Artificial Intelligence and Analyst Productivity*

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Abstract

We provide evidence on the impact of AI on sell-side analysts' productivity, focusing on earnings forecasts. Theory suggests that AI may improve productivity through automation and/or task complementarity. However, potential frictions in the effective use of AI could lead to no productivity gains or even adverse effects. Our results show that AI investments by investment banks lead to an increase in production quantity, as measured by a higher frequency of earning forecasts for covered firms, and an improvement in production quality, as measured by more accurate earnings forecasts. Cross-sectional analyses show that the effect of AI investments is stronger when the forecasting task is more complex, due to either fundamental firm uncertainty or a poor firm information environment. These results suggest that the positive effect of AI on analyst productivity is primarily driven by task complementarity - allowing analysts to focus their efforts on tasks that benefit most from their human skills - rather than by pure automation. We additionally show that AI investment levels the playing field among analysts, leads to investment banks expanding coverage to firms that were not previously covered, and increases analysts' strategic forecasting behaviors. Finally, we observe similar effects on productivity with the introduction of ChatGPT, an alternative proxy for the increased use of AI by analysts.

Keywords: artificial intelligence, AI, machine learning, sell-side analysts, earnings forecasts, productivity, analyst coverage

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I. Introduction

Artificial intelligence (AI) is revolutionizing the way many industries operate. AI presents the potential for a fundamental shift in factor productivity, with some estimates suggesting it has the potential to be as significant as the Industrial Revolution (Abis and Veldkamp 2024), and even the most modest estimates suggesting it is likely to be as significant as the internet. Acemoglu, Autor, Hazell, and Restrepo (2022) report that the financial services industry has the highest level of AI exposure of any 2-digit NAICS industry. Consistent with the potential economic importance of AI for financial services, a growing body of research documents the potential for AI to be used for effective financial analysis and advice, either replacing or complementing human labor (e.g., Cao, Jiang, Wang, and Yang 2024). However, despite the significant potential impact of AI on financial analysis and advice, there is little research into its actual effects on the work of traditional financial analysts. In this study, we focus on the realized effects of AI investments on the productivity of traditional sell-side analysts.

We build on the economic framework of Acemoglu and Restrepo (2019) and Acemoglu (2024) that describes two primary mechanisms through which AI can affect productivity. The first mechanism is automation, in which AI automates, or improves the automation of, simple tasks, replacing human labor. Robo-Analysts are an example of this type of AI application (e.g., Coleman, Merkley, and Pacelli 2022). The second mechanism is task complementarity, in which AI augments human productivity by assisting with basic tasks, enabling humans to focus on more complex work that might not have been feasible without AI or that cannot be fully automated by AI. In this way, AI complements (rather than replaces) human labor.[1] When we consider the use of AI by traditional analysts, we might observe either automation, task complementarity, or both. In addition, behavioral and managerial frictions could hinder the effective use of AI for productivity enhancement, leading to minimal effects, or even negative effects (see Section II).

Based on this framework, we examine (i) whether AI investments by investment banks improve analyst productivity in terms of both the quantity and quality of earnings forecasts and (ii) whether this improvement is due to task complementarity or automation. We conduct additional analyses to provide further insights into the effects of AI on analysts, their forecasts, and the information available to investors. In particular, we examine whether AI investments "level the playing field" across analysts, whether AI-induced productivity increases lead to the coverage of new firms, providing investors with information about previously uncovered firms, and whether AI investments influence analysts' strategic forecasting behaviors, such as optimism and "beatable" forecasts.

We measure AI investments using data on AI-related job postings from Bloom, Hassan, Kalyani, Lerner, and Tahoun (2024), who employ a multi-step approach utilizing text analysis of patent and job posting data to identify jobs that are related to different technologies over the ten-year period from 2010 to 2019. From this data, we identify fifteen investment banks that account for the majority of large and mid-size investment banks in the I/B/E/S database. We then calculate the percentage of job postings from each investment bank that include bigrams

[1] Cao et al. (2024) examine an AI system in which human analyst forecasts are used as an input. They describe this combined AI model as "man + machine." It is important to note that task complementarity differs from the "man + machine", which Cao et al. (2024) describe. In the case of task complementarity, the human drives the overall forecast, but uses AI as a tool to support their work. In the Cao et al. (2024) case, the machine drives the forecast.

related to AI, such as machine learning, learning algorithms, and neural networks. This method of measuring AI investments is similar to approaches used in prior research, such as Fedyk, Hodson, Khimich, and Fedyk (2022) and Babina, Fedyk, He, and Hodson (2024).

To measure analyst productivity, we focus on the frequency and accuracy of analysts' earnings forecasts. This is similar to Kumar (2010) and He et al. (2019), among others, who focus on earnings forecasts as a measure of analyst quality.[2] In our analyses, we control for known determinants of analyst forecast frequency and accuracy. In addition, we control for each investment bank's non-AI technology-related job postings. We also include investment bank-firm fixed effects. In other words, we identify the effects of AI investment on analyst forecast frequency and accuracy using variation within the same investment bank-firm pair over time. Furthermore, we conduct analyses both without and with controls for prior analyst forecast frequency and accuracy for the same analyst-firm pair.

We find that AI investment, measured using the percentage of AI job postings over a three-year window, leads to higher production quantity, as measured by a higher frequency of earnings forecasts for covered firms. In terms of economic significance, a one standard deviation increase in AI investment is associated with a 1.4% increase in the number of annual earnings forecasts. Furthermore, we find that AI investment also leads to a higher frequency of other types of forecasts (e.g., sales, cash flows, etc.). Focusing on production quality, we

[2] While earnings forecasts are not the only output of security analysts, they are one of the most regular and systematic types of forecasts analysts make. Analysts are motivated to issue frequent and accurate earnings forecasts through both brokerage trading incentives and career concerns (e.g., Hong and Kubik 2003; Lehmer, Lourie and Shanthikumar 2022). Earnings forecasts are also used by investors (e.g., Bradshaw, Ertimur and O'brien 2017). Several studies indicate that they are used more heavily by institutional investors than recommendations (e.g., Brown, Call, Clement and Sharp 2015; Malmendier and Shanthikumar 2014; Mikhail, Walther and Willis 2007). Together, earnings forecasts are an important analyst output, which serve as an effective measure of analyst productivity.

find that AI investment leads to an improvement in production quality, as measured by higher earnings forecast accuracy. A one standard deviation increase in AI investment is associated with a 2.3% increase in forecast accuracy.

We next examine whether this improvement in analyst productivity is due to automation or task complementarity. Less complex tasks, that can be more easily reduced to a formulaic process, are more likely to be automated. In contrast, more complex tasks, those that require more varied processes, human judgment, interaction, and private information acquisition, are more likely to benefit from task complementarity, where employees use AI to automate or streamline specific subtasks, allowing them to focus their time and attention on the components that benefit most from their human skills. If AI primarily increases analyst productivity through automation, we would expect a stronger effect for less complex forecasting tasks. If AI increases analyst productivity through task complementarity, we would expect a stronger effect for more complex forecasting tasks.

We examine two types of forecasting complexity. First, we examine fundamental uncertainty. We examine two metrics: earnings forecast dispersion and return volatility. Lower forecast dispersion and lower return volatility suggest that earnings and firm performance are easier to predict based on a more formulaic process and existing public information, whereas higher forecast dispersion and higher return volatility suggest that human judgment, private information, and hard-to-quantify soft information will all be more important. Using these measures, we find that AI investments improve forecast frequency and accuracy more when firms have higher fundamental uncertainty – when there is higher dispersion across analysts' earnings forecasts and when returns are more volatile.

Second, we examine forecasting tasks that are more complex due to a poorer firm information environment. For firms with a poorer information environment, less public information is available, suggesting that acquiring and processing private information will be more important. We measure the information environment using two metrics: firms' management earnings forecasts, a measure of firms' voluntary disclosure, and bid-ask spreads, a measure of information asymmetry. Using these two measures, we find that AI investments improve forecast frequency and accuracy more for firms with poorer information environments – when firms issue less management earnings guidance and when bid-ask spreads are wider. Overall, these results are consistent with the increase in analyst productivity being driven primarily by task complementarity uses of AI rather than simple automation.

To provide further insights into the effects of AI investments on analysts, their forecasts, and the information available to investors, we conduct several additional analyses. First, we examine whether AI investments help level the playing field among analysts. AI has the potential to reduce gaps between analysts in their performance, by providing tools that bridge gaps in skill and resource availability (e.g., Brynjolfsson, Li, and Raymond 2023). Consistent with this idea, we find that AI investments have a more pronounced positive impact on the productivity of analysts who previously underperformed.

Second, we examine whether AI-driven productivity increases lead to an increase in the set of firms that investment banks cover. We find that AI investments result in an expansion of firm coverage, including firms that previously had no analyst coverage. This suggests that AI supports analysts in initiating coverage of harder-to-cover zero-coverage firms, driving a meaningful change in analyst coverage.

Third, we examine whether AI investments affect analysts' strategic forecasting behavior. If AI is used to automate forecasting, it should reduce strategic biases in forecasts (e.g., Coleman, Merkley, and Pacelli 2022). On the other hand, if it is used for task complementarity purposes, it could increase analysts' ability to strategically bias their forecasts. Additionally, AI could increase pressure on analysts to boost productivity and raise concerns about job displacement, increasing incentives to bias. Consistent with task complementarity and increased incentives to bias, we find that AI investments lead analysts to provide more optimistic forecasts overall, but to also walk down forecasts to a beatable level more often, which may help them generate greater brokerage trading volume and please firm management to gain access to future private information.

In our final set of analyses, we examine whether the introduction of ChatGPT impacts analyst productivity. ChatGPT significantly boosted the cultural acceptance and popularity of AI. Although ChatGPT use was restricted at many investment banks due to data security concerns, the rapid shift in AI acceptance and popularity following its introduction likely spurred increased use of available AI resources. Thus, ChatGPT serves as a shock expected to drive an increase in analysts' use of AI. This analysis allows us to provide evidence on the causal impact of AI use on analyst productivity, complementing our primary analyses of AI investments.

We find an increase in analyst forecast frequency and accuracy after the introduction of ChatGPT. This increase is more pronounced for firms with higher fundamental uncertainty and poorer information environments. In other words, our findings regarding the introduction of ChatGPT are consistent with our primary results on AI investments, supporting the idea that

AI use improves analyst productivity through task complementarity, allowing analysts to focus on tasks where human expertise adds the most value.

Our study is the first, to our knowledge, to directly examine the effects of AI investment on analyst research production. A growing body of research examines how AI can be used in financial services. Coleman, Merkley, and Pacelli (2022) and Cao et al. (2024) show that a properly trained AI system can perform better than human analysts at making recommendations and forecasting stock returns. Grennan and Michaely (2021) focus on AI analysis through FinTech firms and find that FinTech AI analysis partially substitutes for traditional sell-side analysis. Together, this research suggests that AI has the potential to improve and/or subsume the work of traditional sell-side analysts. Our results show significant evidence of improvement in sell-side analyst research – both in quantity and quality of production. We find that AI provides more of an improvement for more complex tasks, suggesting that it is currently used for task complementarity – enabling traditional sell-side analysts to focus their efforts more on their human skill advantages – more than pure automation. Together, these results suggest that using AI can increase the value that traditional analysts provide, and that human analysts can still add value in the AI era. Further, we show that traditional analysts' use of AI has unique implications, such as increasing strategic forecast biases, in contrast to decreased biases for Robo-Analysts.

