewQuant}$	11,594	1.193	1.506	0	1	2
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 (N^{ECP}) and column (3)–(4) for the number of distinct host firms associated with those calls 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 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				
	N^{ECP}		N^{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-squared	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. Hedge Fund Earnings Call Participation: Instrumental Variable Estimation

This table reports coefficient estimates from both the first stage linear probability regressions and second stage IV Poisson regressions. AutoAdoption is the indicator variable for the Adoption of AI automation, measured using first-time machine downloads by a hedge fund. TechSalience is the instrumental variable (scaled by 100) for the Adoption of AI automation (AutoAdoption) is the interaction between a fund's historical reliance on SEC filings and the number of first-time local quantitative hedge fund 13F filers. A fund's SEC reliance is measured as focal fundamental funds' SEC downloading intensity in terms of the number of unique firms during the four quarters (t-8 to t-5) prior to any new 13-F filing of local quants. Cumulative local quants' 13-F entries are computed during the immediate past four quarters (t-4, t-1). All dependent variables at quarter t are related to independent variables at quarter t-1. The standard errors are clustered by fund company. 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.

	1st Stage AutoAdoption	2nd Stage N^{ECP}
TechSalience	0.0013***	
	[7.508]	
$\widehat{AutoAdoption}$		2.1916***
		[2.748]
Size	0.0047	0.1889***
	[1.115]	[3.257]
Age	0.0309*	0.3345
	[1.695]	[0.978]
Return	-0.0284	-0.3361
	[-1.160]	[-0.791]
Turnover	0.0321	1.5317***
	[0.128]	[2.928]
Risk	0.3210	1.7957
	[0.384]	[1.496]
Model	LPM	Poisson
Observations	7,325	7,195
Fund FE	Yes	Yes
Time FE	Yes	Yes
Pseudo R-squared		0.5292
Kleibergen–Paap F statistic	54.621	

Table VI. 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 VII. 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 VIII. 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	Sell	Diff.	Buy	Sell	Diff.	Diff.-Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(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	Sell	Diff.	Buy	Sell	Diff.	Diff.-Diff.
	(1)	(2)	(3)	(4)	(5)	(6)	(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 IX. 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 X. 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.
$Downloads^{FM}$	The total number of unique firms manually downloaded in quarters $t-8$ to $t-5$. 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
$\mathrm{N}^{\mathrm{NewQuant}}$	The number of new 13-F filing events of local quant hedge funds for the focal hedge fund in quarters $t-4$ to $t-1$. Sources: partow.net, SEC EDGAR, NBER ZIP Code Distance Database
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 ($\mathrm{N}^{\mathrm{ECP}}$), and columns (3)–(4) for the number of distinct host firms 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 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.

	$\mathrm{N}^{\mathrm{ECP}}$	$\mathrm{N}^{\mathrm{Host}}$	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 $\mathrm{N}^{\mathrm{ECP}}$ (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.

	$\mathrm{N}^{\mathrm{ECP}}$		$\mathrm{N}^{\mathrm{Host}}$	
	(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-squared	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 difference-in-differences 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-squared	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-squared	0.510	0.511
Year-Quarter FEs	Yes	Yes
Fund FEs	Yes	Yes

Table B.5 Robustness of the IV Regression

This table reports robustness checks for the control-function IV Poisson model. Columns (1)–(2) use quantitative hedge funds within 100 km to define local quantitative funds. Columns (3)–(4), (5)–(6), and (7)–(8) redefine the instrumental variable by restricting first-time local quantitative 13F filers to have portfolio sizes of at most 1×, 2×, and 3× the focal fund's number of holdings, respectively. All dependent variables at quarter t are related to independent variables at quarter (t-1). The standard errors are clustered by fund company. 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.

	Local Radius ≤ 100 km		Portfolio Size ≤ 1×		Portfolio Size ≤ 2×		Portfolio Size ≤ 3×	
	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage	1st stage	2nd stage
Dep. Var.	AutoAdoption	N^{ECP}	AutoAdoption	N^{ECP}	AutoAdoption	N^{ECP}	AutoAdoption	N^{ECP}
TechSalience	0.0012***		0.0024***		0.0019***		0.0018***	
	[6.429]		[4.416]		[3.519]		[4.416]	
$\widehat{\text{AutoAdoption}}$		2.0344**		1.7705***		2.0040***		2.3292***
		[2.128]		[2.657]		[3.217]		[2.961]
Size	0.0053	0.1902***	0.0045	0.1794***	0.0043	0.1786***	0.0042	0.1778***
	[1.242]	[3.314]	[1.097]	[2.973]	[1.052]	[2.955]	[1.031]	[2.946]
Age	0.0311*	0.3654	0.0322*	0.4064	0.0318*	0.3851	0.0325*	0.3771
	[1.779]	[1.076]	[1.840]	[1.158]	[1.756]	[1.097]	[1.788]	[1.074]
Return	-0.0269	-0.3448	-0.0254	-0.3897	-0.0245	-0.3825	-0.0244	-0.3756
	[-1.100]	[-0.827]	[-1.025]	[-0.942]	[-0.984]	[-0.927]	[-0.982]	[-0.918]
Turnover	0.0051	1.5238***	-0.0071	1.6993***	-0.0076	1.7035***	-0.0071	1.6881***
	[0.169]	[2.934]	[-0.254]	[3.272]	[-0.268]	[3.250]	[-0.253]	[3.321]
Risk	0.0231	1.9443	0.0414	2.4452**	0.0452	2.4138**	0.0413	2.3904**
	[0.273]	[1.634]	[0.458]	[2.161]	[0.479]	[2.133]	[0.442]	[2.113]
Model	LPM	Poisson	LPM	Poisson	LPM	Poisson	LPM	Poisson
Observations	7,402	7,272	7,359	7,229	7,324	7,194	7,324	7,194
Fund FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared		0.5254		0.5237		0.5048		0.5051
KP F statistic	40.049		18.894		11.996		12.881	

<u>Internet Appendix to</u>

"AI Automation and Effort Allocation: Evidence from Sophisticated Investors"

