ChatGPT and Corporate Policies*

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Abstract

This paper uses ChatGPT, a large language model, to extract managerial expectations of corporate policies from disclosures. We create a firm-level ChatGPT investment score, based on conference call texts, that measures managers' anticipated changes in capital expenditures. We validate the ChatGPT investment score with interpretable textual content and its strong correlation with CFO survey responses. The investment score predicts future capital expenditure for up to nine quarters, controlling for Tobin's q, other predictors, and fixed effects, implying the investment score provides incremental information about firms' future investment opportunities. The investment score also separately forecasts future total, intangible, and R&D investments. High-investment-score firms experience significant future abnormal returns adjusted for factors, including the investment factor. We demonstrate ChatGPT's applicability to measure other policies, such as dividends and employment. ChatGPT revolutionizes our comprehension of corporate policies, enabling the construction of managerial expectations cost-effectively for a large sample of firms over an extended period.

JEL Classification: C81; G14; G31; G32; E22; O33.

Keywords: Corporate Investment, Corporate Policies, Managerial Expectations, Market Efficiency, ChatGPT, Large Language Model, AI, Textual analysis

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1. Introduction

Understanding corporate policies is central to corporate finance. Investment policies, in particular, are key to corporate growth and aggregate fluctuations, with aggregate investment being the most volatile component of GDP (McConnell and Muscarella, 1985; Titman, Wei, and Xie, 2004; Bolton, Chen, and Wang, 2013). According to the neoclassical q-theory, Tobin's q should be a sufficient statistic for describing firms' investment opportunities and policies (Hayashi, 1982; Peters and Taylor, 2017). Nonetheless, private information such as the expectations of corporate managers may not yet be fully incorporated into market prices, even if the market is mostly efficient. Such information is, in general, not available for all firms, despite the availability and usefulness of information for a subset of firms provided by various surveys, e.g., the Duke University/Federal Reserve CFO Surveys and the Conference Board CEO Surveys.[1]

One way via which managers can convey their private information to market participants is through quarterly earnings conference calls that provide a wealth of information, including corporate managers' beliefs and expectations, to the public. Analyzing such information at a large scale is challenging given that the length of a typical call is 8,000 words and thousands of companies report each quarter. Despite the progress in research tools in textual analysis in recent years, extracting complicated information such as the firm's expected investment policy has been beyond the reach of researchers, until the advent of the revolutionary AI tool, ChatGPT. Developed by Open AI, ChatGPT sets itself apart from previous AI models by being able to take long, sophisticated questions and provide detailed, polished answers at the level of human experts.

In this study, we utilize ChatGPT to extract firm-level corporate expectations of future investment policies and study the implications, with an aim to answer the following research

[1]Available at https://www.richmondfed.org/cfosurvey/ and https://www.conference-board.org/topics/CEO-Confidence.

questions: Can an advanced AI model such as ChatGPT help understand corporate policies? Does the ChatGPT-extracted expected investment policy provide information beyond existing measures of investment opportunities, such as Tobin's q or cash flows? Does such information have further implications on asset prices and returns?

The sample of this study consists of 74,586 conference call transcripts for 3,878 unique companies from 2006 to 2020. We provide conference call transcripts with questions about the expected future capital expenditures to the ChatGPT model to retrieve quantitative assessments of future increases and decreases in investment and construct a *ChatGPT Investment Score*. We adopt several methods to validate this measure. First, since the Duke CFO surveys directly ask managers to answer questions regarding their future investment plans, we compare our investment score with the Duke survey responses from CFOs of the same company. We find a strong positive correlation between our measure and the survey answers on firms' expected capital expenditure policy. Second, the time series of the average investment score in our sample and the average future changes in capital expenditure exhibit similar trends over time and align well with each other. Third, we examine the time variation in the industry-level average investment scores and identify patterns consistent with major changes in the economy, e.g., the software and biotech industries expect an increase in investment during the Covid pandemic, in contrast to other industries that substantially cut expected investment. Finally, we ask ChatGPT to provide excerpts from conference call transcripts to support its assignment of the highest and lowest investment scores. The responses from ChatGPT reveal key phrases and sentences that are clearly interpretable by humans. This latter validation provides an important advantage of ChatGPT over some previous AI models – the interpretability of its outputs, which lends credence to the generated investment score.

To the extent that the ChatGPT-based investment score represents firms' investment expectations that are not yet fully incorporated in market prices, we would expect that it provides incremental predictive power to Tobin's q as motivated by the neoclassical q-theory and its extension, total q, that incorporates intangible capital (Peters and Taylor, 2017). We find the ChatGPT investment score bears a significant and positive relationship with future investment, keeping constant other determinants of firm investment. A one-standard-deviation increase in the investment score is associated with a 0.034 standard-deviation increase in capital expenditure in the quarter after the conference call, about two-thirds of the corresponding sensitivity of capital expenditure to total q. This relation is robust to controlling for total q, total cash flows, lagged capital expenditure, other firm characteristics, and firm and time fixed effects, suggesting that the investment score indeed contains new, incremental information derived from managerial private information and expectations. The significant predictive power of the investment score for future investment continues to hold for the subsequent nine quarters, which indicates the long-term nature of managers' expectations. The cumulative increase in future investment over the next nine quarters caused by a one-standard-deviation increase of the investment score is 1.17% of book assets, or 34% of a standard deviation of quarterly capital expenditure. Furthermore, the ChatGPT investment score contains information beyond future physical investment and can help predict other forms of investment, including intangible investment, R&D, and total investment in both the short term and the long run.

Investment-based asset pricing theory predicts (Liu, Whited, and Zhang, 2009) that firms with lower expected returns invest more and the investment factor indeed features prominently in the new standard asset pricing models, e.g., the Fama-French 5-factor model (Fama and French, 2015) and the q5-factor model (Hou, Mo, Xue, and Zhang, 2021). The investment factor implies that high-investment stocks generate lower returns than low-investment stocks. Given that the ChatGPT investment score captures new information regarding firms' future investment opportunities and complements the information in current investment and Tobin's q, the ChatGPT investment score should also be negatively related to future stock returns.

Our tests confirm this hypothesis. We find that the ChatGPT investment score is significantly and negatively associated with raw returns and factor-adjusted abnormal returns over the following quarter, controlling for total q and past returns. A one-standard-deviation increase in the investment score leads to a change of -1.80%, -1.47%, and -1.40% in annualized return, FF5-adjusted return, and $q5$-adjusted return in the quarter subsequent to the earnings call, respectively. Similar to investment, the return predictability also persists for up to nine quarters after the earnings call. The existence of such abnormal returns suggests that the market does not fully incorporate information already contained in public corporate earnings calls, and an advanced AI model like ChatGPT is able to extract such information efficiently. Employing such AI models can, thus, aid investors and potentially make the market more efficient.

Despite the focus of this study on corporate investment policies, we also investigate whether our methodology applies to other corporate policies. In particular, we employ ChatGPT in a similar way to obtain managerial expectations of changes in dividend payment and employment policies and construct ChatGPT-based dividend and employment scores. These AI-based expected policy measures are strongly correlated with the expected policies implied by the Duke CFO Survey responses for the same set of firms. Therefore, our approach has the potential to be applicable to a wide range of corporate policies.

This paper makes several contributions. First, it is the first paper to apply the cutting-edge AI tool, ChatGPT, to extract managerial expectations of corporate policies from corporate earnings calls and validate the AI-based policy measures empirically. Our methodology can be applied to a broad range of policies and expectations. Second, the ChatGPT investment measure provides a new, real-time measure of expected investment that complements the q measures in classical and extended q-theories. Third, our method can be used to expand and complement existing surveys of executives, which can be especially helpful given the decline in survey response rates in the US in the past decade, especially after the Covid pandemic (Pickert, 2023). Fourth, AI interpretability is an important issue, given the increasing prevalence of AI in financial and economic studies and the challenge of explaining certain "black box" models. Our approach allows an interpretable application of AI, as humans can read and understand the arguments given by ChatGPT when making decisions.

We contribute to several lines of literature. First, our paper is related to the literature on the investment-q relation. Despite theories that establish strong links between Tobin's q and investment (Tobin, 1969; Hayashi, 1982; Abel and Eberly, 1994), their empirical relation had been weak.[2] A large literature explains this puzzling discrepancy. For example, Erickson and Whited (2000, 2006) employ GMM to remove measurement errors in q. Philippon (2009) use bond prices to obtain a more accurate measure of q. Peters and Taylor (2017) refine the measurement of q to include intangible capital and finds the resulting measure of total q improves the investment-q relation.[3] In recent years, the investment-q relation changed and has become rather strong (even for plain Tobin's q), due to the fact that variations in future cash flows and q can be both driven by innovation and learning (Andrei, Mann, and Moyen, 2019). Our AI-based investment score provides new information for firms' future investment opportunities that complements Tobin's q and total q, which can help researchers and regulators to better understand corporate investment and its consequences for the economy.

Second, our paper pertains to the feedback literature, in which managers learn from prices in making investments and other corporate decisions (Chen, Goldstein, and Jiang, 2007; Bakke and Whited, 2010; see the surveys Bond, Edmans, and Goldstein, 2012 and Goldstein, 2023 for comprehensive discussions of this literature). Our findings suggest that the other direction of the link is also important: the market can also learn from managers. Information extracted from

[2]See surveys by Hassett and Hubbard (1997) and Caballero (1999).

[3]See also the literature that develops various measures of intangible capital, e.g., Corrado and Hulten (2010, 2014), Eisfeldt and Papanikolaou (2013, 2014), Falato, Kadyrzhanova, Sim, and Steri (2022), and Ewens, Peters, and Wang (2019).

corporate disclosure, such as expected corporate policies, can provide important new insights to investors and the market.

Third, our study relates to the survey and expectations literature. Surveys have been a powerful tool for researchers to obtain access to information that's not available in standard datasets. They are particularly instrumental in obtaining information regarding agents' beliefs and expectations (e.g., D'Acunto, Hoang, and Weber, 2022; Coibion, Gorodnichenko, and Weber, 2022; Weber et al., 2022), studying how they relate to corporate policies (e.g., Coibion, Gorodnichenko, and Kumar, 2018; Coibion, Gorodnichenko, and Ropele, 2020; Candia et al., 2023), or peeking inside corporate operations and decision-making processes (e.g, Graham and Harvey, 2001; Graham, Harvey, and Puri, 2013; Graham, Grennan, Harvey, and Rajgopal, 2022). Our approach can complement existing surveys and generate measures based on executives' plans and discussions for a large sample of firms, and provide a new set of tools and data for researchers.