Our paper also contributes to the broader literature on the effects of AI on productivity. Prior studies suggest that AI can improve productivity (e.g., Fedyk et al. 2022; Czarnitzki, Fernández, and Rammer 2023; Jansen, Nguyen, and Shams 2024). However, Commerford, Dennis, Joe, and Ulla (2022) show that behavioral factors such as algorithm aversion can reduce the effectiveness of AI. Moreover, Dell'Acqua (2022) indicates that high quality AI can lead to lower productivity as employees may exert less effort and time. Our focus on sell-side analysts, within an industry with early and high AI adoption, and with clearly measurable output quantity and quality, adds to our understanding of the economic impact of AI, providing evidence for AI-driven increases in productivity.

The remainder of the paper is organized as follows. Section II discusses additional background and hypothesis development. Section III describes the data and variable measurement, including our measure of AI investment. Section IV presents our main results for the effects of AI investment on analyst productivity. Section V examines the introduction of Chat GPT. Section VI concludes.

II. Institutional and Theoretical Background and Hypothesis Development

AI has the potential to fundamentally change the production of knowledge. While AI is almost certain to be impactful, it can be difficult to predict exactly what effects it will have. AI technology has a long history, with AI-related theorization beginning almost as early as the first computers. However, AI saw strong advances starting in the late 1990s and early 2000s. *Financial Analysts Journal*, a practitioner-facing journal, was publishing articles on using neural networks, a type of AI system, to pick stocks as early as the 1990s (e.g., Wong, Wang, Goh and Quek 1992; Kryzanowski, Galler and Wright 1993). As data availability and computing power grew throughout the 2000s, the power and use of AI methods also grew, both in general, and within financial services. Below, we provide relevant institutional background, discuss economic theory as to the impact that AI should have on analyst productivity, and develop predictions.

2.1. The Generation of Analyst Earnings Forecasts

Sell-side analysts provide a wide range of research and information to investing clients, through both formal reports and through less formal calls and conversations. Earnings forecasts are one of the most frequent and consistent forms of research that analysts produce. For example, analysts typically update one-year-ahead annual earnings forecasts at least four times per year. Earnings forecast quality is also clearly measurable using ex post earnings forecast accuracy. Finally, earnings forecasts are also important to analysts due to both brokerage trading incentives and career concerns (e.g., Hong and Kubik 2003; Lehmer, Lourie, and Shanthikumar 2022). For all of these reasons – the consistency, clear measures of quality, and importance of earnings forecasts to analysts – we focus on analysts' production of earnings forecasts.

In order to generate earnings forecasts, analysts utilize both public and private information, and both hard and soft information. Public hard information, such as annual and quarterly reports, management earnings forecasts, other firm announcements, and macroeconomic and industry data, is all relevant to forming and updating earnings forecasts (Bradshaw, Ertimur, and O'Brien 2017). AI tools are likely to be helpful in extracting, processing, and analyzing this type of data.

Analysts also conduct additional information acquisition to both gain and complement their private information. Analysts often participate in conference calls (Mayew 2008) and speak privately with management, for example, through phone calls and in-person meetings (Soltes 2014), gaining valuable information by doing so. Analysts host investor conferences, directly connecting their clients with firms, but also gaining information that improves their research (Green, Jame, Markov, and Subasi 2014). Personal traits such as extroversion and physical characteristics impact the extent to which analysts can gather this type of forecast-improving information, and the resulting quality of their research, indicating the important role of human characteristics and relationship-building skills in producing high-quality research (see, e.g., Peng, Teoh, Wang, and Yan 2022 and Flam, Green, Lee, and Sharp 2023). We further discuss the potential influence of analysts' incentives and behavioral biases on their forecasts in Section 4.5.

2.2 AI for Financial Analysis

Broadly speaking, there are three sets of evidence related to the use of AI for financial analysis. First, Coleman, Merkley, and Pacelli (2022) examine Robo-Analysts, which produce AI-driven analysis. They identify over 70,000 Robo-Analyst reports from 2003 through 2018, indicating the active use of AI-based analysis during this time. Robo-Analyst recommendations appear less biased and are updated more frequently than traditional analyst recommendations, and have positive investment value. However, as Coleman, Merkley, and Pacelli (2022) discuss, Robo-Analysts have minimal human involvement, and are unlikely to incorporate soft information or to have access to management. They also focus on buy-sell recommendations and rarely issue earnings forecasts. Thus, while work on Robo-Analysts highlights the spread and importance of AI in financial analysis through the 2000s and 2010s, it does not address how traditional analysts might utilize AI in their work.[3]

Second, a growing body of research examines the capabilities of AI tools for analyzing and forecasting companies' financial performance (see, e.g., Avramov, Cheng, and Metzker

[3] Grennan and Michaely (2021) examine a category of FinTech firms called "equity market intelligence FinTechs." This category includes some Robo-Analyst firms, but also includes other non-AI-based FinTechs, such as firms that focus on crowd-sourced financial analysis. They identify over 150 FinTechs that utilize data mining and other advanced data techniques in producing financial advice over the 2010-2017 period.

2023; Kim, Muhn, and Nikolaev 2024).[4] Cao et al. (2024) compare the forecasting abilities of a custom-trained AI analyst (machine), traditional human analysts (man), and an AI tool that uses human analyst forecasts as an input (man + machine). Human analysts do particularly well when forecasting earnings, relative to stock returns or cash flows. Human analysts beat the machine with a probability of 69% for earnings forecasts. The AI system using human forecasts as an input does best. Moreover, Cao et al. (2024) show that the AI system performs relatively better when there is ample publicly available data, while human analysts perform relatively better in forecasting situations that require more private information acquisition, involve less formulaic forecasts, and require judgment. As above, this work indicates the potential value and impact of AI for financial analysis. However, it does not examine how human analysts utilize AI. The "man + machine" model in Cao et al. (2024) is an AI system using human forecasts as an input, not a human using AI as a tool.

This brings us to the third set of relevant background. Our paper is the first, to our knowledge, to examine whether traditional financial analysts take advantage of AI resources to improve their productivity. It is important to note that much of the details of investment banks' in-house AI implementations are proprietary, and there is likely to be a large amount of variation across banks and over time. However, long before the advent of large language models (LLMs) like ChatGPT, AI techniques such as machine learning and natural language processing were being used in investment banks for data collection and analysis, which were used to support the production of research (Deloitte 2023). Chi, Hwang, and Zheng (2024) find that 6% of analyst reports from 2009-2010 explicitly mention the analysis of some form of

[4] A related stream of research examines the capabilities of AI versus humans for credit analysis and lending decisions. See, e.g., Costello, Down and Mehta (2020) and Liu (2022).

alternative data, such as web traffic or satellite data, increasing to 10% by 2015. While analyzing such data does not require AI, it suggests the growing use of data analytics.

Several examples illustrate the use of AI within investment banks during the 2010s. By 2016, Goldman Sachs had developed and utilized a "Data Lake," a vast trove of data on which Goldman Sachs applied machine learning techniques. Research analysts used the outputs of the Data Lake machine learning analyses to support their research (Chavez 2017; Turner 2017). Morgan Stanley's Next Best Action system, announced in 2017, was an AI-based system that provided financial advisors with personalized investment recommendations for clients (Davenport and Bean 2017; Davenport 2020). While financial advisors differ from analysts, this example shows the integration of AI tools into the bank in the mid-2010s. After other efforts to use and integrate AI, JP Morgan Chase created a new position for a head of analytics and data science in 2017, and launched its "Machine Learning Center of Excellence" in 2018 (Bloomberg Law 2017; Parsons 2020). Despite the proprietary nature of investment banks' exact AI applications, it is apparent that many investment banks were investing in AI during the 2010s, and particularly using it to support research.

Thus, sell-side analysts at investment banks were likely to experience varying access to AI resources over the last two decades, both over time and across banks, and these resources have the potential to support increased analyst productivity.

2.3 Theory and Predictions

Acemoglu (2024) outlines four ways in which AI can theoretically affect productivity. Two of these, *automation* and *deepening of automation*, relate to the use of AI to automate simple tasks. In both of these, AI is used to replace human work. We pool these into a single category, which we label *automation. Task complementarity,* in contrast, relates to the use of AI to enhance human productivity. In particular, task complementarity describes using AI to assist with work such that humans can focus time and energy on more value-added work – in other words, using the AI to complement human skills. This allows AI to enhance productivity for more complex tasks. The final way in which AI can affect productivity is through *new labor-intensive products or tasks* – essentially, innovation. Given that we focus on production of an existing product – sell-side analysts' earnings forecasts – we focus on automation and task complementarity in developing our predictions. The first two rows of Figure 1 summarize these uses of AI, and their predicted effects.

We augment Acemoglu's framework by explicitly considering potential frictions to the effective use of AI for productivity enhancement. A lack of knowledge and skills related to AI can decrease the quality of work when AI is used. For example, failing to understand the prevalence of "hallucinations" produced by large language models, lawyers have submitted legal briefs citing cases that never existed (Dahl, Magesh, Suzgum, and Ho 2024). A behavioral resistance to using AI, due to algorithm aversion, can lead to under-reliance on AI-generated information, which lowers output quality, particularly when human-provided information is no longer available (Commerford et al. 2022). In addition, theory and evidence suggests that over-reliance on AI can lead to lower quality work as employees reduce their own effort and become less attentive (Dell'Acqua 2022; Dell'Acqua et al. 2024). Together, these frictions suggest the potential for a weaker or insignificant impact of AI on production quantity, and the potential for decreases in production quality. The third row in Figure 1 summarizes these frictions, and their potential effects on production.

Together, this framework provides a set of testable predictions for the effects of AI on production quantity and quality, and variation in these effects with respect to task complexity (e.g., whether AI is being used for automation or task complementarity). Based on the full framework, we make the following predictions. Regarding production quantity, we predict that AI investments will increase production. There is some tension – frictions may reduce the effectiveness of AI tools for increasing production quantity, and can even lead to no effect. Regarding production quality, we make no specific prediction. AI has the potential to enhance production quality by allowing analysts to reduce simple human errors through automation or to focus their time and effort on more complex tasks through task complementarity. However, firms may choose to enhance production quantity at the expense of quality. Moreover, frictions can lead to the misuse of AI which decreases quality.

When considering whether AI is being used for automation or task complementarity, we focus on task complexity. Less complex tasks, which can be reduced to formulaic processes, are more likely to be automated with AI. In contrast, more complex tasks, which require more diverse processes, such as human judgment, interaction, and private information acquisition, are more likely to benefit from task complementarity. In these cases, humans use AI to automate or streamline subtasks, enabling them to focus their time and attention on tasks that benefit most from their human skills. If AI primarily increases productivity through automation, we would expect a greater increase in productivity for less complex forecasting tasks. If AI primarily increases productivity through task complementarity, we would expect a greater increase in productivity for more complex forecasting tasks.

III. Sample Selection and Variable Measurement

3.1. Measuring AI Investment

Babina et al. (2024) conduct one of the first large-scale examinations of corporate AI investment. As they discuss, "lack of comprehensive data on firm-level AI adoption has posed the key challenge to understanding the adoption patterns and the economic impact of AI technologies." (See, also, Seamans and Raj 2018). Babina et al. (2024) develop a method to measure cumulative AI investment using information from job postings and employee resumes. Fedyk et al. (2022) and Babina et al. (2024) show that job posting and employee resume data effectively capture variation in AI investment across companies and over time.

We adopt a similar approach to measure AI investments made by investment banks, using the percentage of an investment bank's job postings related to AI based on data from Bloom et al. (2024), who conduct text analysis for a large number of technologies. Specifically, Bloom et al. (2024) analyze approximately 200 million job postings from 2010 to 2019, using raw data obtained from Burning Glass, and provide data for each technology, at the location, occupation, industry, and firm levels. We use the firm-level data they generate, which includes the number of job postings from a given firm-year that mention technology-related bigrams for a set of over 200 technologies.