Contents:

IA-1 Identifying earnings conference call participation by hedge funds

As described in the main text, I manually collect 130,699 transcripts of earnings-related conference calls (earnings calls and guidance calls) from LSEG workspace. In this appendix section, I further detail the filters I use for collecting this sample. The earnings call sample covers the universe of the universe of 5,212 US firms during the period of 2006 to 2017. US listed firms tend to host quarterly earnings calls regularly (one call in every fiscal quarter), while non-US listed firms usually host the calls less regularly and usually on a semi-annual basis. [34]

A. Parsing the LSEG earnings conference call transcripts

Each LSEG transcript begins with a title stating the fiscal quarter and year, the host company, and the meeting theme (e.g., "Q2 2013 [Company Name] Earnings Conference Call"). The title is followed by the meeting date and time (GMT). Before the transcript body, two participant rosters appear: (i) *Corporate Participants*, listing each host company participant's name, title, and the company name; and (ii) *Conference Call Participants*, listing each external participant's name, affiliation, and title (typically "Analyst").

The transcript body contains two segments: (i) *Presentation*, containing the operator's[35] introductory remarks and company executives' prepared comments; and (ii) *Questions and Answers*, containing the operator's introductory remarks, questions from external participants, and executives' responses. Within the body, each speech turn is labeled with the speaker's name, company/affiliation, and title, and is assigned an order number within the segment.

I use a Python script to parse the LSEG transcripts and construct two structured datasets: (i) the *Meeting Information* dataset, which includes the host company name, the host ticker (extracted from the transcript filename), the meeting date and time (GMT), the names and titles of company executives, and the names and affiliations of external conference call

[34] I focus on non-US-based firms for two reasons: 1) non-US firms often include this note "Portions of this transcript that are marked (interpreted) were spoken by an interpreter present on the live call. The interpreter was provided by the Company sponsoring the event." at the end of their conference calls. 2) to ensure the consistent coverage across different types of transcript data. For example, in 2014, non-US firms only hold 2278 (64) earnings calls (corporate analyst meetings); while US firms hold 11,358 (448) earnings calls (corporate analyst meetings).

[35] Each transcript includes an operator—the conference call facilitator who manages introductions and the Q&A queue.

participants; and (ii) the *Q&A* dataset, which records the label (speaker name, speaker company/affiliation, and the order number) the text of each speech turn in the *Questions and Answers* segment. The Meeting Information dataset is the primary source for identifying hedge fund participants. When affiliations are missing, I recover them from the Q&A dataset.

B. The fuzzy match process

The affiliations of external conference call participants have reasonably high quality in transcripts, and the main factor that denies a direct name match (with minor adjustments) between the 13F-filer hedge fund list and the affiliations in the Meeting Information dataset is the name variants with varying "completeness". For example, in transcripts, the hedge fund "Cardinal Capital Management, L.L.C." is recorded under the exact the same name or as name variants such as "Cardinal Capital", "Cardinal Capital Management", "Cardinal Capital Management LLC", etc. Based on such a matching pattern in general, I decompose each of the 13F-filer hedge fund names into three parts: *Brand*, *Function Name*, and *Organization Name*. Take "Cardinal Capital Management, L.L.C." for instance, "Cardinal" is the Brand, "Capital" is the Function Name, and "L.L.C." is the Organization Name, and the fuzzy match will focus on the "Main" or the "Brand" part (close to a manual match process). Specifically, the preprocessing of hedge fund names is summarized in four steps:

First, obtain the *Main Name*: split the hedge-fund name at the *separation comma*— a comma followed only by a single element (e.g., "L.L.C."); in such cases, the part before the comma is kept as the Main Name. If no separation comma is present, use the original name as the Main Name.

Second, clean up the Main Name using following steps: (i) capitalize the Main Name; (ii) remove commas, periods, dashes, and quotation marks; (iii) replace " AND " with "&".

Third, extract the *Organization Name* from the current Main Name: *Organization Name* begins with any word in the stop word list of ["INC", "& PARTNERS", "LP", "LLC", "LTD", "& CO", "& COMPANY", "SA"][36]. Once a stop word is located this way, all the remaining elements in the current Main Name and the stop word itself consist of the Organization Name. Update the current Main Name by removing the Organization Name.

[36] Note that the current Main Name has been capitalized and processed as in (2).

Fourth, extract the *Function Name* and *Brand* from the current Main Name: *Function Name* begins with any word in the stop word list of ["INVESTMENT", "ADVISORS", "ASSET", "CAPITAL", "FUND", "MANAGEMENT"]. The stop words are checked in the current Main Name following the order in the list, and once a stop word is located, all the remaining elements in the current Main Name and the stop word itself consists of the Function Name. Get *Brand* by removing the Function Name from the current Main Name.

To avoid cases where generating the Main Name removes too much identifying information, I also generate a simplified candidate called the *Core Name*. The Core Name is defined as the first element if it has more than one character, or as the first two elements otherwise[37]. Lastly, clean up the affiliations in transcripts using the cleanup procedure in Step 2 as above and remove "&" from both the Main Names, the Brands, and the processed affiliations (the Core Name does not contain "&" by construction).

After processing the hedge fund names and obtaining the corresponding Brands and Core Names and cleaning up affiliations, I apply fuzzy match by searching the Main Name, the Brand, and the Core Name among the processed affiliations in transcripts. For each of the affiliations matched in this way, I keep the affiliation itself and the affiliation's participant ("analyst") name, which will be used in the manual check in the next stage. I carefully check the fuzzy-matched candidate affiliations to provide accurate identification of hedge fund conference call participation. The manual check involves heavy internet searches of hedge fund companies and especially for the following reasons:

First, one hedge fund may have a name that is similar to another investment institution, making a seemingly high-quality fuzzy-match case a false identification. For example, Oak Hill Capital Management, LLC is a 13F-filer hedge fund, and it has fuzzy-match candidate affiliations such as "Oak Hill", or even "Oak Hill Capital Management". In this case, I have to review the analysts' employment information to make sure whether the transcript affiliation is the sample hedge fund.[38]

[37] If the second element is to be used in Core Name, skip " AND " or "&".