Finally, our approach provides a step forward for textual analysis. Researchers have utilized textual analysis to analyze unstructured text information such as the levels and extent of sentiment (e.g., Tetlock, 2007; Hanley and Hoberg, 2010; Loughran and McDonald, 2011; Jiang, Lee, Martin, and Zhou, 2019; Jha, Liu, and Manela, 2021), political risk (Hassan, Hollander, Van Lent, and Tahoun, 2019), cyber risk (Florackis et al., 2023), synergies in M&As (Hoberg and Phillips, 2010), or corporate culture (Li, Mai, Shen, and Yan, 2021).[4] Other large language models such as BERT have been increasingly applied in various studies, as in corporate disclosure policies (Cao, Jiang, Yang, and Zhang, 2023), sentiment toward finance (Jha, Liu, and Manela, 2022), etc. Very recently, researchers have started to use ChatGPT to analyze news headlines (Lopez-Lira and Tang, 2023), Federal Reserve announcements (Hansen and Kazinnik, 2023), and innovation success (Yang, 2023). We show that ChatGPT can help to extract information about complex

[4]See Loughran and McDonald (2016) for a comprehensive review of the use of textual analysis in accounting and finance.

concepts such as future corporate policies. Furthermore, such information is interpretable, which can increase AI's use in aiding the decision-making of humans and help to achieve the synergy between man and machine (e.g., Armour, Parnham, and Sako, 2022; Cao, Jiang, Wang, and Yang, 2022; Brogaard, Ringgenberg, and Roesch, 2023).

2. Data

2.1. Data Sources and Sample

We rely on several data sources. First, we use public companies' conference call transcripts as our primary text source for the purpose of extracting firms' outlooks on corporate policies. Second, we obtain the quarterly Duke CFO survey firm-level data which has been analyzed in Graham and Harvey (2001).[5] Third, we utilize Compustat and CRSP to obtain corporate accounting variables and stock returns.

The primary text dataset used in our study encompasses earnings call transcripts from 2006 to 2020, sourced from Seeking Alpha's website.[6] These transcripts are compiled from quarterly earnings calls conducted by senior executives, such as CEOs and CFOs, during which they provide investors and analysts with a comprehensive overview of their firm's overall performance. Along with discussing their company's quarterly performance, executives often provide forward-looking statements and their own assessments of the business. Managers also share their business strategies and operational plans with investors. Furthermore, during the conference calls, analysts and potential investors can pose questions to the management and further explore different aspects of the firms' operations, plans, and performance.

A total of 160,195 earnings call transcripts spanning the years 2006 to 2020 were gathered for analysis. We first merge the earnings call transcripts with CRSP and Compustat databases

[5]We are grateful to John Graham for sharing the data from CFO surveys.

[6]Available at `https://seekingalpha.com/earnings/earnings-call-transcripts`.

by using the stock ticker, the title and date of the earnings calls. The sample size is reduced to 115,620 transcripts after this step. We then obtain financial and balance sheet variables from Compustat, and stock returns from CRSP. After requiring all main variables in our analyses to be non-missing, the final sample consists of 74,586 firm-quarter-level conference calls and merged corporate data from 2006 to 2020, representing 3,878 unique US public firms.

2.2. Variables

Our first measure of investment is *Capital Expenditure*, which is the capital expenditure scaled by total book assets. We also define several variables following Peters and Taylor (2017): *Intangible Capital*, calculated from accumulating Research and Development (R&D) and a proportion of Selling, General, and Administrative (SG&A) expenses; *Physical Capital*, PP&E; *Total Capital*, the sum of *Intangible Capital* and *Physical Capital*; *Total q*, the ratio of market capitalization to *Total Capital*; *Physical Investment*, which is capital expenditure scaled by *Total Capital*; *Intangible Investment*, which is R&D + 0.3 × SG&A expenses, scaled by *Total Capital*; *Total investment*, the sum of *Physical Investment* and *Intangible Investment*. We introduce the ChatGPT-predicted capital expenditure plan *ChatGPT Investment Score* in Section 3.1.

We include the following control variables in our analyses: *Size*, the natural logarithm of total book assets at the end of the quarter; *Total Cash Flow*, as described in Peters and Taylor (2017), the ratio of *Total Capital* to the sum of income before extraordinary items, depreciation expenses, and after-tax *Intangible Investment*; and *Leverage*, the book value of debt divided by total book assets at the end of the quarter. We provide the definitions of all variables in Appendix A.

2.3. Duke CFO Survey

The Duke CFO survey is a comprehensive survey on managerial outlooks on the economy, firm performance, and corporate policies. The survey was initiated by Graham and Harvey (2001) and continued at a quarterly frequency by the Fuqua Business School at Duke University until 2020Q1, after which it is jointly run by Duke and the Federal Reserve Banks of Richmond and Atlanta.[7] We focus on the following survey question:

> "Relative to the previous 12 months, what will be your company's PERCENTAGE CHANGE during the next 12 months? ________% *[Corporate Policy]*"

In the above, *[Corporate Policy]* can refer to a number of corporate policies, including "Capital Spending," "Number of domestic full-time employees," etc. We gather firms' responses to this question on "Capital Spending" and create a variable *CFO Survey Investment* at the firm-quarter level.

We match firms in the Duke CFO Survey data to the conference call data using multiple identifiers, including Compustat's global value keys (GVKEY), CRSP's permanent company number (PERMNO), and the unique respondent id in Duke Surveys. In total, we are able to match 1,707 surveys to their corresponding conference calls. Not all respondents answered all survey questions. Therefore, the sample sizes involving different questions will vary.

3. Method and Summary

3.1. ChatGPT investment score

ChatGPT is an artificial intelligence chatbot developed by OpenAI based on the company's Generative Pre-trained Transformer (GPT) series of large language models. The GPT architecture is based on transformers, which are deep learning models designed to handle sequential data, such as natural language texts. Transformers consist of multiple layers of self-attention mechanisms that allow the model to capture dependencies between words in a sentence. Google's

[7] The survey questions and summary results are available at https://cfosurvey.fuqua.duke.edu/ and https://www.richmondfed.org/research/national_economy/cfo_survey.

BERT (Bidirectional Encoder Representations from Transformers), released in 2018, is the first transformer-based large language model with acclaimed success. Another milestone is the very large GPT-3 model, trained on 45TB of data and with 175 billion parameters, released by OpenAI in June 2020. ChatGPT, launched on November 30, 2022, took the world by surprise with its capability of offering detailed and articulate responses spanning various domains of knowledge.

One way to understand ChatGPT would be to think of it as a giant robot that has read millions of books, papers, and articles, and learned a lot from them. When one types a message or question to ChatGPT, it looks at the words and uses its vast knowledge to understand the meaning behind the words. Once ChatGPT understands the message, it uses what it has learned (through a combination of supervised and reinforcement learning techniques) to come up with the best response in its view.

We prefer using ChatGPT over human reading for conference call text analysis for several reasons. First, ChatGPT provides consistent evaluations because it doesn't have real-time information or personal opinions that could introduce biases. This ensures a reliable, consistent, and objective assessment of conference call content. Second, conference calls can be lengthy, often exceeding seven thousand words, making it challenging for humans to consistently provide accurate responses for reading comprehension tasks. Third, as a machine algorithm, ChatGPT does not have the capacity constraints of humans and can process a large number of texts in a short time frame.

In addition, when compared to other machine learning models such as BERT, ChatGPT is particularly well-suited for analyzing conference calls. Its training in a conversational context enables a better understanding of texts presented in a dialogue format. ChatGPT can effectively maintain context and coherence throughout the conversation, which proves beneficial for handling the interactive nature of back-and-forth exchanges commonly observed during earnings conference calls.

We use ChatGPT 3.5 as the large language model to process texts.[8] ChatGPT has a total limit of 4,096 tokens or around 3,000 words for input and output combined. Therefore, we first split each conference call into several chunks of length less than 2,500 words to conserve sufficient space for output. A typical earnings call is composed of three chunks or parts. To obtain the firms' expected capital expenditure from the earnings call transcripts, we provide the following prompt to ChatGPT.

> The following text is an excerpt from a company's earnings call transcripts. You are a finance expert. Based on this text only, please answer the following question. How does the firm plan to change its capital spending over the next year? There are five choices: Increase substantially, increase, no change, decrease, and decrease substantially. Please select one of the above five choices for each question and provide a one-sentence explanation of your choice for each question. The format for the answer to each question should be "choice - explanation." If no relevant information is provided related to the question, answer "no information is provided."
>
> *[Part of an earnings call transcript.]*

We extract the choice from the response of the model for each chunk of the earnings call and then assign a score of -1, -0.5, 0, 0.5, and 1 for each of the given choices (Decrease substantially; Decrease; No change; Increase; Increase substantially), respectively. If ChatGPT generates an answer "no information is provided," we assign a value of zero to the score. A potential drawback of ChatGPT is its occasional tendency to confidently provide inaccurate information. To combat inaccurate results, we ask ChatGPT to provide an explanation for each answer. We manually read and check the choices and explanations given by ChatGPT for a random sample of conference calls, and find the mismatch rate of choice-explanation to be less than 1%, indicating a high level

[8] The most recent version of ChatGPT based on GPT 4.0 is still prohibitively expensive for analyzing the entire conference call corpus.

of accuracy. Therefore, we do not make any adjustments to the generated choice and assigned score. We then take the average of the scores across multiple chunks of one earnings call to obtain a firm-quarter-level measure, *ChatGPT Investment Score*. Our main results are robust to alternative ways of aggregating text-chunk scores (see Section 4.4).

To understand how ChatGPT was able to infer future investment policies from the conference call transcripts, we construct word clouds for paragraphs with high or low ChatGPT predicted scores (1 and -1). Specifically, we first extract all chunks of conference calls to which ChatGPT assigns an investment score of -1 or 1, respectively. We then ask ChatGPT to provide a one-sentence explanation of the reason for assigning such a score. Based on the answers from ChatGPT, we compile the word clouds of bi-grams for the high and low-investment-score groups and display them in Figure 1.