Our focus is on job postings that mention AI-related bigrams, such as machine learning, learning algorithms, and neural networks. These bigrams represent the most sought-after AI skills in the U.S. labor market since 2010 (Perrault and Clark 2024). We calculate the percentage of job postings from a given investment bank that include these AI-related bigrams. This serves as a measure of the extent to which an investment bank focuses on acquiring AI-related skills, indicating its level of AI investment. The independent variable used in our tests,

% AI Hiring t-3~t-1, is defined as the percentage of AI-related job postings out of all of the investment bank's job postings from year t-3 through year t-1. We use this cumulative measure over the past three years, as we expect it to take time for AI job postings to result in hiring and an increased availability and utilization of AI resources.[5]

3.2. Data and Sample

To conduct our analyses, we require technology job posting data from Bloom et al. (2024) and analyst forecast data from I/B/E/S. We match the data from Bloom et al. (2024) with I/B/E/S using investment bank names, resulting in a sample of fifteen large and mid-size investment banks that provide analyst research and are included in I/B/E/S.[6] These fifteen banks issue 35% of the earnings forecasts in I/B/E/S for our sample firms during our sample period. These investment banks also account for 35% of all I/B/E/S brokers with at least 30 analysts. We also use Compustat data to construct various control variables for the firms covered by these investment banks.

We utilize two sample periods. For our primary analyses examining investment banks' AI investments, our analyst forecast sample period is 2013 through 2020, using job posting data from 2010 through 2019, based on the availability of the job posting data. The 2010s was a period of rapidly growing AI hiring (Perrault and Clark, 2024, Figure 4.2.2). Additionally, for our analyses of the introduction of ChatGPT, we utilize a later sample period, covering 2021 through 2023, as we discuss in Section 5. Our main sample, which is used to examine

[5] The results are similar when we use the ratio of AI-related job postings to all job postings from year t-2 through year t-1, or for year t-1. Results are available upon request.

[6] The fifteen banks are AllianceBernstein, Bank of America Merrill Lynch, Credit Suisse, Deutsche Bank, Goldman Sachs, HSBC, JPMorgan Chase, Macquarie, Morgan Stanley, Nomura, Oppenheimer, Piper Jaffray, Raymond James, Stifel, and William Blair.

investment banks' AI investments, includes 120 investment bank-years with job posting data (fifteen investment banks for eight years), leading to a final sample of 70,923 analyst-firm-year observations. Table 1 provides descriptive statistics for the variables in our final sample. On average, the percentage of AI job postings from year t-3 through year t-1, *% AI Hiring t-3~t-1*, is approximately 1.1%, and the raw number of such three-year cumulative postings is about 570.[7]

Figure 2 summarizes AI-related job postings and other technology-related job postings by our sample investment banks over the period for which job posting data is available (i.e., 2010 through 2019). There was significant variation over time. The figure shows an increasing trend in AI hiring, with rapid growth from 2016 through 2019. Qualitatively, we find significant variation in the timing of AI hiring across investment banks. For example, 25% of the investment banks in our sample were already engaging in AI hiring by 2010, while another 25% did not begin until 2015. Similarly, AI hiring peaked at different times for the investment banks in our sample - peaking as early as 2016 for one investment bank, peaking in 2017 and 2018 for several others, and continuing an upward trajectory through 2019 for others. This variation in the timing of AI hiring increases our power to detect the effects of AI investment on analyst production while controlling for time trends in analyst research.

Analyst-related variables are calculated as is standard in the literature. Appendix A provides detailed variable definitions. Table 2 provides correlations among the variables used in our tests. The percentage of [t-3, t-1] job postings requiring AI-related skills is significantly positively correlated with year t forecast frequency, providing univariate evidence consistent

[7] This percentage is higher than that of other industries in general, consistent with the financial sector being more heavily affected by AI. For example, Law and Shen (2024) report that 0.41% of employees in audit offices in their final sample are classified as AI employees.

with AI investment supporting increased forecast frequency. However, the correlation between AI job postings and forecast accuracy is insignificant.

IV. Research Design and Empirical Results

4.1. Baseline Effects: Analyst Production Quantity and Quality

The issuance of an earnings forecast requires analyst effort. The analyst must incorporate new information into the forecast to determine whether and how to update the forecast amount. If AI investment allows analysts to do this work more efficiently, then they are likely to issue more frequent earnings forecasts, providing investors with additional information, and facilitating additional trading volume for the investment bank.

To examine the relationship between AI investments and analyst production quantity, we estimate the following Poisson model (Cohn, Liu, and Wardlaw 2022),

$$\begin{aligned} Forecast\ Frequency_{ijt} = {} & \beta_1 \%\ AI\ Hiring_{jt\text{-}3\sim t\text{-}1} + \\ & Investment\ Bank\text{-}Level\ Controls + Analyst\text{-}Level\ Controls + \\ & Firm\text{-}Level\ Controls + Forecast\ Frequency_{ijt\text{-}3\sim t\text{-}1} + \\ & Investment\ Bank\text{-}Firm\ FE + Year\ FE + \epsilon_{ijt}. \end{aligned} \tag{1}$$

The unit of analysis is at the analyst-firm-year level. The dependent variable, *Forecast Frequency*, is defined as the number of annual earnings forecasts issued by the analyst for the firm in the year. The variable of interest is *% AI Hiring t-3~t-1*, which captures the percentage of AI job postings over the prior three years. We estimate the model both without, and with, a control for prior forecast frequency over the same period, *Forecast Frequency t-3~t-1*. We cluster standard errors at the firm level (e.g., Coleman, Merkley, and Pacelli 2022).

In addition, we include several variables to control for other factors that may be associated with analyst productivity (e.g., Driskill, Kirk, and Tucker 2020; Lang, Pinto, and Sul 2024). First, we include investment bank-level control variables: each investment bank's general technology-related hiring and size. These variables control for the level of non-AI resources at the investment bank level, including general technology-related investment.[8] Second, we include analyst-level control variables: each analyst's general experience and firm-specific experience. Lastly, we control for firm characteristics that might affect analyst productivity: the total number of analysts covering the firm, firm size, leverage, return on assets (ROA), market-to-book ratio, annual return, annual return volatility, and whether the firm has a loss. We additionally include investment bank-firm fixed effects and year fixed effects to control for time invariant investment bank-firm-specific characteristics and general time trends, which might influence analyst productivity.[9]

The results are reported in Table 3, Columns (1) and (2). Columns (1) and (2) present the results from the model without and with *Forecast Frequency t-3~t-1*, respectively. Consistent with AI enabling analysts to increase production, we find that the coefficients on *% AI Hiring t-3~t-1* are positive and significant at the 1% level in both models.

To gain further insights into the effects of AI investments on analyst production quantity, we also examine other types of forecasts: the number of quarterly earnings forecasts and the number of annual non-earnings forecasts (e.g., sales, cash flows, etc.). In particular, if AI is assisting analysts in increasing overall productivity, it should increase forecast frequency across multiple types of forecasts. Further, if AI is assisting with quantitative analysis in particular, we should see that with increases in component forecasts, such as sales and cash

[8] Because of the positive correlation between AI hiring and other technology hiring, we also replicate all analyses excluding this control. Results remain significant and consistent. Results are available upon request.

[9] All results are similar when using analyst-firm fixed effects instead of investment bank-firm fixed effects.

flows. The results are reported in Table 3, Columns (3) through Columns (6). We find a significantly positive effect of AI investments on all of these forecasts.

In terms of economic magnitudes, the results in Table 3, Columns (2) indicate that a one standard deviation increase in *% AI Hiring t-3~t-1* increases the forecast frequency for annual earnings forecasts by 1.4%.[10] The effects are even larger for other forecasts. For example, the results in Column (6) indicate that a one standard deviation increase in *% AI Hiring t-3~t-1* increases the forecast frequency for annual non-earnings forecasts by 2.8%. These findings suggest that AI resources in investment banks enable analysts to forecast multiple dimensions of firm performance, including drivers of earnings such as sales and cash flows, and earnings at varying horizons, such as quarterly as well as annual.

We use a similar model to examine the relationship between AI investments and analyst production quality. We focus on analyst forecast accuracy as a measure of the quality of the analysts' forecasts. In particular, we estimate the following ordinary least squares model,

$$
\begin{aligned}
Forecast\ Accuracy_{ijt} = {} & \beta_1 \%\ AI\ Hiring_{jt\text{-}3\sim t\text{-}1} + \\
& Investment\ Bank\text{-}Level\ Controls + Analyst\text{-}Level\ Controls + \\
& Firm\text{-}Level\ Controls + Forecast\ Accuracy_{ijt\text{-}3\sim t\text{-}1} + \\
& Investment\ Bank\text{-}Firm\ FE + Year\ FE + \epsilon_{ijt}. \qquad (2)
\end{aligned}
$$

The dependent variable, *Forecast Accuracy*, is defined as -1 times the average forecast error for forecasts issued by the analyst for the firm in the year, where forecast error is the absolute value of the difference between the forecasted EPS and actual EPS, scaled by the stock price

[10] In Column (2), the economic magnitude is calculated as (exp (0.332) - 1) × 0.035 = 1.4%. At the investment bank level, this translates into 4.733 (number of annual earnings forecasts for a firm by a given analyst) × 946 (number of firms covered by analysts at the average investment bank) × 1.4% = 63 additional annual earnings forecasts per investment bank.

at the beginning of the fiscal year. As with Equation (1), we estimate the model both without and with a control for past forecast accuracy, in this case, *Forecast Accuracy t-3~t-1*.

We make no specific prediction for the effect of AI investments on analyst research quality. As summarized in Section 2 and Figure 1, theory is unclear on the effects of AI on production quality. Using AI for automation can either improve quality, e.g., by reducing human errors, or decrease quality, e.g., if used primarily for cost-reduction. In particular, similarly to other cost reduction efforts, companies may accept lower quality in order to achieve lower cost. If used for task complementarity purposes, AI tools should lead to an increase in quality, as AI would allow analysts to focus their time and effort on more complex tasks, leading to higher quality work. Other frictions to optimal AI use, such as incomplete understanding of how to use AI (e.g., Dell'Acqua 2022; Dahl et al. 2024), or algorithm aversion (e.g., Commerford et al. 2022) can lead to decreases in quality.

Results are reported in Table 4. Columns (1) and (2) present the results from the model without and with *Forecast Accuracy t-3~t-1*, respectively. Consistent with AI facilitating higher quality analyst work, we find that the coefficients on *% AI Hiring t-3~t-1* are negative and significant at the 5% levels. Specifically, these results suggest that AI investments improve analyst forecast accuracy. In terms of economic magnitude, a one standard deviation increase in *% AI Hiring t-3~t-1* is associated with a 2.3% increase in forecast accuracy.[11] For a stock with a price of $50 and average forecast accuracy of -0.048, this implies that the earnings forecasts become more accurate by 5.5 cents per share.

[11] In Column (2), the economic magnitude is calculated as $0.035 \times 0.032 \div 0.048 = 2.3\%$.

4.2. Task Complexity: Automation vs. Task Complementarity

As discussed in the introduction and Section 2, task complexity plays an important role in the potential uses of AI (Acemoglu 2024). In particular, tasks that can be more easily reduced to a formulaic work process (less complex tasks) are more likely to be automated through the use of AI. In contrast, tasks that require more varied processes, human judgment, interaction, and private information acquisition, (more complex tasks) are unlikely to be automated. However, such work can still benefit from AI through task complementarity, in which employees use AI to automate or facilitate specific subtasks, allowing them to focus their time on the components that benefit most from their time and attention.

To provide insight into whether AI improves analyst productivity through automation or task complementarity, we examine cross-sectional variation in the positive effect of AI investments on analyst productivity with respect to task complexity, defined as above. If AI merely facilitates automation, we would expect a stronger benefit for less complex forecasting tasks. If AI facilitates task complementarity, we would expect a stronger benefit for more complex forecasting tasks.

