Generative AI and Asset Management*

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Abstract

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JEL Classification: C81, G11, G14, G23

Keywords: Generative AI (GenAI), ChatGPT, Hedge Funds, GenAI Reliance, Portfolio Return, Alpha, Survey, AI Disparity

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1. Introduction

In the asset management industry, information is the key to success. According to Grossman and Stiglitz (1980), sophisticated investors earn alphas by engaging in costly searches for new information and by accurately processing it in a timely manner. However, effectively doing so is challenging due to the vast amount and complexity of potentially useful information for asset pricing (Chen, Cohen, Gurun, Lou, and Malloy, 2020; Martin and Nagel, 2022). Artificial intelligence (AI) has experienced substantial advancement in the past two decades, leading to vast adoptions of the technology by companies to process data and aid their decision-making.[1] However, AI has been highly technical and its applications require special talents, which leads to a scarcity of human capital in this area[2] and a challenge in generating returns on investment with AI.[3]

Generative AI (GenAI), exemplified by ChatGPT, is a significant, disruptive revolution in AI techniques. Their performance in understanding texts, solving problems, and producing answers is truly remarkable and comparable to or exceeds human performance.[4] More importantly, different from previous AI tools, generative AI does not require complicated training and tuning and can be intuitively used by the general public, leading to their rapid adoption, e.g., ChatGPT is the fastest app to reach 100 million users.[5] Given the potential of generative AI, understanding how it is used by investors and its impact on investing thus can have important implications. However, such studies are challenging due to the lack of observable data on the use of generative AI by companies and investors.

[1] See, for example, Webb (2019), Acemoglu, Autor, Hazell, and Restrepo (2022), Babina, Fedyk, He, and Hodson (2024), and Abis and Veldkamp (2024).

[2] Sources: "AI talent war on Wall Street hits Goldman Sachs hardest," November 28, 2023, William Shaw, *Fortune*; "AI talent war heats up in Europe," March 11, 2024, Martin Coulter, *Reuters*; "Inside Silicon Valley's AI talent war," March 28, 2024, *Wall Street Journal* Podcast

[3] Sources: "Can an A.I. hedge fund beat the market?" August 25, 2020, Jeremy Kahn, *Fortune*; "Hedge funds find it's really hard to beat the market With AI," October 6, 2023, Justina Lee, *Bloomberg*.

[4] Sources: "ChatGPT passes exams from law and business schools," January 26, 2023, Samantha Murphy Kelly, *CNN*; "M.B.A. students vs. AI: Who comes up with more innovative ideas?" September 9, 2023, Christian Terwiesch and Karl Ulrich, *Wall Street Journal*.

[5] Source: "ChatGPT sets record for fastest-growing user base," February 2, 2023, Krystal Hu, *Reuters*.

In this paper, we propose a novel approach to measure the reliance on generative AI of investment companies and apply this measure to study the impact of generative AI on the asset management industry. In our study, we focus mostly on hedge funds since they are typically regarded as the most informative investors and earliest adopters of new technologies.[6] We propose to address the following research questions: Are generative AI technologies widely adopted by hedge fund companies? What implications might such adoption have for their performance and the broader financial market?

To construct our measure of generative AI adoption, *GenAI Reliance*, we utilize the 13F quarterly trades of hedge fund companies. We consider two types of information that correlate with trades of hedge fund companies: financial variables about firm fundamentals and information generated by ChatGPT based on conference calls (i.e., AI information). *GenAI Reliance* measures that given the existing financial variables, what additional percentage of the variation in fund portfolio composition can be explained by AI information. In other words, *GenAI Reliance* captures the degree to which fund managers' portfolio decisions are influenced by AI-generated information in addition to the existing set of fundamental variables.

Specifically, we follow a two-step procedure as in Kacperczyk and Seru (2007). In the first step, we look into the explanatory power (i.e. R-squared) of financial variables on hedge fund companies' trades. Next, we calculate the incremental explanatory power when adding AI-generated information. *GenAI Reliance* is estimated as the incremental R-squared through this procedure. The measure is closely related to the coefficient of partial determination, which is commonly used to measure the marginal contribution of new variables when other variables have been included in the regression model.

Our *GenAI Reliance* measure has two advantages. First, by capturing the marginal contribution of AI information to hedge funds' portfolio change, the measure identifies the

[6] For example, a 2018 BarclayHedge survey of hedge fund managers finds that more than half of hedge funds use AI and machine learning in their investment strategies. Source: "Majority of hedge fund pros use AI/machine learning in investment strategies," July 17, 2018, *BarclayHedge*.

usage by portfolio managers for investment purposes, rather than other reasons. Second, our methodology can be applied to all investment companies with holdings information, allowing us to conduct a systematic analysis of the effect of generative AI usage on their performance.

Using the *GenAI Reliance* measure, we first examine the adoption of generative AI among hedge funds (*GenAI Adoption*). To formally test the adoption of AI by hedge funds, we conduct a partial F-test, widely used in the literature (e.g., Greene, 2002, p101). We also estimate the false positive rate during this process and find it to be low, at only around 2%. After adjusting for the false positive rate, we estimate that 21% of hedge funds adopted generative AI in 2022, with the result statistically significant at the 1% level. The adoption rate rises to over 40% in 2023 and approaches 60% in 2024. The time trend of *GenAI Adoption* reveals a sharp, abrupt increase beginning in 2022, coinciding with the release of ChatGPT's underlying base model. These patterns indicate substantial uptake of generative AI among hedge fund companies.

We next study the relation between *GenAI Reliance* and hedge fund performance. We hypothesize that GenAI adoption can enhance hedge fund performance because it strengthens the production of financial knowledge, which is the source of alpha. We test this hypothesis using two methods. Results from panel regressions indicate that hedge funds with higher reliance on ChatGPT earn better returns during the post-ChatGPT period.[7] In addition, we conduct a difference-in-differences (DiD) test to examine whether *GenAI Reliance*'s predictive power for fund performance significantly increases following the introduction of ChatGPT. Our tests show that hedge fund companies with a higher *GenAI Reliance* generate significantly higher raw and risk-adjusted returns. The economic magnitude of this effect is large. An interquartile increase in the reliance on generative AI is associated with a gain of 2-4% in annualized abnormal returns, for different asset pricing

[7] By focusing on the post-GPT period, we limit the sample period to be after the knowledge cutoff of September 2021 for GPT 3.5. This out-of-sample test rules out the possibility of forward-looking bias in using ChatGPT to forecast economic outcomes.

models. Therefore, generative AI does bring substantial benefits to hedge fund companies that adopt this new technology.

To the extent that generative AI is accessible to all, a natural question is whether it benefits all institutions in the asset management industry equally. We find this might not be the case. As highlighted by the model in Abis and Veldkamp (2024), new technologies such as AI and machine learning can significantly contribute to this knowledge production. However, once a dataset is obtained, insights are not immediately or costlessly extracted. Human capital, in the form of skilled financial analysts who can interpret the data, remains equally critical. Moreover, the model suggests that the impact of new technologies on knowledge production depends on firm-specific productivity parameters. In short, generating alpha requires the right combination of people, data, and tools. This framework implies that even though ChatGPT is a publicly available tool, there will be substantial cross-sectional variation in investors' ability to use it effectively.

We examine non-hedge fund companies and find that their AI adoption does not result in significantly better returns. Furthermore, large, older, and more active hedge fund companies are able to leverage generative AI to obtain significant returns, while small, younger, and more passive companies fail to do so. Taken together, the evidence suggests that applying the intuitive GenAI tool productively still requires additional resources such as data and expertise. This also implies that generative AI could enlarge the disparity among investors rather than level the playing field.

We further investigate the potential mechanisms of how generative AI helps with asset management and conduct three sets of tests. First, hedge funds that are better equipped with the necessary AI talents are more likely to utilize generative AI tools such as ChatGPT because the the complementarity between data, tools, and human capital as suggested by Abis and Veldkamp (2024). Thus, we hypothesize that hedge funds that have recruited AI talents prior to the release of ChatGPT are able to generate higher alpha using this new powerful tool. Indeed, we find that hedge funds with AI-skilled human capital generate much higher performance from their use of generative AI, consistent with the notion that these AI talents can use the tools more effectively.

Second, we examine whether generative AI can help funds better analyze certain information. For this purpose, we decompose the *GenAI Reliance* measure into three components regarding macroeconomic, firm-policy, and firm-performance information. We find that firm-level policy and performance information contributes to greater fund performance, indicating that generative AI is mostly useful for funds to analyze firm-specific information.

Third, we examine individual trades to assess whether hedge fund managers generate profits by following GenAI signals. Specifically, we classify trades into those that align with GenAI recommendations and those that do not. Trades in agreement with GenAI generate an average quarterly return of 2.57%, significantly outperforming the 0.35% return of disagreeing trades. This provides micro-level evidence that hedge funds actively incorporate GenAI into their trading decisions.

Does GenAI usage by institutional investors have implications for the financial market? Theories of information predict it would. Several theories (e.g., Goldstein and Yang, 2015) predict that market prices would incorporate the information more quickly, leading to a more efficient market. In addition, information asymmetry theories (e.g., Kim and Verrecchia, 1994) forecast an increase in bid-ask spreads as a group of investors (hedge funds) gains an information advantage against others. Our results are consistent with these predictions and show that the introduction of the new AI tools has important implications in the financial market.

To offer more direct evidence and further validate our methodology, we conduct a survey of hedge fund managers regarding their GenAI usage. The survey results show that the time trend of hedge funds' GenAI adoption is highly consistent with our findings based on the *GenAI Reliance* measure. The vast majority of adopting hedge funds employ GenAI tools for processing financial text data, similar to our setting. Furthermore, the survey-based GenAI adoption bears a significant and positive relationship with the *GenAI Reliance* measure for surveyed funds in our sample, providing direct validation of our measure. The survey also reveals novel insights about in-house AI tools of hedge funds and challenges in the adoption of GenAI technology.

Finally, we carry out a host of additional analyses for further substantiate our findings. First, we expand the information sources to include 10K and 10Q filings, and Wall Street Journal articles in the definition of *GenAI Reliance* measures. We find that the main results remain similar. Interestingly, conference calls constitute the most influential information source. Second, we control for signals generated by traditional textual analysis (Loughran and McDonald, 2011) and validate that our results are indeed driven by the recent advances in GenAI tools. Third, to rule out any potential influence of look-ahead biases in applying the large language models (LLMs), we conduct out-of-sample tests after the knowledge cutoff date of GPT 3.5 and find our results to be robust.

This paper contributes to several streams of literature. First, our research contributes to the literature on the skill and performance of hedge funds and mutual funds. Several studies document evidence of hedge fund and mutual fund skill through examination of their stock holdings, e.g., Wermers (2000); Kacperczyk, Sialm, and Zheng (2005, 2008); Griffin and Xu (2009); Agarwal, Jiang, Tang, and Yang (2013); Aragon, Hertzel, and Shi (2013). Furthermore, a number of studies identify characteristics that distinguish skilled hedge funds, such as strategy distinctiveness (Sun, Wang, and Zheng, 2012), risk exposure to systematic factors (Titman and Tiu, 2011), market timing (Chen and Liang, 2007), market liquidity timing (Cao, Chen, Liang, and Lo, 2013), option positions (Aragon and Martin, 2012), exposure to investor sentiment (Chen, Han, and Pan, 2021), geographical preference (Sialm, Sun, and Zheng, 2020), and unobserved performance (Agarwal, Ruenzi, and Weigert, 2023). Different from these studies, our paper shows that the adoption of disruptive generative AI technology can also contribute substantially to hedge fund performance.

Second, our paper is also related to the use and implications of new technologies and data in asset management, e.g., alternative data (Bonelli and Foucault, 2023), and AI in venture capital investment (Lyonnet and Stern, 2022; Bonelli, 2025). We complement this literature by being the first to study the adoption of ChatGPT, a significant and disruptive revolution in AI technologies, in the asset management industry. Our construction of a unique generative AI reliance measure enables the study of the implications of this disruptive AI technology. Our survey, which to our knowledge is the *first academic survey* of hedge funds on related topics, provides a direct validation of our measure and sheds additional light on issues regarding GenAI adoption.

Third and more generally, our paper contributes to the literature on the impact of AI on the economy and financial markets.[8] Theoretically, AI may come with unexpected costs such as lower price efficiency (Dugast and Foucault, 2023; Colliard, Foucault, and Lovo, 2022; Dou, Goldstein, and Ji, 2023). Empirically, there is evidence on both the positive and negative sides of AI. For instance, Fuster, Goldsmith-Pinkham, Ramadorai, and Walther (2022) show the negative effects of AI on the disparity in the credit markets. Cao, Jiang, Wang, and Yang (2024) find that human wisdom and AI power complement each other in stock analyses.[9] Our paper complements this literature by providing novel evidence of the impact of generative AI adoption on the financial markets, consistent with predictions of information theories (e.g., Kim and Verrecchia, 1994, Goldstein and Yang, 2015).

Different from previous AI advances such as machine learning, generative AI represents

[8] One important early application of AI in the finance industry is robo-advising, which can improve retail investors' welfare (D'Acunto, Prabhala, and Rossi, 2019; Rossi and Utkus, 2024). Algorithmic aversion, however, can hinder AI adoption (Greig, Ramadorai, Rossi, Utkus, and Walther, 2022).

[9] Relatedly, AI affects the real economy such as workforce composition (Babina, Fedyk, He, and Hodson, 2023). Also, data management affects the workforce in the financial services industry (Abis and Veldkamp, 2024).

a major, unexpected breakthrough in AI technologies that first makes AI widely available to the public and investors with low costs. Most related to our paper are several very recent studies that examine the effects of LLMs or generative AI on stock prices and job markets (Eisfeldt, Schubert, and Zhang, 2023), and corporate customer service quality (Brynjolfsson, Li, and Raymond, 2025). Such studies are challenging to conduct in general due to the difficulty in obtaining data on the use of generative AI by companies. We contribute to the literature by conducting the *first large-scale study* of the use of generative AI in the asset management industry. The setting of investment companies, the availability of holdings data, and our methodology allow us to infer the use of generative AI and study its implications. Our findings reveal that despite its accessibility, generative AI may in fact further increase disparities among market participants. This carries implications as society prepares to widely adopt generative AI technologies.[10]

Finally, there is an emerging literature that applies generative AI techniques to research in finance and economics, e.g., evaluating news sentiment (Lopez-Lira and Tang, 2025), classifying Federal Reserve policy stances (Hansen and Kazinnik, 2023), identifying lengthy discussions in earnings transcripts (Kim, Muhn, and Nikolaev, 2023), quantifying information content in answers (Bai, Boyson, Cao, Liu, and Wan, 2023), understanding expected corporate policies and the implications on asset prices (Jha, Qian, Weber, and Yang, 2023), and analyzing corporate culture and its impact (Li, Mai, Shen, Yang, and Zhang, 2023).[11] This literature utilizes the power of generative AI to perform deep analysis of textual data and expand the horizon of economic research.[12] While we also rely on the use of generative AI in the definition of our key measure, we have a distinct focus on studying the implications of AI adoption in the asset management industry.[13]

[10] "Business Schools Are Going All In on AI," April 3, 2024, Lindsay Ellis, *Wall Street Journal*.

[11] See also Korinek (2023) for a discussion of use cases of generative AI in economics research.

[12] A closely related branch of literature has applied large-language models and their foundation – the transformer models – in economic research, e.g., Cong, Tang, Wang, and Zhang (2021), Acikalin, Caskurlu, Hoberg, and Phillips (2022), Jiang, Kelly, and Xiu (2022).

[13] More generally, our paper is also related to the literature on textual analysis in finance (e.g., Tetlock,

2. Institutional Background and Data

In this section, we describe the institutional background of the history and development of ChatGPT, as well as the datasets we use.

2.1. Background on ChatGPT

Developed by OpenAI, ChatGPT (Chat Generative Pre-trained Transformer) represents a significant milestone in natural language processing and AI. The underlying technology of ChatGPT is based on the Transformer architecture of deep learning models (Vaswani et al., 2017), which allows self-attention mechanisms, self-supervised training, and superior performance. Since 2018, Open AI has released increasingly capable Transformer-based pre-trained models, including GPT 1 in 2018, GPT 2 in 2019, and GPT 3 in 2020. GPT 3 was able to complete writing tasks in a much more polished manner than prior versions. These models serve as the predecessors of ChatGPT. OpenAI also made its Application Programming Interface (API) publically available in 2021.[14]

ChatGPT is based on the GPT 3.5 model series, which significantly increases the capabilities of prompt understanding and question answering. The first model in the GPT 3.5 series was released in March 2022 and became publicly available through the API platform.[15] The GPT 3.5 model was then further fine-tuned to produce ChatGPT 3.5 and formally launched to the public through a chat-based interface on November 30, 2022.[16]

ChatGPT is built upon a robust foundation of deep learning and AI advancements. The evolution from GPT-3 to ChatGPT 3.5 involved enhancements in model architecture, training data, and fine-tuning methodologies, including reinforcement learning with human feedback (RLHF). With increased parameters and improved algorithms, ChatGPT

2007; Loughran and McDonald, 2011; Hoberg and Phillips, 2010, 2016; Fisher, Martineau, and Sheng, 2022; Garcia, Hu, and Rohrer, 2023).

[14] Source: "OpenAI's API now available with no waitlist," November 18, 2021, OpenAI.

[15] Source: "New GPT-3 capabilities: Edit & insert," March 15, 2022, OpenAI.

[16] See https://platform.openai.com/.

3.5 exhibits far superior performance in understanding and generating human-like text responses across diverse contexts relative to earlier models. Furthermore, ChatGPT exhibits "emergent abilities" that allow it to tackle even problems in unfamiliar domains. As a result, ChatGPT took the world by surprise and made a remarkable debut, swiftly gaining popularity. By December 4, 2022, ChatGPT had over one million users. Subsequently, in January 2023, it reached a milestone of over 100 million users, positioning it as one of the fastest-growing consumer applications to date.[17]

After the initial release, Open AI made continual improvements to ChatGPT. For example, it released ChatGPT Plus on February 1, 2023, which allows subscribers to access the most recent models and features. On March 1, 2023, Open AI made ChatGPT available through its API services. The latest and most advanced version, ChatGPT 4 was released on March 14, 2023. Figure 1 shows the timeline of the development of ChatGPT.

[Insert Figure 1 Here]

Admittedly, there are other generative AI tools beyond ChatGPT, such as Claude by Anthropic, Gemini by Google, and Llama by Meta. We focus on ChatGPT for at least two reasons. First, ChatGPT was the first powerful large language model tool, allowing us to have a relatively longer sample period. Second, ChatGPT is arguably the most widely used generative AI tool by the public, including professional investors. Thus, it is intuitive to use ChatGPT in this setting. Also, to the extent that other generative AI tools generate signals correlated with ChatGPT, our measure can be viewed as a proxy for hedge funds' use of generative AI tools in general.[18]

[17] According to a February 2024 Pew Research poll, 23% of American adults had tried ChatGPT. Source: "Americans' use of ChatGPT is ticking up, but few trust its election information," March 26, 2024, Pew Research Center.

[18] Some hedge funds may want to use their proprietary generative AI models rather than ChatGPT. However, industry reports suggest that it takes a long time to develop a high-quality generative AI model customized to the financial industry needs (Source: "Finding value in generative AI for financial services," MIT Technology Review, 2023). Therefore it is unlikely that such a model was immediately available during the first few months of ChatGPT, the sample period that our paper focuses on.