[38] Using internet searches of analysts' employment information, I find that these affiliation records are name variants that pertain to Oak Hill Advisors, an investment institution rather than a hedge fund. False identifications from near-identical fuzzy matches such as 'Oak Hill Capital Management' vs 'Oak Hill Capital Management, LLC' are rare.

Second, some hedge funds are affiliated with entities that provide research services to other investors. For example, Zacks Investment Management, Inc. is a hedge fund that is affiliated with Zacks Investment Research, an independent research institution. Without checking analysts' affiliation, it is very likely to mix the research institution's call participation with the hedge fund's participation.

Third, since certain investment banks maintain hedge fund affiliates or divisions (e.g., Sandler O'Neill), verifying analysts' roles and titles is necessary to prevent misclassifying sell-side analysts as buy-side hedge-fund managers.

C. Identifying corporate analyst meeting participation by hedge funds

In addition to these virtual conference calls, I also collect in-person conference calls—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.[39] Parsing these corporate analyst meeting transcripts follows the same steps as outlined in subsection A of IA-1.

The main sample is earnings calls, which are entirely virtual. To examine the participation effect regarding hedge funds' in-person human interactions with corporate management, I rely on the sample of annual or semi-annual corporate analyst meeting to identify hedge fund engagement in in-person interactions. The screenshots below show that the transcripts contain explicit cues about the meeting being held in-person and remotely by webcast. Survey articles also show that buy-side analysts and investors value the in-person conference calls for opportunities of "intimate, private meetings" so that they can "gain a holistic view of the company and ask asset and division-specific questions".[40]

[39] There are other in-person conference calls such as shareholder annual meetings. However, data points on firms' shareholder meetings are significantly fewer (around 20% less than corporate analyst meetings) and also, a lot of conference call participants are unidentifiable (transcribed as "Unidentified Audience Member"). As such, I rely on corporate analyst meetings only to provide a measure for in-person human-interaction-based information acquisition.

[40] See the IHS Markit survey here. "These interactions should include formal Q&A after presentations, as well as informal interactions such as roundtable discussions, breakfast and lunch settings, product breakout sessions, and facility field trips." Also, as pointed out in this survey that covers 40% of respondents from the buy side, the majority of surveyed investors, 85%, prefer to attend the investor day in-person versus accessing the webcast, reporting interaction with management and other investors is "invaluable.".

CORPORATE PARTICIPANTS

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Jennifer L. Hutcheson Ryman Hospitality Properties, Inc. - Executive VP & CFO

Mark Fioravanti Ryman Hospitality Properties, Inc. - President, CEO & Director

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Chris Jon Woronka Deutsche Bank AG, Research Division - Research Analyst

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PRESENTATION

Sarah Martin - Ryman Hospitality Properties, Inc. - VP, Investor Relations

Good morning. I'm Sarah Martin, Vice President of Investor Relations. And it's my pleasure to welcome you to Ryman Hospitality Properties 2024 Investor Day. Thank you for being with us both in person here at the Gaylord Opryland Resort and Convention Center in Nashville, Tennessee and remotely by webcast.

JANUARY 30, 2024 / 2:00PM, RHP.N - Ryman Hospitality Properties Inc To Host an Investor Day

Sarah Martin - Ryman Hospitality Properties, Inc. - VP, Investor Relations

Welcome back. We're going to start Q&A for those in the room. We have 2 mics, one on either side of the room, for the benefit of those on the webcast, if you could state your name and your company, that would be very helpful.

Let's start with Chris.

QUESTIONS AND ANSWERS

Chris Jon Woronka - Deutsche Bank AG, Research Division - Research Analyst

Chris Woronka, Deutsche Bank. So a lot of good content today. And I guess as a question, you guys have a lot of value-add stuff on the radar, both in the quarter, Hospitality segment, also the Entertainment segment. And it seems like if you wanted to with Patrick Moore on board, you could really supercharge Entertainment if you wanted to, but you still have this really great Hospitality company that has a lot of opportunities. So the question really is how do you prioritize growth? And if you had – if someone gave you – if you had $250 million laying around, which you have more than that, but how would you deploy it if you had similar opportunities across both of the businesses?

D. Why LSEG?

This paper uses LSEG (formerly Thompson Reuters/Refinitiv) workspace to manually collect conference call transcripts. There are at least two comparative advantages in using the LSEG conference call data relative to another commonly used data source, Capital IQ:

First, one of the frequently used earnings call databases is Capital IQ. Since my sample period runs from 2006 to 2017, one notable issue about using Capital IQ data is that it has very limited coverage of earnings calls prior to 2009, especially the years of 2006 and 2007 have very low hits. The year of 2006 has below 10% coverage and the year of 2007 covers not more than 20% of the number of hits in the average year from 2009 to 2017. Even the year of 2008 hits only close to 50% of an average subsequent year's coverage. This abnormal low coverage will largely affect the identification process of hedge fund appearances in earnings calls.[41] In contrast, LSEG has very smooth coverage of earnings calls for the universe of US firms across all sample years, as shown in Table I.

Second, for question texts, Capital IQ only reports the first 200 characters, this truncation issue will limit the construction of at least two variables: question length (as one of the conditional participation intensity measures) and question quality (text-based measures such as the number of topics covered). Unlike Capital IQ, LSEG provides original transcript files so that every question can be parsed in its full length.

Overall, the LSEG database is more relevant for the purpose of this study.

[41] The already low participation rate of hedge funds in earnings calls reported in Call et al. (2018) could still be inflated by the fact that the denominator in 2007 and 2008 is reduced by a significant amount.