We measure two distinct drivers of the complexity of analysts' earnings forecasting tasks for a given firm: the firm's fundamental uncertainty and its information environment. We expect that both greater fundamental uncertainty and a poorer information environment will increase the complexity of forecasting earnings. We use two proxies to measure fundamental uncertainty for a given firm-year: *Higher Dispersion*, defined as an indicator variable that equals one if the firm's forecast dispersion (the standard deviation of all forecasts, scaled by the absolute value of the median forecast) for the year is above the median, and *Higher Ret Vol*, defined as an indicator variable that equals one if the firm's return volatility for the year is above the median. Fundamental uncertainty will increase the complexity of the forecasting task, given that prior models (i.e., models that AI might build based upon past data) are less likely to be sufficient to forecast current/future earnings.

In addition, we use two additional proxies to measure a poorer information environment for a given firm-year: *High Bid Ask Spread*, defined as an indicator variable that equals one if the firm's average daily value of bid ask spread (the difference between the quoted closing bid and ask, scaled by the closing price on the day) for the year is above the median, and *Low Voluntary Disclosure*, defined as an indicator variable that equals one if the firm does not issue management earnings guidance in the year. In these cases, additional information collection is likely to be important, involving actions such as site visits, phone calls, and other human tasks, which cannot easily be replicated by AI.

We interact these task-complexity proxies with *% AI Hiring t-3~t-1*, control variables, and fixed effects in Equations (1) and (2) (i.e., we utilize fully interacted models). For forecast frequency, we focus on annual earnings forecasts. Our variables of interest are *% AI Hiring t-3~t-1 × High Dispersion*, *% AI Hiring t-3~t-1 × High Ret Vol*, *% AI Hiring t-3~t-1 × High Bid Ask Spread*, and *% AI Hiring t-3~t-1 × Low Voluntary Disclosure*. If AI primarily supports analyst productivity through automation, we should find negative coefficient estimates on these interaction variables – a lower benefit of AI for more complex forecasting tasks. In contrast, if AI primarily supports analyst productivity through task complementarity, we should find positive coefficient estimates – a higher benefit of AI for more complex forecasting tasks.

We present the results in Table 5. Panel A presents the results for fundamental uncertainty. In Columns (1) and (2), we present results for *High Dispersion*. We find significantly positive coefficients on *% AI Hiring t-3~t-1 × High Dispersion* for both forecast frequency and forecast accuracy. Columns (3) and (4) present the results for *High Ret Vol*. We also find significantly positive coefficients on *% AI Hiring t-3~t-1 × High Ret Vol* for both forecast frequency and forecast accuracy. Together, these results indicate that the positive effects of AI investments on analyst production quantity and quality are stronger for higher dispersion stocks and more volatile stocks, which are likely to be more complex to forecast, suggesting that analysts primarily use AI for task complementarity purposes.

Panel B presents the results for variation with respect to firms' information environments. Columns (1) and (2) present the results from *High Bid Ask Spread*. We find that the coefficients on *% AI Hiring t-3~t-1 × High Bid Ask Spread* are significantly positive for both forecast frequency and forecast accuracy. Columns (3) and (4) present the results from *Low Voluntary Disclosure*. We find a significantly positive coefficient on *% AI Hiring t-3~t-1 × Low Voluntary Disclosure* for forecast frequency in Column (3), but do not find a significant result for forecast accuracy in Column (4). These results suggest that the positive effects of AI investments on analyst production quantity and quality are generally stronger for stocks with a poorer information environment. This again suggests that analysts primarily use AI for task complementarity purposes.

Together, the results in Table 5 suggest that analysts use AI resources to assist in their overall work through task complementarity, rather than automation. Through task complementarity, AI resources enable analysts to focus their time and efforts on more complex forecasting tasks, where human skills and judgment can add greater value.

4.3. Analyst Abilities: Leveling the Playing Field

Several studies have shown that AI tools are particularly impactful in improving the productivity of less-skilled employees (e.g., Brynjolfsson, Li, and Raymond 2023; Peng, Kalliamvakou, Cihon and Demirer 2023; Noy and Zhang 2023). While some analysts possess extensive expertise and access to resources that improve their productivity, others with limited expertise and fewer resources may struggle to perform at the same level. AI has the potential to reduce these disparities by providing tools that bridge gaps in skill and resource availability.

We measure analysts' firm-specific forecasting ability based on their past forecast accuracy for the given firm. Specifically, we construct *Inferior Analysts*, defined as an indicator variable that equals one if the analyst's forecast accuracy in the past three years is below the median, and zero otherwise. We interact this variable with *% AI Hiring t-3~t-1*, control variables, and fixed effects in Equations (1) and (2) (i.e., we utilize fully interacted models), consistent with Table 5. For forecast frequency, we continue to focus on annual earnings forecasts. Our variable of interest is *% AI Hiring t-3~t-1* × *Inferior Analysts*.

We present the results in Table 6. We find significantly positive coefficients on *% AI Hiring t-3~t-1* × *Inferior Analysts* for both forecast frequency and forecast accuracy. These results suggest that the positive effects of AI investments on analyst production quantity and quality are stronger for analysts with previously poorer performance, consistent with AI resources helping to level the playing field across analysts. Moreover, the effects of AI investments on forecast frequency and accuracy are concentrated in this half of analysts.

4.4. New Analyst Coverage

In this section, we examine whether AI-induced production increases affect the number of firms that analysts cover, and which firms they choose to cover. In particular, AI investments positively impact analyst productivity, and an investment bank could choose to use this increased productivity to increase the number of firms it covers. Given the significant market benefits of analyst coverage, e.g., improved stock liquidity and improved incorporation of information into stock prices (e.g., Bradshaw, Ertimur and O'brien 2017), this has the potential to significantly improve the overall information environment of firms and benefit investors.

To examine the relationship between AI investments and analyst firm coverage, we estimate the following Poisson model (Cohn, Liu, and Wardlaw 2022),

$$\begin{aligned}\#\,Firms\ Covered_{jt} &= \beta_1 \%\ AI\ Hiring_{jt\text{-}3\sim t\text{-}1} + \\ &\quad Investment\ Bank\text{-}Level\ Controls + \#\,Firms\ Covered_{jt\text{-}3\sim t\text{-}1} + \epsilon_{jt}. \quad (3)\end{aligned}$$

The unit of analysis is at the investment bank-year level. The dependent variable, *# Firms Covered*, is defined as the number of all firms covered by analysts in the investment bank in the year. The variable of interest is *% AI Hiring t-3~t-1*. We control for the lagged dependent variable, consistent with Equations (1) and (2). Given the small sample size, we do not include fixed effects in this analysis. The results are reported in Table 7, Column (1). Consistent with our expectation, we find that the coefficient on *% AI Hiring t-3~t-1* is positive and significant at the 5% level, suggesting that AI investments increase analysts' firm coverage.

Furthermore, to examine whether the increase in firm coverage is indeed due to the initiation of new coverage, we disaggregate *# Firms Covered* into the number of firms covered in the year that were also previously covered by analysts in the investment bank (*# Existing*) and the number of firms that are newly covered by analysts in the investment bank in the year (*# New*). Finally, we further break down *# New* into two categories: the number of firms newly covered by analysts in the investment bank in the year that were covered by at least one analyst in I/B/E/S, from a different brokerage, in the previous year *(# New-Previously NonZero*

Coverage) and the number of firms newly covered by analysts in the investment bank in the year that were not covered by any analysts in I/B/E/S in the previous year (*# New-Previously Zero Coverage Firms*). Mola, Rau, and Khorana (2013) show that going from non-zero to zero coverage has significant effects on stock liquidity, and even increases the chances of companies delisting, while Li and Yu (2015) find evidence that analyst coverage initiations reduce firms' cost of capital through increasing investor recognition, highlighting the economic significance of non-zero vs. zero coverage.

The results are reported in Table 7, Columns (2) through (5). While we do not find a significant coefficient in Column (2), we observe a significantly positive coefficient in Column (3), suggesting that the association between AI investments and firm coverage reported in Column (1) is explained by the initiation of new coverage. We also find significantly positive coefficients in Columns (4) and (5). Notably, the result in Column (5) indicates that AI investments enable analysts to expand their coverage to firms without analyst coverage, which may be more difficult to forecast due to insufficient information. This finding is also consistent with the idea that AI improves analyst productivity through task complementarity.

4.5. Analysts' Strategic Forecasting Behavior

We also explore how AI investments affect strategic biases in analysts' forecasts. Prior literature provides both theoretical and empirical evidence of analysts strategically biasing earnings forecasts given their incentive structures. In particular, analysts are likely to optimistically bias earnings forecasts in order to generate brokerage trading volume (e.g., Beyer and Guttman 2011; Jackson 2005; Lehmer, Lourie, and Shanthikumar 2022), and to "walk down" earnings forecasts to a beatable level in order to curry favor with management and gain access to future private information from management (e.g., Richardson, Teoh, Wysocki 2004; Ke and Yu 2006).

It is unclear whether and how AI resources in investment banks will affect such biases. AI automation, such as Robo-Analysts, has been shown to be less biased than research conducted by human analysts, as it is less influenced by cognitive biases and incentives (Coleman, Merkley, and Pacelli 2022). However, AI investments may also increase pressure on analysts to boost productivity while also raising concerns about job displacement (e.g., Violino 2024). This pressure and concern could potentially lead to more biased research aimed at increasing brokerage trading volume and pleasing firm management to gain access to private information. Furthermore, Ke and Yu (2006) show that analysts can use such strategic forecasting behavior to curry favor with management and gain future information – introducing bias into forecasts *without* reducing current forecast accuracy, while potentially improving future accuracy. In the same way that task complementarity uses of AI can facilitate other human efforts such as information acquisition, exercise of judgment, etc., AI may facilitate more strategic forecasting behavior.

To examine the relationship between AI investments and analyst forecast biases, we estimate the following ordinary least squares model,

$$\begin{aligned} &\textit{Forecast Optimism or Walkdown}_{ijt} = \beta_1\%\ \textit{AI Hiring}_{jt\text{-}3\sim t\text{-}1} + \\ &\quad \textit{Investment Bank-Level Controls} + \textit{Analyst-Level Controls} + \\ &\quad \textit{Firm-Level Controls} + \textit{Forecast Optimism or Walkdown}_{ijt\text{-}3\sim t\text{-}1} + \\ &\quad \textit{Investment Bank-Firm FE} + \textit{Year FE} + \epsilon_{ijt}. \qquad (4) \end{aligned}$$

The unit of analysis is at the analyst-firm-year level. We use two dependent variables that reflect analyst bias: *Forecast Optimism*, defined as the average forecast optimism for forecasts issued by the analyst for the firm in the year, where forecast optimism is the difference between the forecasted EPS and actual EPS scaled by the absolute value of actual EPS, and *Walkdown*, defined as an indicator variable that equals one if the first forecast is greater than the actual EPS and the last forecast is less than or equal to the actual EPS for the year, and zero otherwise. As with Equations (1) and (2), we estimate the model both without and with a control for past forecast bias, in this case, *Forecast Optimism t-3~t-1* and *Walkdown t-3~t-1*.

Results are reported in Table 8. Columns (1) and (2) present the results from *Forecast Optimism* without and with *Forecast Optimism t-3~t-1*, respectively. We find that the coefficients on *% AI Hiring t-3~t-1* are positive and significant at the 10% level in both columns, suggesting that analysts in investment banks with higher AI investments tend to provide more optimistically biased forecasts in general. Columns (3) and (4) present the results from *Walkdown* without and with *Walkdown t-3~t-1*, respectively. We find that the coefficients on *% AI Hiring t-3~t-1* are positive and significant at the 1% levels in both columns, suggesting that analysts in investment banks with higher AI investments tend to exhibit the walkdown behavior to allow firms to more easily beat or meet analyst earnings forecasts.