2.2. Data: AI-generated Signals

The data used in this study come from various sources. ChatGPT is utilized to generate AI-predicted information about public firms from conference call transcripts. Specifically, ChatGPT is queried with questions about firms' future policies in various areas, such as investment, employment, etc. For instance, one question we ask is *"Over the next quarter, how does the firm anticipate a change in its employment."* ChatGPT will answer this question based on earnings conference call transcripts. The set of questions is based on those in Jha, Qian, Weber, and Yang (2023, 2024).[19] We follow their methodologies and extend the sample to the third quarter of 2024. There are a total of 14 signals, or *GPT Score*s, generated by ChatGPT, covering firms' expectations about macroeconomic, industry, and firm-specific performance and policy outcomes. The complete list of questions is reported in Table IA.1 of the Internet Appendix.

We focus on information from earnings conference calls for two reasons. First, it is well-documented that this data source is important for investors and well-accepted in the finance literature (e.g., Li, Mai, Shen, and Yan, 2021; Li, Mai, Shen, Yang, and Zhang, 2023). Second, Jha, Qian, Weber, and Yang (2023) show that signals from ChatGPT are high-quality and can be used to predict firms' future corporate policies and returns. Thus, we hypothesize that hedge funds may use ChatGPT to analyze earnings conference call texts to help with their investment decisions.

It is important to point out that the AI-generated information based on call texts may not necessarily reflect new information given the public nature of conference calls, but AI can still help fund managers process a large amount of unstructured data with forward-looking predictions. For this study, it does not matter whether the information from ChatGPT is new or not, as such information can aid managers' investment decisions in either case.

[19] We thank these authors for sharing data with us. The data include scores generated by ChatGPT before the second quarter of 2023 on the 14 questions listed in Table IA.1 in the Internet Appendix.

2.3. Data: Other Variables

Other data sources include Institutional (13F) Holdings from Thomson Reuters/LSEG, fundamental and market information data about portfolio firms from CRSP, Compustat, and I/B/E/S, and manual classification of 13F investment companies that operate hedge funds.[20] We calculate the portfolio returns in quarter $t + 1$ for each investment company i, based on its 13F holdings at the end of quarter t. *Return* is defined as the weighted average cumulative monthly return across all holdings in quarter $t + 1$, where the weight is the value of stock j held by i at the end of quarter t divided by the total value of all stocks held by i at the end of quarter t. We also calculate weighted average risk-adjusted returns using CAPM, the Fama-French three-factor model, and the Fama-French-Carhart four-factor model (Fama and French, 1993; Carhart, 1997). Take *CAPM Alpha* as an instance, at the end of quarter t, we use the monthly stock returns in the past 36 months to estimate the beta on the risk factor and calculate abnormal return as the difference between realized stock return minus stock return estimated with beta. *CAPM Alpha* is the weighted average cumulative monthly abnormal return across all holdings. *FF3 Alpha* and *FF4 Alpha* are constructed analogously.

In addition, we control for investment companies and their holdings characteristics. *Size* is the natural logarithm of total holdings value. *Age* is the number of years since an investment company's first 13F report. *Turnover* is the minimum of purchases and sales over average total holdings values of the current quarter and the previous quarter, following Carhart (1997). *Risk* is the standard deviation of quarterly portfolio returns in the past two years. *Past Return* is the portfolio return in the previous quarter. In the Appendix, we provide a detailed definition for each variable.

[20] The classification is based on several sources, including online business name datasets such as Bloomberg, company websites, and Form ADVs filed by investment companies. Our classification method is based on Agarwal, Jiang, Tang, and Yang (2013) and extends to recent years.

3. Reliance on Generative AI Information (*GenAI Reliance*)

In this section, we discuss how we construct our measure of the reliance on AI information. We also provide a proxy for AI adoption by hedge funds.

3.1. *GenAI Reliance*: Measure Construction

To measure the reliance on AI by hedge funds, we estimate the responsiveness of a hedge fund manager's portfolio changes to AI-predicted signals. We call this measure *GenAI Reliance*. For AI-generated information, we obtain ChatGPT-predicted signals as in Jha, Qian, Weber, and Yang (2023). Specifically, for each portfolio firm in each quarter, we query ChatGPT, based on the firm's conference call transcripts, a total of 14 questions covering the firm managers' expectations about macroeconomic, industry, and firm-specific performance and policy outcomes. For example, one question we ask is "Over the next quarter, how does the firm anticipate a change in its revenue?" ChatGPT generates a signal ranging from –1 to 1 for each question, where a positive (negative) value indicates an increase (decrease) in future expectations while zero suggests no expected changes.

Next, we construct *GenAI Reliance* using a methodology similar to Kacperczyk and Seru (2007), who measure a fund's reliance on public information. Specifically, we estimate *GenAI Reliance* using a two-step procedure. In the first step, at the end of each quarter t and for each investment company i, we run the following two regression models across the investment company's holdings changes in quarter t:

$$HoldingChange_{i,j,t} = \gamma_{i,t} \cdot X_{j,t-1} + \varepsilon_{i,j,t} \tag{1}$$

$$HoldingChange_{i,j,t} = \Sigma_{j=1}^{J} \beta_{i,t} \cdot GPT\ Score_{j,t-1} + \gamma_{i,t} \cdot X_{j,t-1} + \varepsilon_{i,j,t} \tag{2}$$

where $HoldingChange_{i,j,t}$ denotes a percentage change in split-adjusted holdings of stock j

held by an investment company *i* from time *t - 1* to *t*.[21] $X_{j,t-1}$ is a host of financial variables about firm fundamentals at the end of quarter $t-1$, including market capitalization, book-to-market, return on assets, stock return, and change in the analyst recommendation consensus. Note that analyst recommendation is an aggregate outcome of analysts' research based on various information sources in the public domain, including the earnings conference call transcripts. This variable has been used by the literature to capture information in the public domain (e.g., Kacperczyk and Seru, 2007).[22] Thus, we benchmark against the public information available to fund managers without the deployment of generative AI tools.

GPT Score includes 14 signals generated by ChatGPT, covering firms' expectations about macroeconomic, industry, and firm-specific performance and policy outcomes. Note that the cross-sectional regressions are conducted separately for each investment company *i* and quarter *t*. We define the R^2 from equation (1) as $R^2_{fundamental,i,t}$, and the R^2 from (2) as $R^2_{AI,i,t}$.

In the second step, we define *GenAI Reliance* of investment company *i* at time *t* as the difference between these two R^2s, which is presented as follow:

$$GenAI\ Reliance_{i,t} = R^2_{AI,i,t} - R^2_{fundamental,i,t} \tag{3}$$

The incremental R^2 estimated through this procedure is closely related to the coefficient of partial determination, which is commonly used to measure the marginal contribution of a new variable when other variables have been included in the model. Intuitively, *GenAI Reliance* quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT in addition to the existing set of fundamental variables. As a robustness check, we also create an alternative reliance

[21] Adding a new stock position would imply an infinite increase, so we set $HoldingChange_{i,j,t}$ to 100% for these cases, following Kacperczyk and Seru (2007).

[22] We use information at the end of quarter t-1 to ensure that such information is available to fund managers when they make portfolio changes during quarter t.

measure *GenAI Reliance Alt*, defined as the difference in R^2 (i.e., *GenAI Reliance*) scaled by R^2 in equation (1) and report the results in Section 8.5.

Given that generative AI is a recent phenomenon, we restrict our sample period from the first quarter of 2016 to the third quarter of 2024. Our final sample consists of 644 unique hedge fund companies and 11,921 company-quarter observations. Table 1 reports the summary statistics for key variables of interest and control variables. Overall, our sample exhibits significant cross-sectional variation in *GenAI Reliance*. The average value of *GenAI Reliance* equals 0.260, with a standard deviation of 0.218 and an inter-quartile range of 0.321.

[Insert Table 1 Here]

Our *GenAI Reliance* measure has several advantages. First, by examining the marginal contribution of ChatGPT information to hedge funds' portfolio change, it is likely to pick up the usage by portfolio managers for investment analysis purposes rather than other reasons. Second, our methodology can be applied to all hedge funds with holdings information, allowing us to conduct a systematic analysis of the impact of generative AI on hedge fund performance.

3.2. Generative AI Adoption and Time Trends

One important question is how widely ChatGPT is used by hedge funds. A fund is more likely to use ChatGPT if its *GenAI Reliance* is higher, but how high does the *GenAI Reliance* have to be in order for us to say a fund is using ChatGPT? To measure that, we use a partial F-test, which tests whether the model's explanatory power is significantly improved by adding additional variables. Specifically, it is calculated as

$$F_{i,t} = \frac{(RSS_{fundamental,i,t} - RSS_{AI,i,t})/p}{RSS_{AI,i,t}/(n-k)} \tag{4}$$

where $RSS_{fundamental,i,t}$ is the residual sum of squares of the model with firm fundamentals only, i.e., Equation (1), while $RSS_{AI,i,t}$ is the residual sum of squares of the full model after adding the fundamental information generated by ChatGPT, i.e., Equation (2). p is the number of predictors added to the full model and equals 14 in our case since we have 14 ChatGPT scores. n is the number of observations used to estimate Equations (1) and (2) in a given fund quarter. k is the number of coefficients (including the intercept) in the full model and equals 20 since we have five variables about firm fundamentals, 14 ChatGPT scores, and an intercept.

We conduct the partial F-test for each hedge fund company-quarter. A hedge fund company is considered a generative AI adopter for a quarter if its F-test is significant at the 1% level. We then calculate the percentage of funds with significant partial F-tests among all funds for each period, which we name as *GenAI Adoption*. Figure 2 presents the four-quarter moving average of *GenAI Adoption* at a quarterly frequency. The percentage was low and smooth before 2021 and increased dramatically in 2022.[23]

The partial-F test also serves as a way to estimate the false positive rate. It is possible that a fund happens to obtain information that correlates with ChatGPT signals, but does not actually use ChatGPT, then their *GenAI Reliance* may be overestimated.With a p-value of 0.01, we expect a false positive rate of 1%, so even if funds do not use generative AI at all, we will still find 1% of the funds having a positive and significant F-test. According to the figure, the percentage of funds with significant F-tests is around 3%. Thus, the false-positive rate contributed by our measure is estimated to be around 2% (i.e., 3% total false-positive rate minus 1% false-positive rate contributed by the F-test itself). This estimate suggests that our measure misattributes about 2% of funds that do not use generative AI but happen to have trading strategies that correlate with ChatGPT signals as ChatGPT users.[24]

[23]In Figure IA.1 in the Internet Appendix, we present the time series of average p-values. Before 2022, the average p-value hovers around 0.5. However, it begins to decline substantially in 2022, with a notable drop by the end of 2022 and early 2023—reaching approximately 0.3. This decline is economically meaningful and consistent with our main narrative.

[24]An alternative explanation of the 2% adoption rate before 2021 could be that those funds were using an

At the end of 2022, the percentage increases to 23%, subtracting the average positive rate of 2%, we can infer that 21% of funds adopted ChatGPT in 2022. This number further increases to over 40% in 2023 and close to 60% in 2024. This is a notable adoption rate and is consistent with the speed at which the general public subscribes to ChatGPT.

[Insert Figure 2 Here]

The time-series pattern in Figure 2 suggests a significant increase in generative AI adoption starting in 2022, which corresponds with the release of the first model in GPT 3.5 series along with API tools in March 2022. This is also consistent with the fact that ChatGPT 3.5 was later introduced in November 2022 to the public.[25] These findings serve as a validation test for our reliance measure, indicating its ability to capture the rising usage trend of ChatGPT.[26] If *GenAI Reliance* merely captures the cases where hedge funds use information correlated with ChatGPT signals without using ChatGPT itself, then we do not expect a significant jump in generative AI usage around the introduction of ChatGPT.

One way to validate our measure is to check whether GenAI adoption is persistent over time. In each quarter, hedge funds are classified as GenAI adopters and non-adopters based on whether their *GenAI Reliance* is significant at the 1% level using a partial F-test. We then calculate the probability of GenAI adoption in the subsequent four quarters for GenAI adopters and non-adopters. We report the persistence of GenAI adoption in Figure IA.3. We find that GenAI adopters are more likely to continue using GenAI in future quarters compared with non-adopters. This finding suggests that GenAI Reliance is picking up new technology use.

in-house generative AI tool then. In this case, the F-test also captures the early users of generative AI, and thus, the true false positive rate would be even lower.

[25] Sources: "New GPT-3 capabilities: Edit & insert," March 15, 2022, OpenAI; and "ChatGPT: Optimizing language models for dialogue," November 30, 2022, OpenAI.

[26] We also reproduce Figure 2 using different cutoffs for p-values (0.01, 0.05, and 0.1) and report in Figure IA.2 in the Internet Appendix. The trend of GenAI Adoption is robust to the choice of cutoff. All three lines suggest that hedge funds began adopting GenAI in 2022 and increasingly do so in subsequent years. This suggests that the choice of p-value does not matter here.

To provide direct validation of our measure, we conduct a survey among hedge funds and ask whether they use generative AI tools for investment purposes. Evidence from both graphical and regression analyses of the survey data supports the validity of our *GenAI Reliance* measure (see e.g., Figure 3). Details of the survey and additional insights from the survey are discussed in Section 7 and survey questions are listed in Table IA.2.

4. Generative AI and Fund Performance

In this section, we test whether generative AI is associated with performance in the asset management industry with a focus on hedge fund companies first and then including other asset management firms.

4.1. *GenAI Reliance* and Hedge Fund Performance

Our novel *GenAI Reliance* measure captures the responsiveness of a fund manager's portfolio allocations to changes in AI-generated information. Since the prior studies show that AI-generated information is useful in predicting future corporate policies and returns (e.g., Jha, Qian, Weber, and Yang, 2023), we hypothesize that funds with high *GenAI Reliance* tend to outperform funds with low *GenAI Reliance*.

To test this hypothesis, our empirical analysis starts with linking future performance and *GenAI Reliance*. Since the base model for ChatGPT was released in March 2022, hedge funds likely started to use new versions of GPT models in the second quarter of 2022. Therefore, we examine the performance of hedge funds after that. We test with both raw returns and abnormal returns (i.e., alphas).

It also serves as an out-of-sample test because we effectively limit the sample period to be after the knowledge cutoff of September 2021 for GPT 3.5, the version of ChatGPT available to funds at its initial release. Therefore, since ChatGPT cannot use any information after September 2021, we eliminate the concern of forward-looking bias in using ChatGPT to forecast economic and financial outcomes.

We first test the relationship between *GenAI Reliance* and raw returns of hedge funds for the sample period after the introduction of GPT services, i.e., from the third quarter of 2022 to the third quarter of 2024. Specifically, we consider the following regression.

$$Return_{i,t} = \beta \cdot GenAI\ Reliance_{i,t-1} + \gamma \cdot Control_{i,t-1} + \alpha_t + \varepsilon_{i,t} \tag{5}$$

where i and t index hedge fund investment company and quarter. *Control* includes *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*. α represents time (i.e., year-quarter) fixed effects.

Table 2 Panel A shows that the coefficient on *GenAI Reliance* is positive and mostly statistically significant across various specifications. This provides supportive evidence that hedge funds with higher reliance on generative AI can produce better performance in the future. Moreover, we repeat this analysis considering other measures for performance, including *CAPM Alpha*, *FF3 Alpha* and *FF4 Alpha*. We replace the dependent variable in equations (5) by these risk-adjusted returns.

$$Alpha_{i,t} = \beta \cdot GenAI\ Reliance_{i,t-1} + \gamma \cdot Control_{i,t-1} + \alpha_t + \varepsilon_{i,t} \tag{6}$$

[Insert Table 2 Here]

We report the results in Table 2 Panel B. Our findings still hold when using risk-adjusted returns as dependent variables. The economic magnitude is also substantial. Taking the specification with *FF4 Alpha* and time-fixed effects (Column (6)) as an example, a one-standard-deviation change in *GenAI Reliance* is associated with a 0.41% increase in the Fama-French four-factor alpha, or 1.6% annually.

To sharpen our analysis, we consider the new development in generative AI as an exogenous shock to hedge fund investment companies and conduct a difference-in-differences (DiD) test as follows:

$$Return_{i,t} = \beta_1 \cdot GenAI\ Reliance_{i,t-1} \times Post\ GPT_t + \beta_2 \cdot GenAI\ Reliance_{i,t-1} + \gamma \cdot Control_{i,t-1} + \alpha_t + \varepsilon_{i,t} \tag{7}$$

where *Post GPT* is an indicator variable equal to one if the fund performance is measured in and after the third quarter of 2022 and zero otherwise. Note that when adding time fixed effects, α_t subsumes *Post GPT*. *Control* includes *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*. *Return* is the raw portfolio return in a quarter. α represents time (i.e., year-quarter) fixed effects. The sample period for this test is from the beginning of 2016 to the third quarter of 2024. We expect to find a positive coefficient on the interaction term if generative AI has a positive effect on hedge fund performance.

[Insert Table 3 Here]

Table 3 Panel A confirms our hypothesis. The coefficient on *GenAI Reliance* × *Post GPT* is positive and statistically significant across specifications with and without time-fixed effects and control variables. Focusing on the last two columns with time fixed effects, the coefficient on *GenAI Reliance* is indistinguishable from zero, suggesting that there is no pre-trend.

We reproduce this analysis by replacing raw returns with risk-adjusted returns:

$$Alpha_{i,t} = \beta_1 \cdot GenAI\ Reliance_{i,t-1} \times Post\ GPT_t + \beta_2 \cdot GenAI\ Reliance_{i,t-1} + \gamma \cdot Control_{i,t-1} + \alpha_t + \varepsilon_{i,t} \tag{8}$$

where i and t index hedge fund investment company and quarter. *Alpha* is *CAPM Alpha*, *FF3 Alpha* or *FF4 Alpha*.

Table 3 Panel B presents similar findings using risk-adjusted returns. Again, the economic magnitude is large. An interquartile increase in *GenAI Reliance* (0.321) is associated with a 45-bps to 87-bps increase in quarterly risk-adjusted returns, depending on factor models used, and equivalent to 2%-4% annual alphas.

We further examine which investment companies benefit more from the use of generative AI. One hypothesis is that this convenient and powerful new tool would help to level the playing field for hedge fund companies with different resources and capabilities. On the other hand, large hedge funds may be able to combine their resources with generative AI to further increase their competitive advantage. Therefore, it is an empirical question which types of hedge fund companies are most effective in utilizing generative AI in their investment. We conduct subsample analyses based on fund characteristics.

In Table IA.3, we compare the sensitivity of fund company performance to *GenAI Reliance*, i.e., the coefficient of the interaction term in Equation (7), for top and bottom quintile hedge fund companies defined by firm characteristics, including *Size*, *Age*, *Risk*, *Turnover*, and *Past Return*. The results show that larger, older, and more active fund companies are able to leverage generative AI and generate superior performance, while the usage by small, younger, and less active firms does not yield significant returns. The difference in coefficients between the top quintile and the bottom quintile is also statistically significant for these characteristics, including *Size*, *Age*, and *Turnover*. Sorting on other characteristics does not suggest significant differences. Overall, the results suggest that fund companies with more resources benefit the most from the use of generative AI, suggesting a potential synergy between the novel AI tool with other resources such as data and expertise.