IA-2 Summary statistics of hedge fund participation in corporate analyst meetings

Table C.2 Descriptive Statistics of in-person Conferences and HF 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

IA-3 Identifying SEC EDGAR downloading by hedge funds

A. Processing SEC EDGAR server log data

In 2013, the SEC began releasing log file data of internet search traffic for EDGAR filings in response to a Freedom of Information Act (FOIA) request.[42] There have been two rounds of EDGAR log file releases. The first round consisted of datasets covering the period from January 1st, 2003 to March 31st, 2017, with updates released on an annual basis. The second round began with logs from May 19th, 2020 onwards, where updates are released quarterly.[43] However, the second-round dataset omits a key variable, the accessor's IP address that was present in the first-round dataset. Despite having the last three digits masked, the IP addresses in the first round suffice for making reasonable inferences of SEC downloaders' names. Hence, only the EDGAR logs from the first release period are relevant for my study.[44] SEC did not retain logs for the period of September 24th, 2005 to May 14th, 2006. To eliminate the possibility of misclassifying automated downloaders into non-adopters during this gap in the log file data, I focus exclusively on EDGAR log files from the post-gap first release period from May 15th, 2006 to March 31st, 2017.

A practical complication is that the fourth octet of IP addresses in the EDGAR logs is obfuscated (e.g., 191.191.191.abc). We therefore match on the first three octets (i.e., /24 blocks) to the ARIN-identified ranges. This approach is facilitated by the fact that managers often register entire /24 blocks (from .0 to .255); when only part of a block is registered to the manager, the remaining holders are typically unrelated to financial services, which limits false positives. The EDGAR log files include the unique SEC document accession number, the timestamp of each request, the filer's Central Index Key (CIK), the file size, and the IPv4 address with the last three digits masked (e.g., "XXX.XXX.XXX.tqj," where "X" denotes a digit from 0 to 9).[45] The EDGAR log files do not include the filing type, report date, or filing date of the accessed documents. By

[42] These records of historical access to the EDGAR server are available online at: https://www.sec.gov/data-research/sec-markets-data/edgar-log-file-data-sets, and the earliest log file can be traced back to January 1st, 2003.

[43] The updating was suspended in July 2023 due to a technical problem and restarted in October 2024.

[44] Obtaining Ips for the second period is not viable as my submission of FOIA request regarding IP information post 2020 was declined.

[45] Additional fields include the file size, whether the accessor is self-identified as a web crawler, whether the accessor landed on the index page of a document, the accessor's browser, etc. The full variable list is available at: https://www.sec.gov/data-research/sec-markets-data/edgar-log-file-data-sets.

matching each log entry with the SEC master filing index using the unique document accession number, I can retrieve these fields of the corresponding SEC filings,[46] which enables a more detailed analysis of sophisticated investor demand for SEC disclosures.

There is a total of 364 13-F filing hedge funds as SEC EDGAR server accessors. The top five most frequently downloaded filing types are as follows: 13F-HR (45,153,152 downloads, accounting for 33.44% of the full sample downloading activities), 4 (21,314,525, 15.79%), SC 13G/A (15,297,358, 11.33%), 8-K (8,406,077, 6.23%), and SC 13G (7,932,072, 5.87%). The automated downloading activity of Form 13D/F/G and Form 4, just as public company filings, contain value-relevant information on underlying portfolio stocks' future performance.[47] In contrast, Form 10-Q and Form 10-K were downloaded 1,559,142 times (1.15%, ranked 9th) and 1,971,463 times (1.46%, ranked 12th), respectively.[48]

Based on the most frequently downloaded SEC filing types, it is evident that hedge funds are also interested in information related to other investors' portfolio (e.g., Form 13F) and insider trading (e.g., Form 4). To identify the companies held by Form 13F filers,[49] I use data from EDGAR-Parsing—a project that provides parsed SEC Form 13F filings from 1999 through the end of 2020[50]. This dataset includes the SEC accession number, the filer's CIK (representing the investment institution), and the CIKs of the holding stocks[51]. By matching these records with the SEC log file data using accession numbers, I identify the companies hedge funds may be analyzing through their downloads of 13F filings. I apply a similar approach to Form 13D and 13G filings, using a separate

[46] These quarterly "master.idx" files are available from the SEC at https://www.sec.gov/Archives/edgar/full-index/, while Software Repository for Accounting and Finance at the University of Norte Dame provides zipped versions for direct downloading.
[47] The strong interest of hedge funds (as active information acquirers) in 13F (as well as 13D/G) filings echoes the findings in Agarwal, Jiang, Tang, and Yang (2013), who show that hedge funds delay the equity holding disclosure through amendments to Form 13F to protect their valuable private information.
[48] The document types (as in SEC master filing index) rank from 7 to 12 by number of sample hedge fund downloading activities are: 13F-HR/A, 13F-NT, SC 13D/A, 3, 10-Q, 424B2, and 10-K.
[49] Note that the Compustat CIK-GVKEY links are for public companies only.
[50] SEC updates Form 13F datasets at: https://www.sec.gov/data-research/sec-markets-data/form-13f-data-sets. The datasets are later than my sample period, which will be discussed in Section 3.3.
[51] The uniqueness of SEC accession number will be enough for the merging. The filer's CIK (i.e., the institution's CIK) is here just for description purposes.

parsed dataset covering the period from November 1993 to May 2021.[52] This dataset includes the accession number and the CIKs of the companies held by the filers. For insider trading data (Forms 3, 4, and 5), I use parsed datasets obtained directly from the SEC, which also contain accession numbers and issuer CIKs (i.e., firm identifiers).[53] I then use the Compustat CIK-GVKEY linkage table to merge the SEC filers with mainstream finance databases. This linkage enables me to merge accessed filers with conference call hosting companies that were held by sample hedge funds.

B. Identifying hedge funds in SEC EDGAR logs

The relevant sample of hedge funds are fundamental, discretionary funds, part of whose information acquisition activities entail human interactions. Since quantitative hedge funds do not rely on such interactions, I exclude them from my sample by requiring a hedge fund to appear at least once in an earnings conference call throughout the sample period. To identify hedge funds' SEC footprint, I combine (i) the SEC's EDGAR sever log files, (ii) IP registrar data from the American Registry for Internet Numbers (ARIN) and networkdb.io, and (iii) institution taxonomy data from Thomson Reuters.[54]

I start by identifying call-attending hedge funds, then manually determine their associated IP address ranges based on fund names and physical addresses.[55] For each 13-F filing hedge fund, I obtain the IP address information via name searching. Specifically, I manually search all these hedge fund names in the "Organization Lookup" by NETWORKSDB,[56] a free IP geolocation service powered by DB-IP (limited to 300 searches per day). All identified IP addresses are then cross verified using the American Registry for Internet Numbers (ARIN) WHOIS and WHOWAS database.[57] This process

[52] Jan Philipp (2021), "A database for blockholders in US-listed firms including all Form 13D and Form 13G filings.", the data set is available at: https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/61Z64Q

[53] https://www.sec.gov/data-research/sec-markets-data/insider-transactions-data-sets

[54] I thank Rich Sias for making this proprietary data available to me.