[Insert Figure 1 Here]

The word clouds reveal distinct themes. Both word clouds contain certain common bigrams that are associated with capital expenses, such as: “cash flow," “capital spend," “capital expenditure," etc. In the word cloud for low-investment-score texts (subfigure (a)), we see bigrams such as “cost reduction," “significantly reduce," “substantially reduce," “reduce cost," etc., indicating management plans to reduce capital expenditure. On the other hand, subfigure (b) for high-investment-score texts shows bigrams such as “revenue grow," “revenue growth," “term growth," “growth opportunity," etc., suggesting management’s willingness to invest in growth. We also provide several example text excerpts from conference call texts with high and low investment scores in Appendix B. The examples demonstrate similar topics as shown in the word clouds but offer more detailed reasoning, e.g., “accelerate our investments in Safety Products, Intelligrated and other growth opportunities,” and “the optimization plan includes some business and international market exits, all of which had negligible margin.”

To create a visual representation of the changes in *ChatGPT Investment Score* over time, we compose an aggregate ChatGPT investment score by taking the cross-sectional average across all firms for each quarter in our sample. We then plot the time series of this aggregate ChatGPT investment score with that of the average change in capital expenditure in Figure 2. The trends in the two time series are very similar over our entire sample period. Note that we focus on the trends, not the specific levels, since the two investment variables are constructed using completely different approaches. Furthermore, the aggregate ChatGPT investment score correctly identifies the 2007-2009 Great financial crisis and the 2020 Covid-19 crisis, as well as the investment booms following crisis periods. The evidence from the figure indicates that our ChatGPT-based measure captures what it is intended to, i.e., firms' expected investment.

[Insert Figure 2 Here]

In Figure 3, we drill down to the industry level and show the yearly trend across major industry sectors. Again, the ChatGPT investment score identifies reasonable trends in industry investment across economic cycles, through booms and busts. The ChatGPT-generated score captures the hardest-hit industries in the two crises: the Retail/Wholesale sector in 2007-2009, and the Transport/Energy sector in 2020. It also captures the resilience of the Software/Biotech industry during the Covid-19 pandemic. Furthermore, the industries that were most bullish in expected capital investment following the 2007-2009 financial crisis were transportation/energy and manufacturing, signaling strong demand and recovery in these sectors.

[Insert Figure 3 Here]

3.2. Summary Statistics

Table 1 displays descriptive statistics for the 74,586 earnings conference calls between 2006 and 2020 with non-missing financial information, which constitutes our main sample. As indicated in Panel A, a typical firm spends 2.74% of capital expenditure in a given quarter. The average *ChatGPT Investment Score* is 0.012, calculated by averaging the scores of many chunks from a single earnings call. Panel B compares the difference in the variables of interest between samples with high and low ChatGPT investment scores. Firms in both samples have similar company sizes on average, but firms with high investment scores have greater *Capital expenditure*, *Intangible investment*, *R&D expenditure*, *Total q*, and lower *Stock returns*.[9]

[Insert Table 1 Here]

We provide the distribution of the ChatGPT investment score in Figure 4. As described in Section 3.1, we split each conference call into text-chunks of about 2,500 words to adhere to OpenAI token requirements. In subfigure (a) we see that about three-fourths of the text-chunks do not indicate any change in capital expenditure by firms. This is followed by 11% of the text-chunks showing an increase, and 10.8% showing a decrease in capital expending. A further 1.87% and 0.32% of the text chunks show significant increases and decreases in capital expenditure.

For each conference call, we average the text-chunk scores to obtain the ChatGPT investment score for the firm. The distribution of the firm-level score, shown in subfigure (b), is approximately symmetric with a mode around zero. Approximately half of the firms have a non-zero investment score, suggesting that a substantial number of firms mention plans to modify their capital investment in conference calls.

[Insert Figure 4 Here]

[9] We provide the definitions of all variables in Appendix A.

4. Empirical Results

4.1. ChatGPT vs. CFO Survey Results

To the extent that we use ChatGPT to extract managerial forecasts about future corporate policies, AI-predicted policies should be closely related to managerial beliefs on the same issues expressed in surveys. Merging our final sample of conference call data with the CFO survey data yields a sample of 1,338 firm-quarter observations. We relate the CFO Survey-based investment measure with the AI-predicted investment measure in the following regression, for firm-quarter (i,t),

$$CFO\ Survey\ Investment_{i,t} = \beta ChatGPT\ Investment\ Score_{i,t} + (\alpha_{Ind} + \alpha_t) + \epsilon_{i,t}, \quad (1)$$

where α_{Ind} and α_t are industry and time fixed effects, using the 10 industries provided in Duke CFO Survey. Table 2 reports the results.

[Insert Table 2 Here]

Table 2 shows that *CFO Survey Investment* and *ChatGPT Investment Score* are strongly positively related, with a statistical significance at the 1% level. Column (1) shows that the R-squared from a simple regression without fixed effects is 1.4% . Column (2) shows that the correlation stays significant after including industry and time fixed effects. A one-standard-deviation increase in the *ChatGPT Investment Score* is associated with a 4.0% higher (or 0.1 standard-deviation increase in) expected capital expenditure over the next 12 months.

In summary, AI-predicted corporate policies are positively correlated with managerial beliefs, demonstrating ChatGPT's ability to extract pertinent information from large texts and the potential to complement large-scale human surveys.

4.2. ChatGPT investment score, Tobin's q, and Future Investments

The neoclassical theory of investment posits that Tobin's q should be a sufficient statistic of firms' future investment opportunities (Hayashi, 1982). Early empirical challenges in testing the theory have been addressed by various improvements in the measurement of q (e.g., Abel and Blanchard, 1986; Erickson and Whited, 2000, 2006, 2012; Philippon, 2009; Gala and Gomes, 2013; Peters and Taylor, 2017). In particular, Peters and Taylor (2017) show that the investment-q relation can be substantially improved by incorporating intangible capital into the capital measurement. The total q of Peters and Taylor (2017) proves to be a strong predictor of future investment activities, both physical and intangible.

However, given that total q still depends on the market capitalization of the firm, it might not incorporate all managerial private information about growth opportunities. Hence, the potential exists to improve the estimation of future investment opportunities through the AI-predicted investment measure, which we extract from managerial briefings. We examine the following regressions to study the incremental predictive power of our measure for future investments, for firm-quarter (i, t),

$$Capital\ Expenditure_{i,t+2} = \beta_1 ChatGPT\ Investment\ Score_{i,t} + (\beta_2 Total\ q_{i,t}) + (\beta_3 Capital\ Expenditure_{i,t} + \gamma Controls_{i,t}) + \alpha_i + \alpha_t + \epsilon_{i,t}, \quad (2)$$

where firm and time fixed effects are included. We cluster standard errors at the firm level. We skip quarter $t+1$ since earnings calls typically occur 30 to 60 days after the end of quarter t.

Table 3 shows that *ChatGPT Investment Score* positively predicts *Capital Expenditure* in the next period, with coefficients statistically significant at 1% levels. Columns (1) to (4) demonstrate that this finding is robust to the inclusion of firm and time fixed effects and controlling for lagged capital expenditure and Total q and other common predictors of investment. A one standard deviation increase in *ChatGPT Investment Score* is associated with 0.034 to 0.052 standard-deviation increase in capital expenditure in the calendar quarter following the earnings call, equivalent to 63.3% to 96.8% of the corresponding sensitivity of capital expenditure to the total q. Therefore, *ChatGPT Investment Score* provides substantial incremental information about firms' growth opportunities, above and beyond information in Tobin's q and other common variables.

[Insert Table 3 Here]

Given that our prompt to ChatGPT asks about the firm's policy in the next year, we further examine whether *ChatGPT Investment Score* has predictive power for investments at horizons longer than one quarter. In Table 4, we estimate regression (2) by replacing the dependent variable with investment in future quarters. *ChatGPT Investment Score* is positively associated with future investment for up to 9 quarters after the conference call. The coefficients are statistically significant at the 5% level or higher. The slopes for *ChatGPT Investment Score* for quarters $n = 2$ to 10 sum to 6.37%, which implies that a one standard deviation increase in *ChatGPT Investment Score* is associated with a 1.17% increase in capital expenditure in the next nine quarters, or an increase of 0.34 quarterly standard deviation.

[Insert Table 4 Here]

Peters and Taylor (2017) argue that intangible investment has become increasingly important in the economy and find Total q to be a good predictor of both physical and intangible investment. Table 5 shows that *ChatGPT Investment Score* significantly and positively predicts future investment measured in different ways, including *Physical Investment*, *Intangible Investment*, *Total Investment*, and *R&D*, controlling for Total q. *ChatGPT Investment Score* positively predicts *Physical Investment*, *Intangible Investment*, *Total Investment*, and *R&D* in the next period, with coefficients statistically significant at 1% levels. The results are robust to the inclusion of firm and time fixed effects and controlling for Total q, the lagged dependent variable, and other controls. Compared to *Intangible Investment*, the predicting power of ChatGPT is larger for *Physical Investment*. Furthermore, Table 6 shows that the predictive power for *Total Investment* also lasts for up to 9 quarters after the earnings call. Untabulated results show similar long-term patterns for other measures of investment.

[Insert Table 5 Here]

Overall, the evidence indicates that our AI-based investment measure contains substantial new information for firms' growth opportunities over the short and medium term, suggesting the far-reaching impact of the expected investment measure on corporate policies and its long-term association with the environment in which companies operate.

[Insert Table 6 Here]

4.3. ChatGPT Predicted Investment and Returns

An investment factor is central in determining asset returns. The current leading factor models, the Fama-French 5-factor model (Fama and French, 2015) and the q-factor model (Hou, Xue, and Zhang, 2015; Hou et al., 2021), all contain an investment factor. The investment factor reflects that high-investment stocks generate lower returns than low-investment stocks. Furthermore, the expected investment growth factor in the q-5 factor model also indicates that it is important to estimate future investment changes. To the extent that *ChatGPT Investment Score* captures new information regarding firms' future investment opportunities and complements the information in current investment and Tobin's q, we expect *ChatGPT Investment Score* to be negatively related to future stock returns.