4.2. *GenAI Reliance* and Other Asset Management Firms

Hedge funds are arguably pioneers in applying AI and machine learning to their investment strategies. However, recent developments in intuitive AI applications such as ChatGPT make it more accessible to broader user groups, such as mutual funds and other money managers. Therefore, we examine whether these asset managers also use generative AI and, more importantly, boost their portfolio performance.

We reproduce the analyses from equations (5) and (8) in Section 4.1 for asset management companies that do not operate hedge funds (which we label as *Non-Hedge Funds*) and report the findings in Table 4.

[Insert Table 4 Here]

In contrast to their hedge fund peers, we find mixed evidence on whether these asset managers can generate superior performance, albeit having an increasing usage of generative AI after it becomes available. While using *FF4 Alpha* as a performance measure provides weak evidence that non-hedge funds may improve performance by using generative AI, their raw returns decrease when they adopt such technology. In addition, Table 4 Panel B presents a direct comparison between these non-hedge funds and hedge funds. We observe a clear difference between these two groups of investment companies. Columns (1) and (2) show that, during the *Post GPT* period, hedge funds can boost their performance by using generative AI. Columns (3) and (4) further confirm that the advent of generative AI allows hedge funds to transform AI applications into better performance.

Why do other financial institutions (e.g., mutual funds) not benefit as much? These results are surprising but also consistent with economic intuition because mutual funds and hedge funds have different investment strategies, constraints, and incentives. Hedge funds operate with less regulatory oversight, allowing them to experiment more freely with advanced AI models and sophisticated trading algorithms. In contrast, mutual funds have narrow mandates and are subject to higher scrutiny from regulators and investors. Hedge funds may have complementary resources (data, expertise, alternative signals) that enhance AI's impact, whereas mutual funds may lack the infrastructure to fully leverage these tools.

Nonetheless, there could still be a subset of mutual funds that are particularly active and may benefit more from the advanced AI models. Thus, we conduct an additional test where we focus on other asset management firms (i.e., non-hedge funds) that are more active in trading. Specifically, we sort these investment companies into quintiles by *Turnover* and examine the highest *Turnover* quintile. The results are reported in Table IA.4. We find weak evidence that the most active group of non-hedge fund investment companies, including mutual funds, can benefit from using GenAI.

These findings could be due to various advantages that hedge funds enjoy relative to other asset managers. For example, hedge funds have better access to data, and can process data and execute trades more quickly. They may also combine other information or trading skills with AI-generated information to further improve performance. In sum, the results indicate that generative AI may need to be combined with other resources or expertise in order to produce superior investment returns.

5. How does AI Help Hedge Fund Performance?

So far, we show that generative AI helps hedge funds obtain better performance. In this section, we explore potential economic channels. First, we look into whether hedge funds invest more in human capital in AI so that they can use the tools better. Second, we examine whether generative AI helps funds to analyze certain data better. Next, we explore whether hedge fund managers trade in alignment with, or contrary to, signals generated by ChatGPT.

5.1. Combination with AI Talent

To understand the outperformance of hedge funds that have higher *GenAI Reliance*, we explore one potential channel of AI investment by hedge funds. Anecdotal evidence shows that hedge funds heavily invest in human capital in the area of AI so that they can have the talent to use the tools better. To test this idea, we focus on a subset of hedge funds with greater capacity in applying AI tools and expect our findings to be more pronounced. Following Cao, Jiang, Yang, and Zhang (2023) and Abis and Veldkamp (2024), we use Burning Glass hiring data, including the textual descriptions of each job, to identify jobs that require using machine learning and AI. We classify an investment company as *AI Hedge Fund* if it has such AI-related jobs before the release of ChatGPT. Investment companies hiring AI talents are more likely to adopt new technology, and more importantly, are able to overcome hurdles facing new and advanced technology with their AI-skilled employees. We hypothesize that these funds have a greater likelihood of using generative AI to produce better performance.

[Insert Table 5 Here]

Table 5 shows that our main findings hold for all hedge funds and, more importantly, are much stronger within AI hedge funds. With respect to economic magnitude, among all hedge funds, a one-standard-deviation increase in *GenAI Reliance* leads to an increase of 0.25% in quarterly portfolio return. On top of that, it results in a significant increase of 1.07% – adding up to a total increase of 1.32% in quarterly return – for AI hedge funds. These results suggest that the combination of AI talent with the tools is likely to be a driving force for *GenAI Reliance* effect on fund performance. This is consistent with the complementarity between humans and machines documented in the existing literature (e.g., Cao, Jiang, Wang, and Yang, 2024).

5.2. Strength of Analyzing Certain Data

Another potential channel is that ChatGPT is good at analyzing certain data and providing predictions. To test this idea, we further explore the granular components of AI-generated information. The 14 GPT scores generated by ChatGPT with earnings conference calls can be naturally separated into three groups: 1) Macro, 2) Firm Policy, and 3) Firm

Performance.[27] We repeat our methodology for defining *GenAI Reliance*, and every time only add information generated by ChatGPT for each respective group in equation (2). We then create the decomposed *GenAI Reliance* measures for each group: *GenAI Reliance Macro*, *GenAI Reliance Firm Policy*, and *GenAI Reliance Firm Performance*, helping us pinpoint what kind of information hedge funds use to provide superior performance.

[Insert Table 6 Here]

We repeat regression analyses in equations (7) and (8) by replacing *GenAI Reliance* with one of the three decomposed measures and report the results in Table 6. We observe that the interaction between *GenAI Reliance Macro* and *Post GPT* is indistinguishable from zero for *Return* but significant for *FF4 Alpha*, suggesting that reliance on AI information about macroeconomics weakly helps with fund performance. On the other hand, both *GenAI Reliance Firm Policy* and *GenAI Reliance Firm Performance* have a significant and positive relation with hedge fund performance during the *Post GPT* period, regardless of performance measures. AI-generated information about firm policy is particularly useful, as the magnitude of the coefficient is more than twice as much as that of AI information about firm performance.

These findings suggest possible channels that generative AI tools enhance performance in asset management. First, generative AI is more useful for hedge funds to select individual stocks rather than conduct sector or market timing conditional on the macroeconomy. One notable advantage of generative AI is that it can process a tremendous amount of textual data and is especially efficient when hedge fund companies face thousands of stocks to make informed investment decisions. On the other hand, generative AI is less important when hedge funds need information about the industry, U.S. market, or global market,

[27] The Macro group contains information regarding the global economy, the US economy and a firm's industry; the Firm Policy group pertains to a firm's wages, employment, capital expenditure, and cost of capital; the Firm Performance group is about a firm's earnings, revenue, financial prospects, and product market.

since they are unlikely to look into portfolio firms' filings or conference calls to collect such information. Moreover, our findings also indicate that firm policy is informative about stock return, consistent with Jha, Qian, Weber, and Yang (2023). Therefore, generative AI helps hedge funds extract valuable information from voluminous public data and reap benefits from the stock market.

5.3. Do Hedge Funds Trade in Alignment with GenAI Signals?

When hedge fund managers receive signals from generative AI regarding various aspects of portfolio firms, they may have different interpretations. Some managers trade in alignment with these signals, while others trade in the opposite direction. To explore this further, we examine another channel through which hedge funds may generate profits from generative AI by analyzing individual trades within each fund to assess which are more profitable.

Specifically, for each hedge fund company in each quarter, we fit the two regressions as in Equations (1) and (2) using its holding changes. We then obtain two predicted values for $HoldingChange_{i,j,t}$, one based on fundamentals only and the other based on fundamentals and *GPT Score*. We denote them as $Predictions^{fundamental}_{i,j,t}$ and $Predictions^{AI}_{i,j,t}$, respectively. Next, we compare these two predictions and consider $Predictions^{fundamental}_{i,j,t}$ as a benchmark for how much an investment company should trade. When $Predictions^{AI}_{i,j,t}$ is greater than $Predictions^{fundamental}_{i,j,t}$, it indicates that GenAI recommends increasing the position for stock j at quarter t relative to recommendations by fundamentals. When $Predictions^{AI}_{i,j,t}$ is less than $Predictions^{fundamental}_{i,j,t}$, GenAI recommends reducing the position. After having the recommendation to buy or sell, we look at the actual trades and define a trade as *Agree* if *HoldingChange* is positive (negative) and the recommendation from GenAI is buy (sell). Otherwise, we define a trade as *Disagree*. We then calculate the performance at the investment company level.

$$Agree\ Return_{i,t+1} = \frac{\sum HoldingChange_{i,j,t} \cdot Return_{j,t+1} \cdot I(Agree_{i,j,t})}{\#\ Agree\ Trades_{i,t}} \tag{9}$$

$$Disagree\ Return_{i,t+1} = \frac{\sum HoldingChange_{i,j,t} \cdot Return_{j,t+1} \cdot I(Disagree_{i,j,t})}{\#\ Disagree\ Trades_{i,t}} \tag{10}$$

where $Return_{j,t+1}$ is the quarterly return for stock j in quarter $t+1$, expressed in percentage points. $I(Agree_{i,j,t})$ and $I(Disagree_{i,j,t})$ are indicator variables equal to one if the holding change is agreed or disagreed, respectively, between GenAI recommendation and the investment company's actual decision. # $Agree\ Trades_{i,t}$ (# $Disgree\ Trades_{i,t}$) is the number of trades where the actual trades agree (disagree) with GenAI recommendations. These two measures proxy the average returns generated among agreed and disagreed trades, weighted by how much the position was increased or decreased.[28] We also define *Agree – Disagree Return* as the difference between *Agree Return* and *Disagree Return*.

[Insert Table 7 Here]

Table 7 Panel A presents the summary statistics for three performance measures at the company-quarter level. On average, *Agree Return* is 2.57% per quarter and is higher than *Disagree Return* of 0.35%. The mean of *Agree – Disagree Return* is 2.22%, and is statistically significant with a *t-statistic* of 9.96. Panel B provides the results using the DiD setting. We find that hedge funds with higher *GenAI Reliance* can boost their performance when their holding changes align with GenAI recommendations. When their holding changes do not align with GenAI recommendations, funds with high and low *GenAI Reliance* perform quite similarly. These findings provide direct evidence on how hedge funds generate profit using GenAI.

Overall, our results indicate that AI-consistent trades generate significantly higher returns and explain a meaningful portion of within-fund-quarter performance variation. These findings provide stronger micro-level evidence that hedge funds are actively incorporating generative AI into their decision-making processes.

[28] One advantage of our measures is that we do not need to separate actual buys and sells. Take *Agree Return* as an instance, if an actual trade is a sell (i.e., *HoldingChange* is negative) and the subsequent return is negative, it will lead to a higher *Agree Return* since the investment company avoids a bad investment.

6. GenAI and Price Efficiency and Liquidity in the Stock Market

Does GenAI usage by institutional investors have implications for the financial market? In this section, we examine how GenAI-supported trading relates to market information efficiency and liquidity. We connect our analysis to established theories of information in financial markets to provide a clear theoretical foundation for our empirical tests.

We first study whether GenAI-supported trading influences price efficiency. Here, the prediction by the existing theoretical literature is ambiguous due to the diverse information possessed by various market participants. The availability of generative AI tools to process public information can have opposite effects on the private information acquisition of investors and, hence, the market efficiency. On the one hand, when hedge funds use generative AI tools to generate and trade on signals about fundamentals, the stock price incorporates more information, which may decrease the benefit of generating other private information about the same fundamentals (e.g., hedge fund managers talking less to corporate insiders to generate private information). This substitution effect has been suggested by theory papers such as Verrecchia (1982) and Diamond (1985). Furthermore, the wide availability of the generative AI tool to analyze common information may facilitate the coordination of investors, which, according to the "beauty-contests" theories such as Morris and Shin (2002) and Colombo, Femminis, and Pavan (2014), may induce inefficiency in the acquisition of information by investors. Dou, Goldstein, and Ji (2023)'s model also predicts that AI-powered trading may lead to collusion among investors, leading to lower price efficiency. Both strands of theories above suggest that the wide availability of generative AI tools could decrease the information efficiency of the financial market.

On the other hand, generative AI could enhance the market efficiencies due to at least two reasons. First generative AI tools could significantly reduce the information processing costs which could encourage more information generation (e.g., Grossman and Stiglitz, 1980). Second, Goldstein and Yang (2015) shows that information diversity can enhance market efficiency through complementarities across different fundamentals. Since generative AI lowers the cost of analyzing corporate disclosures such as earnings calls, it reduces the uncertainty of traders to collect information about other fundamentals about the firms, thereby improving information efficiency of the market.

Ultimately, this becomes an empirical question. To examine the effect of generative AI on market efficiency, we study stock price reactions around earnings announcements. The literature generally finds that stock prices underreact to earnings information, as evidenced by the existence of Post-Earnings Announcement Drift (PEAD) (e.g., Bernard and Thomas, 1989). If generative AI helps investors to process the earnings information more efficiently, we should see a stronger immediate reaction of stock prices to earnings news (CAR[0,1]) and weaker PEAD (CAR[2,61]) for stocks that have a higher exposure to GenAI via hedge funds.

To test this hypothesis, we create a stock-level GenAI intensity measure based on our fund-level *GenAI Reliance* measure. Specifically, for each stock j in quarter t, we calculate the ownership-weighted average of fund-level reliance as follows

$$\textit{GenAI-Trade Intensity}_{j,t} = \frac{\sum_{f \in \mathcal{F}} \left(\textit{Shares}_{j,f,t} \times \textit{GenAI Reliance}_{f,t} \right)}{\textit{Shares Outstanding}_{j,t}} \tag{11}$$

where *Shares Outstanding* is the total number of shares outstanding and *Shares* is the number of shares owned by hedge fund f. $\mathcal{F}$ represents all hedge fund investment companies in our sample. Stocks traded more heavily by hedge funds with higher GenAI Reliance tend to exhibit greater *GenAI-Trade Intensity*.

We then regress stock price reactions (CAR[0,1] and CAR[2,61]) to earnings announcements on *GenAI-Trade Intensity*, Post-GPT, and their interaction term. We include various control variables. For instance, we control for earnings surprise, defined as the difference between actual earnings and the median I/B/E/S forecast, scaled by the stock price at the end of the corresponding quarter, following Hirshleifer and Sheng (2022). If generative

AI improves price efficiency, we expect a positive coefficient on the interaction term for CAR[0,1] and a negative coefficient for CAR[2,61], consistent with faster incorporation of earnings news into prices. Our results, shown in Table 8, indicate that stocks with higher reliance tend to have significantly stronger immediate reactions and weaker drift, suggesting more efficient pricing of earnings news. This is consistent with the story that GenAI improves hedge fund trading.

[Insert Table 8 Here]

In addition, we study how GenAI-supported trading affects market liquidity. As we document, although generative AI such as ChatGPT provides a new tool for investors to analyze public information, investors differ in both the speed and skills of adopting this tool. This finding is consistent with the strands of literature that suggest that public news events can lead to differential interpretations by traders based on variation in the traders' skill (see, e.g., Kandel and Pearson, 1995; Kim and Verrecchia, 1994; Rubinstein, 1993). In particular, Kim and Verrecchia (1994) suggests that information asymmetry and bid-offer spreads might be greater after a public announcement because earnings announcements provide information that allows certain traders to make judgements about a firm's performance that are superior to the judgements of other traders. The implication of these theories in our context is that the stocks' bid-ask spread is affected by hedge funds' trading based on GenAI information. When a subset of hedge funds possess the ability to use generative AI tools to better analyze public information about a stock, the stock might experience an increase in bid-ask spread due to the presence of informed trading Glosten and Milgrom (1985).

We regress stocks' daily bid-ask spread on *GenAI-Trade Intensity*, while controlling for stock size, return on assets, book-to-market, institutional ownership, stock fixed effects, and time fixed effects. Panel A of Table IA.5 shows that over the entire period post ChatGPT (i.e., 2022-2024), there is no significant association between the two variables. However, a more careful year-by-year analysis reveals a different story. In 2022, we find that stocks' bid-ask spread is significantly higher if the stocks are traded more by hedge funds with high *GenAI Reliance*. Moreover, when we include an interaction term between *GenAI-Trade Intensity* and the earnings day indicator (Panel B), we find that the effect of *GenAI-Trade Intensity* on spread is 7 times higher on news days than other days. This finding is consistent with the prediction in Kim and Verrecchia (1994) that earnings announcements and the conference calls provide an opportunity for hedge funds to use ChatGPT to make better judgements about firms' performance than those not using the tool. However, this advantage goes down as more hedge funds adopt the tool for investment analysis. Our estimate and the survey results show that about 20% of hedge funds were using generative AI tools in 2022. This percentage increases sharply to 60% by 2024. Indeed, we find no significant increase in bid-ask spread on earnings days for stocks highly traded by GenAI funds in 2024. If anything, stocks' bid-ask spread decreases in 2024, possibly due to reduced information asymmetry when the majority of hedge funds adopt the same tool.

Overall, our findings provide empirical support for the strands of theories that suggest the release of public information presents opportunities for the skilled investors to learn about firm values, which could lead to both higher bid-ask spread and higher information efficiency in equilibrium prices. Furthermore, our paper highlights how skilled investors can gain an edge in analyzing public information. Our findings reveal one such avenue—skillfully leveraging generative AI tools.

7. Generative AI Adoption of Hedge Funds: Evidence from A Survey

To provide more direct evidence on the use of generative AI (GenAI) in the hedge fund industry, we collaborate with CoreData Research, a market research firm that conducts investor surveys for financial institutions, and carry out a survey of hedge fund managers in 2025. We start with the list of hedge funds in our sample. Of these, 33 hedge funds participated in our survey. Given the opaque and secretive nature of the hedge fund industry, this sample size is substantial. The hedge funds included in the survey are major players in the industry: 77% manage more than $1 billion in assets under management (AUM), and 51% manage over $10 billion. Since our sample covers only hedge funds that file 13F forms, they tend to be larger. To assess the representativeness of our sample and ensure that insights drawn from our sample are broadly applicable, we also collect surveys from 12 additional funds, bringing the total number of participating funds to 45. In our analysis of the survey results, we report and discuss the results from both our sample and the overall sample.

In the survey, we ask nine questions about the usage of GenAI in their funds, along with a few demographic questions about the fund and the person who responds to the survey. Given the nature of this paper, the main questions are directly focused on the use of GenAI for investment purposes. For example, the first question we ask is: "*Q1. Does your hedge fund use generative AI tools, including in-house tools, for investment purposes (e.g., processing data, improving trading strategies)?*" In addition, the survey questions cover various aspects of GenAI usage, ranging from the year of adoption to the challenges funds face in implementation. The full list of questions is presented in the Internet Appendix Table IA.2.

In this section, we first present several important results as summary evidence from the survey. Then, we use the data from the survey to validate our *GenAI Reliance* measure. Finally, we provide new insights from the survey that are difficult to obtain from traditional data sources.

7.1. Summary Evidence

The data from our survey allows us to provide several important pieces of evidence on whether and how hedge funds adopt GenAI for their investment decisions. The first question in the survey we ask is: "*Does your hedge fund use generative AI tools, including* *in-house tools, for investment purposes (e.g., processing data, improving trading strategies)?"* Figure 4 shows the percentage of hedge funds that answered "Yes" or "No" to this question. In our sample, 70% said that they use GenAI tools, while 30% did not. Note that this question specifically targets the usage *for investment purposes only*. The fraction is likely to be larger if we account for other purposes. We find a similar pattern for the overall survey sample. These findings suggest that GenAI is widely adopted among hedge funds.