[55] I retrieve hedge fund address information by looking at their form ADV, official websites as well as other internet searches.

[56] https://networksdb.io/

[57] Although allowing for the search type of "Entity", the ARIN Whois usually yields no search results when using organization names as input. Currently, I use a single cross-sectional snapshot of the ARIN WHOIS registry to obtain the IP ranges registered to each manager. I use ARIN's WHOWAS on-demand service to retrieve the historical start and end dates for those IP ranges and make sure the IP candidate was an active hedge fund IP during the sample period.

yields a set of candidate manager–IP matches that anchor our linkage between investment managers and their network identities. Additionally, I carefully check the geolocations of the resulting IP address ranges to ensure the accuracy of the matches. This IP collection and validation process results in a final sample of 364 hedge funds associated with 733 distinct IP ranges.

After identifying the available IP address ranges of the target hedge funds, I merge the hedge fund IP range list with the full SEC EDGAR log file dataset using the available IP information. As described in the data section of the main text, the last three digits of each accessor's IP address in the log file are masked and thus the IP address cannot be directly linked to known IP ranges. Following the method of Crane, Crotty, and Umar (2023), I treat the masked portion of the IP address as "0". For example, an IP address recorded as "XXX.XXX.XXX.tqj" is replaced with "XXX.XXX.XXX.0". I then create a mapping between the EDGAR server accessor and the sample hedge funds by identifying processed IP addresses in the log files that fall within a sample hedge fund's IP range.

It is worth mentioning that processing EDGAR log files presents significant challenges due to the sheer volume of data. For decades, the SEC has been recognized for mandating extensive disclosure from public companies and institutional investors, resulting in EDGAR, a vast repository of filings. Unsurprisingly, this abundant supply of public information generates substantial demand. On a single day, the EDGAR server can receive millions of access requests, and the total size of daily log files can exceed one gigabyte in size (Ryans, 2007). Importing and combining years of these daily log files into a unified dataset can take days and ultimately produce a multi-terabyte record of historical EDGAR server activity.[58]

[58] I thank HPC at the University of Arizona for facilitating me to perform IP matches between call-attending 13-F filing hedge funds and SEC log files.

IA-4 Summary statistics of hedge fund IP addresses and SEC EDGAR footprints

Table IA-2 Descriptive Statistics of Sample HF IP and SEC Downloading Activities

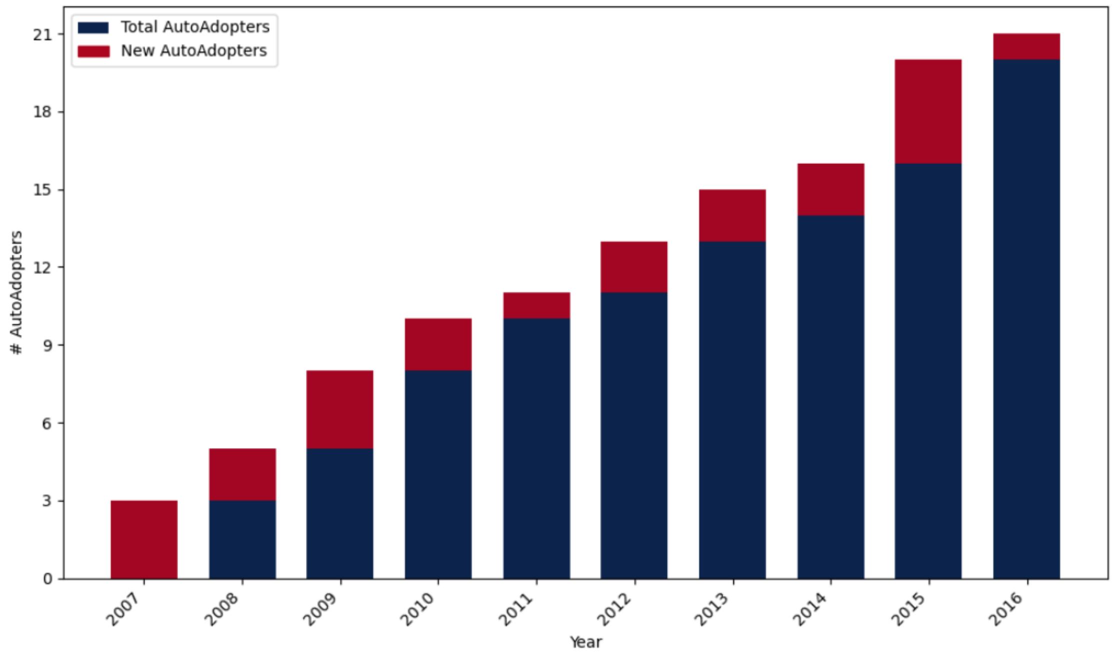
This table reports the summary statistics of sample hedge fund IPs and their daily SEC footprints, with classification of IP type (AI or Non-AI) and IP status (Machine or Human). The sample period is from May 15th, 2006, to March 31st, 2017. An AI IP is an IP that adopts AI automation, and a non-AI IP 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%

IA-5 More figures on automation adoption and earnings call participation

A. New Automation Adopters vs. Total Adopters

Figure IA-5A shows a bar chart of automation adopters from 2007 to 2016. Dark-blue bars indicate the total number of automation adopters by year; Dark-red bars on top mark new automation adopters added in that year.



IA-6 Earnings call sample questions

B. Constructing the alternative question count variable

In the main text, I examine the effect of AI automation adoption on earnings call participation along both intensive margins and extensive margins. Conditional on participation, I examine the number of questions asked by an institution participant, which is represented by only one person (an analyst or an investment manager) during an earnings call. The naïve way of computing the conditional call participation intensity is to count the number of speaking turns for a given analyst, assuming that each turn represents a question. However, this assumption can be quickly challenged with two issues when being taken to the data: in any earnings call, we can see that i) a lot of speaking turns do not contain a valid question, as marked in red in sample questions below, and ii) for some speaking turns (especially the first or the second ones), more than one question is asked, as boldfaced in the following transcript.[59]

To adjust for the mismatches between analyst speaking turns and the number of questions asked, I take these steps to construct an adjusted question count variable: (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.

Example 1: Q&A from the Progressive Corporation Conference Call on Feb 27, 2009

*Operator

>>The next question is from Dan Johnson from Citadel.[60]

***Dan Johnson, Citadel Investment Group - Analyst**

[59] In the interest of space, I replace the answers from corporate managers—such as CEO, CFO—with ellipses.

[60] According to MarketScreener, "Dan Johnson (Daniel B. Johnson) was at Citadel Investment Group, which he joined in 2004 as the insurance analyst in the firm's newly formed fundamental equity long/short business. After five successful years as an analyst, he became portfolio manager of the Financials team based in Chicago, managing a multi-billion dollar fund and a team of five professionals."

>>Great, thank you very much. **Two if you would, please.** Just a little bit about the outlook on commercial auto in light of the -- what you listed as, obviously, the economic downturn but also increased competition; And then can you hit the -- a little bit on Massachusetts, what went right and what didn't go right in 2008? Thank you.

*Glenn Renwick, The Progressive Corporation - CEO

>>Start with commercial. ……

***Dan Johnson, Citadel Investment Group - Analyst**

>>Did that have notable impact on your production in the state during the year?

*Glenn Renwick, The Progressive Corporation - CEO

>>No, I don't think that would be fair to say that it really had a notable effect……

***Dan Johnson, Citadel Investment Group - Analyst**

>>**Great, thank you very much.**

Example 2: Q&A from the MarkWest Energy Partners Conference Call on May 08, 2014

*Operator

>>Louis Shamie, Zimmer Partners.[61]

***Louis Shamie, Zimmer Lucas Partners - Analyst**

>>Hello. Good morning, guys, and congratulations on the continued execution and the great volume growth in the Marcellus and Utica. **I had a few questions.** I guess the first would be just regarding the capital that you spent, and thinking about the returns. It was great to get the guidance on pace of distribution growth and the increasing coverage over the next couple of years. Reading some of the sell side research, there's been a lot of questions or maybe misunderstanding about the returns that you're getting on the billions of dollars of capital that you're putting to work in the Northeast. What kind of clarity can you give to allow people to get a sense of how you receive a return on investment as these plants ramp up, considering that you continue to put money to work and expand capacity at a pretty fast clip as the existing capacity fills?

[61] According to MarketScreener, "Louis Shamie is a Principal at Zimmer Partners LP. Mr. Shamie was previously employed as an equity Analyst by Zimmer Lucas Partners LLC."

*Frank Semple, MarkWest Energy Partners LP - Chairman, President, & CEO

>>You're right, Louis. ……

***Louis Shamie, Zimmer Lucas Partners - Analyst**

>>Frank, I've got you hitting like $1 billion at some point in 2016 in terms of a run rate. Hopefully, my numbers come out all right. Thank you for that clarity.

*Frank Semple, MarkWest Energy Partners LP - Chairman, President, & CEO

>>Again, it is a real front and center issue for us, and we get it because of the amount of capital that we're spending. ……

***Louis Shamie, Zimmer Lucas Partners - Analyst**

>>That was great, and thank you for the detail, Frank. The one other question I had was regarding the dry gas window in the Utica. It seems like there's been a lot of producer attention shifting to there, and it seems like from what limited data is out there, there's some monster wells there. What's MarkWest's strategy for approaching that? How much of your budget or description for 2014 and 2015 is allocated or budgeted for addressing that?

*Frank Semple, MarkWest Energy Partners LP - Chairman, President, & CEO

>>Yes. ……

***Louis Shamie, Zimmer Lucas Partners - Analyst**

>>**Hello, Randy.**

*Randy Nickerson, MarkWest Energy Partners LP - EVP & Chief Commercial Officer

>>Louis, you're right. ……

*Frank Semple, MarkWest Energy Partners LP - Chairman, President, & CEO

>>Yes. ……

***Louis Shamie, Zimmer Lucas Partners - Analyst**

>>**It's pretty exciting, and I wish you guys the best of luck on the further development of all these exciting opportunities.**

*Frank Semple, MarkWest Energy Partners LP - Chairman, President, & CEO

>>Thanks, Louis.

Example 3: Q&A from the Nortek Inc Conference Call on Nov 04, 2015

*Operator

>>Jeff Gates, Gates Capital Management.[62]

***Jeff Gates, Gates Capital - Analyst**

>>Can you talk about the confidence in terms of prospects, your prospects, for cash generation going into 2016 in terms of the capital plan, working capital, cash outlays, restructuring, **number one? And number two**, can you talk about Ergotron and the -- is that a completely standalone business and is there any benefits in the other divisions from having that business?

*Michael Clarke, Nortek, Inc. - President, CEO

>>Do you want to take the -- take the first one and I will take the second one?

*Al Hall, Nortek, Inc. - SVP, CFO

>>Yes, so with respect to -- I talked earlier on a prior question about our capital structure, but our cash flow in the third quarter here was strong. ……

*Michael Clarke, Nortek, Inc. - President, CEO

>>Yes, and let me just add a couple of things to that? ……

*Al Hall, Nortek, Inc. - SVP, CFO

>>It has a bunch of products that are in strong growth markets and we expect that to continue. There is a limited amount of working capital and capital expenditure requirements relative to their operations. ……

*Michael Clarke, Nortek, Inc. - President, CEO

>>Yes, did that answer you, Jeff?