Collectively, analysts in investment banks with high AI investments tend to provide more optimistic forecasts but revise them downward before firms' earnings announcements, indicating potential strategic forecasting behavior driven by incentives such as brokerage trading incentives and the desire to curry favor with management. While this may be optimal from the analyst and investment bank's perspectives, it may be important for investors to consider such incentives and biases when trading based on analysts' earnings forecasts (e.g., Malmendier and Shanthikumar 2007, Mikhail, Walther and Willis 2007; Malmendier and Shanthikumar 2014).

V. The Impact of ChatGPT 3.5: An Exogenous Shock to AI Use

Our primary analyses, reported in Section 4, focus on investment bank-specific investments in AI. Open AI's public and free release of ChatGPT 3.5 on November 30, 2022, marked a dramatic shift in the use of AI. ChatGPT's conversational interactive style allowed lay users to quickly and easily start using AI tools. Because Open AI provided free access, its use expanded rapidly, reaching 1 million users within a week, and 100 million users in less than two months (UBS 2023; Hu 2023). Following the introduction of ChatGPT 3.5, AI use became commonplace, and other AI systems were rapidly introduced. We expect this shift in the cultural awareness and acceptance of AI to increase analysts' use of AI. The introduction of ChatGPT 3.5 also led to a rapid increase in easily accessible and digestible information about AI, potentially increasing analysts' knowledge about AI tools and reducing the impact of frictions such as lack of knowledge and algorithm aversion. Together, the introduction of Chat GPT 3.5 serves as a shock to analysts' AI use. The introduction was also exogenous to investment banks, driven by Open AI, allowing us to provide evidence on the causal impact of AI use on analyst productivity. Specifically, to supplement our primary analyses reported in Section 4, we repeat those analyses in the following subsections using the introduction of ChatGPT as an alternative proxy for analysts' AI use.[12]

5.1. Baseline Effects: Analyst Production Quantity and Quality

To examine changes in analyst productivity after the introduction of ChatGPT, we estimate the following model,

[12] We replicate all analyses except for new analyst coverage analyses. Because we have only one year of post-ChatGPT data, and the level of observations for the coverage test is at the investment bank-year-level, we have insufficient power to replicate the coverage test using the introduction of ChatGPT.

$$\begin{aligned}Forecast\ Frequency_{ijt}\ or\ Forecast\ Accuracy_{ijt}\\ &= \beta_1 Post\ ChatGPT + Investment\ Bank\text{-}Level\ Controls\\ &+ Analyst\text{-}Level\ Controls + Firm\text{-}Level\ Controls\\ &+ Investment\ Bank\text{-}Firm\ FE\\ &+\ \epsilon_{ijt}. \qquad (5)\end{aligned}$$

For this analysis, we focus on a sample period from 2021 through 2023, covering the three years surrounding the introduction of ChatGPT, and we continue to use our sample investment banks. *Post ChatGPT* is defined as an indicator variable that equals one for 2023 (after ChatGPT was introduced), and zero otherwise. We use the same control variables used in Equations (1) and (2). We do not use year fixed effects as year fixed effects subsume *Post ChatGPT*, which is our variable of interest in this analysis.

Before estimating Equation (5), we plot the means for *Forecast Frequency* and *Forecast Accuracy* over time around the introduction of ChatGPT, as shown in Figure 3, Panel A. This figure shows that there are noticeable increases in forecast frequency and accuracy after the introduction of ChatGPT (i.e., 2023).

Next, we estimate Equation (5) and present the results in Table 9 Panel A. Columns (1) and (2) report the results for forecast frequency and accuracy, respectively. In both columns, we find significantly positive coefficients on *Post ChatGPT*. These findings suggest that the introduction of ChatGPT improves analyst production quantity and quality, consistent with our main findings in Tables 3 and 4, and support a causal relation between AI use and analyst productivity.

5.2. Task Complexity: Automation vs. Task-Complementarity

To better attribute our results from Equation (5) to the introduction of ChatGPT and to examine whether the increase in AI use around ChatGPT provides task complementarity similarly to investment banks' AI investments, we investigate the cross-sectional variation in ChatGPT's effect on analyst productivity with respect to task complexity.

We measure task complexity using four measures, as described in Section 4.2: *Higher Dispersion*, *Higher Ret Vol*, *High Bid Ask Spread*, and *Low Voluntary Disclosure*. We first examine the trends in differences in *Forecast Frequency* and *Forecast Accuracy* over time from 2021 to 2023 between groups with high and low forecasting complexity based on these measures. The results are presented in Figure 3, Panel B. We find that, following the introduction of ChatGPT (i.e., 2023), forecast frequency and accuracy tend to increase more for the groups that are more complex to forecast, relative to the groups that are less complex to forecast.

Next, we examine this cross-sectional variation using regression analyses. To do so, we interact our task complexity proxies with *Post ChatGPT* and control variables in Equation (5). We include both investment bank-firm fixed effects and year fixed effects, but we do not interact the task complexity proxies with the fixed effects, as our variables of interest would be subsumed if we did so (given that we have only one post-year). Our variables of interest are *Post ChatGPT* × *High Dispersion*, *Post ChatGPT* × *High Ret Vol*, *Post ChatGPT* × *High Bid Ask Spread*, and *Post ChatGPT* × *Low Voluntary Disclosure*.

We present the results in Table 9, Panels B and C. Panel B presents the results from *High Dispersion* and *High Ret Vol*. Panel C presents the results from *High Bid Ask Spread* and *Low Voluntary Disclosure.* The main effect of ChatGPT introduction is subsumed by year fixed effects. The coefficient on the interaction term captures the differential effect of ChatGPT for more complex forecasting tasks. Across all panels and columns, we find that our coefficients of interest are significantly positive, suggesting that the positive effects of

ChatGPT on analyst production quantity and quality are stronger for firms that are more complex to forecast. These findings are also consistent with the results from investment banks' AI investments in Table 5.

5.3. Additional Analyses: Analyst Abilities and Strategic Forecasting Behavior

We also examine whether the effect of the introduction of ChatGPT on analyst productivity is stronger for analysts with previously lower performance. We use *Inferior Analysts*, as defined in Section 4.3, and interact this variable with *Post ChatGPT* and control variables in Equation (5), similar to Table 9, Panels B and C. The results are reported in Table 9, Panel D. We find that the coefficients on *Post ChatGPT* × *Inferior Analysts* are significantly positive in both columns. These results suggest that the introduction of ChatGPT has a stronger effect on the productivity of analysts with previously poorer performance, consistent with our results in Table 6, which examines investment banks' AI investments, and with the idea that AI can help level the playing field.

Lastly, we examine changes in analysts' strategic forecasting behavior after the introduction of ChatGPT. To do this, we replace the dependent variable in Equation (5) with our measures of forecast bias used in Section 4.5. We present the results in Table 9, Panel E. While we do not find a significant coefficient on *Post ChatGPT* in Column (1), we find a significantly positive coefficient on *Post ChatGPT* in Column (2). This finding suggests that the introduction of ChatGPT increases analysts' strategic forecasting behavior, consistent with our results in Table 8, which examines investment banks' AI investments, and with the idea that AI increases strategic analyst forecast behavior.

Overall, all results in Section 5, where we use the introduction of ChatGPT as a shock to AI usage, are consistent with our results in Section 4, which examines investment banks' AI investments.

VI. Conclusion

The growing use and integration of AI into financial services raises questions around the impact of AI on traditional financial analysis. Our study provides the first large-sample evidence of the effects of AI investment in the financial services industry on sell-side analysts' research, specifically their earnings forecasts. We find an increase in both the frequency and accuracy of earnings forecasts following AI investments, suggesting that AI facilitates increased production quantity and quality.

Consistent with AI being used for task complementarity purposes, allowing analysts to focus their time and effort on less formulaic value-added tasks, collecting private information, building relationships, and exercising judgment, the effect of AI is stronger for more complex forecasting tasks. In particular, the effect of AI on both forecast frequency and accuracy is stronger for firms with higher fundamental uncertainty, as measured by earnings forecast dispersion and stock return volatility – firms for which past data is less likely to lead to a strong model for current and future earnings. The effect of AI is also stronger for firms with poorer information environments, as measured by low voluntary disclosure and high bid-ask spreads, for which private information acquisition is likely to be more important.

We conduct additional analyses that provide insight into the effects of AI for both traditional analysts and investors. AI helps to level the playing field across analysts – enhancing research productivity the most for analysts who were previously less accurate.

Investment banks take advantage of AI-induced productivity gains to initiate coverage of companies which were not previously covered, providing novel information to investors. And analysts' strategic forecasting behaviors – optimistic forecasts in general, and "beatable" forecasts just before the earnings announcement – increase with AI investments, in contrast to the effects of more automated AI analysis such as Robo-Analysts.

Finally, we exploit the introduction of Chat GPT, which provides an exogenous shock to the use of AI, to examine the causal effects of AI use on analyst productivity. We find that ChatGPT has similar effects as investment banks' AI investments – the introduction of ChatGPT increases forecast quantity and quality, provides a stronger improvement in earnings forecasts for firms with higher fundamental uncertainty or poorer information environments, levels the playing field, and increases strategic forecasting behavior.

Together, our results address fundamental questions surrounding the use and effects of AI in the economy. In particular, while prior and concurrent research examines AI analysts and the capabilities of AI systems, ours is the first paper to examine how AI affects traditional analysts. Theory is unclear on whether AI will be used to replace or supplement human productivity, what effect it will have on quality, and whether it will have a greater effect on easy-to-automate tasks or more complex tasks. Our study also yields practical insights for those who are hoping to make better use of AI. Knowledge-intensive companies can potentially make the best use of AI by focusing on task complementarity.

The primary caveat to our study is that we focus on realized effects for a large cross-section of analysts and banks. We lack visibility into the specific implementations at each bank. Future research that takes a more focused behind-the-scenes approach, such as Groysberg, Healy and Maber (2011) or Soltes (2014), can complement our work. As AI systems continue to evolve and become increasingly complex and capable, it will also be important to examine if and how the use of AI in financial analysis, and the role of human analysts, changes. Uses of AI will vary significantly across industries, over time, and even across companies within an industry. Our study helps to advance our knowledge in this area, and provides a general framework for the productivity effects of AI for existing products/services, which can be used in future studies.

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Appendix A. Variable definitions

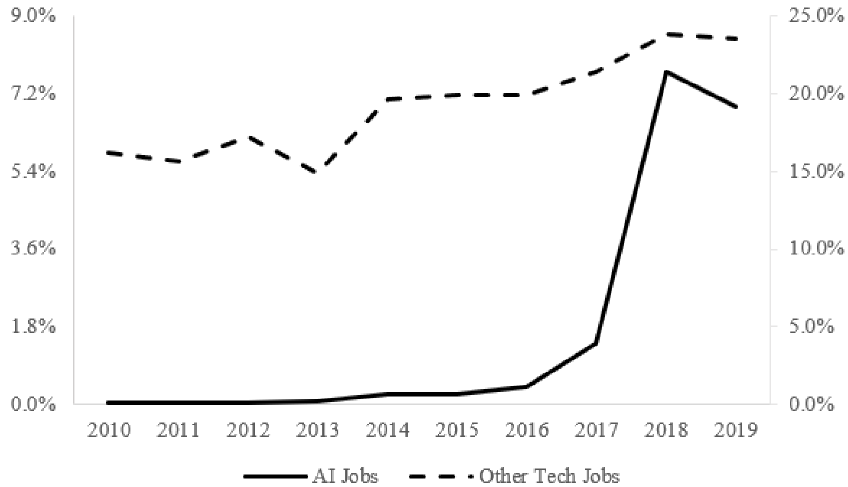
Variable	Description
% AI Hiring	The ratio of AI-related job postings to all job postings in the year.
# Firms Covered	The number of all firms covered by analysts in the investment bank in the year.
Analyst General Exp	The natural logarithm of the number of years since the analyst first appeared in IBES.
Analyst Firm Exp	The natural logarithm of the number of years since the analyst-firm pair first appeared in IBES.
Firm # Analysts	The natural logarithm of the number of all analysts following the firm in the year.
Firm Ann Ret	Annual market-adjusted stock return in the year.
Firm Leverage	The ratio of total debt to total assets at the end of the year.
Firm Loss	An indicator variable that equals one if the firm's net income in the year is negative, and zero otherwise.
Firm MTB	The ratio of market value of equity to book value of equity at the end of the year.
Firm Ret Vol	The standard deviation of monthly returns in the year.
Firm ROA	The ratio of net income to total assets in the year.
Firm Size	Firm size measured as the natural logarithm of market value of equity at the end of the year.
Forecast Accuracy	The average accuracy of forecasts issued by the analyst for the firm in the year, where forecast accuracy is calculated as the absolute value of the difference between the forecasted EPS and actual EPS scaled by the stock price at the beginning of the fiscal year (multiplied by (-1)).
Forecast Frequency	The number of annual earnings forecasts issued by the analyst for the firm in the year.
Forecast Optimism	The average optimism of forecasts issued by the analyst for the firm in the year, where forecast optimism is calculated as the difference between the forecasted EPS and actual EPS scaled by the absolute value of actual EPS.
High Bid Ask Spread	An indicator variable that equals one if the firm's average daily value of bid ask spread (the difference between the quoted closing bid and ask, scaled by the closing price on the day) for the year is above the median, and zero otherwise.

High Dispersion	An indicator variable that equals one if the firm's forecast dispersion (the standard deviation of all forecasts, scaled by the absolute value of the median forecast) for the year is above the median, and zero otherwise.
High Ret Vol	An indicator variable that equals one if the firm's return volatility for the year is above the median, and zero otherwise.
Inferior Analysts	An indicator variable that equals one if the analyst's forecast accuracy for the past three years is below the median, and zero otherwise.
Investment Bank Size	The natural logarithm of the number of analysts in the investment bank in the year.
Low Voluntary Disclosure	An indicator variable that equals one if the firm does not issue management earnings guidance in the year, and zero otherwise.
Other Tech Hiring	The natural logarithm of other non-AI technology-related job postings in the year.
Post ChatGPT	An indicator variable that equals one for 2023 (after ChatGPT was introduced), and zero otherwise.
Walkdown	An indicator variable that equals one if the first forecast is greater than the actual EPS and the last forecast is less than or equal to the actual EPS for the year, and zero otherwise.

Figure 1. Artificial intelligence – A Framework for potential uses and frictions to use

	Description/Definition	Effect on Production Quantity	Effect on Production Quality
Automation	AI use to automate tasks which were previously not automated, or to enhance the productivity of other automation tools, such as existing machinery or software	Increase, especially for simpler/easier-to-automate tasks	Increase, no change, and decrease are all possible, depends on automation details
Task Complementarity	AI provides information or tools which enhance human productivity; Frees humans to focus time/effort on value-added/non-automated tasks	Increase, especially for more complex/ harder-to-automate tasks	Increase, especially for more complex/ harder-to-automate tasks
Psychological and Managerial Frictions	Lack of knowledge/skills → mistakes in use; Algorithm aversion → psychological resistance to use; Overreliance → lower human effort and attention	No clear prediction	Decreases in quality if AI is misused

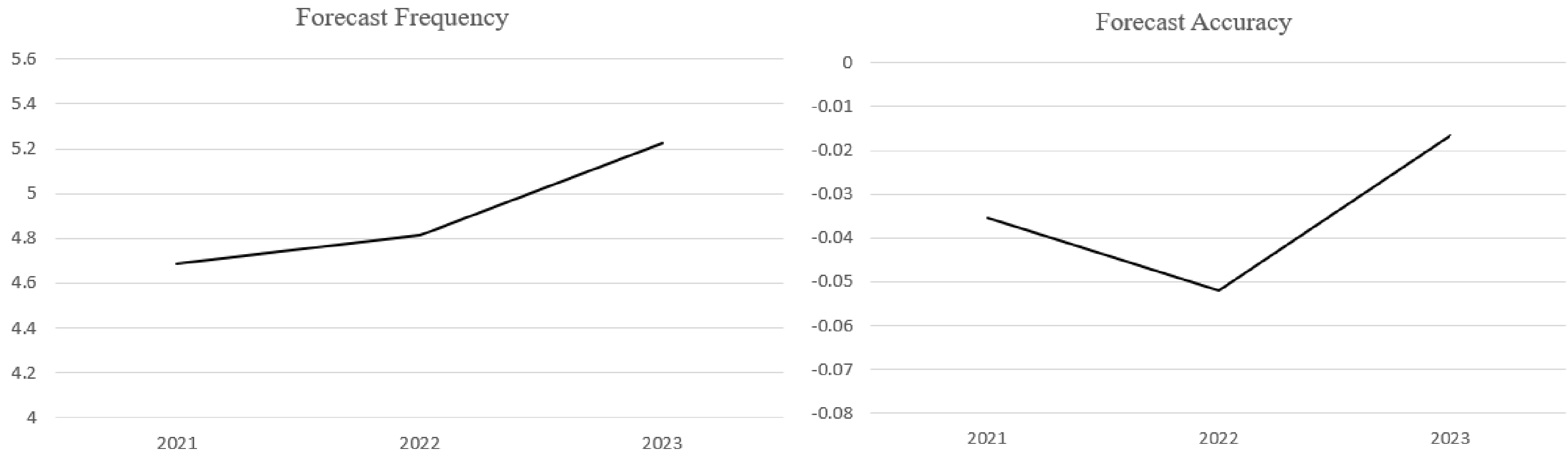
Figure 2. Time trends in AI-related jobs and other technology-related jobs, as a percentage of total job postings, for sample investment banks



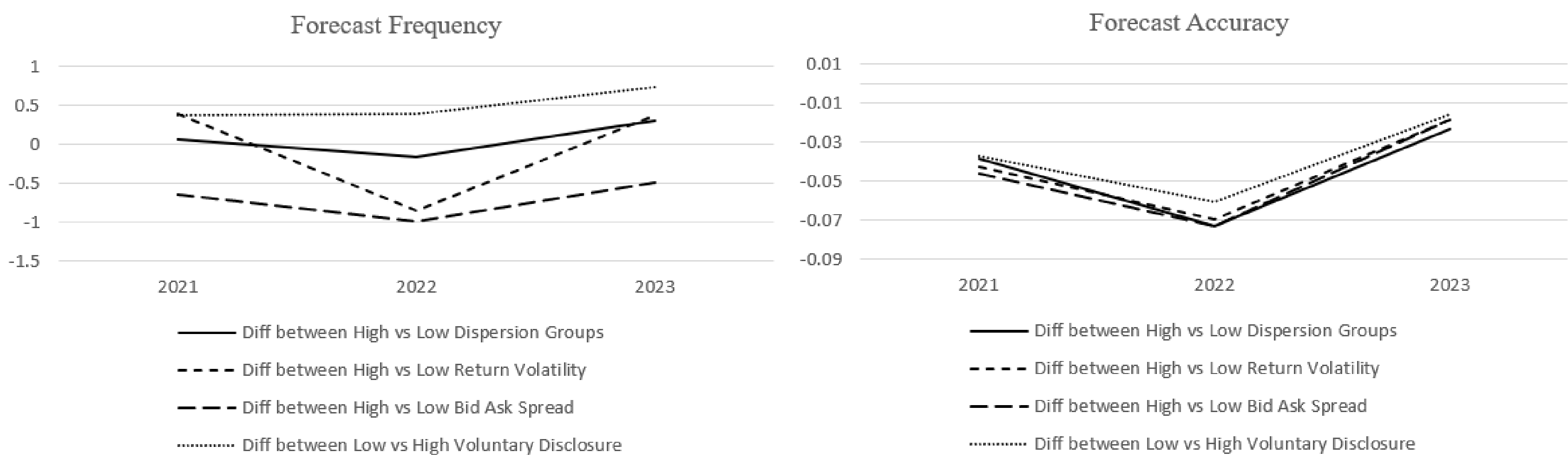
This figure presents the time trend in the average percentage of AI-related job postings (solid line and left axis) and the average percentage of other-technology job postings (dotted line and right axis) for our sample investment banks between 2010 and 2019.

Figure 3. The effect of ChatGPT on analyst productivity

Panel A. Forecast frequency and accuracy over time around the introduction of ChatGPT, November 30, 2022



Panel B. The difference in forecast frequency and accuracy between groups of firms, based on complexity of forecasting, over time around the introduction of ChatGPT, November 30, 2022



Panel A displays the means of *Forecast Frequency* and *Forecast Accuracy* from 2021 to 2023. *Forecast Frequency* is defined as the number of annual earnings forecasts issued by the analyst for the firm in the year, and *Forecast Accuracy* is defined as the average accuracy of forecasts issued by the analyst for the firm in the year, where forecast accuracy is calculated as the absolute value of the difference between the forecasted EPS and actual EPS scaled by the stock price at the beginning of the fiscal year (multiplied by (-1)). Panel B displays the differences in the means of *Forecast Frequency* and *Forecast Accuracy* between two groups from 2021 to 2023. The groups are based on the following variables: (i) *Higher Dispersion*, defined as an indicator variable that equals one if the firm's forecast dispersion (the standard deviation of all forecasts, scaled by the absolute value of the median forecast) for the year is above the median, and zero otherwise, (ii) *Higher Ret Vol*, defined as an indicator variable that equals one if the firm's return volatility for the year is above the median, and zero otherwise, (iii) *High Bid Ask Spread*, defined as an indicator variable that equals one if the firm's average daily value of bid ask spread (the difference between the quoted closing bid and ask, scaled by the closing price on the day) for the year is above the median, and zero otherwise, and (iv) *Low Voluntary Disclosure*, defined as an indicator variable that equals one if the firm does not issue management earnings guidance in the year, and zero otherwise.

Table 1. Descriptive statistics

VARIABLES	**Mean**	**SD**	**p5**	**p25**	**Median**	**p75**	**p95**
% AI Hiring t-3~t-1	0.011	0.035	0.000	0.000	0.001	0.006	0.045
Raw AI Hiring t-3~t-1	570.280	2195.515	0.000	0.000	9.000	103.000	3509.000
Forecast Frequency t	5.296	2.780	1.000	4.000	5.000	7.000	11.000
Forecast Accuracy t	-0.048	0.230	-0.130	-0.015	-0.005	-0.002	0.000
Forecast Optimism t	0.080	0.755	-0.474	-0.071	-0.009	0.073	0.922
Walkdown t	0.239	0.426	0.000	0.000	0.000	0.000	1.000
Other Tech Hiring t-3~t-1	7.071	2.174	3.434	5.412	7.019	8.871	10.653
Investment Bank Size t	4.691	0.546	3.829	4.205	4.736	5.242	5.481
Analyst General Exp t	2.414	0.773	1.099	1.946	2.485	3.045	3.497
Analyst Firm Exp t	1.628	0.673	0.693	1.099	1.609	2.197	2.773
Firm # Analysts t	2.823	0.569	1.792	2.485	2.890	3.258	3.664
Firm Size t	8.664	1.703	5.788	7.515	8.672	9.834	11.511
Firm Leverage t	0.340	0.270	0.000	0.141	0.298	0.479	0.847
Firm ROA t	0.022	0.143	-0.240	0.004	0.040	0.087	0.186
Firm MTB t	3.891	42.433	0.198	1.447	2.668	5.033	16.028
Firm Ann Ret t	0.006	0.349	-0.575	-0.167	0.014	0.182	0.555
Firm Ret Vol t	0.097	0.057	0.038	0.058	0.081	0.119	0.212
Firm Loss t	0.233	0.423	0.000	0.000	0.000	0.000	1.000

This table presents the descriptive statistics of variables in our final sample. Detailed variable definitions are provided in Appendix A.

Table 2. Correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) *% AI Hiring t-3~t-1*	1.000									
(2) *Forecast Frequency t*	0.095*	1.000								
(3) *Forecast Accuracy t*	-0.006	0.008*	1.000							
(4) *Forecast Optimism t*	0.007*	0.033*	-0.016*	1.000						
(5) *Walkdown t*	0.032*	0.149*	0.036*	0.030*	1.000					
(6) *Other Tech Hiring t-3~t-1*	0.255*	0.115*	0.016*	0.016*	0.012*	1.000				
(7) *Investment Bank Size t*	0.085*	0.098*	0.013*	0.022*	0.003	0.765*	1.000			
(8) *Analyst General Exp t*	-0.014*	-0.015*	0.032*	-0.017*	0.018*	0.042*	0.020*	1.000		
(9) *Analyst Firm Exp t*	-0.006*	0.032*	0.061*	-0.013*	0.030*	0.050*	0.019*	0.552*	1.000	
(10) *Firm # Analysts t*	0.001	0.185*	0.101*	-0.051*	0.042*	-0.004	0.021*	0.040*	0.128*	1.000
(11) *Firm Size t*	0.060*	0.191*	0.252*	-0.054*	0.003	0.096*	0.082*	0.064*	0.201*	0.594*
(12) *Firm Leverage t*	0.056*	0.023*	-0.047*	0.055*	-0.013*	0.077*	0.055*	0.025*	-0.019*	-0.030*
(13) *Firm ROA t*	-0.017*	0.063*	0.247*	-0.018*	0.002	0.037*	0.062*	0.043*	0.139*	0.213*
(14) *Firm MTB t*	-0.005	-0.007*	0.010*	-0.005	-0.007*	0.001	0.000	-0.003	0.003	0.018*
(15) *Firm Ann Ret t*	0.006*	-0.035*	0.136*	-0.108*	-0.094*	-0.017*	-0.024*	0.023*	0.008*	-0.002
(16) *Firm Ret Vol t*	0.098*	-0.020*	-0.297*	0.013*	0.021*	-0.008*	-0.071*	-0.036*	-0.137*	-0.185*
(17) *Firm Loss t*	0.022*	-0.049*	-0.217*	0.061*	0.010*	-0.030*	-0.056*	-0.041*	-0.127*	-0.115*

Variables	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(11) *Firm Size t*	1.000						
(12) *Firm Leverage t*	-0.008*	1.000					
(13) *Firm ROA t*	0.391*	-0.011*	1.000				
(14) *Firm MTB t*	0.024*	-0.017*	0.016*	1.000			
(15) *Firm Ann Ret t*	0.184*	0.005	0.094*	0.012*	1.000		
(16) *Firm Ret Vol t*	-0.459*	0.059*	-0.467*	-0.011*	0.076*	1.000	
(17) *Firm Loss t*	-0.366*	0.037*	-0.673*	-0.009*	-0.098*	0.489*	1.000

This table presents Pearson correlations from the variables in our final sample. * denotes significant correlations at the 10% level or lower. Detailed variable definitions are provided in Appendix A.

Table 3. AI Investment and analyst production quantity: Forecast frequency

	Poisson					
	(1)	(2)	(3)	(4)	(5)	(6)
	Annual EPS		**Quarterly EPS**		**Annual Other Metrics**	
VARIABLES	*Dependent Variable = Forecast Frequency t*					
% AI Hiring t-3~t-1	**0.331*****	**0.332*****	**0.440*****	**0.439*****	**0.638*****	**0.588*****
	(4.88)	**(4.89)**	**(6.12)**	**(6.12)**	**(9.35)**	**(8.68)**
Other Tech Hiring t-3~t-1	-0.005	-0.005	-0.007*	-0.007*	-0.065***	-0.066***
	(-1.48)	(-1.42)	(-1.78)	(-1.79)	(-16.72)	(-17.12)
Investment Bank Size t	-0.016	-0.016	-0.039***	-0.039***	0.104***	0.102***
	(-1.25)	(-1.27)	(-2.89)	(-2.89)	(7.65)	(7.57)
Analyst General Exp t	0.011*	0.011*	0.009	0.009	-0.003	-0.000
	(1.69)	(1.65)	(1.35)	(1.35)	(-0.39)	(-0.01)
Analyst Firm Exp t	-0.107***	-0.103***	-0.098***	-0.099***	-0.099***	-0.124***
	(-14.67)	(-12.55)	(-13.15)	(-11.84)	(-13.01)	(-15.24)
Firm # Analysts t	0.052***	0.052***	0.055***	0.055***	0.048***	0.043***
	(3.68)	(3.70)	(3.75)	(3.74)	(3.42)	(3.08)
Firm Size t	0.075***	0.075***	0.079***	0.079***	0.066***	0.068***
	(10.88)	(10.82)	(10.49)	(10.50)	(8.94)	(9.43)
Firm Leverage t	0.059***	0.059***	0.063***	0.063***	0.022	0.023
	(3.70)	(3.70)	(3.61)	(3.61)	(1.35)	(1.46)
Firm ROA t	0.016	0.016	-0.009	-0.009	0.042	0.043
	(0.46)	(0.46)	(-0.25)	(-0.25)	(1.14)	(1.16)
Firm MTB t	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.34)	(0.33)	(-0.51)	(-0.50)	(0.75)	(0.75)
Firm Ann Ret t	-0.065***	-0.065***	-0.075***	-0.075***	-0.057***	-0.058***
	(-8.83)	(-8.82)	(-10.04)	(-10.05)	(-7.79)	(-8.02)
Firm Ret Vol t	0.284***	0.284***	0.177**	0.177**	0.138**	0.128*
	(4.11)	(4.12)	(2.48)	(2.48)	(2.05)	(1.90)
Firm Loss t	-0.002	-0.002	-0.010	-0.010	-0.003	-0.003
	(-0.23)	(-0.23)	(-1.08)	(-1.08)	(-0.32)	(-0.34)
Forecast Frequency t-3~t-1		-0.002		0.001		0.001***
		(-1.42)		(0.38)		(10.01)
Observations	70,923	70,923	70,923	70,923	70,923	70,923
Investment Bank-Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

This table presents the results from the model that tests the association between AI investment and analyst forecast frequency. The sample observations are at the analyst-firm-year level. The sample period is from 2013 to 2020. The variable of interest is *% AI Hiring t-3~t-1*, defined as the ratio of AI-related job postings to all job postings from year t-3 through year t-1. The dependent variable, *Forecast Frequency*, is defined as the number of annual earnings forecasts, quarterly earnings forecasts, or annual non-earnings forecasts issued by the analyst for the firm in the year. Detailed definitions of control variables are provided in Appendix A. All t-statistics (reported in parentheses) are computed based on robust standard errors clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Table 4. AI Investment and analyst production quality: Forecast accuracy

	OLS	
	(1)	(2)
VARIABLES	*Dependent Variable = Forecast Accuracy t*	
% AI Hiring t-3~t-1	**0.031****	**0.032****
	(2.07)	**(2.15)**
Other Tech Hiring t-3~t-1	-0.000	0.000
	(-0.33)	(0.18)
Investment Bank Size t	0.002	0.000
	(0.49)	(0.09)
Analyst General Exp t	0.003*	0.003*
	(1.82)	(1.89)
Analyst Firm Exp t	-0.006***	-0.005**
	(-3.18)	(-2.53)
Firm # Analysts t	0.000	-0.003
	(0.03)	(-0.50)
Firm Size t	0.052***	0.047***
	(7.60)	(8.10)
Firm Leverage t	0.001	0.001
	(0.22)	(0.23)
Firm ROA t	0.073**	0.076**
	(2.10)	(2.27)
Firm MTB t	-0.000	-0.000
	(-0.25)	(-0.01)
Firm Ann Ret t	-0.013**	-0.009
	(-2.00)	(-1.55)
Firm Ret Vol t	-0.348***	-0.326***
	(-6.53)	(-6.36)
Firm Loss t	0.000	0.003
	(0.04)	(0.62)
Forecast Accuracy t-3~t-1		0.346***
		(4.39)
Observations	70,923	70,923
Investment Bank-Firm FE	Yes	Yes
Year FE	Yes	Yes
R-squared	0.773	0.779

This table presents the results from the model that tests the association between AI investment and analyst forecast accuracy. The sample observations are at the analyst-firm-year level. The sample period is from 2013 to 2020. The variable of interest is *% AI Hiring t-3~t-1*, defined as the ratio of AI-related job postings to all job postings from year t-3 through year t-1. The dependent variable is *Forecast Accuracy*, defined as the average accuracy of forecasts issued by the analyst for the firm in the year, where forecast accuracy is calculated as the absolute value of the difference between the forecasted EPS and actual EPS scaled by the stock price at the beginning of the fiscal year (multiplied by (-1)). Detailed definitions of control variables are provided in Appendix A. All t-statistics (reported in parentheses) are computed based on robust standard errors clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Table 5. The effect of AI Investment on analyst productivity conditional on complexity of forecasting

Panel A. Fundamental uncertainty

X=	***High Dispersion***		***High Ret Vol***	
	Poisson	**OLS**	**Poisson**	**OLS**
	(1)	(2)	(5)	(6)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*	*Forecast Frequency t*	*Forecast Accuracy t*
% AI Hiring t-3~t-1	-0.097	-0.004	0.108	0.001
	(-0.96)	(-1.45)	(1.16)	(0.06)
% AI Hiring t-3~t-1 × X	**0.903*****	**0.109*****	**0.584*****	**0.075***
	(6.49)	**(2.99)**	**(3.91)**	**(1.89)**
Observations	70,770	70,770	70,923	70,923
Controls	Yes	Yes	Yes	Yes
Investment Bank-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls and Fixed Effects × *X*	Yes	Yes	Yes	Yes
R-squared		0.795		0.796

Panel B. Information environment

X=	***High Bid Ask Spread***		***Low Voluntary Disclosure***	
	Poisson	**OLS**	**Poisson**	**OLS**
	(1)	(2)	(3)	(4)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*	*Forecast Frequency t*	*Forecast Accuracy t*
% AI Hiring t-3~t-1	0.122	-0.003	-0.421***	0.007
	(1.37)	(-1.16)	(-3.85)	(0.87)
% AI Hiring t-3~t-1 × X	**0.429*****	**0.079****	**1.148*****	**0.038**
	(2.97)	**(1.98)**	**(8.31)**	**(1.41)**
Observations	70,900	70,900	70,923	70,923
Controls	Yes	Yes	Yes	Yes
Investment Bank-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls and Fixed Effects × *X*	Yes	Yes	Yes	Yes
R-squared		0.791		0.788

This table presents the results from cross-sectional tests that test the association between AI investment and analyst productivity conditional on the complexity of forecasting. The sample observations are at the analyst-firm-year level. The sample period is from 2013 to 2020. *% AI Hiring t-3~t-1* is defined as the ratio of AI-related job postings to all job postings from year t-3 through year t-1. The dependent variables are *Forecast Frequency*, defined as the number of annual earnings forecasts issued by the analyst for the firm in the year, and *Forecast Accuracy*, defined as the average accuracy of forecasts issued by the analyst for the firm in the year, where forecast accuracy is calculated as the absolute value of the difference between the forecasted EPS and actual EPS scaled by the stock price at the beginning of the fiscal year (multiplied by (-1)).The cross-sectional variables are defined as follows: (i) *Higher Dispersion*, defined as an indicator variable that equals one if the firm's forecast dispersion (the standard deviation of all forecasts, scaled by the absolute value of the median forecast) for the year is above the median, and zero otherwise, (ii) *Higher Ret Vol*, defined as an indicator variable that equals one if the firm's return volatility for the year is above the median, and zero otherwise, (iii) *High Bid Ask Spread*, defined as an indicator variable that equals one if the firm's average daily value of bid ask spread (the difference between the quoted closing bid and ask, scaled by the closing price on the day) for the year is above the median, and zero otherwise, and (iv) *Low Voluntary Disclosure*, defined as an indicator variable that equals one if the firm does not issue management earnings guidance in the year, and zero otherwise. All t-statistics (reported in parentheses) are computed based on robust standard errors clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Table 6. The effect of AI Investment on analyst productivity conditional on analysts' abilities

	Poisson	**OLS**
	(1)	(2)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*
% AI Hiring t-3~t-1	-0.064	0.000
	(-0.64)	(0.08)
% AI Hiring t-3~t-1 × Inferior Analysts	**0.776*** **	**0.083** **
	(5.30)	**(2.16)**
Observations	70,923	70,923
Controls	Yes	Yes
Investment Bank-Firm FE	Yes	Yes
Year FE	Yes	Yes
Controls and Fixed Effects × *Inferior Analysts*	Yes	Yes
R-squared		0.783

This table presents the results from cross-sectional tests that test the association between AI investment and analyst productivity conditional on analysts' abilities. The sample observations are at the analyst-firm-year level. The sample period is from 2013 to 2020. *% AI Hiring t-3~t-1* is defined as the ratio of AI-related job postings to all job postings from year t-3 through year t-1. The dependent variables are *Forecast Frequency*, defined as the number of annual earnings forecasts issued by the analyst for the firm in the year, and *Forecast Accuracy*, defined as the average accuracy of forecasts issued by the analyst for the firm in the year, where forecast accuracy is calculated as the absolute value of the difference between the forecasted EPS and actual EPS scaled by the stock price at the beginning of the fiscal year (multiplied by (-1)). *Inferior Analysts* is defined as an indicator variable that equals one if the analyst's forecast accuracy for the past three years is below the median, and zero otherwise. All t-statistics (reported in parentheses) are computed based on robust standard errors clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Table 7. AI Investment and firm coverage

	Poisson				
	(1)	(2)	(3)	(4)	(5)
VARIABLES	*# Firms Covered t*	*# Existing t*	*# New t*	*# New-Previously NonZero Coverage Firms t*	*# New-Previously Zero Coverage Firms t*
% AI Hiring t-3~t-1	**0.954****	**0.979**	**1.143*****	**0.892***	**1.904***
	(2.26)	**(1.36)**	**(2.67)**	**(1.89)**	**(1.95)**
Other Tech Hiring t-3~t-1	-0.091***	-0.096***	-0.084***	-0.095***	-0.033
	(-5.17)	(-5.59)	(-3.44)	(-3.77)	(-0.67)
Investment Bank Size t	0.258***	0.363***	0.710***	0.712***	0.922***
	(4.33)	(6.57)	(6.61)	(8.73)	(5.26)
Lagged Dep Var t-3~t-1	0.001***	0.002***	0.001***	0.002***	-0.000
	(11.88)	(10.72)	(2.73)	(3.55)	(-0.16)
Observations	120	120	120	120	120

This table presents the results from the model that tests the association between AI investment and analyst firm coverage. The sample observations are at the investment bank-year level. The sample period is from 2013 to 2020. The variable of interest is *% AI Hiring t-3~t-1*, defined as the ratio of AI-related job postings to all job postings from year t-3 through year t-1. The dependent variables are *# Firms Covered*, defined as the number of all firms covered by analysts in the investment bank in the year, *# Existing*, defined as the number of firms continuously covered by analysts in the investment bank in the year, *# New*, defined as the number of firms newly covered by analysts in the investment bank in the year, *# New-Previously NonZero Coverage*, defined as the number of firms newly covered by analysts in the investment bank in the year that were also covered by another analyst in a different brokerage in the previous year, *# New-Previously Zero Coverage Firms*, defined as the number of firms newly covered by analysts in the investment bank in the year that were not covered by any analysts in the previous year. Detailed definitions of control variables are provided in Appendix A. All t-statistics (reported in parentheses) are computed based on robust standard errors. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Table 8. AI Investment and strategic analyst forecasting behavior

	OLS			
	(1)	(2)	(3)	(4)
VARIABLES	*Forecast Optimism t*	*Forecast Optimism t*	*Walkdown t*	*Walkdown t*
% AI Hiring t-3~t-1	**0.221***	**0.232***	**0.296*****	**0.249*****
	(1.84)	**(1.89)**	**(4.29)**	**(3.45)**
Other Tech Hiring t-3~t-1	-0.007	-0.006	-0.006	-0.005
	(-1.13)	(-1.05)	(-1.56)	(-1.29)
Investment Bank Size t	-0.000	-0.004	-0.019	-0.022*
	(-0.02)	(-0.20)	(-1.53)	(-1.75)
Analyst General Exp t	0.011	0.014	0.002	-0.002
	(1.17)	(1.37)	(0.30)	(-0.27)
Analyst Firm Exp t	0.000	0.003	-0.025***	-0.006
	(0.02)	(0.25)	(-3.94)	(-0.90)
Firm # Analysts t	0.040	0.058	0.032*	0.062***
	(1.11)	(1.58)	(1.92)	(3.65)
Firm Size t	0.061***	0.049**	0.031***	0.016*
	(3.04)	(2.38)	(3.63)	(1.73)
Firm Leverage t	0.080**	0.089**	-0.019	-0.015
	(1.98)	(2.15)	(-1.01)	(-0.78)
Firm ROA t	-0.346***	-0.360***	-0.161***	-0.204***
	(-2.68)	(-2.79)	(-3.57)	(-4.59)
Firm MTB t	0.000	0.000	-0.000**	-0.000**
	(0.83)	(0.76)	(-2.42)	(-2.43)
Firm Ann Ret t	-0.241***	-0.232***	-0.147***	-0.135***
	(-9.08)	(-8.95)	(-14.07)	(-13.37)
Firm Ret Vol t	-0.014	-0.039	0.520***	0.512***
	(-0.06)	(-0.15)	(5.64)	(5.59)
Firm Loss t	0.111***	0.137***	0.006	0.006
	(2.99)	(3.69)	(0.50)	(0.53)
Forecast Optimism t-3~t-1		-0.227***		
		(-10.33)		
Walkdown t-3~t-1				-0.359***
				(-31.41)
Observations	69,909	69,909	69,909	69,909
Investment Bank-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R-squared	0.400	0.412	0.290	0.319

This table presents the results from the model that tests the association between AI investment and strategic analyst forecasting behavior. The sample observations are at the analyst-firm-year level. The sample period is from 2013 to 2020. The variable of interest is *% AI Hiring t-3~t-1*, defined as the ratio of AI-related job postings to all job postings from year t-3 through year t-1. The dependent variables are *Forecast Optimism*, defined as the average optimism of forecasts issued by the analyst for the firm in the year, where forecast optimism is calculated as the difference between the forecasted EPS and actual EPS scaled by the absolute value of actual EPS, and *Walkdown*, defined as an indicator variable that equals one if the first forecast is greater than the actual EPS and the last forecast is less than or equal to the actual EPS for the year, and zero otherwise. Detailed definitions of control variables are provided in Appendix A.

All t-statistics (reported in parentheses) are computed based on robust standard errors clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.

Table 9. The effect of ChatGPT

Panel A. The effect of ChatGPT on analyst productivity

	Poisson	**OLS**
	(1)	(2)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*
Post ChatGPT	**0.014****	**0.016*****
	(2.33)	**(9.75)**
Observations	31,397	31,397
Controls	Yes	Yes
Investment Bank-Firm FE	Yes	Yes
Year FE	No	No
R-squared		0.821

Panel B. The effect of ChatGPT on analyst productivity conditional on complexity of forecasting: Fundamental uncertainty

X=	***High Dispersion***		***High Ret Vol***	
	Poisson	**OLS**	**Poisson**	**OLS**
	(1)	(2)	(3)	(4)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*	*Forecast Frequency t*	*Forecast Accuracy t*
X	0.067	-0.117***	-0.044	-0.020
	(0.78)	(-4.51)	(-0.53)	(-0.94)
Post ChatGPT × X	**0.049*****	**0.033*****	**0.037*****	**0.026*****
	(3.61)	**(9.08)**	**(2.69)**	**(7.36)**
Observations	31,304	31,304	31,397	31,397
Controls	Yes	Yes	Yes	Yes
Investment Bank-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls × *X*	Yes	Yes	Yes	Yes
R-squared		0.829		0.823

Table 9. The effect of ChatGPT (continued)

Panel C. The effect of ChatGPT on analyst productivity conditional on complexity of forecasting: Information environment

X=	***High Bid Ask Spread***		***Low Voluntary Disclosure***	
	Poisson	**OLS**	**Poisson**	**OLS**
	(1)	(2)	(3)	(4)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*	*Forecast Frequency t*	*Forecast Accuracy t*
X	0.132	-0.125***	-0.066	-0.037*
	(1.06)	(-3.92)	(-0.43)	(-1.72)
Post ChatGPT* × *X	**0.050*** **	**0.025*** **	**0.025***	**0.020*** **
	(3.78)	**(7.36)**	**(1.77)**	**(8.20)**
Observations	31,316	31,316	31,397	31,397
Controls	Yes	Yes	Yes	Yes
Investment Bank-Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls × *X*	Yes	Yes	Yes	Yes
R-squared		0.825		0.822

Panel D. The effect of ChatGPT on analyst productivity conditional on analysts' abilities

	Poisson	**OLS**
	(1)	(2)
VARIABLES	*Forecast Frequency t*	*Forecast Accuracy t*
Inferior Analysts	0.209*	-0.049**
	(1.89)	(-2.16)
Post ChatGPT* × *Inferior Analysts	**0.022***	**0.027*** **
	(1.77)	**(8.40)**
Observations	24,317	24,317
Controls	Yes	Yes
Investment Bank-Firm FE	Yes	Yes
Year FE	Yes	Yes
Controls × *Inferior Analysts*	Yes	Yes
R-squared		0.835

Table 9. The effect of ChatGPT (continued)

Panel E. The effect of ChatGPT on strategic analyst forecasting behavior

	OLS	
	(1)	(2)
VARIABLES	*Forecast Optimism t*	*Walkdown t*
Post ChatGPT	**0.014**	**0.064*****
	(0.89)	**(4.76)**
Observations	29,909	29,909
Controls	Yes	Yes
Investment Bank-Firm FE	Yes	Yes
Year FE	No	No
R-squared	0.627	0.456

This table presents the results from the models that test the effects of ChatGPT. The sample observations are at the analyst-firm-year level. The sample period is from 2021 to 2023. *Post ChatGPT* is defined as an indicator variable that equals one for 2023 (after ChatGPT was introduced), and zero otherwise. Panel A presents the results from the model that tests the effect of ChatGPT on analyst productivity. Panel B presents the results from the model that tests the effect of ChatGPT on analyst productivity conditional on firms' fundamental uncertainty. Panel C presents the results from the model that tests the effect of ChatGPT on analyst productivity conditional on firms' information environments. Panel D presents the results from the model that tests the effect of ChatGPT on analyst productivity conditional on analysts' abilities. Panel E presents the results from the model that tests the effect of ChatGPT on strategic analyst forecasting behavior. Detailed definitions of the variables are provided in Appendix A. All t-statistics (reported in parentheses) are computed based on robust standard errors clustered at the firm level. ***, **, * indicate significance at the 1%, 5%, and 10% levels, respectively, using two-tailed tests.