Next, we ask hedge funds the year when they adopted GenAI tools. Figure 5 plots the proportions of hedge funds that started to adopt GenAI in different years. In our sample, only 6% used the tool before 2022, which is before the release of ChatGPT. 15% began to adopt GenAI tools in 2022, the year ChatGPT was released. This number then rises to 12% and 30% for 2023 and 2024, respectively. These figures illustrate the gradual process for hedge funds to use GenAI tools for investment purposes. While there were early movers, GenAI was not used by the majority of hedge funds until 2024.

7.2. Validation for *GenAI Reliance*

The survey data allow us to directly learn from hedge fund managers about their GenAI usage. One downside is its small sample size. Our *GenAI Reliance* measure can be applied to the entire universe of 13F hedge funds; however, it is relatively indirect. Thus, it is important to compare the measures of GenAI usage via the two methods.

We start by comparing the adoption rates. Figure 3 plots the cumulative percentage of hedge funds that use the GenAI tool over time from the survey data. We find a striking consistency of the adoption rates calculated based on the survey data and our *GenAI Reliance* measure. According to the survey data, for the hedge funds in our sample, 6% of them adopted GenAI tools before 2022, that number increases to 21% by the end of 2022, and then to 33% by 2023, and 63% in 2024. The corresponding adoption percentages according to our *GenAI Reliance* measure (from Figure 2) are 2% (before 2022), 21% (2022), 40% (2023), and 60% (2024). This provides the first direct validation of the *GenAI Reliance* measure.

Taking a step further, we query hedge funds on the way they use GenAI tools for investment decisions. Figure 6 shows the results for this question. Both our survey sample and the overall survey sample show similar findings. 91% of the adopting funds indicate that they use GenAI tools for "*Processing and analyzing data/text (e.g., news, earnings conference call)*," which is the most prevalent reason for using these tools. Furthermore, 65% of them use GenAI for "*Enhancing investment decisions/strategies (e.g., due diligence, screening, investment idea generation, alpha generation, portfolio optimization)*." The fact that a vast majority of hedge funds use GenAI tools for data analysis provides additional validation for our methodology, which leverages financial text data (e.g., earnings calls) to infer hedge funds' reliance on GenAI.

[Insert Table 9 Here]

Next, we examine the relation between our *GenAI Reliance* measure and the generative AI adoption reported by hedge funds. In Table 9, we regress *GenAI Reliance* on GenAI adoption reported by the surveyed hedge funds. We control for size, age, turnover, risk, and past return of the portfolio. The adoption of GenAI reported by hedge funds is positively and significantly associated with our *GenAI Reliance* measure. This provides further direct validation that our *GenAI Reliance* measure captures hedge funds' use of GenAI in a meaningful way.

7.3. New Insights from Survey

The survey data not only serves as an independent data source to validate our measure, but also provides additional insights that we could not learn from our earlier analyses.

First, to learn how useful hedge funds think of GenAI, we directly ask the question *"To what extent do you think generative AI tools influence your fund's investment decisions?"* Figure 7 shows that among the hedge funds that report using GenAI, close to 90% deem GenAI to have some influence, and over 50% think the influence is either moderate or significant. This is consistent with the high adoption rate of GenAI by hedge funds.

Second, we ask the question *"Did your firm have in-house AI tools (including all machine and AI models, not limited to generative AI) before ChatGPT was released in November 2022?"* In Figure 8, we find that the majority of the hedge funds did not have in-house AI tools before ChatGPT's release. Only about 35% of hedge funds have used in-house AI tools before ChaptGPT. Note that this number includes not only generative AI tools, but also other AI tools such as machine learning models. Why did so few hedge funds have internal generative AI tools prior to ChatGPT is beyond the scope of our paper. Our conjecture is that it is due to the high training cost of AI and the lack of expertise.[29] Such high costs might be beyond what most hedge funds are willing to pay, except for the very few large quant funds. After ChatGPT's release, about 10% of hedge funds now use both in-house AI tools and ChatGPT or similar generative AI tools, and about 15% have fine-tuned or trained their own generative AI models in-house. Therefore, although some hedge funds employ in-house AI tools, our findings suggest that most hedge funds benefit from the introduction of public GenAI tools such as ChatGPT.

Lastly, we want to understand what prevents hedge funds from using GenAI tools effectively. We ask the question *"How challenging is it to integrate with workflow when using generative AI tools?"* As Figure 9 shows, over 70% of the hedge funds report the task to be moderately challenging, very challenging, or extremely challenging. When asked about how challenging it is to have in-house expertise, again, over 70% of hedge funds in our sample state that it is at least moderately challenging (Figure 10). Among them, 30% report very challenging and 14% say extremely challenging. These results highlight the difficulty of hedge funds in effectively using generative AI tools without proper AI talent. This evidence is also consistent with our earlier finding that in-house AI skill is instrumental

[29]According to a study by Epoch AI, the estimated hardware, cloud compute, and energy cost to train GPT-3 in 2020 was around $6.5 million, and that for GPT-4 in 2023 was around $120 million. Link to the article: https://epoch.ai/blog/how-much-does-it-cost-to-train-frontier-ai-models.

for hedge funds to benefit from GenAI usage (Section 5.1).

8. Additional Analyses and Robustness

In this section, we provide a few additional tests. First, we expand the text sources to include 10K/10Q and news articles from the *Wall Street Journal* when measuring *GenAI Reliance*. Second, we take into account the traditional textual analysis measure in creating our *GenAI Reliance* measure. Third, we explore how ChatGPT outages may affect hedge fund companies. Next, we conduct additional analysis to relieve the concern of forward-looking bias in using ChatGPT. Finally, as robustness checks, we consider the alternative date for the DiD test and construct alternative measures of *GenAI Reliance*.

8.1. Do Information Sources Matter?

Our *GenAI Reliance* is based on the signals generated by ChatGPT from earnings conference call transcripts. If a hedge fund manager uses ChatGPT to analyze data other than earnings calls, and if the signals extracted from those data are not highly correlated with the signals from the earnings data, we may get a low estimate of *GenAI Reliance* even though the manager uses ChatGPT to conduct investment analysis. Also, it is interesting to examine whether adding expanded information sources can help improve the *GenAI Reliance* measure.

We construct a more comprehensive measure of *GenAI Reliance* where we combine those additional data sources with conference calls. Specifically, we use the same methodology to extract GPT scores from all 10-K and 10-Q filings and articles from the *Wall Street Journal* (WSJ) as we do for conference call transcripts in our sample period, resulting in three distinct sets of 14 GPT scores. We associate a WSJ article with a public company if the company is mentioned in the article. Because using the entire set of 42 ($14 \times 3 = 42$) individual GPT scores in the regression would significantly reduce the sample of funds for which we can estimate their *GenAI Reliance*. To create a comprehensive measure, for each of the 14 questions, we take a simple average among the GPT scores from the three information sources and recreate a robustness measure of *GenAI Reliance* based on all three information sources.

[Insert Table 10 Here]

We then report the regression results in Table 10. Panel A of Table 10 presents the results of this measure in the main DiD test with fund performance. It shows that funds with higher GenAI Reliance perform better after ChatGPT was released, consistent with the result based on only conference call information. In Panel B, we use an average measure from the conference call and 10K&10Q and find a similar and stronger result. Therefore, hedge funds benefit more from using GenAI tools to analyze information in conference calls and 10K&10Q than WSJ.

8.2. *GenAI Reliance* after Controlling for Traditional Textual Measure

Our key measure is developed from earnings conference call transcripts. Such data are available to investment companies for analyzing potentially valuable information disclosed by firms, even in the absence of AI. To isolate information uniquely extracted by generative AI tools, we control the output from the traditional textual analysis method, i.e., bag of words (e.g., Loughran and McDonald, 2011), on the same conference call data. Specifically, we calculate Loughran-McDonald (LM) negative and positive sentiment as the number of LM negative and positive words divided by the total number of words in the transcripts. We add the two sentiment measures to Equations (1) and (2) as additional information about firm fundamentals and repeat our calculation for *GenAI Reliance* in Equation (3). We label this alternative measure as *GenAI Reliance* (*LM Adjusted*), which isolates information incremental to traditional textual analysis.

[Insert Table 11 Here]

We reproduce our baseline regressions in Table 11. The findings are qualitatively similar to the results in Table 3. In other words, *GenAI Reliance* (*LM Adjusted*) is highly correlated with *GenAI Reliance* and the outperformance is driven by generative AI's contribution to trading activities, instead of information readily available from traditional textual analysis.

8.3. ChatGPT Outages

To provide further support for the effect of AI on the fund industry, we use ChatGPT outages as exogenous shocks. We hypothesize that if the effect of *GenAI Reliance* on fund performance is indeed from ChatGPT, this effect will be smaller when there are major ChatGPT outages because fund managers cannot use ChatGPT to aid their decisions when the tool is down.

To test this idea, we collect outage occurrences from the OpenAI website. To exploit outages as exogenous shocks on the usage of ChatGPT, we estimate the following DiD regression with a focus on risk-adjusted returns,

$$\begin{aligned} Alpha_{i,t} = {} & \beta_1 \cdot GenAI\ Reliance_{i,t-1} \times Post\ GPT_t \times Outage_t + \beta_2 \cdot GenAI\ Reliance_{i,t-1} \times Post\ GPT_t \\ & + \beta_3 \cdot GenAI\ Reliance_{i,t-1} + \gamma \cdot Control_{i,t-1} + \alpha_t + \varepsilon_{i,t}, \end{aligned} \tag{12}$$

where *Outage* is the logarithm of the number of outages in a quarter i and t index hedge fund investment company and quarter. *Alpha* is *Return*, *CAPM Alpha*, *FF3 Alpha* or *FF4 Alpha*. *Control* includes *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*. α represents time (i.e., year-quarter) fixed effects.

We report the results in Table IA.6. The coefficient on the triple interaction term is negative and significant for *Return* and *CAPM Alpha*, suggesting that the effect of ChatGPT on fund performance is weaker when ChatGPT experiences a large number of outages. The economic magnitude is large. The reduction in the effect is insignificant when we use *FF3 Alpha* or *FF4 Alpha*. Based on our survey results, Figure IA.4 shows that only around 20% of hedge funds find outages to affect their investment workflow and processes moderately or significantly and 80% of funds do not find a noticeable impact.

Overall, there is weak evidence that ChatGPT outages may negatively affect fund managers because the tool is unavailable during those times, and potentially undermine managers' confidence in the tool.

8.4. Forward-looking Bias

Forward-looking bias can arise when using ChatGPT to process historical data. If a fund manager or any user runs ChatGPT on information from earlier years, the model may already "know" about events or facts that occurred after those years because its training data includes future information. It could inadvertently use knowledge that would not have been available at the time, leading to results with forward-looking bias. Our study alleviates this concern for several reasons.

First, at the initial release, ChatGPT and GPT 3.5's knowledge cutoff date is September 2021. Thus, it was trained on data available only up to that point, and does not know about events after that date. The performance tests focusing on only post-GPT period, including the baseline findings in Table 2 Panel A, serve as an out-of-sample test because we effectively limit the sample period to be after the knowledge cutoff date of September 2021 for GPT 3.5, the version of ChatGPT available to funds at its initial release. We use the same version of GPT 3.5 to process conference call transcripts and create *GenAI Reliance*. Therefore, since ChatGPT cannot use any information after September 2021, we eliminate the concern of forward-looking bias in using ChatGPT to forecast economic and financial outcomes.

Second, we also repeat the DiD setting, focusing on a shorter sample period: from 2021Q4 to 2024Q3. Therefore, we limit this sample period to after the knowledge cutoff date for GPT 3.5. This test serves as another out-of-sample test. In Table IA.7, we show that the results are robust to using this sample period.

8.5. Robustness

We further provide results from several robustness tests. First, we conduct an alternative DiD test. In the main specification, we use the release of the base GPT 3.5 model in March 2022 as the cutoff for the DiD analysis. The refined model was released as ChatGPT 3.5 through the chat-based interface to the public in November 2022. Therefore, an alternative way to conduct the DiD analysis is to use the formal release date of ChatGPT 3.5 to define the post-period. We construct a dummy variable *Post ChatGPT*, which equals one for performance in the first quarter of 2023 and onwards, and zero otherwise. We then re-run the performance regression and report the results in Table IA.8. The coefficient on the interaction term is positive and significant, suggesting that funds that have a higher *GenAI Reliance* tend to outperform after the release of ChatGPT. This is consistent with our main specification.

Second, we consider an alternative measure for our key variable of interest. As a robustness check, we create *GenAI Reliance Alt*, defined as the percentage increase in R^2, i.e.,

$$GenAI\ Reliance\ Alt_{i,t} = \frac{R^2_{AI,i,t} - R^2_{fundamental,i,t}}{R^2_{fundamental,i,t}}. \tag{13}$$

The rationale for this alternative measure is to benchmark against the explanatory power of fundamental information. We then redo our analyses in Tables 2 and 3. Our results, reported in Table IA.9 are qualitatively similar when we use this alternative measure and show again that the adoption of generative AI is associated with significant increases in hedge fund performance, both in terms of raw and risk-adjusted returns.

Finally, instead of using GenAI Reliance, we use a generative AI adopter indicator. This is an extensive margin test that allows us to hold fixed fund characteristics. Since we use the third quarter of 2022 as the cutoff for *Post GPT*, we define the first two quarters of 2022 as the early adoption period, given that the base GPT-3.5 model was released in March 2022. Based on the *GenAI Reliance*, we first identify possible first movers among hedge funds using the partial-F test and require a significant p-value of 0.01 or less in any of the first two quarters of 2022. We also require *GenAI Reliance* to be economically meaningful to affect the overall fund performance and thus consider a hedge fund to be an early adopter if its *GenAI Reliance* is in the top quintile of the cross-section. In other words, we define *Early Adopters* as those with both statistically and economically significant reliance on GenAI when the base GPT-3.5 model was released.

We report the results in Table IA.10. These results are similar to those from our main specification in the paper (Table 3). The β_2 coefficient on the Early Adopter indicator is generally insignificant, suggesting that the early adopting companies do not earn superior performance during the pre-period. However, there is a significant increase in their performance relative to nonadopters post ChatGPT.

9. Conclusion

In this paper, we develop a novel measure of the usage or reliance on generative AI (*GenAI Reliance*) of investment companies based on their portfolio holdings and AI-predicted information. We study the adoption and implications of generative AI in hedge funds and other asset management companies. Utilizing *GenAI Reliance*, we find a dramatic increase in the use of generative AI by hedge fund companies after the introduction of ChatGPT.

Hedge fund companies with higher *GenAI Reliance* produce superior returns, both unadjusted and risk-adjusted. For example, an interquartile change in the *GenAI Reliance* is associated with an increase of 2-4% in annualized hedge fund returns. In investigating the source of the superior performance, we find hedge fund companies generate more returns from using AI-predicted firm-specific information related to firm policies and performance than from macroeconomic and sectorwise information. Not all investment companies benefit equally from the invention of generative AI: Non-hedge fund companies do not produce significant returns. Furthermore, large and more active hedge fund companies adopt the technology early and perform better than others. We also verify that hedge funds' superior profits arise when they trade consistently with GenAI recommendations.

To validate our methodology, we conduct a survey of hedge fund managers regarding their GenAI usage. The time trend of GenAI adoption and the way hedge funds use these tools, as reported in the survey, are highly consistent with our findings using the GenAI Reliance measure. As a further validation, the survey-based GenAI adoption is significantly and positively associated with our GenAI Reliance measure for funds in our sample that participated in the survey. The survey also reveals additional insights regarding in-house AI tools and the challenge in the adoption of GenAI technology.

Our study also shows that GenAI adoption has consequences for the financial market. While hedge funds' adoption of GenAI in their investment improves market efficiency, it initially increases information asymmetry. These findings provide novel evidence consistent with predictions of information theories.

Overall, our findings shed light on the use and implications of generative AI technology and suggest that despite being intuitive to use, generative AI may need to be combined with other resources, such as data and expertise, to be productive for the adopting companies. Importantly, the benefits of generative AI predominantly accrue to larger players who possess the resources to effectively implement and leverage such technologies, potentially widening disparities within the industry. Our findings also carry implications in broader societal contexts, as the increasingly wide adoption of AI[30] has the potential to not only increase productivity but also exacerbate inequality.[31]

[30] See, for example, "JPMorgan pitches in-house chatbot as AI-based research analyst," July 26, 2024, Stephen Morris and Joshua Franklin, *Financial Times*.

[31] This echoes recent debates about the effects of AI, e.g., "Unregulated AI Will Worsen Inequality, Warns Nobel-Winning Economist Joseph Stiglitz," August 1, 2023, Sophie Bushwick, *Scientific American*. "AI's economic peril to democracy," March 14, 2024, Stephanie A. Bell and Anton Korinek, *Brookings*.

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Appendix A: Definitions of Variables

Variable	Definition
Age	The number of years since a hedge fund company's first 13F report.
Agree Return	The one-quarter-ahead performance for trades that align with GPT predictions, calculated at the hedge fund investment company level: $AgreeReturn_{i,t+1} = \frac{\sum HoldingChange_{i,j,t} \cdot Return_{j,t+1} \cdot I(Agree_{i,j,t})}{\#\ Agree\ Trades_{i,t}}$ where i, j and t index hedge fund, stock and quarter. *HoldingChange* is the percentage change in stock, *Return* is the quarterly return for stock, I(*Disagree*) equals one if the actual holding change aligns with the GenAI recommendation, and # *Disagree Trades* is the number of trades where the actual trades agree with GenAI recommendations.
Agree – Disagree Return	*Agree Return* minus *Disagree Return*.
AI Hedge Fund	An indicator variable equal to one if a hedge fund has AI-skilled workers and zero otherwise.
BM	The book-to-market value for a portfolio firm.
CAPM Alpha	At the end of quarter t, we use the monthly stock returns in the past 36 months to estimate the beta on the risk factor and calculate risk-adjusted return in quarter $t+1$ as the difference between realized stock return and stock return estimated with beta. *CAPM Alpha* is the weighted average cumulative monthly abnormal return across all holdings, where the weight is the value of stock j held by i at the end of quarter t divided by the total value of all stocks held by i at the end of quarter t.
CAR	The cumulative abnormal return based on the market model during two windows, [0, 1] and [2, 61], where day 0 is the earnings announcement date.
Disagree Return	The one-quarter-ahead performance for trades against GPT predictions, calculated at the investment company level: $Disagree\ Return_{i,t+1} = \frac{\sum HoldingChange_{i,j,t} \cdot Return_{j,t+1} \cdot I(Disagree_{i,j,t})}{\#\ Disagree\ Trades_{i,t}}$ where i, j and t index hedge fund investment company, stock and quarter. *HoldingChange* is the percentage change in stock, *Return* is the quarterly return for stock, I(*Disagree*) equals one if the actual holding change is against the GenAI recommendation, and # *Disagree Trades* is the number of trades where the actual trades disagree with GenAI recommendations.
Earnings Surprise	The difference between actual earnings and the median forecast from I/B/E/S detail file during the 30 days before the quarterly earnings announcement, scaled by the quarter-end stock price.
FF3 Alpha	The weighted average risk-adjusted returns using the Fama-French three-factor model. The construction is analogous to *CAPM Alpha*.