***Jeff Gates, Gates Capital - Analyst**

>>Yes, I guess so. I guess the other question I have is clearly a path to shareholder value here is less debt and more float, and I am just wondering what your long-term plan is for addressing those two issues.

*Al Hall, Nortek, Inc. - SVP, CFO

>>So long term, the Board -- my long term is 56 days.

*Michael Clarke, Nortek, Inc. - President, CEO

>>56 days.

---

[62] According to MarketScreener, Jeff Gates (Mr. Jeffrey L. Gates) is the founder and a Managing Partner at Gates Capital Management, Inc."

*Al Hall, Nortek, Inc. - SVP, CFO

>>But the Board and the Company long term is focused, definitely focused, on where are we going with our capital structure? ……

***Jeff Gates, Gates Capital - Analyst**

>>**Okay, thank you.**

B. Earnings call sample questions for automation-adopting hedge funds vs. non-adopters

One key part of my ongoing empirical endeavor is to conduct textual analysis of hedge fund questions during earnings calls. This test is to provide a more nuanced text-based picture for how hedge funds acquire information differently when they incur more effort at the intensive margin. This is also part of first textual evidence of changes in hedge fund information acquisition behavior in the age of AI. In this table, I show a sample of hedge fund questions asked during earnings calls following the adoption of automated downloads of SEC filings, with Panel A covering automation-adopting-hedge funds (AHFs) and Panel B non-adopters.[63] Panel C lists word lists under each topic and other non-topic question-level indicator variables.

Using a dictionary-based method combined with large language models, each question is tagged with multiple labels including three main topics covered (if any) and whether it is a follow-up questions.[64] In each table, I include the unique call-level Refinitiv transcript ID and the ticker for the call-hosting firm.[65] Only hedge fund analysts' questions are picked out of the call (with analyst name partly anonymized). Following the full-text question column, I further include three topic categories classified and ranked based on the appearances of the associated keywords under each pre-specified topic labels. A follow-up question is one separate question that inherits the same topic of the prior question's without

[63] The small sample of non-adopters in Panel B happen to be never-adopters, meaning that the hedge funds never used AI automation to download SEC filings throughout the sample period.

[64] In results that are not tabulated yet, I further add more labels based on the full text of each question including indicator variables for a consistency-checking question, a quantitative inquiry, a hypothetical question, and a forward-looking question. The word lists corresponding to these extra question labels are also presented in Panel C of this appendix table.

[65] Each firm's conference call is uniquely assigned with a Refinitiv transcript ID, which is pinned down at the firm-call-date level. For example, the transcript id of "138684759800" points to the fourth quarter 2012 Deluxe Corporation earnings conference call held on January 24, 2013.

initiating a new one.[66] Out of space-saving considerations, I include topic acronyms for each of the nine topics, whose full names along with corresponding word lists are displayed on Panel C. For example, "FS" is short for "Financial Statement" and "MS" stands for "Market Strategy".

As a further intensive margin analysis of hedge fund information acquisition behavior, I provide preliminary evidence that automation-adopting hedge funds (AHFs) inquire about more topics and ask more follow-up questions compared to non-adopters.

[66] The topic variables and the follow-up indicator would be set to missing if a question only contains greeting or salutation remarks, or appreciative remarks or any other words that used to initiate, continue, or conclude a conversation.

Panel A. Topic Categorization for AHFs' Earnings Call Questions

Analyst Name	Hedge Fund	Refinitiv Transcript ID	Full Question	Topic 1	Topic 2	Topic 3	Follow-up	Ticker
Ben ***	Apollo Global Management	138684759800	Hey, guys. Quick question and a follow-up to Jamie's. Can you help us think about visibility into the business like giving full year guidance here? You mentioned if your equations change as the year goes on maybe you'll adjust up or downward. I'm just trying to think about how much confidence we should put behind that? What the visibility you have into contractual revenues might be?	FS	FR		0	DLX
Ben ***	Apollo Global Management	138684759800	Yes. So, the key drivers or your assumption on the rate of decline on checks and I'm curious -- is there a way to have much visibility into the business?	FS			1	DLX
Ben ***	Apollo Global Management	138684759800	That's very helpful. The other question I had is, if you could help us think any more about, and I	FS	MS		0	DLX

			know you guys were thinking about what you do want to disclose, but some of the growth rates are so impressive in the Marketing and Other Services segments and sub-segments. Just to help us think about incremental margins on revenue relative to the traditional check business which appears to be at very high incremental margins.						
Ben ***	Apollo Global Management	138684759800	Got it. Thanks.						DLX
David ***	Berman Capital	138894587007	Just a real -- real quickly, your designer sales program, can you embellish on that? Do you feel -- I think you've got 90 people or something in 119 stores. Do you kind of feel -- how do you feel that's worthwhile? How can you tell that it's actually adding incrementally more than what it's costing? And the second question		PS	MS		0	HVT

			would relate to the new stores, if you can embellish further about how they are doing through in July, August, I think another one in October. How are the three new stores doing? Thank you very much.					
David ***	Berman Capital	138894587007	All right. Excellent, excellent. And if you can just talk about -- your payout ratio, as I understand it, is about 25%. And I understand you're a cyclical business. And I'm impressed that you pay $1.00 dollar dividends every now and again. You've, I think, paid $2.00 in the last three years. So your cash balance would be probably be close to $4.00 if you didn't do that. I'd like to see a high dividend -- annual dividend. And also I see you have a share purchase program. Just FYI, we much prefer the cash one-time dividend. But if you can just	SV	FS		0	HVT

			comment on the dividend, the annual dividend. If that was higher, I think that would be helpful to investors long term.					
David ***	Berman Capital	138894587007	Well, yes. I understand that. I wouldn't otherwise suggest it except that you are throwing out cash even in bad times; you have proven that. And you do have the $1.50 in share in cash. So I don't think one is too worried about your being able to make it given how well you did during the bad times.	SV			1	HVT
David ***	Berman Capital	138894587007	Yes. Okay, all right. Well, let's keep on going, guys.					HVT
David ***	Berman Capital	138894587007	Thank you very much.					HVT
Aaron ***	Wexford Capital	140881646464	Good quarter. I just wanted to have a couple of answers on the adjusted numbers. I was just trying to understand how you talked about outperforming your group across your markets. I just	MS	FS		0	XHR

			wanted to understand -- when you take out the disruption and then take out the reclassification, what you think the overall adjusted RevPAR might be? In the calculations you've talked about is somewhere in the 6%s. Is that a fair way to look at it, same on same?					
Aaron ***	Wexford Capital	140881646464	Okay, perfect. The other question I had was, you ended up the quarter with a lot of cash on the balance sheet; even more than I thought. Obviously, as a new company you always want to have a little more flexibility. But it's actually, if you compare yourselves to the peers on your pro forma guidance, you are looking at something, like, under 3 times. That's way below peers, and you are also at a valuation that's well below peers. The way I look at this is, either you should	FS	SV	CS	0	XHR

			either be more aggressively returning capital or looking at share repurchase. Though, as REIT, it may not be the best use of capital. What I see is, it looks to me like you should be paying out a lot more cash here. So, help me understand how you guys think about that?					
Aaron ***	Wexford Capital	140881646464	Sorry. Just to follow up on that point. Just trying to understand the math that you look at when you consider acquisitions versus a higher payout, or at least using more of the cash, given unencumbered assets and a lot of room on your revolver, as well. Just trying to understand the thought process of not at least returning some amount of that total $320 million of cash, and then using a little bit of debt, which seems to make a lot of sense given how low the rates	FS	CS		1	XHR

			that you can borrow at, as well. Any more commentary on how you think about the balance of capital usage?					

Panel B Topic Categorization for Non-adopters' Earnings Call Questions

Analyst Name	Hedge Fund	Refinitiv Transcript ID	Full Question	Topic 1	Topic2	Topic3	Follow-up	Ticker
Justin ***	Gates Capital	138066497494	Hi, thanks. It looks like the inventory dollars were up a bit year-over-year and maybe a bit up in days as well. Could you talk a little bit about what's going on there in inventory?	MS			0	EXP
Justin ***	Gates Capital	138066497494	Okay, and I think you'd previously said you thought or the Company thought about the imports required to meet US demand in cement this year should be about 10%. Is there any update on that? Do you still expect there to be some imports for the full year?	MS	FS		0	EXP
Dennis ***	Act II Partners	139635827760	Thanks. You had mentioned, I think at the past pro forma, that free cash flow per share on average for 2013/2014 was $1.93. You talked about, I think, $35 million free cash flow on	FS			0	GTN

			average for the Schurz stations. If you subtract the cost of debt, I come up with $2.17 per share free cash flow on average for 2015/2016 without any growth next year. Is my math correct?					
Dennis ***	Act II Partners	139635827760	Well I thought the figure you gave was 2013/2014, so I'm talking about 2015/2016.	FS			1	GTN
Dennis ***	Act II Partners	139635827760	Yes. And that's true of Schurz as well?	FS			1	GTN
Dennis ***	Act II Partners	139635827760	All right. Thanks.					GTN
Angelo ***	Brookfield Asset Management	138750268587	Hey, it is actually Angelo filling in for Alex. But I want to say nice quarter and I did notice that LPG with regard to the wholly-owned fleet is actually decreasing. So just want to see if you can put a little bit more meat around what is that capacity there, assuming a more normal 75% kind of industry level. And	FS	CS		0	TRN

			then just also following that up with given the cash flow back half the debt capacity of the corporate level, what, just run though for us the priorities of where you see of M&A side and with regards to buybacks what else can you do there, you just have an extreme amount of liquidity in our view.					
Angelo ***	Brookfield Asset Management	138750268587	All right, I appreciate that, but just getting back to the piece I was more hitting on is, I understand you are still delevering and you have the amortization in that wholly-owned lease fleet, but if I look at a lot of your comps they are running 75% LTD across that platform and your -- our numbers are (inaudible) this morning. You are now sub 40. So it just seems that there quite a bit of debt capacity at that level.	CS			1	TRN

Angelo ***	Brookfield Asset Management	138750268587	Okay. Thank you.						TRN

Panel C Word Lists associated with Topics

Topic Categorization	Word List
Topic	
Financial Statement	balance sheet, tax rate, income statement, FIFO, cash, operating cost, gross margin, PP&E, capex, capital, expenses, margin growth, EBITDA, EPS, SG&A, receivable and payable, buyback, repurchase, depreciation, amortization, Investment, cash flow, run rate
Shareholder Governance	compensation, agreement, contract, shareholder, board, manager
Stakeholder Governance	employee, supplier, customer, compensation, agreement, contract
Market Strategy	expansion, expand, growth, market, market share, exposure, project, price, competitor, product, international, acquire, acquisition, merger
Production Strategy	production, product, labor, property, raw, plant, material, scale, services, supply chain
Capital Structure	debt, debt ratio, equity, leverage, bond, bondholder, investment-grade
Stock Valuation	stock, price, shares
Firm Risk	risk, risk profile, macroeconomic, inflation, political risk, policy uncertainty, cybersecurity, supply chain risk, business plan, operational risk, bankruptcy, reorganization, lawsuits, litigation, climate risk, pollution, ESG, environmental
Portfolio Management	portfolio, buy shares, sell shares, equity, bond, index, benchmark
Consistency-check	confused, break that out, break out (on), you talked about, you said that, you mentioned that, you mention that, a comment earlier that, i heard that, reconcile
Quantitative	pro-forma, quantify, how much (of), numbers, particular areas, surprises, sustainable, (right) math, what percentage of

Hypothetical	assume, assumption, imply, expectation, expected, end up, possible, indication, if, indicate, believe
Forward-looking	year-over-year, timeline, look out (toward next year), time frame, potential, foresee, project it out, would you expect, anticipate, long-term, plan to, will, would, in the next couple of years, expect, going to (see), outlook, would be, look forward, look to do, strategic moves, when, the possibility of, indication, next quarter, seek, intend, estimate, aim, target, commit

References to Internet Appendix

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