In Table 7, we test this hypothesis by regressing future quarterly returns on *ChatGPT Investment Score*, controlling for Total q and past returns. We find that the AI-predicted investment measure is negatively associated with returns of the following quarter, and the abnormal quarterly returns adjusted for the Fama-French 5-factor model and the q-5 factor model, with a statistical significance at the 1% level. The slope of the investment score is -9.80%, -8.00%, and -7.63% for the raw return, the FF5-adjusted return, and the q5-adjusted return, respectively. Economically, a one-standard-deviation increase in the investment score leads to a decrease of 1.80%, 1.47%, and 1.40% in annualized return, FF5-adjusted return, and q5-adjusted return in the quarter subsequent to the earnings call, respectively.

[Insert Table 7 Here]

Table 8 further shows that this finding persists for up to 9 quarters for abnormal returns in the future. The negative association of *ChatGPT Investment Score* with future abnormal returns is statistically significant at the 5% or higher levels for q5-adjusted returns for quarters $n = 2$ to 10, and significant for FF5-adjusted returns for quarters $n = 2$ to 6 as well as $n = 9, 10$. On average, a one-standard-deviation increase in the investment score leads to a change of -1.54% in annualized q5-adjusted returns for each quarter $n = 2$ to 10, and -1.10% in annualized FF5-adjusted return for each quarter $n = 2$ to 6, respectively.

[Insert Table 8 Here]

The results in this section show that the ChatGPT investment score can predict long-term future returns and is thus of substantial value to investors.

4.4. Robustness Check

This section conducts robustness tests of the previous results. We consider an alternative definition of the ChatGPT investment score, *ChatGPT Investment Alt. Score*, in which we take the largest value of ChatGPT answers among all chunks of an earnings call. Specifically, we take the text-chunk with the greatest absolute value of ChatGPT-assigned investment score, and assign the corresponding signed score to the conference call. If there are two text-chunks with extreme investment scores with equal absolute value but opposite signs, we assign 0 to the conference call. This measure can be justified on the ground that the most salient information conveyed by the manager in the entire earnings call should be used to define the score. Table 9 shows that our main results for future investment and returns are robust to this measure. In Table 9, *ChatGPT Investment Alt. Score* positively predicts *Capital Expenditure* in the next period, with coefficients statistically significant at 1% levels. Columns (1) to (4) demonstrate that this finding is robust to the inclusion of firm and time fixed effects and controlling for lagged capital expenditure and Total q. A one standard deviation increase in *ChatGPT Investment Alt. Score* is associated with 0.026 to 0.035 standard deviation increase in capital expenditure in the calendar quarter following the earnings call.

The results in Table 9 provide further evidence that ChatGPT can predict firms' future capital expenditure, and the precise way of how we construct our firm-level measure from chunk-level responses does not matter.

[Insert Table 9 Here]

5. ChatGPT and Other Corporate Policies

So far, we have focused on firms' investment policy. The methodology we develop, however, can be equally applied to extract firms' expectations about other corporate policies. We consider two important discretionary policies: dividend payment and hiring. We follow the method described in Section 3.1, but replacing "capital spending" with "dividend payment" and "employment," respectively, to construct *ChatGPT dividend score* and *ChatGPT employment*

Score. Specifically, we input the following prompt into the model.

> The following text is an excerpt from a company's earnings call transcripts. You are a finance expert. Based on this text only, please answer the following questions. 1. How does the firm plan to change its dividend payment over the next year? 2. How does the firm plan to change its number of employees over the next year? There are five choices: Increase substantially, increase, no change, decrease, and decrease substantially. Please select one of the above five choices for each question and provide a one-sentence explanation of your choice for each question. The format for the answer to each question should be "choice - explanation." If no relevant information is provided related to the question, answer "no information is provided. Please answer each question independently."
>
> *[Part of an earnings call transcript.]*

The ChatGPT model provides a combination of choice-explanation for the two questions separately. For each question, we assign a score of -1, -0.5, 0, 0.5, and 1 for each of the given choices (decrease substantially, decrease, no change, increase, and increase substantially), respectively. If ChatGPT generates an answer "no information is provided," we assign a value of zero to the score. We then take the average of the scores across multiple chunks of one earnings call to obtain a firm-quarter-level measure of *ChatGPT Dividend Score* and *ChatGPT Employment Score*.

Table 10 validates that *ChatGPT Dividend Score* and *ChatGPT Employment Score* are significantly and positively associated with the answers to the Duke CFO Surveys. Column (1) and (2) shows that the R-squared from a simple dividend or employee regression is 2.3% and 0.7% without fixed effects. Column (3) and Column (4) show that the correlation stays significant at the 1% level after including industry and time fixed effects. A one standard deviation increase in *ChatGPT Dividend Score* is associated with a 0.11 standard deviation increase in *CFO Survey*

Dividend. A one-standard-deviation increase in *ChatGPT Employment Score* is associated with a 0.07 standard-deviation increase in *CFO Survey Employment*.

Combined with our previous findings, Table 10 adds supportive evidence that ChatGPT can extract valuable information regarding corporate policies from earnings conference calls and has the potential to complement traditional surveys of corporate executives.

[Insert Table 10 Here]

6. Concluding Remarks

In this paper, we use the cutting-edge large language model, ChatGPT, to extract managerial expectations of corporate policies from corporate disclosure. We construct a ChatGPT investment score that measures the extent to which managers expect to increase or decrease capital expenditures in the future. The ChatGPT investment score is supported by interpretable textual content and is strongly correlated with survey responses from CFOs. The investment score bears a strong, positive correlation with future investment both in the short term and long term, even after controlling for Tobin's q ratio and other predictors of investment, indicating that managers convey new information about firms' future investment opportunities in conference calls that ChatGPT helps to extract. Furthermore, firms with high investment scores experience significantly negative future abnormal returns, consistent with investment-based asset pricing theory.

Our findings have several implications. First, they suggest that ChatGPT can be used to extract valuable information about corporate policies that is not otherwise available to investors. Second, they demonstrate that ChatGPT can be used to improve the predictions of future investment and returns. Third, our approach can be used to expand and complement traditional surveys of executives. Fourth, we provide a new application of AI that produce interpretable outputs for humans.

We conducted several robustness checks to validate the results, and they consistently supported the main findings. Additionally, we extended our analysis to other corporate policies, namely dividend payment and hiring, and found that ChatGPT can effectively extract firms' expectations regarding these policies as well. Our study provides a first look at the potential of ChatGPT to extract managerial expectations and corporate policies. We believe that our findings have important implications for companies, investors, policymakers, and researchers.

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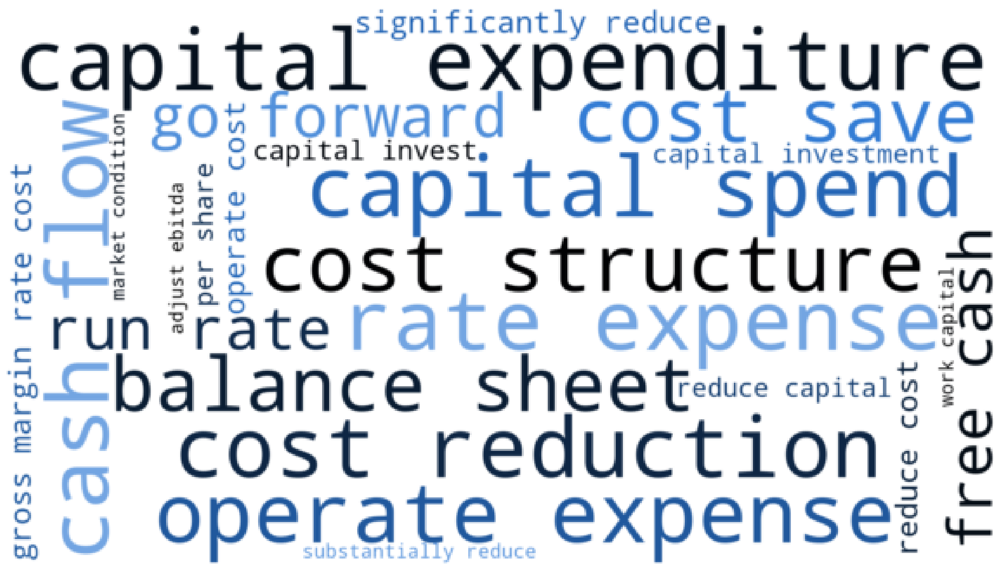
Figure 1. Word Clouds for texts with high and low ChatGPT investment score

This figure represents important bigrams associated with the ChatGPT investment score. We document the most frequent 25 bigrams associated with conference call texts with high and low ChatGPT investment scores. We lemmatize each word to account for differing grammatical noun and verb forms. We also exclude stop words and bigrams that contain time-related words, such as "year," "quarter," etc. More frequent bigrams are shown with bigger text fonts.

(a) Bigrams associated with high ChatGPT investment scores.



(b) Bigrams assoicated with low ChatGPT investment scores.

Figure 2. ChatGPT investment score vs. realized investment

This figure shows the time series of the average quarterly ChatGPT investment score and average future four-quarter change in capital expenditure. ChatGPT investment score is calculated based on conference call texts of the firm (described in Section 3.1). We calculate the change in capital expenditure as the difference between the average capital expenditure for the four quarters following the current quarter (t+1 to t+4) and the average capital expenditure for the four quarters prior to the current quarter (t-4 to t-1).

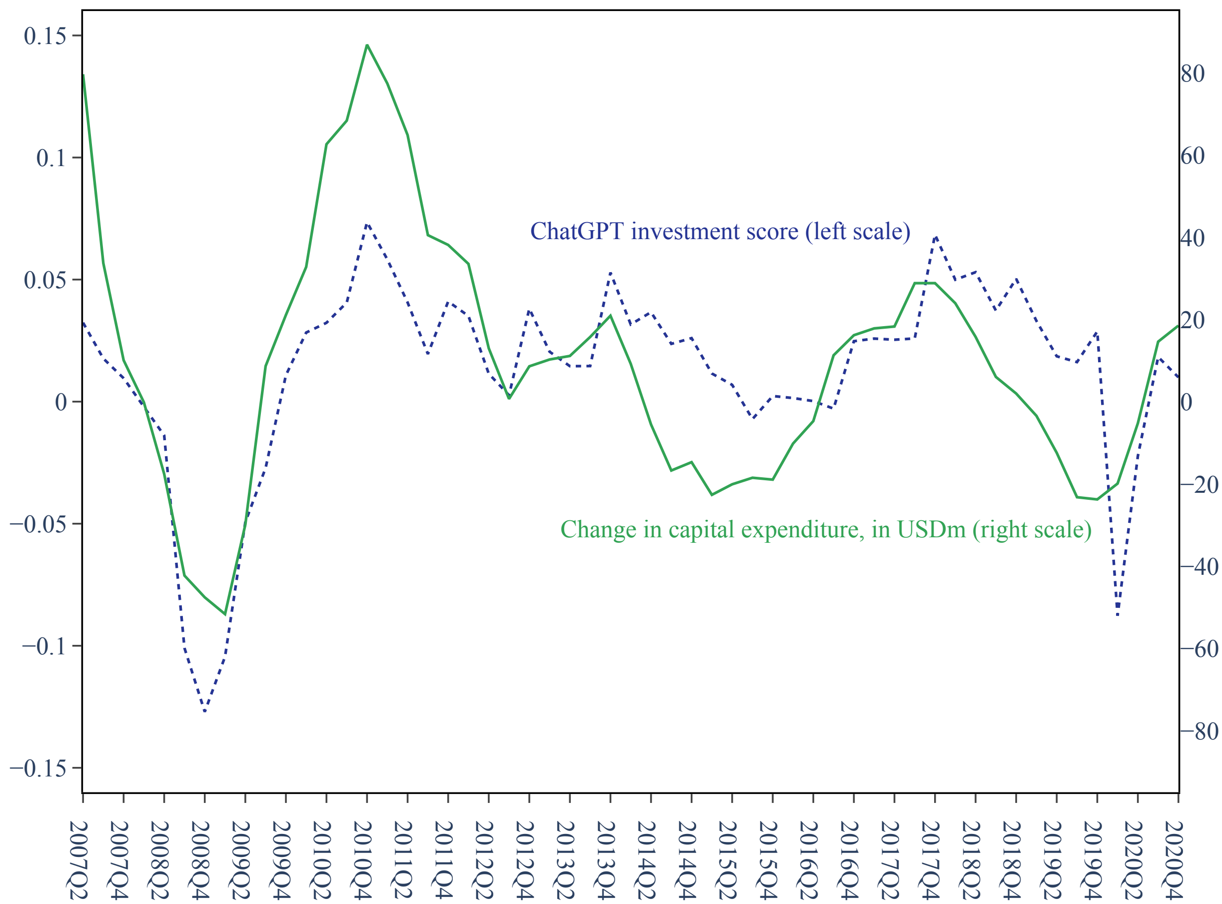


Figure 3. ChatGPT investment score across industries.

This figure represents average yearly ChatGPT investment score across industries. ChatGPT investment score is calculated based on conference call texts of the firm (described in Section 3.1). The firms are aggregated into ten industries, following the Duke CFO survey (Graham and Harvey, 2001).

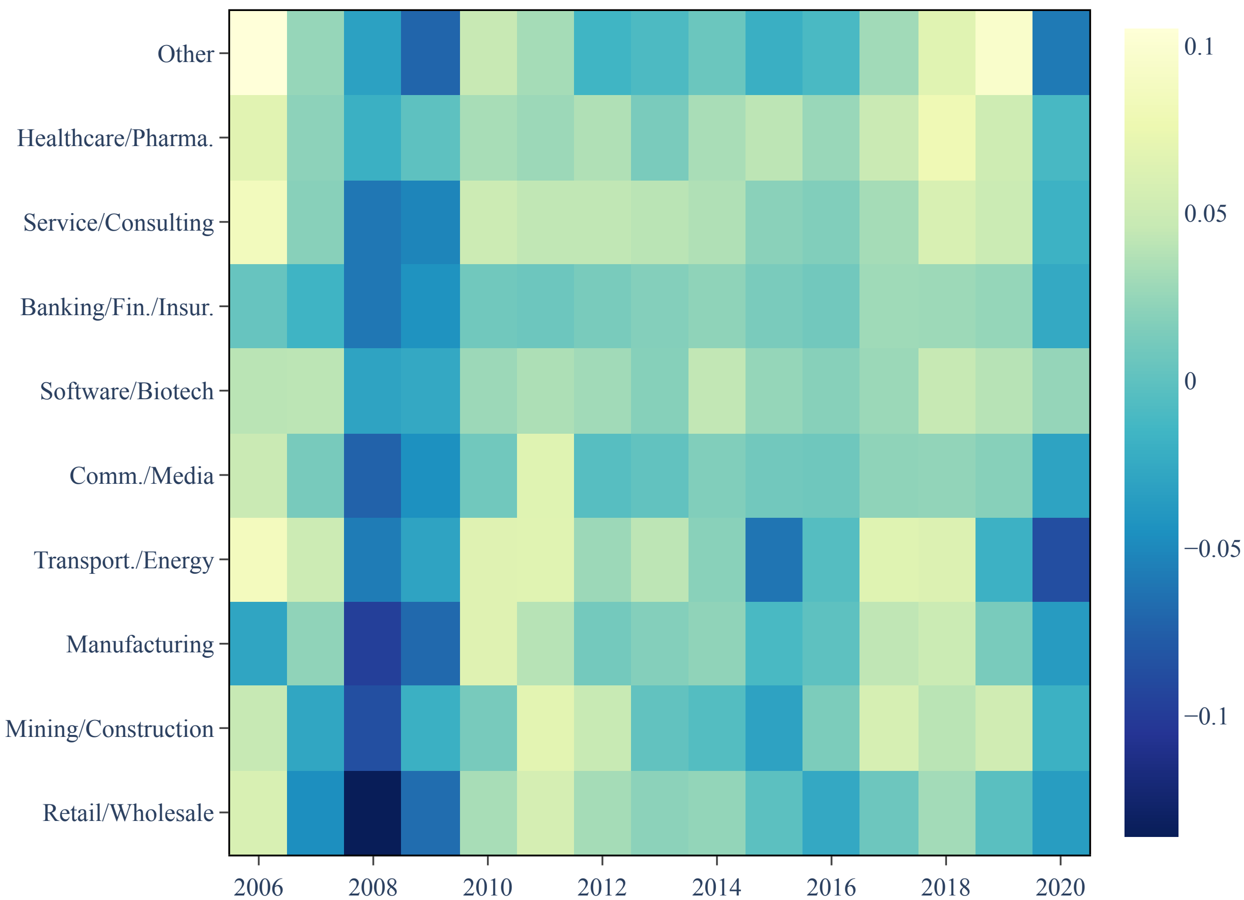
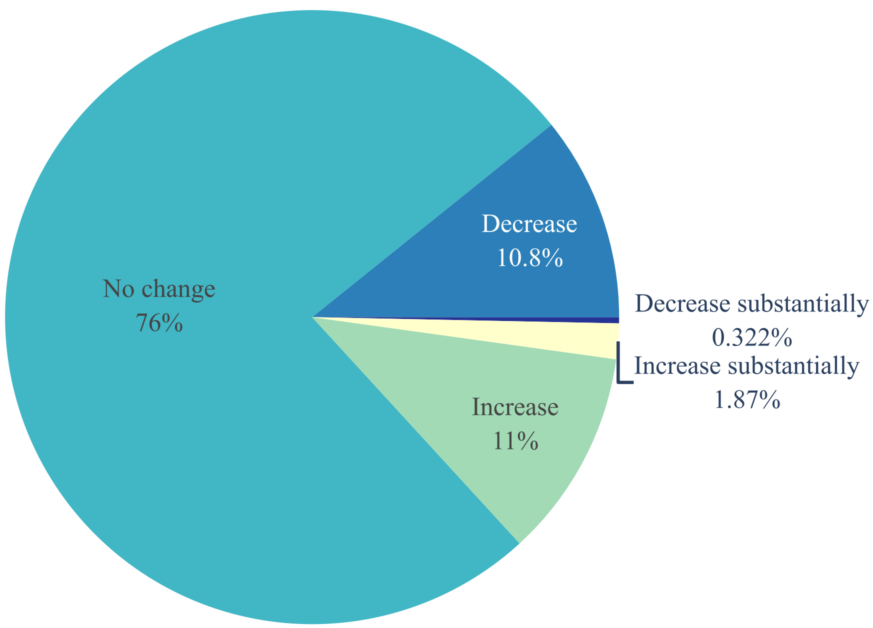


Figure 4. Distribution of ChatGPT investment score

This figure presents the distributions of ChatGPT investment score across text-chunks and conference calls. Each conference call is divided into text-chunks of length around 2,500 words (usually three to four text-chunks per conference call), to accommodate the ChatGPT's token limit. We average the score across text-chunks to obtain the ChatGPT investment score for the conference call.

(a) Distribution of ChatGPT response for text-chunks.



(b) Distribution of ChatGPT investment score for conference calls.

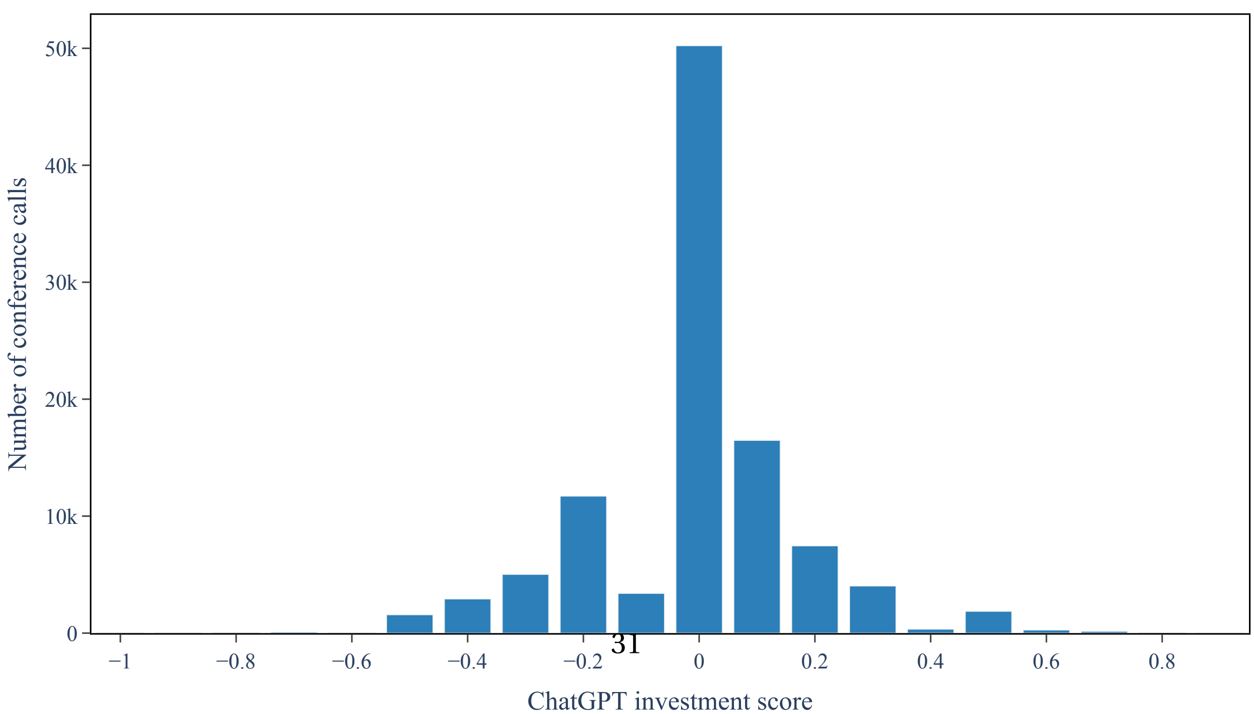


Table 1. Summary Statistics

Panel A displays the descriptive statistics of the investment plan derived from earnings call transcripts utilizing ChatGPT (*ChatGPT Investment Score*) and the characteristics of firms participating in the earnings call. Panel B presents the mean firm characteristics and the mean difference for each characteristic across two subsamples based on the ChatGPT investment score. The low (high) subsample is made up of earnings call transcripts with a *ChatGPT Investment Score* less (higher) than zero. The sample comprises Compustat firms with earnings conference call transcripts and non-missing financial variables from 2006 to 2020. Variables are winsorized at 1%. All variables are defined in Appendix A.

Panel A: Descriptive statistics of the whole sample

	Mean	Median	SD	P25	P75	N
ChatGPT Investment Score	0.014	0	0.184	0	0.120	74,586
ChatGPT Investment Alt. Score	0.245	0	0.328	0	0.500	74,586
Investment Measures						
Capital Expenditure (%)	2.738	1.533	3.434	0.643	3.399	74,586
Intangible Capital Stock ($M)	5300.296	835.640	14133.363	211.294	3499.445	74,586
Physical Capital Stock ($M)	2473.551	258.084	6641.118	39.462	1367.580	74,586
Intangible Investment (%)	1.991	1.556	1.899	0.614	2.717	74,586
Physical Investment (%)	2.837	1.313	4.079	0.502	3.320	74,586
Total Investment (%)	4.864	3.593	4.242	2.214	5.971	74,586
R&D (%)	1.630	1.056	1.952	0.268	2.192	39,098
Return Measures						
Return (Annualized, %)	14.379	10.677	100.919	-39.851	60.101	74,586
FF5-adjusted Return (%)	-2.192	-1.557	94.492	-49.214	43.047	74,586
q5-adjusted Return (%)	0.769	0.065	95.039	-47.312	45.515	74,586
Controls						
Total q	1.164	0.853	1.044	0.471	1.464	74,586
Total Cash Flow	0.033	0.035	0.064	0.011	0.065	74,586
Leverage	0.230	0.174	0.219	0.046	0.350	74,586
Book Assets ($M)	7487.329	1480.084	17538.899	346.560	5563.839	74,586

Panel B: Comparison between firms with low and high ChatGPT Investment Score

	Mean			
Variables	Low Score	High Score	Difference	t-stat.
Capital Expenditure (%)	2.71	3.06	-0.35	-29.50***
Intangible Capital Stock ($M)	5586.91	5933.43	-346.52	-6.75***
Physical Capital Stock ($M)	3034.33	2879.58	154.75	6.12***
Intangible Investment (%)	1.59	1.94	-0.35	-60.68***
Physical Investment (%)	2.73	3.20	-0.47	-33.34***
Total Investment (%)	4.34	5.17	-0.84	-58.51***
R&D (%)	1.10	1.53	-0.43	-55.66***
Return (Annualized, %)	17.15	13.86	3.29	9.68***
FF5-adjusted Return (%)	-3.09	-2.23	-0.86	-2.72***
q5-adjusted Return (%)	2.09	0.13	1.95	6.20***
Total q	0.86	1.42	-0.56	-161.21***
Total Cash Flow	0.03	0.05	-0.02	-87.90***
Leverage	0.29	0.20	0.09	127.60***
Book Assets ($M)	8360.63	8472.94	-112.31	-1.74*
Number of observations	147,442	190,202		

Table 2. ChatGPT Predictions vs. CFO Survey Results

This table presents coefficients from a firm-quarter level estimation that regresses the Duke CFO Survey-based measure on the ChatGPT predicted measure of corporate capital expenditure in the next 12 months. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. *CFO Survey Investment* is the expected capital expenditure change for the next year mentioned by corporate executives during the CFO survey conducted by Duke University. Variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by industry. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)
	CFO Survey Investment	
ChatGPT Investment Score	30.83***	21.78***
	(4.36)	(3.57)
Industry FE	N	Y
YearQtr FE	N	Y
R-squared	0.014	0.070
N	1338	1325

Table 3. ChatGPT Investment Score, Tobin's q, and Future Investment

This table reports coefficients from a firm-quarter level estimation that regresses firms' real capital expenditure for the next quarter on the predicted capital expenditure by ChatGPT using earnings call transcripts. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. The dependent Variable *Capital Expenditure* is the real capital expenditure scaled by book assets for quarter $t+2$. Control variables include *Total q* (Peters and Taylor, 2017), *Capital Expenditure*, *Total Cash Flow*, *Market Leverage* and *Firm Size* in quarter t. All variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)	(3)	(4)
	Capital Expenditure$_{t+2}$			
ChatGPT Investment Score$_t$	0.966***	0.795***	0.683***	0.638***
	(15.64)	(13.24)	(12.16)	(11.37)
Total q_t		0.379***		0.177***
		(12.44)		(6.53)
Capital Expenditure$_t$			0.115***	0.114***
			(9.98)	(9.92)
Total Cash Flow$_t$			0.889**	0.535
			(3.00)	(1.83)
Leverage$_t$			-2.795***	-2.535***
			(-16.94)	(-14.97)
Size$_t$			-0.006	-0.008
			(-0.14)	(-0.19)
Firm FE	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y
R-squared	0.694	0.697	0.707	0.708
N	74,586	74,586	74,586	74,586

Table 4. AI Predictions and Long-Term Investment

This table presents coefficients from a firm-quarter level estimation that regresses firms' real capital expenditure in subsequent quarters on the predicted capital expenditure by ChatGPT using earnings call transcripts. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. The dependent Variable *Capital Expenditure* is the real capital expenditure scaled by book assets for quarter $t+n$. Control variables include *Total q, Capital Expenditure, Total Cash Flow, Market Leverage,* and *Firm Size* in quarter t. All variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(n=3)	(n=4)	(n=5)	(n=6)	(n=7)	(n=8)	(n=9)	(n=10)
	Capital Expenditure$_{t+n}$							
ChatGPT Investment Score$_t$	0.804***	1.044***	0.998***	0.788***	0.626***	0.663***	0.493***	0.315***
	(13.88)	(18.29)	(16.48)	(13.96)	(10.86)	(11.96)	(9.05)	(5.56)
Total q_t	0.184***	0.159***	0.241***	0.293***	0.256***	0.174***	0.187***	0.194***
	(7.12)	(6.71)	(8.41)	(9.22)	(8.24)	(6.28)	(6.29)	(6.04)
Capital Expenditure$_t$	0.151***	0.445***	0.044***	-0.114***	-0.032***	0.257***	-0.051***	-0.162***
	(17.55)	(40.06)	(5.21)	(-12.28)	(-4.08)	(20.61)	(-6.08)	(-18.68)
Total Cash Flow$_t$	1.034***	2.108***	1.146***	-0.037	-0.286	1.136**	1.004**	0.249
	(3.56)	(7.16)	(4.22)	(-0.13)	(-0.96)	(2.85)	(3.08)	(0.74)
Leverage$_t$	-2.156***	-1.274***	-2.185***	-2.420***	-1.903***	-0.911***	-1.455***	-1.472***
	(-13.19)	(-9.10)	(-12.61)	(-12.50)	(-10.47)	(-5.34)	(-7.87)	(-7.22)
Size$_t$	-0.033	-0.059	-0.121*	-0.172**	-0.195***	-0.165***	-0.195***	-0.205***
	(-0.83)	(-1.74)	(-2.56)	(-3.23)	(-3.78)	(-3.63)	(-3.70)	(-3.57)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.712	0.774	0.707	0.710	0.709	0.732	0.708	0.717
N	73,437	72,354	71,003	68,215	65,393	63,267	60,437	57,799

Table 5. AI Predictions, Tobin's q, and Various Types of Investment

This table presents coefficients from a firm-quarter level estimation that regresses firms' investment in the subsequent year on the predicted capital expenditure by ChatGPT. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. We define *Total q* and various investment variables following Peters and Taylor (2017): *Intangible Capital*, calculated from accumulating R&D and a proportion of SG&A expenses; *Physical Capital*, the PP&E; *Total Capital*, the sum of *Physical capital* and *Intangible capital*; *Total q*, the ratio of market capitalization to *Total Capital*; *Physical Investment*, capital expenditure scaled by *Total Capital*; *Intangible Investment*, R&D + 0.3 × SG&A expenses, scaled by *Total Capital*; *TotalIinvestment*, the sum of *Physical investment* and *Intangible investment*. Control variables include *Total q*, *Total Cash FLow*, *Market Leverage*, *Firm Size* dependent variables in quarter t. All variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Physical Investment$_{t+2}$		*Intangible Investment*$_{t+2}$		*Total Investment*$_{t+2}$		*R&D*$_{t+2}$	
ChatGPT Investment Score$_t$	1.362***	0.810***	0.261***	0.091***	1.659***	0.918***	0.288***	0.130***
	(17.71)	(12.16)	(12.31)	(5.72)	(20.19)	(13.22)	(8.84)	(5.42)
Total q$_t$		0.490***		0.219***		0.850***		0.201***
		(13.40)		(16.10)		(20.82)		(12.49)
Physical Investment$_t$		0.115***						
		(9.10)						
Intangible Investment$_t$				0.446***				
				(24.48)				
Total Investment$_t$						0.151***		
						(13.16)		
R&D$_t$								0.488***
								(25.07)
Control Variables	Y	Y	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.693	0.712	0.859	0.899	0.658	0.692	0.855	0.906
N	74,586	74,586	74,586	74,586	74,586	74,586	39,029	36,631

Table 6. AI Predictions and Long-Term Investment

This table reports coefficients from a firm-quarter level estimation that regresses firms' real capital expenditure in subsequent quarters on the predicted capital expenditure by ChatGPT using earnings call transcripts. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. Dependent Variable *Total investment* is the sum of *Physical investment* and *Intangible investment* for quarter $t+n$. Control variables include *Total q*, *Capital Expenditure*, *Total Cash FLow*, *Market Leverage* and *Firm Size* in quarter t. Variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1) n=3	(2) n=4	(3) n=5	(4) n=6	(5) n=7	(6) n=8	(7) n=9	(8) n=10
	$Total\ Investment_{t+n}$							
$ChatGPT\ Investment\ Score_t$	1.020***	1.183***	1.186***	0.972***	0.758***	0.733***	0.597***	0.424***
	(14.83)	(17.31)	(16.22)	(13.67)	(10.79)	(10.55)	(8.78)	(6.14)
$Total\ q_t$	0.758***	0.453***	0.753***	0.851***	0.688***	0.354***	0.527***	0.547***
	(19.70)	(13.28)	(17.78)	(18.37)	(14.98)	(8.18)	(11.71)	(11.76)
$Total\ Investment_t$	0.188***	0.455***	0.0725***	-0.0739***	-0.00486	0.262***	-0.0305***	-0.132***
	(21.70)	(43.88)	(8.28)	(-7.77)	(-0.58)	(20.96)	(-3.30)	(-14.65)
$Total\ Cash\ Flow_t$	0.131	2.267***	1.564***	0.120	-0.483	1.617***	1.579***	0.619
	(0.33)	(5.71)	(3.88)	(0.28)	(-1.08)	(2.89)	(3.26)	(1.29)
$Leverage_t$	-2.537***	-1.371***	-2.313***	-2.500***	-1.975***	-0.870***	-1.618***	-1.688***
	(-12.54)	(-7.94)	(-10.47)	(-10.10)	(-8.44)	(-3.90)	(-6.70)	(-6.45)
$Size_t$	-0.213***	-0.368***	-0.358***	-0.411***	-0.442***	-0.535***	-0.453***	-0.463***
	(-3.31)	(-7.34)	(-4.99)	(-4.88)	(-5.56)	(-7.91)	(-5.82)	(-5.50)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.695	0.763	0.680	0.678	0.677	0.704	0.671	0.680
N	73,437	72,354	71,003	68,215	65,393	63,267	60,437	57,799

Table 7. ChatGPT Investment Score and Future Returns

This table reports coefficients from a firm-quarter level estimation that regresses firms' Stock performance in the next quarter on the predicted capital expenditure by ChatGPT using earnings call transcripts. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. The dependent variable *Stock Performance* is one of the following three measures in quarter $t+2$: Annualized Quarterly Raw Return (*Return*); Annualized Quarterly Fama-French 5-factor alpha (*FF5-Adjusted Return*); Annualized Quarterly q-factor alpha (*q5-Adjusted Return*). Control variables include *Total q* and *Return* in quarter t. All variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Return_{t+2}$		$FF5\text{-}Adjusted\ Return_{t+2}$		$q5\text{-}Adjusted\ Return_{t+2}$	
$ChatGPT\ Investment\ Score_t$	-17.74***	-9.795***	-16.10***	-8.002***	-14.78***	-7.634***
	(-8.33)	(-4.51)	(-7.15)	(-3.50)	(-6.65)	(-3.38)
$Total\ q_t$		-15.64***		-13.10***		-12.72***
		(-19.51)		(-15.78)		(-14.99)
$Return_t$		-0.0156***		-0.0395***		-0.0252***
		(-3.09)		(-7.31)		(-4.63)
Firm FE	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y
R-squared	0.232	0.239	0.0864	0.0935	0.0824	0.0880
N	74,586	74,586	74,586	74,586	74,586	74,586

Table 8. AI Predictions and Long-Term Returns

This table reports coefficients from a firm-quarter level estimation that regresses firms' Stock performance in subsequent quarters on the predicted capital expenditure by ChatGPT using earnings call transcripts. *ChatGPT Investment Score* measures the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts. The dependent variable *Stock Performance* is one of the following three measures in quarter $t+n$: Annualized Quarterly Raw Return (*Return*); Annualized Quarterly Fama-French 5-factor alpha (*FF5-Adjusted Return*); Annualized Quarterly q-factor alpha (*q5-Adjusted Return*). Control variables include *Total q* and *Return* in quarter t. Variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

Panel A: AI Predictions and Long-Term Raw Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
	$Return_{t+n}$							
ChatGPT Investment Score$_t$	-11.63***	-14.17***	-9.086***	-5.914***	-8.403***	-3.049	-6.443***	-2.980
	(-5.39)	(-6.62)	(-4.31)	(-2.60)	(-3.92)	(-1.39)	(-2.88)	(-1.29)
Total q$_t$	-13.29***	-9.240***	-9.822***	-8.795***	-8.038***	-8.362***	-6.716***	-5.594***
	(-17.64)	(-12.55)	(-12.89)	(-12.01)	(-10.76)	(-11.14)	(-8.74)	(-6.93)
Return$_t$	-0.0165***	-0.0668***	0.0111**	-0.0206***	0.0000600	-0.0283***	-0.0281***	0.00569
	(-3.17)	(-13.20)	(2.08)	(-3.90)	(0.01)	(-5.08)	(-4.85)	(0.93)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.227	0.239	0.225	0.226	0.227	0.225	0.228	0.224
N	73,437	72,354	71,003	68,215	65,393	63,267	60,437	57,799

Panel B: AI Predictions and FF5-Adjusted Alpha Raw Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
	FF-5 factor Adjusted $Alpha_{t+n}$							
$ChatGPT\ Investment\ Score_t$	-5.528**	-3.889*	-5.946***	-6.648***	-2.218	-1.025	-5.970**	-4.863**
	(-2.50)	(-1.73)	(-2.71)	(-2.92)	(-0.99)	(-0.45)	(-2.53)	(-2.09)
$Total\ q_t$	-11.59***	-10.51***	-8.728***	-7.089***	-6.911***	-7.679***	-7.273***	-6.323***
	(-14.55)	(-13.45)	(-10.67)	(-8.85)	(-8.52)	(-9.07)	(-8.72)	(-7.17)
$Return_t$	-0.0235***	-0.0376***	-0.0132**	-0.0294***	-0.00203	0.0148**	0.00189	0.00134
	(-4.31)	(-6.85)	(-2.37)	(-5.18)	(-0.36)	(2.41)	(0.31)	(0.21)
Firm	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.0867	0.0917	0.0896	0.0906	0.0892	0.0928	0.0967	0.0911
N	73,437	72,354	71,003	68,215	65,393	63,267	60,437	57,799

Panel C: AI Predictions and $q5$-Adjusted Alpha Raw Return

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	n=3	n=4	n=5	n=6	n=7	n=8	n=9	n=10
	q5-Adjusted $Alpha_{t+n}$							
$ChatGPT\ Investment\ Score_t$	-8.329***	-9.343***	-8.413***	-9.722***	-8.764***	-8.316***	-9.012***	-5.977**
	(-3.74)	(-4.22)	(-3.84)	(-4.20)	(-3.98)	(-3.62)	(-3.78)	(-2.47)
$Total\ q_t$	-9.640***	-8.606***	-8.819***	-7.923***	-8.648***	-9.215***	-8.237***	-6.830***
	(-11.72)	(-10.43)	(-10.43)	(-9.53)	(-10.22)	(-10.60)	(-9.08)	(-7.31)
$Return_t$	-0.0460***	-0.0282***	0.00228	-0.00958*	-0.00314	-0.00683	-0.0167***	0.0119*
	(-8.31)	(-5.07)	(0.41)	(-1.68)	(-0.55)	(-1.11)	(-2.72)	(1.89)
Firm	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.0838	0.0846	0.0829	0.0836	0.0871	0.0875	0.0903	0.0863
N	73,437	72,354	71,003	68,215	65,393	63,267	60,437	57,799

Table 9. Robustness Check: Alternative measure of ChatGPT investment score

This table presents coefficients from a firm-quarter level estimation that regresses firms' real capital expenditure in subsequent quarters on the predicted capital expenditure by ChatGPT using a different approach from Table 3. *ChatGPT Investment Alt. Score* assigns the ChatGPT-based text-chunk investment score with the largest absolute value to an earnings call. The dependent variable *Capital Expenditure* is the real capital expenditure scaled by book assets for quarter $t+2$. Control variables include *Total q*, *Capital Expenditure*, *Total Cash FLow*, *Market Leverage* and *Firm Size* in quarter t. All variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)	(3)	(4)
		$\textit{Capital Expenditure}_{t+2}$		
$\textit{ChatGPT Investment Alt. Score}_t$	0.372***	0.329***	0.286***	0.275***
	(12.71)	(11.57)	(10.67)	(10.30)
$\textit{Total } q_t$		0.404***		0.190***
		(13.22)		(6.98)
$\textit{Capital Expenditure}_t$			0.112***	0.112***
			(9.80)	(9.74)
$\textit{Total Cash Flow}_t$			1.063***	0.669**
			(3.57)	(2.29)
$\textit{Leverage}_t$			-2.898***	-2.610***
			(-17.58)	(-15.42)
$\textit{Size}_t$			-0.0126	-0.0148
			(-0.29)	(-0.34)
Firm FE	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y
R-squared	0.693	0.697	0.707	0.707
N	74,586	74,586	74,586	74,586

Table 10. ChatGPT and Other Corporate Policies: Dividends and Employment

This table presents coefficients from a firm-quarter level estimation that regresses the Duke CFO Survey-based measure with the ChatGPT predicted measure for other corporate policies. The dependent variable *CFO Survey Dividend* or the *CFO Survey Employment* is the expected change in dividend payout or the number of employees for the next year mentioned by corporate executives in the Duke CFO survey. *ChatGPT Dividend Score* or *ChatGPT Employment Score* measures the dividend payout or the number of employees derived from firms' earnings call transcripts by ChatGPT of the same quarter. All variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by industry. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1)	(2)	(3)	(4)
	CFO Survey Dividend		*CFO Survey Employment*	
ChatGPT Dividend Score	45.62***	30.46***		
	(3.99)	(3.93)		
ChatGPT Employment Score			22.64***	18.01***
			(3.00)	(5.20)
Industry FE	N	Y	N	Y
YearQtr FE	N	Y	N	Y
R-squared	0.023	0.117	0.007	0.044
N	666	661	1322	1311

Appendix A: Definitions of Variables

Variable	Definition
ChatGPT Investment Score	We ask ChatGPT to provide a response about the firm's capital expenditure plan in the next year from chunks of earnings call transcripts. Based on the response from the model, we assign a score of -1, -0.5, 0, 0.5, and 1 for each of the given choices: Substantial Decrease; Decrease; No change; Increase; Substantial Increase. We then take the average of the scores across multiple chunks of one earnings call.
ChatGPT Investment Alt. Score	We ask ChatGPT to provide a response about the firm's capital expenditure plan in the next year from chunks of earnings call transcripts. Based on the response from the model, we assign a score of -1, -0.5, 0, 0.5, and 1 for each of the given choices: Substantial Decrease; Decrease; No change; Increase; Substantial Increase. We then take the score from the chunk with the largest absolute value across multiple chunks of one earnings call as the final score for that earnings call.
ChatGPT Dividend Score	We ask ChatGPT to provide a response about the firm's dividend payout plan in the next year from chunks of earnings call transcripts. Based on the response from the model, we assign a score of -1, -0.5, 0, 0.5, and 1 for each of the given choices: Substantial Decrease; Decrease; No change; Increase; Substantial Increase. We then take the average of the scores across multiple chunks of one earnings call.
ChatGPT Employee Score	We ask ChatGPT to provide a response about the firm's number of workforce plan in the next year from chunks of earnings call transcripts. Based on the response from the model, we assign a score of -1, -0.5, 0, 0.5, and 1 for each of the given choices: Substantial Decrease; Decrease; No change; Increase; Substantial Increase. We then take the average of the scores across multiple chunks of one earnings call.
Capital Expenditure	Capital Expenditure (CAPX) at the end of the quarter, scaled by book assets.
Physical Capital Stock	Property, Plant and Equipment at the end of the quarter.
Intangible Capital Stock	Based on the measure of annual *Intangible Capital Stock* proposed by Peters and Taylor (2017), which applies the perpetual inventory method to firms' intangible investments defined as Research and Development (R&D) and 0.3 × selling, general, and administrative (SG&A) spending at the end of the year, we apply the same method to derive a quarterly measure of *Intangible Capital Stock* assuming a 2.5% quarterly depreciation rate.
Total Capital Stock	The sum of *Physical Capital Stock* and *Intangible Capital Stock* at the end of the quarter.

(continued)

Variable	**Definition**
Physical Investment	Capital Expenditure (CAPX) at the end of the quarter, scaled by *Total Capital Stock*.
Intangible Investment	Research and Development (R&D) and 0.3 × selling, general, and administrative (SG&A) spending at the end of the quarter, scaled by total capital stock.
R&D	Research and Development (R&D), scaled by *Total Capital Stock*.
Return	Annualized buy-and-hold returns over one quarter.
FF5-Adjusted Return	Average monthly Fama-French 5-factor abnormal return over one quarter multiplied by 12.
q5-Adjusted Return	Average monthly q5-factor abnormal return over one quarter multiplied by 12.
Total q	The ratio of market capitalization (Compustat items $prcc_f * csho$), plus the book value of debt (*dltt* + *dlc*), minus the firm's current assets (*act*), to *Total capital stock*, as defined in Peters and Taylor (2017).
Total Cash Flow	Divide total capital by the sum of income before extraordinary items plus depreciation expenses plus after-tax intangible investment (the marginal tax rate is assumed to be 30%).
Size	The natural logarithm of total book assets at the end of the quarter.
Leverage	The sum of long-term debt (*dlttq*) and short-term debt (*dlcq*) divided by the sum of long-term debt and short-term debt plus the market value of equity (cshoq*prccq) at the end of the quarter.
CFO Survey Investment	Executives' response about the firm's capital expenditure plan for the next year during the Dukey CFO survey. It is a percentage change compared to the capital expenditure in the past 12 months.
CFO Survey Dividend	Executives' response about the firm's Dividend payout plan for the next year during the Dukey CFO survey. It is a percentage change compared to the dividend payout in the past 12 months.
CFO Survey Employment	Executives' response about the firm's Dividend payout plan for the next year during the Dukey CFO survey. It is a percentage change compared to the number of empoyees in the past 12 months.

Appendix B: Examples of Texts with Predicted Investment Scores

Category	Example Texts from Conference Call Transcripts
Increase (Score=1)	"We committed approximately $250 million of incremental growth capital expenditures compared to our previous allocated budget for new projects to accelerate our investments in Safety Products, Intelligrated and other growth opportunities. These are high-return investments expected to generate triple-digit IRRs. Kingdom, India, the UAE and China." "Capital expenditures continued to be higher as we provisioned existing orders and built out for SaaS and PaaS growth. As a reminder, our cloud data centers are built using our own engineered systems. So while CapEx is a cost to other cloud providers, a good portion of our CapEx is essentially a hardware sale which we sell as a cloud subscription." "We invested $3.1 billion in capital expenditures, consistent with our plan for accelerated investment, as we added both commercial and consumer global cloud capacity to meet near-term and longer-term customer demand." "We have identified several key strategic initiatives for 2015 to sustain the growth rate of our business. We plan to make significant capital investments in our facilities and infrastructure, and we continue to strengthen our human capital in compliance, manufacturing and sales. We also have a solid slate of plan launches throughout the year."
Decrease (Score=−1)	"We have significantly lowered our capital spending plans and are aggressively pursuing operating efficiencies and cost savings as we continue to ramp up production from our major projects, all of which will support cash flow moving forward." "As mentioned, the optimization plan includes some business and international market exits, all of which had negligible margin. For perspective, these businesses and markets were a drag of about 20 basis points on 2019 revenue growth and about 40 basis points on 2019 margins. We are also lowering our 2020 CapEx forecast by $10 million to incorporate the exit. " "After next year we will not have that roughly $50 million to $60 million spend that we'll have this year and next year on El Dorado. So our CapEx will be down substantially, which will affect - that's a boost of $50 million to $60 million." "We are transforming our manufacturing footprint in a way that will enable us to improve flexibility and profitability, while also lowering capital expenditures."

Appendix C: Additional Empirical Results

Table A.1. ChatGPT Investment Score and Long-Term Investment: Consistent Sample

This table reports coefficients from a firm-quarter level estimation that regresses firms' real capital expenditure in subsequent quarters on the predicted capital expenditure by ChatGPT keeping the sample constant across different quarters. *ChatGPT Investment Score* is the capital expenditure change predicted by ChatGPT from firms' earnings call transcripts in quarter t. The dependent variable *Capital Expenditure* is the real capital expenditure scaled by book assets for quarter $t+n$. Control variables include *Total q*, *Capital Expenditure*, *Total Cash Flow*, *Market Leverage* and *Firm Size* in quarter t. Variables are defined in Appendix A. In all panels, the t-statistics, in parentheses, are based on standard errors clustered by firm. ***, **, * denote statistical significance at the 0.01, 0.05, and 0.10 levels, respectively.

	(1) n=3	(2) n=4	(3) n=5	(4) n=6	(5) n=7	(6) n=8	(7) n=9	(8) n=10
	Capital Expenditure$_{t+n}$							
ChatGPT Investment Score$_t$	0.823***	1.076***	0.984***	0.790***	0.642***	0.672***	0.512***	0.320***
	(12.41)	(16.87)	(14.55)	(12.81)	(10.46)	(11.65)	(9.05)	(5.66)
Total q$_t$	0.196***	0.170***	0.252***	0.314***	0.265***	0.180***	0.191***	0.202***
	(6.55)	(6.47)	(7.79)	(8.93)	(8.01)	(6.31)	(6.24)	(6.20)
Capital Expenditure$_t$	0.138***	0.458***	0.0306***	-0.124***	-0.0349***	0.269***	-0.0580***	-0.163***
	(14.02)	(37.40)	(3.39)	(-12.68)	(-4.33)	(20.86)	(-6.97)	(-18.44)
Total Cash Flow$_t$	0.979***	2.308***	1.361***	0.00131	-0.169	1.298***	1.093***	0.279
	(2.90)	(6.77)	(4.39)	(0.00)	(-0.54)	(3.10)	(3.26)	(0.82)
Leverage$_t$	-2.056***	-1.193***	-2.300***	-2.470***	-1.861***	-0.792***	-1.422***	-1.458***
	(-10.30)	(-6.97)	(-10.93)	(-11.03)	(-9.14)	(-4.34)	(-7.34)	(-7.02)
Size$_t$	0.0140	-0.0271	-0.0738	-0.146**	-0.187***	-0.174***	-0.193***	-0.206***
	(0.30)	(-0.72)	(-1.38)	(-2.47)	(-3.45)	(-3.73)	(-3.56)	(-3.54)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
YearQtr FE	Y	Y	Y	Y	Y	Y	Y	Y
R-squared	0.721	0.782	0.716	0.723	0.714	0.736	0.708	0.717
N	57280	57280	57280	57280	57280	57280	57280	57280