(continued)

Variable	**Definition**
FF4 Alpha	The weighted average risk-adjusted returns using the Fama-French-Carhart four-factor model. The construction is analogous to *CAPM Alpha*.
GenAI Adoption	For each hedge fund company in our survey sample, *GenAI Adoption* is an indicator equal to one if the time is after the fund starts using generative AI tools for investment purposes, and zero before the starting year.
GenAI Reliance	Reliance on generative AI information quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. We estimate *GenAI Reliance* using a two-step procedure. In the first step, at the end of each quarter t and for each investment company i, we run the following two regression models across the investment company's stock j trades in quarter t: $HoldingChange_{i,j,t} = \gamma_{i,t} \cdot X_{j,t-1} + \varepsilon_{i,j,t}$ and $HoldingChange_{i,j,t} = \Sigma_{j=1}^{J} \beta_{i,t} \cdot GPT\ Score_{j,t-1} + \gamma_{i,t} \cdot X_{j,t-1} + \varepsilon_{i,j,t}$ where $X_{j,t-1}$ is a host of financial variables about firm fundamentals in quarter $t-1$, including market capitalization, book-to-market, return on assets, stock return, and change in the analyst recommendation consensus. *GPT Score* includes 14 signals generated by ChatGPT, covering firms' expectations about macroeconomic, industry, and firm-specific performance and policy outcomes. A full list of signals is in Table IA.1 in the Internet Appendix. We define the R^2 from the first equation as $R^2_{fundamental,i,t}$, and the R^2 from the second equation as $R^2_{AI,i,t}$, and $GenAI\ Reliance_{i,t} = R^2_{AI,i,t} - R^2_{fundamental,i,t}$.
GenAI Reliance Alt	An alternative measure of *GenAI Reliance*, defined as the $R^2_{AI,i,t} - R^2_{fundamental,i,t}$ (i.e., *GenAI Reliance*) scaled by $R^2_{fundamental,i,t}$. See the definition of *GenAI Reliance* for details.
GenAI Reliance (*LM Adjusted*)	An alternative measure of *GenAI Reliance*. When calculating $R^2_{AI,i,t}$ and $R^2_{fundamental,i,t}$, we add Loughran-McDonald positive and negative sentiment to control for information from traditional textual analysis about firm fundamentals, where the sentiment is defined as the number of positive words and negative words, respectively, divided by the number of words in the conference call transcripts. This alternative measure isolates the reliance on generative AI information beyond the information from traditional textual analysis.

(continued)

Variable	Definition
GenAI Reliance Firm Performance	A decomposed *GenAI Reliance* measure and the construction is analogous to *GenAI Reliance*, except that *GPT Score* only includes signals about a firm's earnings, revenue, financial prospects, and product market.
GenAI Reliance Firm Policy	A decomposed *GenAI Reliance* measure and the construction is analogous to *GenAI Reliance*, except that *GPT Score* only includes signals about a firm's wages, employment, capital expenditure, and cost of capital.
GenAI Reliance Macro	A decomposed *GenAI Reliance* measure and the construction is analogous to *GenAI Reliance*, except that *GPT Score* only includes signals about the global economy, the U.S. economy, and a firm's industry.
GenAI-Trade Intensity	The ownership-weighted average of fund-level GenAI Reliance to capture trade intensity by hedge funds that use generative AI to make trading decisions.
Hedge Fund	An indicator variable if an investment company is a hedge fund company and zero otherwise.
INST	The ownership of a stock by institutional investors.
MarketCap	The natural logarithm of the market capitalization of a stock.
Past Return	The one-quarter-lagged *Return*.
Post ChatGPT	An indicator variable equal to one for performance in the first quarter of 2023 and onwards, and zero otherwise.
Post GPT	An indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise.
Return	The weighted average cumulative monthly return across all holdings in quarter $t+1$, where the weight is the value of stock j held by i at the end of quarter t divided by the total value of all stocks held by i at the end of quarter t.
Risk	The standard deviation of quarterly portfolio returns in the past two years.
ROA	Net income divided by total assets for a portfolio firm.
Size	The natural logarithm of total holdings value.
Turnover	The minimum of purchases and sales over average total holdings values of the current quarter and the previous quarter, following Carhart (1997).

Figure 1. Timeline of ChatGPT

This figure presents the timeline of the milestones in the development of ChatGPT.

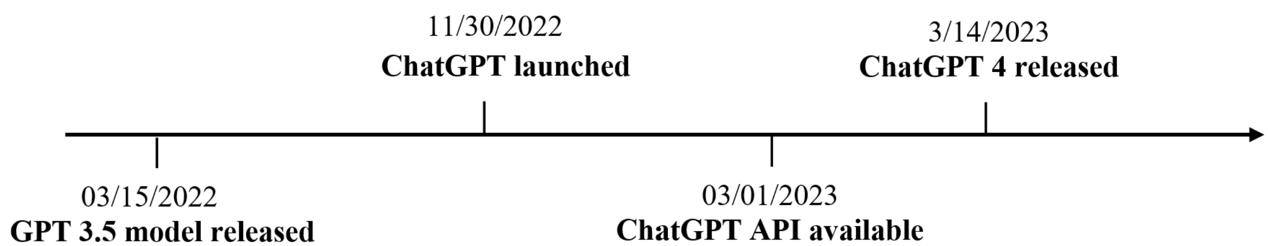

Figure 2. Trend of Generative AI Adoption

This figure plots the generative AI adoption from 2016 to 2024 at the quarterly frequency. A fund is defined as a generative AI adopter in a quarter if its *GenAI Reliance* is significant at 1% level with a partial F-test.

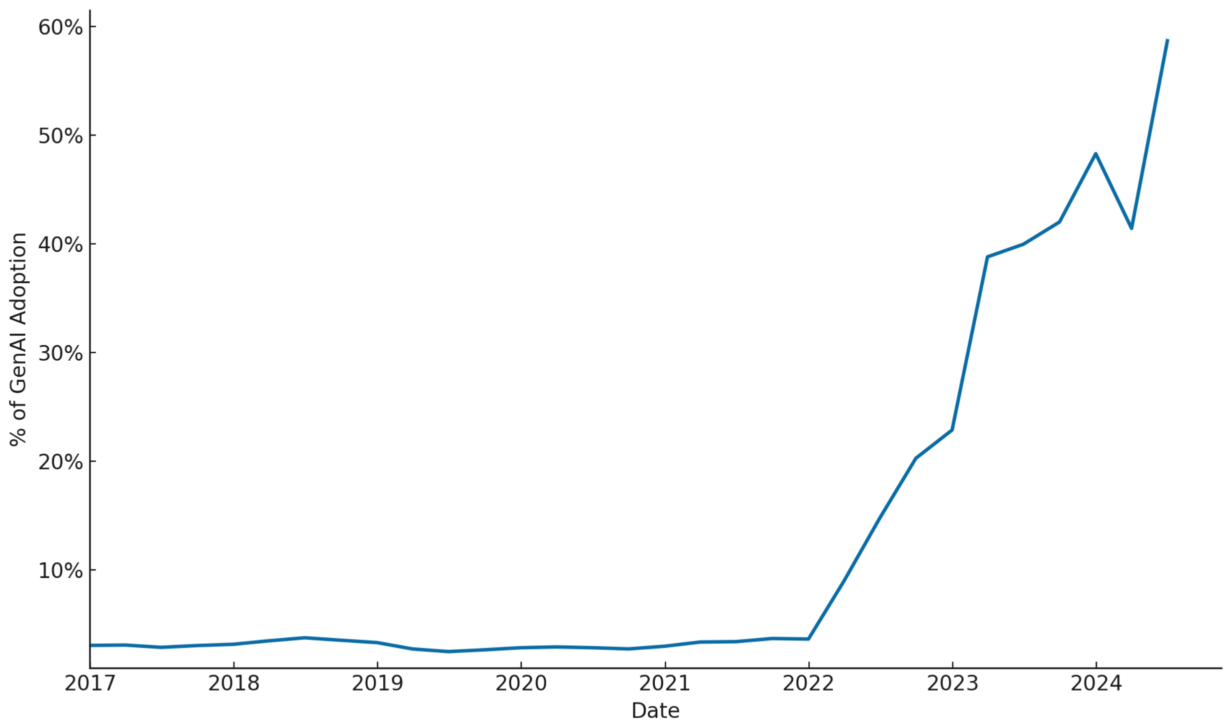

Figure 3. Trend of Generative AI Adoption from Hedge Fund Survey

This figure plots the time series of generative AI adoption from a survey among hedge funds. We ask the following question: "*When did your hedge fund start using generative AI tools for investment purposes?*" We calculate the number of funds that adopted GenAI in each year as a percentage of surveyed funds (including those that never adopted GenAI) and then report the cumulative fraction over time. The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall survey sample" refers to the sample of all surveyed funds. The full list of questions is presented in the Internet Appendix Table IA.2.

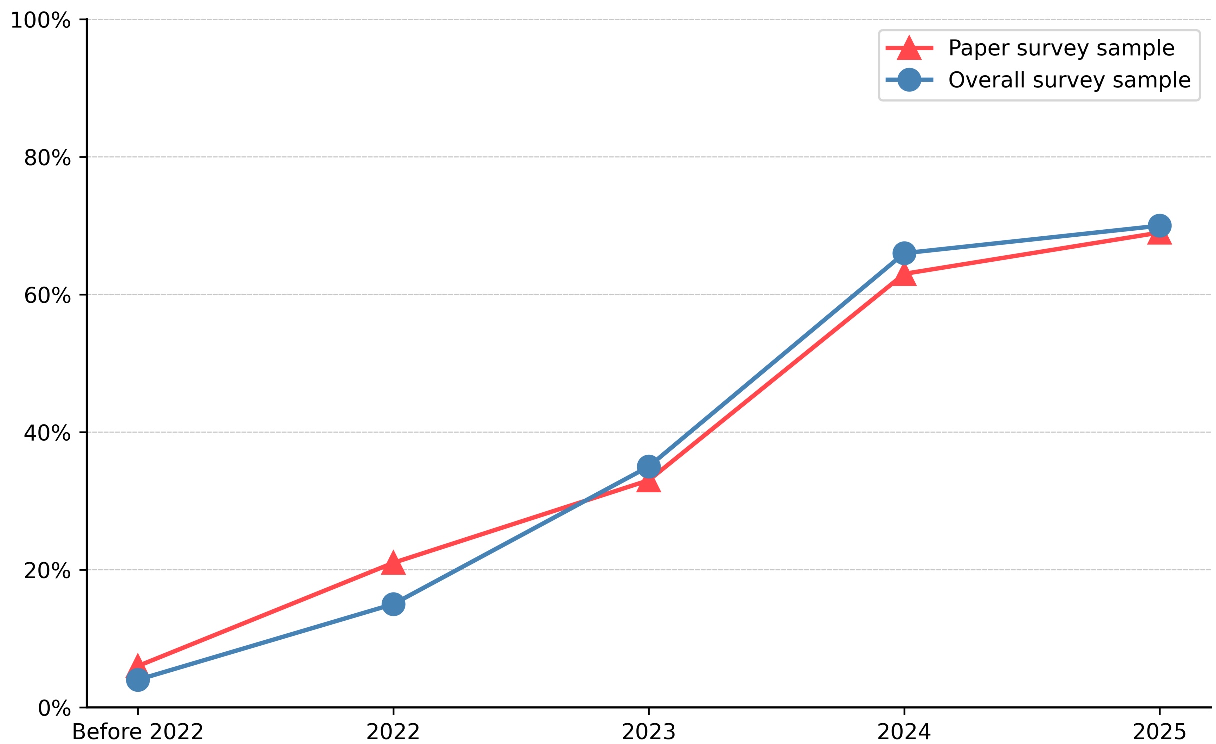

Figure 4. Generative AI Adoption from Hedge Fund Survey

This figure plots the generative AI adoption from a survey among hedge funds. We ask the following question: "*Does your hedge fund use generative AI tools, including in-house tools, for investment purposes (e.g., processing data, improving trading strategies)?*" The fund can answer "Yes" or "No." The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions is presented in the Internet Appendix Table IA.2.

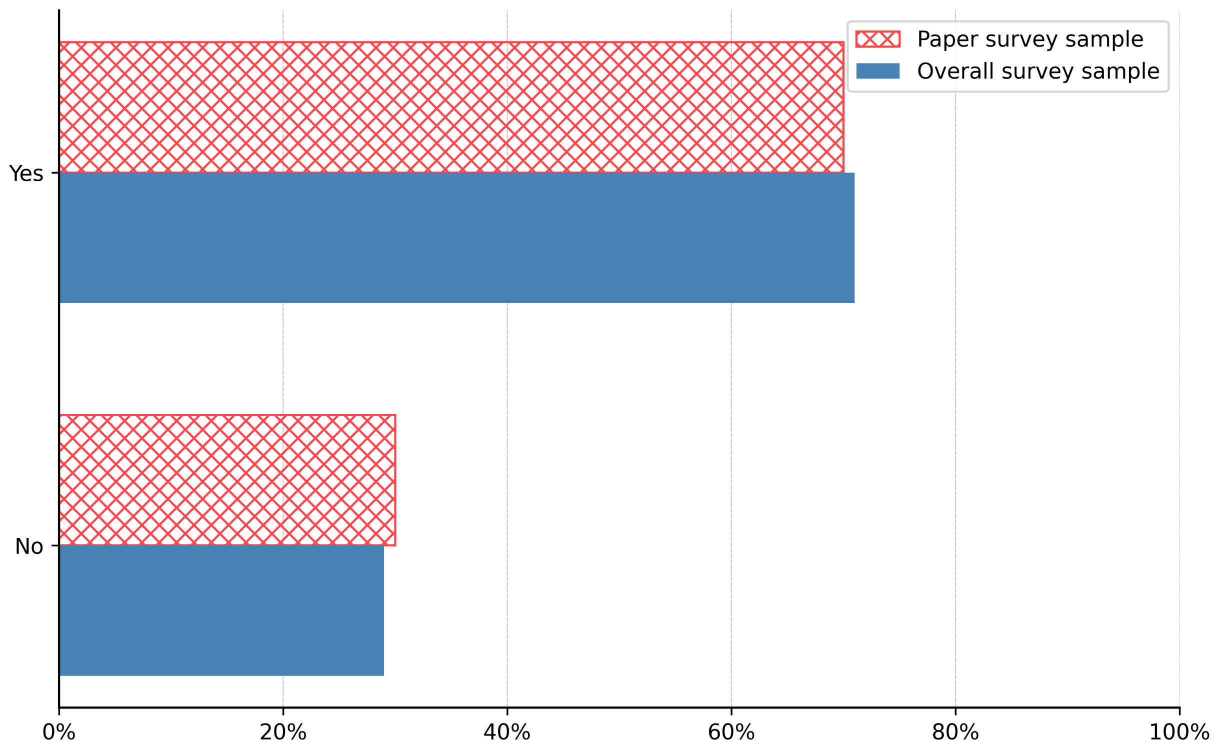

Figure 5. Generative AI Adoption from Hedge Fund Survey: Adoption Year

This figure plots the generative AI adoption from a survey among hedge funds. We ask the following question: *"When did your hedge fund start using generative AI tools for investment purposes?"* The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

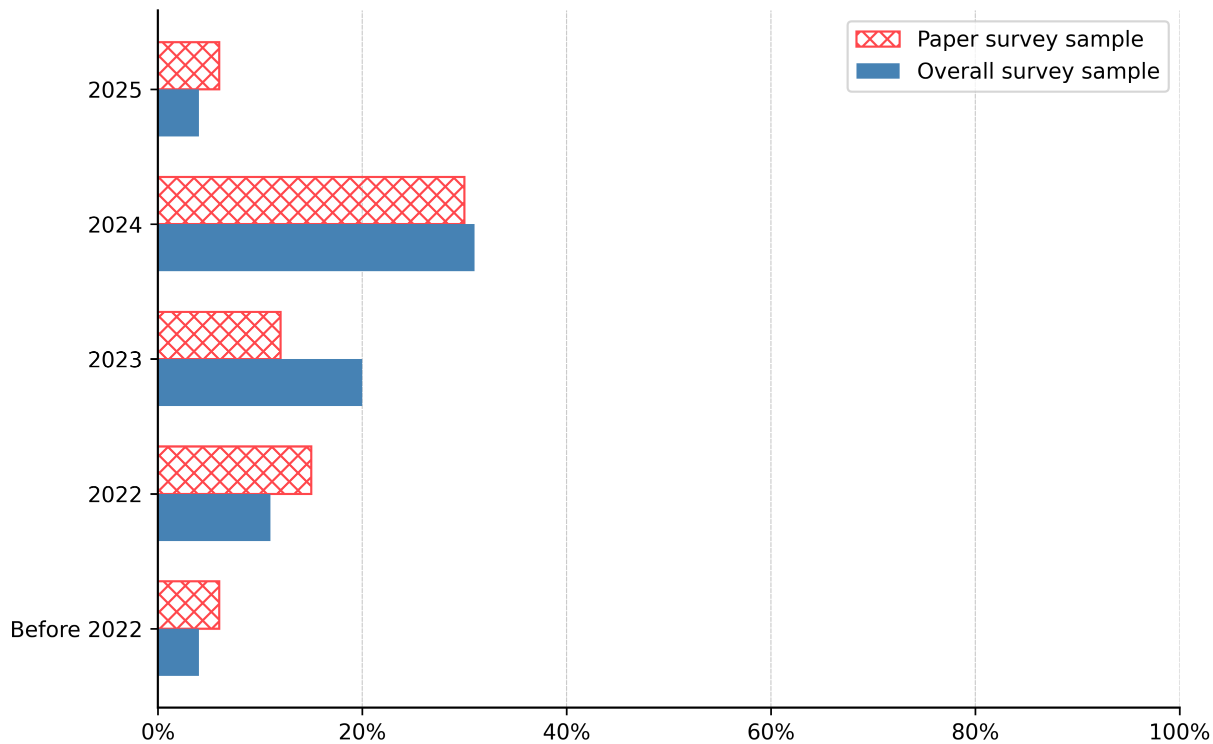

Figure 6. How Do Hedge Funds use Generative AI?

This figure plots answers to questions about generative AI adoption from a survey among hedge funds. We ask the following question: *"How do you use generative AI tools for your investment purposes? (Select all that apply)"* The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

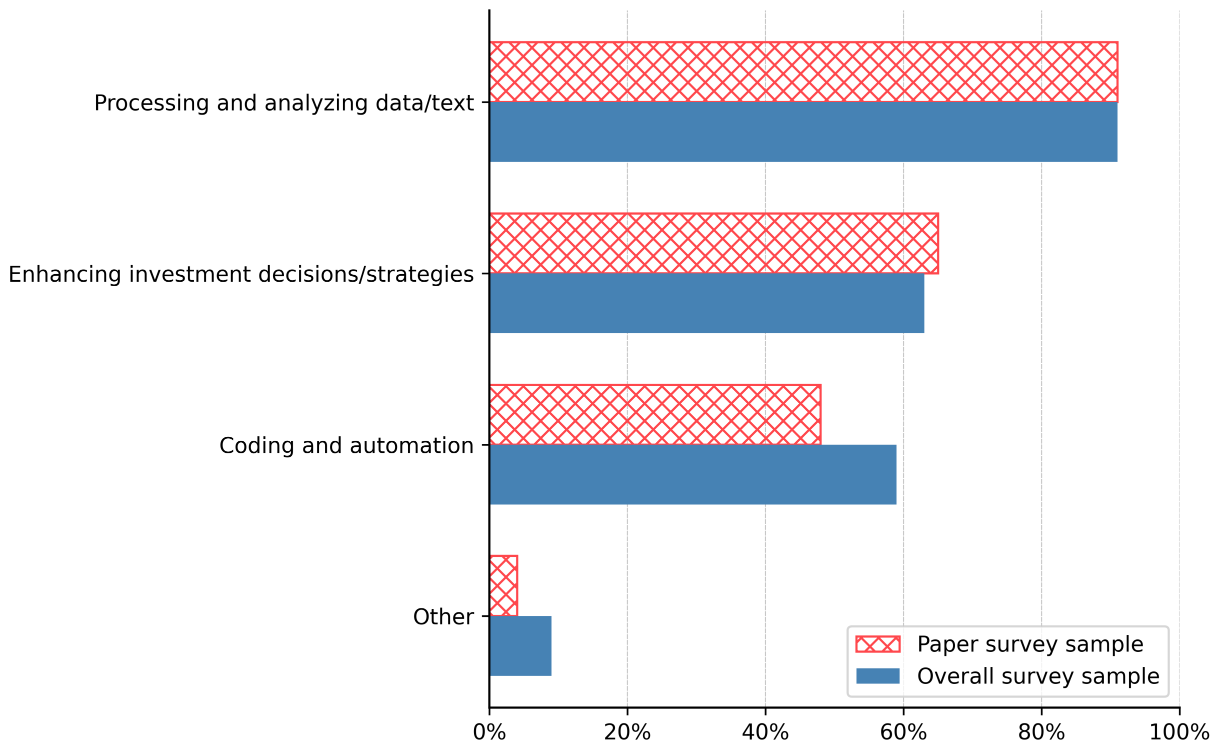

Figure 7. Generative AI's Influence on Hedge Funds

This figure plots answers to questions about generative AI adoption from a survey among hedge funds. We ask the following question: *"To what extent do you think generative AI tools influence your fund's investment decisions?"* The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

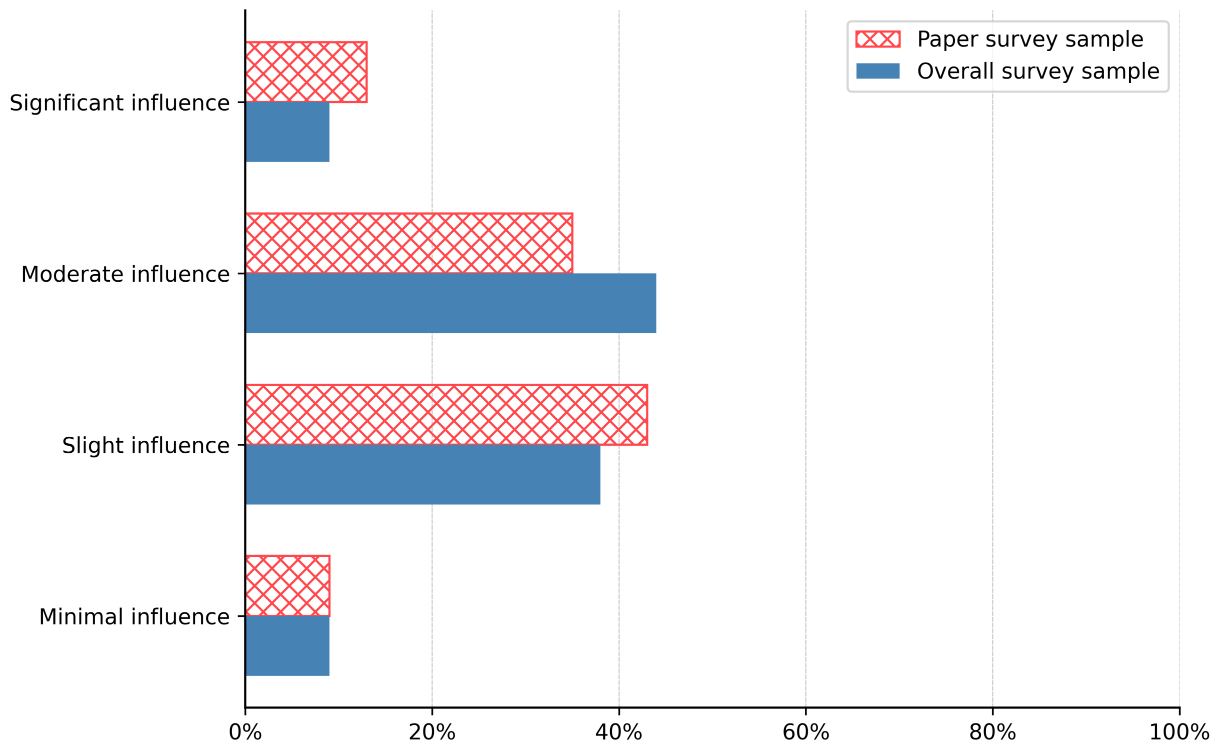

Figure 8. Did Hedge Funds Have in-house AI Tools before ChatGPT?

This figure plots answers to questions about generative AI adoption from a survey among hedge funds. We ask the following question: "*Did your firm have in-house AI tools (including all machine and AI models, not limited to generative AI) before ChatGPT was released in November 2022?*" The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

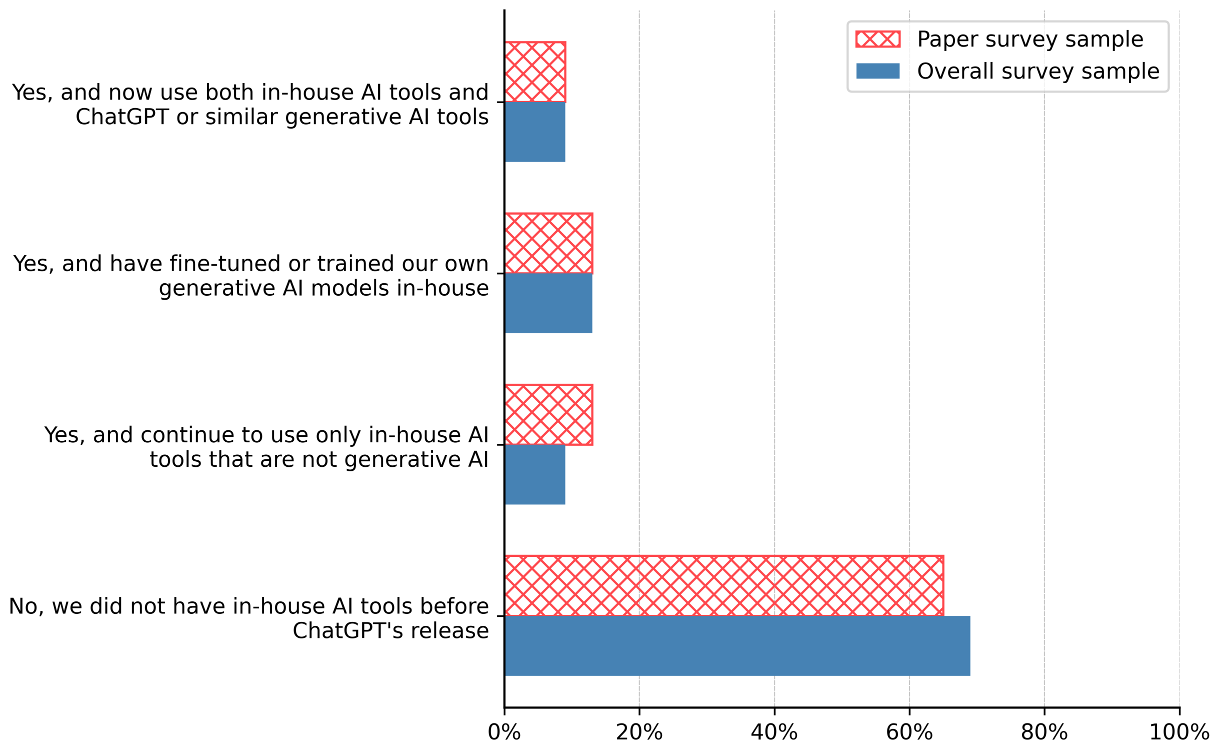

Figure 9. Generative AI Adoption Challenge: Workflow Integration

This figure plots answers to questions about generative AI adoption from a survey among hedge funds. We ask the following question: *"On a scale of 1-5, how challenging are the following issues when using generative AI tools? (1. Not at all a challenge, 2. Slightly challenging, 3. Moderately challenging, 4. Very challenging, 5. Extremely challenging)."* For this graph, the question is about "Integration with existing hedge fund workflows." The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

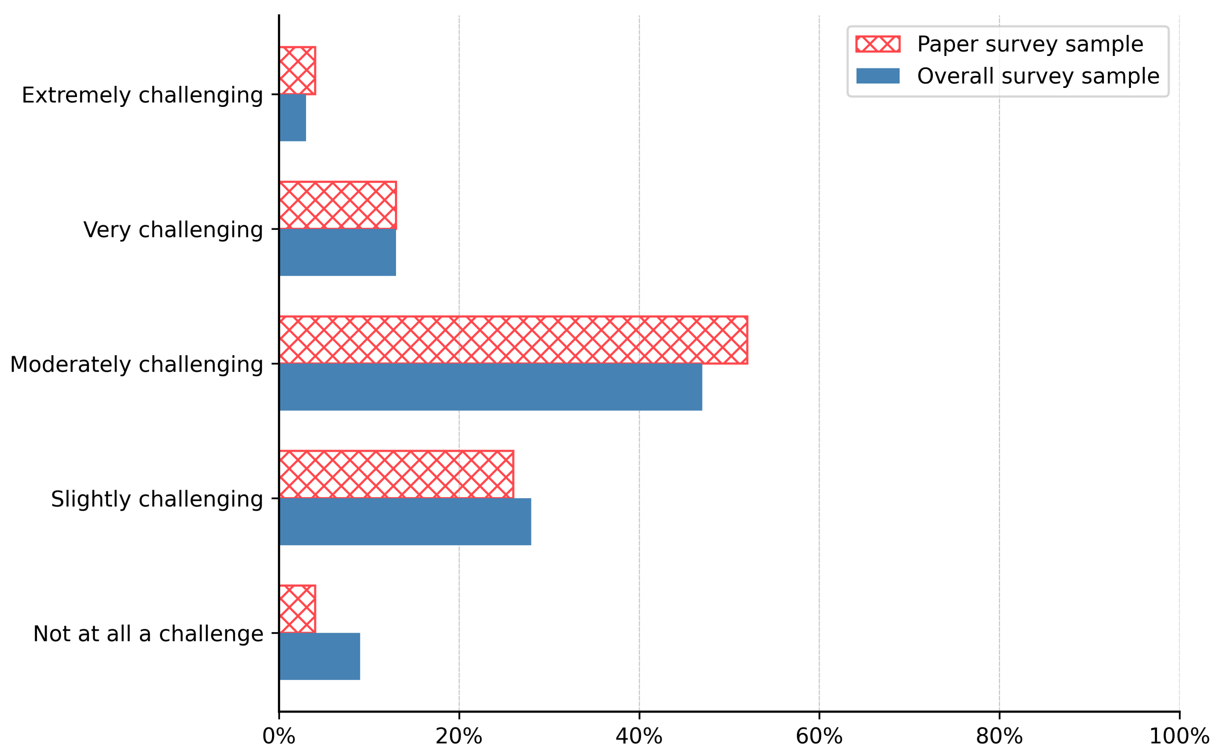

Figure 10. Generative AI Adoption Challenge: In-house Expertise

This figure plots answers to questions about generative AI adoption from a survey among hedge funds. We ask the following question: "*On a scale of 1-5, how challenging are the following issues when using generative AI tools? (1. Not at all a challenge, 2. Slightly challenging, 3. Moderately challenging, 4. Very challenging, 5. Extremely challenging).*" For this graph, the question is about "Lack of in-house AI expertise." The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

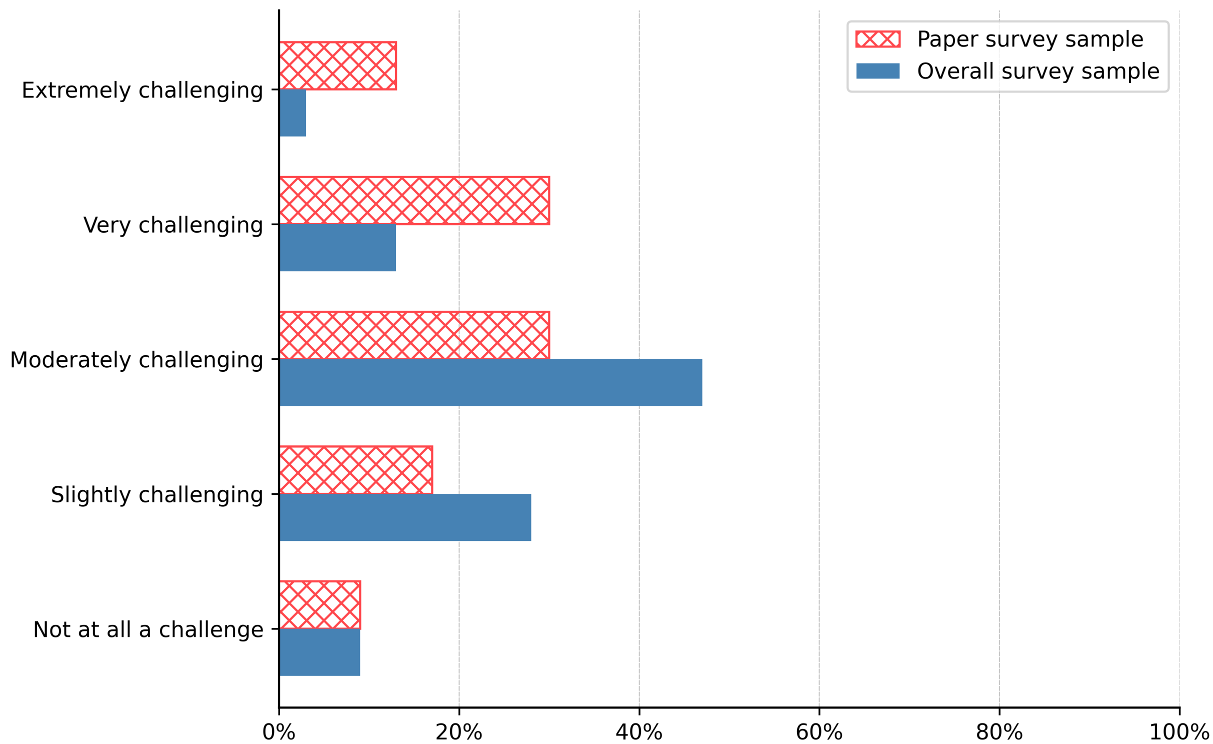

Table 1. Summary Statistics

This table reports the summary statistics. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Return* is the portfolio holdings return, expressed in percentage points (%). *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors), expressed in percentage points (%). *Size* is the natural logarithm of total holdings value. *Age* is the number of years since a hedge fund company's first 13F report. *Turnover* is the minimum of purchases and sales scaled by total holdings value. *Risk* is the standard deviation of quarterly portfolio returns in the past two years.

Variables	(1) N	(2) Mean	(3) St. Dev.	(4) P25	(5) Median	(6) P75
GenAI Reliance	11,921	0.260	0.218	0.077	0.201	0.398
GenAI Reliance Alt	11,921	3.913	5.301	1.175	2.222	4.382
Return	11,921	3.021	10.490	-1.290	3.988	8.281
CAPM Alpha	11,921	-1.555	5.195	-3.445	-1.369	0.396
FF3 Alpha	11,921	-1.624	4.565	-3.230	-1.398	0.175
FF4 Alpha	11,921	-1.622	4.754	-3.252	-1.425	0.154
Size	11,921	7.042	1.655	5.848	6.876	8.031
Age	11,921	15.230	8.556	8.500	13.250	20.500
Turnover	11,921	0.172	0.156	0.051	0.116	0.257
Risk	11,921	0.094	0.054	0.052	0.086	0.126
Past Return	11,921	3.045	10.080	-0.732	4.124	8.157

Table 2. GenAI Reliance and Hedge Fund Performance

This table reports the relation between performance and reliance on generative AI information. *Return* is the portfolio holdings return. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *Size* is the natural logarithm of total holdings value. *Age* is the number of years since a hedge fund company's first 13F report. *Turnover* is the minimum of purchases and sales scaled by total holdings value. *Risk* is the standard deviation of quarterly portfolio returns in the past two years. *Past Return* is the lagged *Return*. The sample period is from the third quarter of 2022 to the third quarter of 2024. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

Panel A: Raw return

	(1)	(2)	(3)	(4)
Dep. Var.		*Return*		
GenAI Reliance	3.697***	3.190***	1.522***	0.929
	(6.18)	(5.05)	(3.03)	(1.61)
Size		0.036		0.086
		(0.51)		(1.25)
Age		-0.170***		-0.001
		(-8.29)		(-0.05)
Turnover		0.232		0.821
		(0.29)		(1.19)
Risk		10.342**		22.920***
		(2.27)		(4.74)
Past Return		0.078***		-0.112***
		(4.46)		(-3.61)
Observations	2,066	2,066	2,066	2,066
R-squared	0.013	0.056	0.582	0.595
Time FE	No	No	Yes	Yes

Panel B: Risk-adjusted returns

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*CAPM Alpha*		*FF3 Alpha*		*FF4 Alpha*	
GenAI Reliance	1.533***	1.619***	1.784***	1.798***	1.879***	1.893***
	(3.14)	(3.07)	(3.59)	(3.38)	(3.54)	(3.36)
Size	0.108	0.157**	-0.026	0.045	-0.020	0.043
	(1.59)	(2.10)	(-0.40)	(0.61)	(-0.32)	(0.59)
Age	-0.082***	-0.023	-0.011	0.001	-0.033*	0.005
	(-5.02)	(-1.15)	(-0.69)	(0.07)	(-1.87)	(0.24)
Turnover	0.514	0.917	1.604**	1.865***	1.346**	1.773***
	(0.74)	(1.29)	(2.44)	(2.76)	(2.05)	(2.62)
Risk	3.216	6.011	8.007	8.789*	9.550*	10.055*
	(0.72)	(1.26)	(1.64)	(1.72)	(1.75)	(1.78)
Past Return	-0.122***	-0.218***	-0.012	-0.129***	-0.017	-0.140***
	(-7.42)	(-6.61)	(-0.83)	(-3.66)	(-1.12)	(-4.11)
Observations	2,066	2,066	2,066	2,066	2,066	2,066
R-squared	0.059	0.099	0.014	0.053	0.015	0.057
Time FE	No	Yes	No	Yes	No	Yes

Table 3. GenAI Reliance and Hedge Fund Performance: DiD

This table reports the relation between performance and reliance on generative AI information. *Return* is the portfolio holdings return. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *Size* is the natural logarithm of total holdings value. *Age* is the number of years since a hedge fund company's first 13F report. *Turnover* is the minimum of purchases and sales scaled by total holdings value. *Risk* is the standard deviation of quarterly portfolio returns in the past two years. *Past Return* is the lagged *Return*. The sample period is from the first quarter of 2016 to the third quarter of 2024. The *t*-statistics, in parentheses, are based on standard errors clustered by fund. **p* <.1; ***p* <.05; ****p* <.01.

Panel A: Raw return

	(1)	(2)	(3)	(4)
Dep. Var.		*Return*		
GenAI Reliance × *Post GPT*	2.873***	3.703***	1.171**	1.224**
	(3.86)	(4.75)	(2.03)	(2.25)
GenAI Reliance	0.824*	-0.854*	0.351	-0.278
	(1.95)	(-1.82)	(1.30)	(-1.01)
Size		-0.132***		-0.078***
		(-2.77)		(-3.24)
Age		-0.057***		0.014***
		(-6.64)		(3.03)
Turnover		1.150**		0.198
		(2.38)		(0.84)
Risk		27.772***		11.438***
		(13.11)		(5.48)
Past Return		-0.162***		0.092***
		(-14.96)		(5.74)
Post GPT	-0.053	-1.047***		
	(-0.30)	(-5.04)		
Observations	11,921	11,921	11,921	11,921
R-squared	0.002	0.045	0.787	0.790
Time FE	No	No	Yes	Yes

Panel B: Risk-adjusted returns

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*CAPM Alpha*		*FF3 Alpha*		*FF4 Alpha*	
GenAI Reliance × *Post GPT*	1.411**	1.633***	2.629***	2.445***	2.725***	2.537***
	(2.39)	(2.83)	(4.81)	(4.46)	(4.69)	(4.46)
GenAI Reliance	-0.536*	-0.396	-0.673***	-0.538**	-0.608**	-0.511*
	(-1.77)	(-1.27)	(-2.62)	(-2.00)	(-2.32)	(-1.85)
Size	-0.118***	-0.115***	-0.112***	-0.108***	-0.112***	-0.113***
	(-3.28)	(-3.23)	(-3.50)	(-3.32)	(-3.60)	(-3.52)
Age	0.002	0.004	0.002	0.002	-0.001	0.002
	(0.32)	(0.54)	(0.35)	(0.35)	(-0.19)	(0.33)
Turnover	-0.444	-0.447	-0.633**	-0.558*	-0.658**	-0.547*
	(-1.35)	(-1.37)	(-2.19)	(-1.86)	(-2.28)	(-1.82)
Risk	0.359	-2.541	-5.556***	-8.684***	-5.878***	-8.069***
	(0.19)	(-0.79)	(-4.03)	(-3.43)	(-3.96)	(-2.95)
Past Return	-0.032***	0.048***	-0.018***	-0.016	-0.017***	-0.018
	(-5.25)	(3.02)	(-3.44)	(-1.19)	(-3.01)	(-1.31)
Post GPT	-1.168***		-0.592***		-0.556***	
	(-8.04)		(-4.20)		(-3.72)	
Observations	11,921	11,921	11,921	11,921	11,921	11,921
R-squared	0.009	0.096	0.011	0.066	0.011	0.063
Time FE	No	Yes	No	Yes	No	Yes

Table 4. GenAI Reliance: Hedge Funds vs Other Asset Management Firms

This table reports the relation between performance and reliance on AI information. *Return* is the portfolio holdings return. *FF4 Alpha* is the portfolio holdings return after adjusting for Fama-French-Carhart four factors. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *Hedge Fund* is an indicator variable if an investment company is a hedge fund company and zero otherwise. *Size* is the natural logarithm of total holdings value. *Age* is the number of years since a hedge fund company's first 13F report. *Turnover* is the minimum of purchases and sales scaled by total holdings value. *Risk* is the standard deviation of quarterly portfolio returns in the past two years. *Past Return* is the lagged *Return*. In both panels, the sample period is from the third quarter of 2022 to the third quarter of 2024 for columns (1) to (2) and from the first quarter of 2016 to the third quarter of 2024 for columns (3) to (4). The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

Panel A: Non-hedge fund companies

	(1)	(2)	(3)	(4)
Sampe Period	Post-GPT period		DiD	
Dep. Var.	*Return*	*FF4 Alpha*	*Return*	*FF4 Alpha*
GenAI Reliance × *Post GPT*			-0.508**	0.177
			(-2.12)	(0.78)
GenAI Reliance	-0.661**	0.510**	-0.141	0.377***
	(-2.57)	(2.42)	(-1.35)	(3.44)
Size	0.024	0.015	-0.024**	-0.042***
	(0.82)	(0.70)	(-2.37)	(-3.39)
Age	0.009	0.008	0.010***	-0.006**
	(1.23)	(1.26)	(6.69)	(-2.57)
Turnover	1.161*	1.069*	-0.705***	-1.841***
	(1.83)	(1.73)	(-3.29)	(-5.83)
Risk	29.865***	6.454**	18.011***	-13.747***
	(8.25)	(2.26)	(12.79)	(-9.31)
Past Return	-0.121***	-0.095***	0.076***	-0.033***
	(-5.00)	(-5.80)	(8.17)	(-5.89)
Observations	6,384	6,384	39,970	39,970
R-squared	0.826	0.085	0.884	0.140
Time FE	Yes	Yes	Yes	Yes

Panel B: Hedge fund companies vs. non-hedge fund companies

	(1)	(2)	(3)	(4)
Sampe Period	Post-GPT period		DiD	
Dep. Var.	*Return*	*FF4 Alpha*	*Return*	*FF4 Alpha*
GenAI Reliance × Post GPT × Hedge Fund			1.893***	2.140***
			(3.23)	(4.13)
GenAI Reliance × Post GPT			-0.514**	0.166
			(-2.14)	(0.73)
GenAI Reliance × Hedge Fund	1.285**	1.170***	-0.449*	-0.649***
	(2.30)	(2.71)	(-1.69)	(-2.78)
GenAI Reliance	-0.565**	0.505**	-0.104	0.347***
	(-2.21)	(2.38)	(-1.00)	(3.19)
Size	0.042	0.017	-0.034***	-0.055***
	(1.55)	(0.77)	(-3.45)	(-4.83)
Age	0.008	0.007	0.012***	-0.005**
	(1.07)	(1.13)	(7.94)	(-2.38)
Turnover	0.980**	1.457***	-0.285*	-1.196***
	(2.07)	(3.43)	(-1.82)	(-5.77)
Risk	26.405***	7.437***	14.318***	-12.923***
	(8.73)	(3.20)	(12.42)	(-11.18)
Past Return	-0.120***	-0.089***	0.080***	-0.025***
	(-6.24)	(-6.57)	(10.03)	(-4.98)
Observations	8,424	8,424	51,709	51,709
R-squared	0.762	0.082	0.860	0.121
Time × Company Type FE	Yes	Yes	Yes	Yes

Table 5. GenAI Reliance and Hedge Fund Performance: AI Hedge Funds

This table reports how AI investment affects the relation between performance and reliance on AI information. *Return* is the portfolio holdings return. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *AI Hedge Fund* is an indicator variable equal to one if a hedge fund has AI-skilled workers and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
Dep. Var.		*Return*		
GenAI Reliance × *Post GPT* × *AI Hedge Fund*	3.536**	4.582**	3.862**	4.902**
	(2.05)	(2.47)	(2.10)	(2.41)
GenAI Reliance × *Post GPT*	1.098*	1.090*	1.156**	1.148**
	(1.85)	(1.83)	(2.06)	(2.04)
Observations	11,921	11,921	11,921	11,921
R-squared	0.787	0.787	0.790	0.791
Control variables	No	No	Yes	Yes
Time FE	Yes		Yes	
Time × AI Hedge Fund FE		Yes		Yes

Table 6. GenAI Reliance and Hedge Fund Performance: Decomposition

This table reports how the relation between performance and reliance on AI information depends on the types of AI-generated information. *Return* is the portfolio holdings return. *FF4 Alpha* is the portfolio holdings return after adjusting for Fama-French-Carhart four factors. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. We separate fundamental information generated by ChatGPT into three groups: 1) Macro, 2) Firm Policy, and 3) Firm Performance and create decomposed *GenAI Reliance* measures for each respective group: *GenAI Reliance Macro*; *GenAI Reliance Firm Policy*; *GenAI Reliance Firm Performance*. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*Return*	*FF4 Alpha*	*Return*	*FF4 Alpha*	*Return*	*FF4 Alpha*
GenAI Reliance Macro × *Post GPT*	1.375	4.909***				
	(0.67)	(2.88)				
GenAI Reliance Macro	-0.536	-1.651**				
	(-0.58)	(-2.32)				
GenAI Reliance Firm Policy × *Post GPT*			3.704***	4.868***		
			(2.72)	(3.91)		
GenAI Reliance Firm Policy			-0.655	-0.916		
			(-0.96)	(-1.45)		
GenAI Reliance Firm Performance × *Post GPT*					1.306**	2.031***
					(1.96)	(3.45)
GenAI Reliance Firm Performance					-0.434	-0.445*
					(-1.50)	(-1.66)
Observations	11,921	11,921	11,921	11,921	11,921	11,921
R-squared	0.790	0.080	0.790	0.081	0.790	0.080
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes

Table 7. GenAI Predictions and Hedge Fund Trades

This table reports the relation between trade performance and reliance on generative AI information. Panel A reports the summary statistics of trade performance and Panel B reports the regressions. *Agree Return* measures the one-quarter-ahead performance for trades that align with GPT predictions, while *Disagree Return* is the performance for trades against GPT predictions. *Agree – Disagree Return* is *Agree Return* minus *Disagree Return*. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

Panel A: Summary Statistics

Variables	(1) N	(2) Mean	(3) St. Dev.	(4) P25	(5) Median	(6) P75
Agree Return	11,840	2.566	24.990	-1.978	0.352	3.263
Disagree Return	11,840	0.353	5.406	-1.196	0.041	1.597
Agree – Disagree Return	11,840	2.198	24.010	-2.274	0.261	3.425

Panel B: Trade Performance

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. Var.	*Agree – Disagree Return*		*Agree Return*		*Disagree Return*	
GenAI Reliance × *Post GPT*	8.100***	7.274***	8.395***	7.265***	0.564	0.277
	(3.02)	(2.64)	(3.14)	(2.65)	(0.90)	(0.43)
Observations	11,840	11,840	11,840	11,840	11,840	11,840
R-squared	0.007	0.051	0.009	0.061	0.009	0.031
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	No	Yes	No	Yes

Table 8. GenAI-Trade Intensity and Market Reaction around Earnings Announcements

This table reports the relation between trade intensity by hedge funds on stocks and market reactions around earnings announcements. Dependent variable *CAR* is the cumulative abnormal return based on the market model during two windows, [0, 1] and [2, 61], where day 0 is the earnings announcement date. *GenAI-Trade Intensity* measures the trade intensity by hedge funds that use generative AI to make trading decisions. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *Earnings Surprise* is the difference between actual earnings and the median forecast from I/B/E/S detail file during the 30 days before the quarterly earnings announcement, scaled by the quarter-end stock price. *MarketCap* is the natural logarithm of the market capitalization of a stock. *ROA* is net income divided by total assets. *BM* is the book-to-market value. *INST* is the ownership of a stock by institutional investors. The *t*-statistics, in parentheses, are based on standard errors clustered by fund. **p* <.1; ***p* <.05; ****p* <.01.

	(1)	(2)	(3)	(4)
Dep. Var.	CAR [0, 1]		CAR [2, 61]	
GenAI-Trade Intensity × *Post GPT*	0.365***	0.372***	-1.076**	-0.866**
	(2.83)	(2.84)	(-2.57)	(-2.34)
GenAI-Trade Intensity	-0.010	-0.001	0.241	0.193
	(-0.17)	(-0.02)	(0.96)	(1.08)
Earnings Surprise	0.008***	0.008***	-0.003**	-0.002***
	(28.86)	(28.97)	(-2.42)	(-2.77)
MarketCap	-0.000	-0.001	-0.004**	-0.006***
	(-0.90)	(-1.21)	(-2.46)	(-5.61)
ROA	0.003	0.003	0.128***	0.043***
	(0.66)	(0.64)	(3.78)	(2.65)
BM	0.000	0.000	0.056***	0.049***
	(0.03)	(0.07)	(8.72)	(11.01)
INST	-0.004	-0.005	0.058***	0.029***
	(-1.18)	(-1.34)	(3.56)	(3.12)
Post GPT	-0.002		0.001	
	(-1.00)		(0.09)	
Observations	25,066	25,066	25,066	25,066
R-squared	0.061	0.065	0.011	0.039
Time FE	No	Yes	No	Yes

Table 9. GenAI Reliance and Generative AI Adoption from Survey

This table reports the relation between *GenAI Reliance* and the generative AI adoption reported by hedge funds. For each hedge fund company in our survey sample, *GenAI Adoption* is an indicator equal to one if the time is after the fund starts using generative AI tools for investment purposes, and zero before the starting year. It remains zero throughout the sample period for hedge fund companies that do not use generative AI. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Size* is the natural logarithm of total holdings value. *Age* is the number of years since a hedge fund company's first 13F report. *Turnover* is the minimum of purchases and sales scaled by total holdings value. *Risk* is the standard deviation of quarterly portfolio returns in the past two years. *Past Return* is the lagged *Return*. *p <.1; **p <.05; ***p <.01.

	(1)	(2)
Dep. Var.	*GenAI Reliance*	
GenAI Adoption	0.045**	0.034**
	(2.43)	(2.09)
Size	-0.033***	-0.033***
	(-12.15)	(-13.12)
Age	-0.005***	-0.005***
	(-6.81)	(-6.90)
Turnover	-0.312***	-0.304***
	(-9.58)	(-9.74)
Risk	0.945***	0.939***
	(4.32)	(4.55)
Past Return	-0.002	-0.001
	(-1.17)	(-0.75)
Observations	829	906
R-squared	0.369	0.369
Time FE	Yes	Yes
Sample period	2016–2023	2016–2024

Table 10. GenAI Reliance: Combine Different Data Sources

This table reports the relation between performance and reliance on generative AI information, where we include various information sources for hedge funds, including conference calls transcripts, SEC Form 10K and 10Q, and *Wall Street Journal* articles. *Return* is the portfolio holdings return. *FF4 Alpha* is the portfolio holdings return after adjusting for Fama-French-Carhart four factors. *GenAI Reliance* quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. When constructing *GenAI Reliance* in equation (3), we take the average of *GPT Score* across different information sources for each of 14 signals. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

Panel A: Conference Call + 10K&10Q + *Wall Street Journal* (Average)

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
GenAI Reliance × *Post GPT*	1.365**	1.792***	2.434***	2.472***
	(2.40)	(3.56)	(4.89)	(4.79)
GenAI Reliance	-0.314	-0.359	-0.594***	-0.547***
	(-1.16)	(-1.58)	(-2.90)	(-2.59)
Observations	11,921	11,921	11,921	11,921
R-squared	0.790	0.117	0.071	0.072
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Panel B: Conference Call + 10K&10Q (Average)

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
GenAI Reliance × *Post GPT*	1.244**	1.852***	2.625***	2.636***
	(2.25)	(3.80)	(5.38)	(5.30)
GenAI Reliance	-0.285	-0.368	-0.704***	-0.671***
	(-1.06)	(-1.58)	(-3.45)	(-3.19)
Observations	11,921	11,921	11,921	11,921
R-squared	0.790	0.117	0.072	0.072
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table 11. Alternative GenAI Reliance Measure: Controlling Traditional Textual Analysis

This table reports the relation between performance and reliance on AI information from a DiD test. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *GenAI Reliance* (*LM Adjusted*) is an alternative definition of *GenAI Reliance* that quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. Specifically, we add Loughran-McDonald positive and negative sentiment in Equations (1) and (2) as additional information about firm fundamentals so that *GenAI Reliance* measures qualitative information beyond traditional textual measures. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *Size* is the natural logarithm of total holdings value. *Age* is the number of years since a hedge fund company's first 13F report. *Turnover* is the minimum of purchases and sales scaled by total holdings value. *Risk* is the standard deviation of quarterly portfolio returns in the past two years. *Past Return* is the lagged *Return*. The t-statistics, in parentheses, are based on standard errors clustered by fund. **p* <.1; ***p* <.05; ****p* <.01.

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
GenAI Reliance (*LM Adjusted*) × *Post GPT*	1.252**	1.720***	2.257***	2.252***
	(2.15)	(2.81)	(4.04)	(3.91)
GenAI Reliance	-0.558**	-0.388	-0.507**	-0.425
	(-1.99)	(-1.30)	(-1.99)	(-1.64)
Observations	11,399	11,399	11,399	11,399
R-squared	0.798	0.102	0.084	0.082
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Internet Appendix of "Generative AI and Asset Management"

This internet appendix includes the following figures and tables used in the paper:

Figure IA.1. Average *p*-value of Partial F-test

This figure plots the four-quarter moving average *p*-value of the partial F-test based on *GenAI Reliance* at the quarterly frequency.

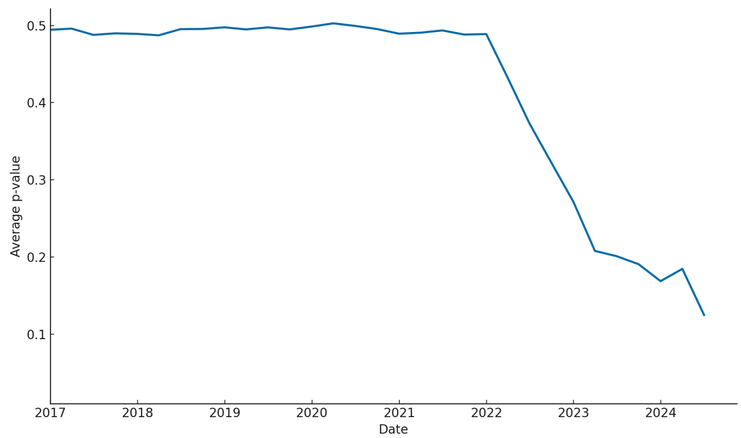

Figure IA.2. GenAI Adoption by Different *p*-value Cutoff

This figure plots GenAI Adoption using the partial F-Test with three cutoffs on *p*-value at the quarterly frequency. A hedge fund is defined as a GenAI adopter in a quarter if its GenAI Reliance is significant at 1%, 5% or 10% level.

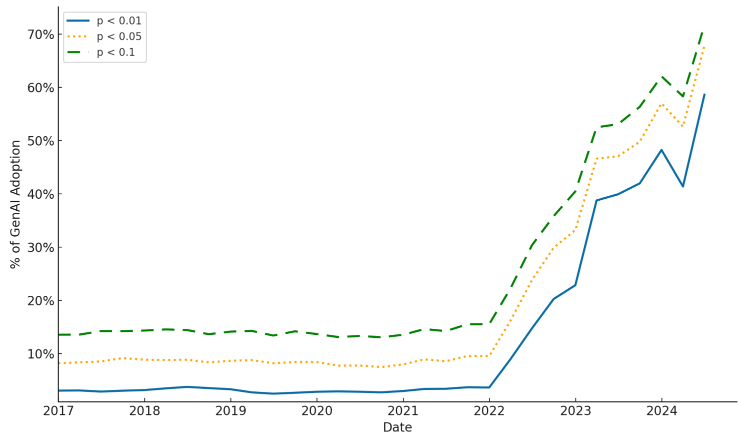

Figure IA.3. Persistence of GenAI Adoption

This figure plots the persistence of GenAI Adoption in the four quarters after initial adoption. Each quarter, hedge funds are classified as GenAI Adopter and Non-Adopter based on whether their *GenAI Reliance* is significant at 1% level using a partial-F test. Solid line represents the probability of GenAI adoption in the subsequent four quarters for GenAI Adopter, and dotted line represents the probability for Non-Adopter.

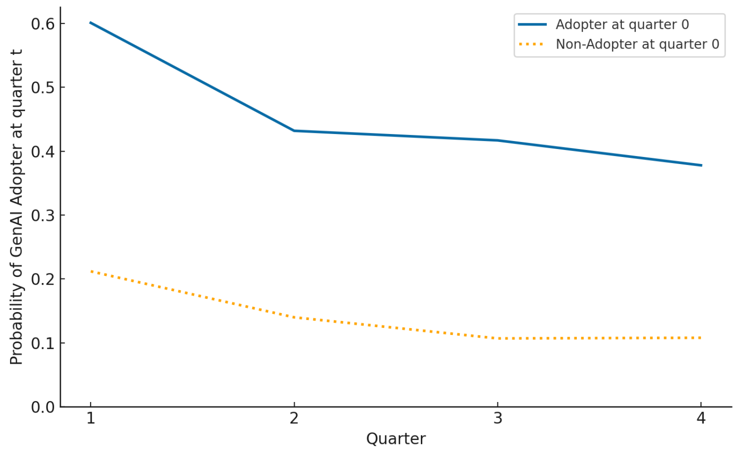

Figure IA.4. Do ChatGPT Outages Affect Hedge Funds?

This figure plots answers to questions about generative AI adoption from a survey among hedge funds. We ask the following question: *"Have outages of ChatGPT or other generative AI tools affected your investment workflow and processes?"* The "Paper survey sample" refers to the sample of surveyed funds that are also in our main-analysis sample. The "Overall" sample refers to the sample of all surveyed funds. The full list of questions and answers is presented in the Internet Appendix Table IA.2.

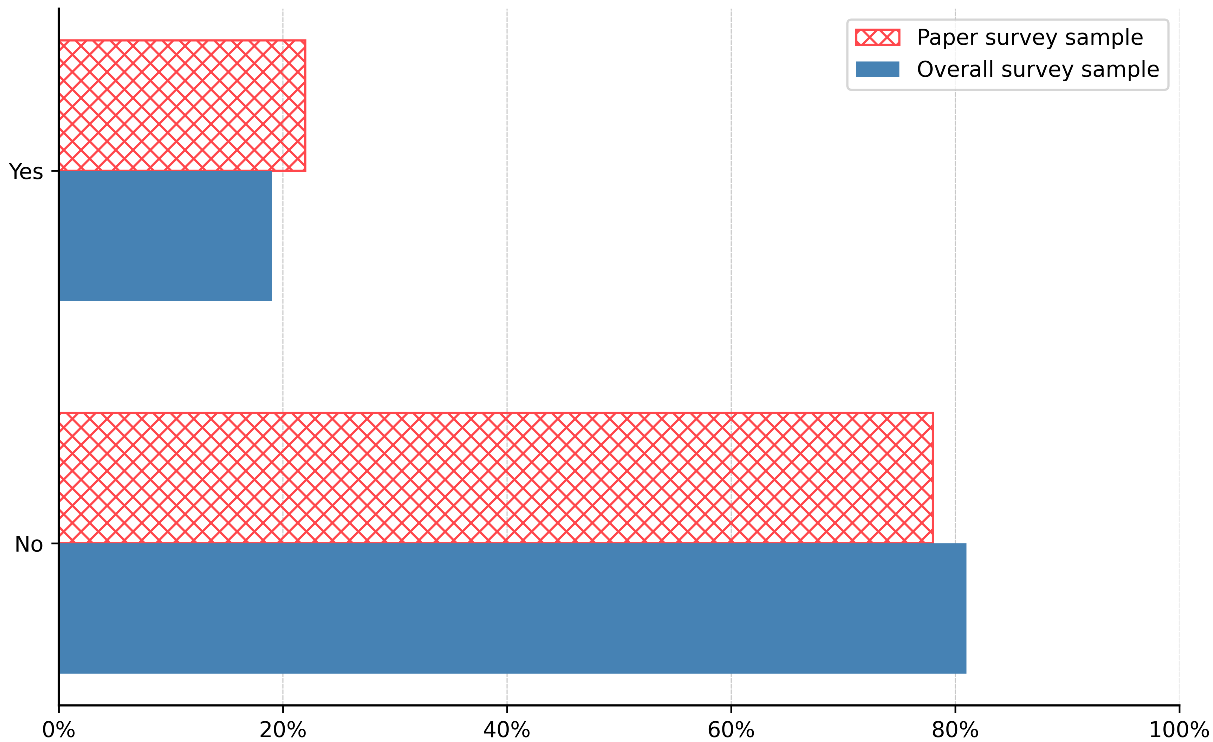

Table IA.1. List of Questions to Generate AI Information

This table reports the list of questions used to query ChatGPT and generate forward-looking information/signal based on firms' earnings conference call transcripts. These questions are based on Jha, Qian, Weber, and Yang (2023, 2024).

	Over the next quarter, how does the firm anticipate a change in:
No.	Topic
1	optimism about the US economy?
2	optimism about the global economy?
3	optimism about the financial prospects of their firm?
4	optimism about the financial prospects of its industry?
5	its earnings?
6	its revenue?
7	its wages and salaries expenses?
8	demand for its products or services?
9	production quantity of its products?
10	prices for its products or services?
11	prices for its inputs or commodities?
12	its cost of capital or hurdle rate?
13	its capital expenditure?
14	its employment?

Table IA.2. Survey Questions on Generative AI Adoption in Hedge Funds

Q1. Does your hedge fund use generative AI tools, including in-house tools, for investment purposes (e.g., processing data, improving trading strategies)?

- ☐ Yes
- ☐ No

Q2. Why don't you use generative AI tools? Please select all that apply.

- ☐ Accuracy and reliability of AI-generated outputs
- ☐ Compliance and regulatory concerns
- ☐ Data security and confidentiality risks
- ☐ Integration with existing hedge fund workflows
- ☐ Lack of in-house AI expertise
- ☐ Cost of AI tools
- ☐ Other (please specify): ____________________

Q3. Which generative AI tools do you use for investment purposes? Please select all that apply.

- ☐ ChatGPT
- ☐ Claude
- ☐ Google Gemini
- ☐ Llama (Meta)
- ☐ In-house tools
- ☐ Other (please specify): ____________________

Q4. How do you use generative AI tools for your investment purposes? Please select all that apply.

- ☐ Processing and analyzing data/text (e.g., news, earnings conference call)
- ☐ Enhancing investment decisions/strategies (e.g., due diligence, screening, investment idea generation, alpha generation, portfolio optimization)
- ☐ Coding and automation
- ☐ Other (please specify): ____________________

Q5. When did your hedge fund start using generative AI tools for investment purposes?

- ☐ Before 2022 (e.g., BERT, GPT early versions)
- ☐ 2022 but before ChatGPT release (e.g., GPT API)
- ☐ 2022 but after ChatGPT release
- ☐ 2023
- ☐ 2024
- ☐ 2025

(continued)

Q6. To what extent do you think generative AI tools influence your fund's investment decisions?
☐ Minimal influence
☐ Slight influence
☐ Moderate influence
☐ Significant influence

Q7. Did your firm have in-house AI tools (including all machine and AI models, not limited to generative AI) before ChatGPT was released in November 2022?
☐ Yes, but later replaced them entirely with ChatGPT or similar generative AI tools
☐ Yes, and now use both in-house AI tools and ChatGPT or similar generative AI tools
☐ Yes, and have fine-tuned or trained our own generative AI models in-house
☐ Yes, and continue to use only in-house AI tools that are not generative AI
☐ No, we did not have in-house AI tools before ChatGPT's release

Q8. On a scale of 1–5, how challenging are the following issues when using generative AI tools? (1. Not at all a challenge, 2. Slightly challenging, 3. Moderately challenging, 4. Very challenging, 5. Extremely challenging)
☐ Accuracy and reliability of AI-generated outputs
☐ Compliance and regulatory concerns
☐ Data security and confidentiality risks
☐ Integration with existing hedge fund workflows
☐ Lack of in-house AI expertise
☐ Cost of AI tools
☐ Other (please specify): ______________________

Q9. Have outages of ChatGPT or other generative AI tools affected your investment workflow and processes?
☐ Yes, significantly
☐ Yes, but only moderately
☐ No noticeable impact
☐ No, we have backup solutions or alternative tools

Table IA.3. GenAI Reliance and Hedge Fund Company Characteristics

This table reports the relation between performance and reliance on AI information between subsamples partitioned by fund characteristics, including *Size*, *Age*, *Turnover* (TO), *Risk*, and *Past Return* (PRet). Each variable is sorted into quintiles in each year and the table compares Q1, the lowest quintile, and Q5, the highest quintile. *Return* is the portfolio holdings return. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The *t*-statistics, in parentheses, are based on standard errors clustered by fund. **p* <.1; ***p* <.05; ****p* <.01 for the regression coefficients (two-tailed) and for the difference of coefficients (one-tailed).

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Subsamples	Size Q1	Size Q5	Age Q1	Age Q5	TO Q1	TO Q5	Risk Q1	Risk Q5	PRet Q1	PRet Q5
Dep. Var.	*Return*									
GenAI Reliance × *PostGPT*	0.872	3.602***	0.576	5.674***	0.792	3.016***	0.942	-0.151	1.024	-0.623
	(0.62)	(2.71)	(0.59)	(2.92)	(0.63)	(2.72)	(0.78)	(-0.10)	(0.92)	(-0.44)
Diff in Coeff. (Q5 – Q1)	2.730*		5.098***		2.224*		-1.093		-1.647	
p-value	0.079		<0.001		0.092		0.286		0.180	
Observations	2,377	2,383	2,872	2,093	2,388	2,381	2,387	2,380	2,383	2,383
R-squared	0.760	0.862	0.760	0.850	0.815	0.831	0.879	0.720	0.784	0.689
Control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.4. GenAI Reliance and Most Active non-Hedge Funds

This table reports the relation between performance and reliance on generative AI information for active non-hedge funds. We sort investment companies that are not hedge funds into quintiles based on their *Turnover* and define the subsample of investment companies with the highest quintile of *Turnover* as active non-hedge funds. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

Dep. Var.	(1) *Return*	(2) *CAPM Alpha*	(3) *FF3 Alpha*	(4) *FF4 Alpha*
GenAI Reliance × *Post GPT*	-0.678	1.076	2.114***	2.009**
	(-0.79)	(1.35)	(2.61)	(2.48)
Observations	4,964	4,964	4,964	4,964
R-squared	0.832	0.155	0.149	0.153
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table IA.5. GenAI-Trade Intensity and Bid Ask Spread

This table reports the relation between trade intensity by hedge funds on stocks and bid-ask spread. Dependent variable *Bid-Ask Spread* is the difference between ask price and bid price divided by their midpoint at daily frequency. *GenAI-Trade Intensity* measures the trade intensity by hedge funds that use generative AI to make trading decisions. *Earnings Day* is an indicator variable equal to one on the day of earnings announcement and zero otherwise. *MarketCap* is the natural logarithm of the market capitalization of a stock. *ROA* is net income divided by total assets. *BM* is the book-to-market value. *INST* is the ownership of a stock by institutional investors. The *t*-statistics, in parentheses, are based on standard errors clustered by fund. **p* <.1; ***p* <.05; ****p* <.01.

Panel A: Bid-Ask Spread at Daily Frequency

	(1)	(2)	(3)	(4)
Sample Period	2022	2023	2024	2022–2024
Dep. Var.	*Bid-Ask Spread*			
GenAI-Trade Intensity	0.079**	0.069	-0.138***	-0.013
	(2.04)	(1.03)	(-3.08)	(-0.32)
MarketCap	-0.062***	-0.066***	-0.042***	-0.073***
	(-15.79)	(-14.83)	(-8.80)	(-25.42)
ROA	0.035***	-0.001***	-0.004***	-0.001***
	(5.55)	(-3.91)	(-4.60)	(-2.71)
BM	0.037***	-0.001	0.002**	0.002*
	(8.47)	(-0.60)	(2.19)	(1.91)
INST	-0.126***	-0.056***	-0.038**	-0.040**
	(-4.31)	(-3.19)	(-2.45)	(-2.45)
Observations	913,390	956,175	940,671	2,588,219
R-squared	0.656	0.680	0.682	0.639
Time FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes

Panel B: Bid-Ask Spread on Earnings Announcement Days

	(1)	(2)	(3)	(4)
Sample Period	2022	2023	2024	2022–2024
Dep. Var.	*Bid-Ask Spread*			
GenAI-Trade Intensity × *Earnings Day*	0.539**	-0.073	0.027	0.105
	(2.39)	(-1.30)	(0.30)	(1.26)
GenAI-Trade Intensity	0.079**	0.069	-0.138***	-0.013
	(2.03)	(1.03)	(-3.08)	(-0.33)
Earnings Day	0.009***	0.009***	0.001	0.005***
	(4.40)	(5.42)	(0.42)	(4.50)
MarketCap	-0.062***	-0.066***	-0.042***	-0.073***
	(-15.79)	(-14.83)	(-8.80)	(-25.42)
ROA	0.035***	-0.001***	-0.004***	-0.001***
	(5.55)	(-3.91)	(-4.60)	(-2.71)
BM	0.037***	-0.001	0.002**	0.002*
	(8.47)	(-0.60)	(2.19)	(1.91)
INST	-0.126***	-0.056***	-0.038**	-0.040**
	(-4.31)	(-3.19)	(-2.45)	(-2.45)
Observations	913,390	956,175	940,671	2,588,219
R-squared	0.656	0.680	0.682	0.639
Time FE	Yes	Yes	Yes	Yes
Stock FE	Yes	Yes	Yes	Yes

Table IA.6. GenAI Reliance and Hedge Fund Performance: ChatGPT Outages

This table reports how ChatGPT outage affects the relation between performance and reliance on AI information. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *Outage* is the number of ChatGPT outages in a given quarter. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
GenAI Reliance × *Post GPT* × *Outage*	-0.976*	-1.340***	-0.386	-0.062
	(-1.95)	(-2.74)	(-0.78)	(-0.12)
GenAI Reliance × *Post GPT*	2.746***	3.915***	3.056***	2.565***
	(2.89)	(4.09)	(3.41)	(2.77)
Observations	11,921	11,921	11,921	11,921
R-squared	0.790	0.104	0.083	0.082
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table IA.7. GenAI Reliance After ChatGPT Knowledge Cutoff Date

This table reports the relation between performance and reliance on generative AI information for the period after September 2021, the knowledge cutoff date for GPT 3.5 and ChatGPT. *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The sample period is from the fourth quarter of 2021 to the third quarter of 2024. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
GenAI Reliance × *Post GPT*	6.853***	6.565***	4.738***	4.242***
	(4.21)	(4.47)	(4.10)	(3.54)
GenAI Reliance	-3.329***	-2.478**	-1.828**	-1.817**
	(-3.09)	(-2.56)	(-2.34)	(-2.24)
Observations	1,923	1,923	1,923	1,923
R-squared	0.643	0.172	0.079	0.079
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table IA.8. GenAI Reliance and Hedge Fund Performance: ChatGPT Release

This table reports the relation between performance and reliance on AI information. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *GenAI Reliance* is defined in equation (3), which quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT. *Post ChatGPT* is an indicator variable equal to one for performance in the first quarter of 2023 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
GenAI Reliance × *Post ChatGPT*	0.871	1.284**	2.410***	2.399***
	(1.43)	(2.11)	(4.23)	(4.12)
GenAI Reliance	-0.172	-0.218	-0.399	-0.354
	(-0.64)	(-0.80)	(-1.63)	(-1.41)
Observations	11,921	11,921	11,921	11,921
R-squared	0.790	0.102	0.082	0.081
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table IA.9. Alternative GenAI Reliance Measure

This table reports the relation between performance and reliance on AI information. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). *GenAI Reliance Alt* is an alternative measure of *GenAI Reliance* that quantifies the degree to which changes in portfolio holdings are influenced by fundamental information generated by ChatGPT, where $GenAI\ Reliance\ Alt_{i,t} = (R^2_{AI,i,t} - R^2_{fundamental,i,t})/R^2_{fundamental,i,t}$. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The sample period is from the third quarter of 2022 to the third quarter of 2024 in Panel A and from the first quarter of 2016 to the third quarter of 2024 in Panel B. The *t*-statistics, in parentheses, are based on standard errors clustered by fund. **p* <.1; ***p* <.05; ****p* <.01.

Panel A: During Post-GPT period

Dep. Var.	(1) *Return*	(2) *CAPM Alpha*	(3) *FF3 Alpha*	(4) *FF4 Alpha*
GenAI Reliance Alt	0.024**	0.026**	0.033***	0.036***
	(1.97)	(2.28)	(2.78)	(2.99)
Observations	2,066	2,066	2,066	2,066
R-squared	0.595	0.095	0.050	0.059
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Panel B: DiD

Dep. Var.	(1) *Return*	(2) *CAPM Alpha*	(3) *FF3 Alpha*	(4) *FF4 Alpha*
GenAI Reliance Alt × *Post GPT*	0.038**	0.037**	0.051***	0.053***
	(2.37)	(2.33)	(3.60)	(3.63)
GenAI Reliance Alt	-0.012	-0.008	-0.015*	-0.014*
	(-1.21)	(-0.86)	(-1.88)	(-1.75)
Observations	11,921	11,921	11,921	11,921
R-squared	0.790	0.102	0.081	0.080
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes

Table IA.10. GenAI Reliance and Early Adopter

This table reports the relation between performance and early adopters of GenAI. *Early Adopter* is an indicator variable equal to one if 1) a hedge fund company has a significant *GenAI Reliance* at 1% level in any of the first two quarters of 2022 but does not have a significant *GenAI Reliance* through 2021 based on partial F-tests, and 2) its *GenAI Reliance* is in the top quintile in the cross section. *Post GPT* is an indicator variable equal to one for performance in the third quarter of 2022 and onwards, and zero otherwise. *Return* is the portfolio holdings return. *CAPM Alpha* (*FF3 Alpha*/*FF4 Alpha*) is the portfolio holdings return, after adjusting for the market risk factor (Fama-French three factors/Fama-French-Carhart four factors). Control variables include *Size*, *Age*, *Turnover*, *Risk*, and *Past Return*, defined in the Appendix. The t-statistics, in parentheses, are based on standard errors clustered by fund. *p <.1; **p <.05; ***p <.01.

	(1)	(2)	(3)	(4)
Dep. Var.	*Return*	*CAPM Alpha*	*FF3 Alpha*	*FF4 Alpha*
Early Adopter × *Post GPT*	0.879	1.574**	1.903***	1.897***
	(1.18)	(2.26)	(2.94)	(2.89)
Early Adopter	0.249	-0.246	-0.448*	-0.395
	(1.61)	(-0.69)	(-1.78)	(-1.58)
Observations	8,512	8,512	8,512	8,512
R-squared	0.802	0.095	0.079	0.079
Control variables	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes