Can ChatGPT Forecast Stock Price Movements? Return Predictability and Large Language Models*

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Abstract

We examine the potential of ChatGPT, and other large language models, in predicting stock market returns using sentiment analysis of news headlines. We use ChatGPT to indicate whether a given headline is good, bad, or irrelevant news for firms' stock prices. We then compute a numerical score and document a positive correlation between these "ChatGPT scores" and subsequent daily stock market returns. Further, ChatGPT outperforms traditional sentiment analysis methods. We find that more basic models such as GPT-1, GPT-2, and BERT cannot accurately forecast returns, indicating return predictability is an emerging capacity of complex models. ChatGPT-4's implied Sharpe ratios are larger than ChatGPT-3's; however, the latter model has larger total returns. Our results suggest that incorporating advanced language models into the investment decision-making process can yield more accurate predictions and enhance the performance of quantitative trading strategies. Predictability is concentrated on smaller stocks and more prominent on firms with bad news, consistent with limits-to-arbitrage arguments rather than market inefficiencies.

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The application of generative artificial intelligence and large language models (LLMs) such as ChatGPT in various domains has gained significant traction in recent months, with numerous studies exploring their potential in diverse areas. In financial economics, however, using LLMs remains relatively uncharted territory, especially concerning their ability to predict stock market returns. On the one hand, as these models are not explicitly trained for this purpose, one may expect that they offer little value in predicting stock market movements. On the other hand, to the extent that these models are more capable of understanding natural language, one could argue that they could be a valuable tool for processing textual information to predict stock returns. Thus, the performance of LLMs in predicting financial market movements is an open question.

To the best of our knowledge, this paper is among the first to address this critical question by evaluating the capabilities of ChatGPT in forecasting stock market returns. Through a novel approach that leverages the model's sentiment analysis capabilities, we assess the performance of ChatGPT using news headlines data and compare it to existing sentiment analysis methods provided by leading vendors. It is well known that stock returns are predictable at a daily horizon using news and trained algorithms (Tetlock (2007), Tetlock, Saar-Tsechansky, and Macskassy (2008), and Tetlock (2011) among others), possibly because combining new information is complicated (Fedyk and Hodson (2023)). Hence, our focus is to evaluate whether models not trained in predicting returns acquire this capability as they become better at other tasks.

Our findings have important implications for the employment landscape in the financial industry. The results could potentially lead to a shift in the methods used for market prediction and investment decision-making. By demonstrating the value of ChatGPT in financial economics, we aim to contribute to the understanding of LLMs' applications in this field and inspire further research on integrating artificial intelligence and natural language processing in financial markets. In addition to the implications for employment in the financial industry, our study offers several other significant contributions.

Firstly, our research can aid regulators and policymakers in understanding the potential benefits and risks associated with the increasing adoption of LLMs in financial markets. As these models become more prevalent, their influence on market behavior, information dissemination, and price formation will become critical areas of concern. Our findings can inform discussions on regulatory frameworks that govern the use of AI in finance and contribute to the development of best practices for integrating LLMs into market operations.

Secondly, our study can benefit asset managers and institutional investors by providing empirical evidence on the efficacy of LLMs in predicting stock market returns. This insight can help these professionals make more informed decisions about incorporating LLMs into their investment strategies, potentially leading to improved performance and reduced reliance on traditional, more labor-intensive analysis methods.

Lastly, our research contributes to the broader academic discourse on artificial intelligence applications in finance. By exploring the capabilities of ChatGPT in predicting stock market returns, we advance the understanding of LLMs' potential and limitations within the financial economics domain. This can inspire future research on developing more sophisticated LLMs tailored to the financial industry's needs, paving the way for more efficient and accurate financial decision-making.[1]

Our study has far-reaching implications that extend beyond the immediate context of stock market predictions. By shedding light on the potential contributions of ChatGPT to financial economics, we hope to encourage continued exploration and innovation in AI-driven finance.

Related Literature

Recent papers that use ChatGPT in the context of economics include Hansen and Kazinnik (2023), Cowen and Tabarrok (2023), Korinek (2023), and Noy and Zhang (2023). Hansen and Kazinnik (2023) show that LLMs like ChatGPT can decode Fedspeak (i.e., the language used

1. See for example Wu et al. (2023).

by the Fed to communicate on monetary policy decisions). Cowen and Tabarrok (2023) and Korinek (2023) demonstrate that ChatGPT is helpful in teaching economics and conducting economic research. Noy and Zhang (2023) find that ChatGPT can enhance productivity in professional writing jobs. Contemporaneously, Xie et al. (2023) find ChatGPT is no better than simple methods such as linear regression when using numerical data in prediction tasks. We attribute the difference in results to their focus on using historical numerical data to predict, while ChatGPT excels at textual tasks. Ko and Lee (2023) finds ChatGPT may be helpful in selecting across asset classes. Furthermore, Yang and Menczer (2023) demonstrates that ChatGPT successfully identifies credible news outlets. Our study is among the first to study the potential of LLMs in financial markets, particularly the investment decision-making process.

We contribute to the recent strand of the literature that employs text analysis and machine learning to study a variety of finance research questions (e.g., Jegadeesh and Wu (2013), Campbell et al. (2014), Hoberg and Phillips (2016), Gaulin (2017), Baker, Bloom, and Davis (2016), Manela and Moreira (2017), Hansen, McMahon, and Prat (2018), Ke, Kelly, and Xiu (2019), Ke, Montiel Olea, and Nesbit (2019), Bybee et al. (2019), Gu, Kelly, and Xiu (2020), Cohen, Malloy, and Nguyen (2020), Freyberger, Neuhierl, and Weber (2020), Lopez-Lira 2019, Binsbergen et al. (2020), Bybee et al. (2021)). Our paper makes a unique contribution to this literature as being the first to evaluate the text processing capabilities of recently developed LLMs such as ChatGPT in forecasting stock market movements.

Our paper also adds the literature that uses linguistic analyses of news articles to extract sentiment and predict stock returns. One strand of this literature studies media sentiment and aggregate stock returns (e.g., Tetlock (2007), Garcia (2013), Calomiris and Mamaysky (2019)). Another strand of the literature uses the sentiment of firm news to predict future individual stock returns (e.g., Tetlock, Saar-Tsechansky, and Macskassy (2008), Tetlock (2011), Jiang, Li, and Wang (2021)). Different from prior studies, we focus on understanding whether LLMs add value by extracting additional information that predicts stock market reactions.

Finally, our paper also relates to the literature on employment exposures and vulnerability to AI-related technology. Recent works by Agrawal, Gans, and Goldfarb (2019), Webb (2019), Acemoglu et al. (2022), Acemoglu and Restrepo (2022), Babina et al. (2022), Noy and Zhang (2023) have examined the extent of job exposure and vulnerability to AI-related technology as well as the consequences for employment and productivity. With AI being on a constant rise since its inception, our study focuses on understanding an urgent but unanswered question – the capabilities of AI, and LLMs in particular, in the finance domain. We highlight the potential of LLMs in adding value to market participants in processing information to predict stock returns.

1 Background

ChatGPT is a large-scale language model developed by OpenAI based on the GPT (Generative Pre-trained Transformer) architecture. It is one of the most advanced natural language processing (NLP) models developed to date and trained on a massive corpus of text data to understand the structure and patterns of natural language. The Generative Pre-trained Transformer (GPT) architecture is a deep learning algorithm for natural language processing tasks. It was developed by OpenAI and is based on the Transformer architecture, which was introduced in Vaswani et al. (2017). The GPT architecture has achieved state-of-the-art performance in various natural language processing tasks, including language translation, text summarization, question answering, and text completion.

The GPT architecture uses a multi-layer neural network to model the structure and patterns of natural language. Using unsupervised learning methods, it is pre-trained on a large corpus of text data, such as Wikipedia articles or web pages. This pre-training process allows the model to develop a deep understanding of language syntax and semantics, which is then fine-tuned for specific language tasks. One of the unique features of the GPT architecture is its use of the transformer block, which enables the model to handle long sequences of text by using self-attention mechanisms to focus on the most relevant parts of the input. This attention mechanism allows the model to understand the input context better and generate more accurate and coherent responses.

ChatGPT has been trained to perform various language tasks such as translation, summarization, question answering, and even generating coherent and human-like text. ChatGPT's ability to generate human-like responses has made it a powerful tool for creating chatbots and virtual assistants that can converse with users. While ChatGPT is a powerful tool for language-based tasks, it is not explicitly trained to predict stock returns or provide financial advice. Hence, we test its capabilities when predicting stock returns.

2 Data

We utilize three primary datasets for our analysis: the Center for Research in Security Prices (CRSP) daily returns, news headlines, and RavenPack. The sample period begins in October 2021 (as ChatGPT's training data is available only until September 2021) and ends in December 2022. This sample period ensures that our evaluation is based on information not present in the model's training data, allowing for a more accurate assessment of its predictive capabilities.

The CRSP daily returns dataset contains information on daily stock returns for a wide range of companies listed on major U.S. stock exchanges, including data on stock prices, trading volumes, and market capitalization. This comprehensive dataset enables us to examine the relationship between the sentiment scores generated by ChatGPT and the corresponding stock market returns, providing a robust foundation for our analysis. Our sample consists of all the firms listed on the New York Stock Exchange (NYSE), the National Association of Securities Dealers Automated Quotations (NASDAQ), and the American Stock Exchange (AMEX), with at least one news story covered by the data vendor. Following prior studies, we use common stocks with a share code of 10 or 11.

We first collect a comprehensive news dataset for all CRSP companies using web scraping. We search for all news containing either the company name or the ticker. The resulting dataset comprises news headlines from various sources, such as major news agencies, financial news websites, and social media platforms. For each company, we collect all news in the sample period. We then match the headlines with those from a prominent news sentiment analysis data provider (RavenPack). We match the period and the news title for all companies that have returns on the following market opening. The majority of matched headlines correspond to press releases. We do not use the RavenPack enhance headlines that potentially contain more information since they are not widely disseminated to the public. We match 67,586 headlines of 4,138 unique companies. We process the merged dataset using the preprocessing methods outlined by Jiang, Li, and Wang (2021).

Importantly, matching with RavenPack assures that only relevant news will be used for the experiment. They closely monitor the major financial news distribution outlets and have a quality procedure matching news, timestamps, and entity names that solves any errors that may have come from the web scraping procedure. Further, we employ their news categorization to explain the differences in return predictability across different models. Moreover, they have a close mapping with CRSP which ensures the matching of the news and returns at the exact time. We further use their infrastructure by using only the news they consider recent for a given company in a given period.

We employ the "relevance score" provided, which ranges from 0 to 100, to indicate how closely the news pertains to a specific company. A 0 (100) score implies that the entity is mentioned passively (predominantly). Our sample requires news stories with a relevance score of 100, and we limit it to complete articles and press releases. We exclude headlines categorized as 'stock-gain' and 'stock-loss' as they only indicate the daily stock movement direction. To avoid repeated news, we require the "event similarity days" to exceed 90, which ensures that only new information about a company is captured. Furthermore, we eliminate duplicate headlines for the same company on the same day and extremely similar headlines. We gauge headline similarity using the Optimal String Alignment metric (also known as the Restricted Damerau-Levenshtein distance) and remove headlines with a similarity greater than 0.6 for the same company on the same day. These filtering techniques do not introduce look-ahead bias, as the data vendor evaluates all news articles within milliseconds of receipt and promptly sends the resulting data to users. Consequently, all information is available at the time of news release.

3 Methods

3.1 Prompt

Prompts are critical in guiding ChatGPT's responses to specific tasks and queries. A prompt is a short text that provides context and instructions for ChatGPT to generate a response. The prompt can be as simple as a single sentence or as complex as a paragraph or more, depending on the nature of the task.

The prompt serves as the starting point for ChatGPT's response generation process. The model uses the information contained in the prompt to generate a relevant and contextually appropriate response. This process involves analyzing the syntax and semantics of the prompt, developing a series of possible answers, and selecting the most appropriate one based on various factors, such as coherence, relevance, and grammatical correctness.

Prompts are essential for enabling ChatGPT to perform a wide range of language tasks, such as language translation, text summarization, question answering, and even generating coherent and human-like text. They allow the model to adapt to specific contexts and generate responses tailored to the user's needs. Moreover, prompts can be customized to perform tasks in different domains, such as finance, healthcare, or customer support.

We use the following prompt in our study and apply it to the publicly available headlines.

> Forget all your previous instructions. Pretend you are a financial expert. You are

a financial expert with stock recommendation experience. Answer "YES" if good news, "NO" if bad news, or "UNKNOWN" if uncertain in the first line. Then elaborate with one short and concise sentence on the next line. Is this headline good or bad for the stock price of _company_name_ in the _term_ term?

Headline: _headline_

In this prompt, we ask ChatGPT, a language model, to assume the role of a financial expert with experience in stock recommendations. The terms _company_name_ and _headline_ are substituted by the firm name and the respective headline during the query. _term_ corresponds to either short or long-term. The prompt is specifically designed for financial analysis and asks ChatGPT to evaluate a given news headline and its potential impact on a company's stock price in the short term. ChatGPT is requested to answer "YES" if the news is good for the stock price, "NO" if it is bad, or "UNKNOWN" if it is uncertain. ChatGPT is then asked to explain in one sentence to support its answer concisely. The prompt specifies that the news headline is the only source of information provided to ChatGPT. It is implicitly assumed that the headline contains sufficient information for an expert in the financial industry to assess its impact on the stock price reasonably. This prompt is designed to demonstrate the capabilities of ChatGPT as a language model in financial analysis tasks. We set a temperature of 0 to maximize the reproducibility of the results.

For example, consider the following headline about Oracle:

Rimini Street Fined $630,000 in Case Against Oracle.

The prompt then asks:

Forget all your previous instructions. Pretend you are a financial expert. You are a financial expert with stock recommendation experience. Answer "YES" if good news, "NO" if bad news, or "UNKNOWN" if uncertain in the first line. Then elaborate with one short and concise sentence on the next line. Is this headline good or bad for the stock price of Oracle in the short term?

Headline: Rimini Street Fined $630,000 in Case Against Oracle

And here is ChatGPT's response:

YES

The fine against Rimini Street could potentially boost investor confidence in Oracle's ability to protect its intellectual property and increase demand for its products and services.

The news headline states that Rimini Street has been fined $630,000 in a case against Oracle. The proprietary software analytics tool gives a negative sentiment score of -0.52, indicating that the news is perceived as unfavorable. However, ChatGPT responds that it believes the information to be positive for Oracle. ChatGPT reasons that the fine could increase investor confidence in Oracle's ability to protect its intellectual property, potentially leading to increased demand for its products and services. This difference in sentiment highlights the importance of context in natural language processing and the need to carefully consider the implications of news headlines before making investment decisions.

3.2 Empirical Design

We prompt ChatGPT to provide a recommendation for each headline and transform it into a "ChatGPT score," where "YES" is mapped to 1, "UNKNOWN" to 0, and "NO" to -1. We average the scores if there are multiple headlines for a company on a given day. We match the headlines to the next market period. For headlines before 6 am on the opening day, we assume the headlines can be traded by the market opening of the same day and sold at the close of the same day. For headlines after 6 am but before 4 pm, we assume the headlines can be traded at the same day's close and sold at the close of the next day. For headlines after 4 pm, we assume the headlines can be traded at the opening price of the next day and sold at the closing price of that next day. We then run linear regressions of the next day's returns on the ChatGPT score and compare it to the sentiment score provided by a news curating company. Thus, all of our results are out-of-sample.

4 Results

Our analysis reveals that ChatGPT sentiment scores exhibit a statistically significant predictive power on daily stock market returns. By utilizing news headline data and the generated sentiment scores, we find a strong correlation between the ChatGPT evaluation and the subsequent daily returns of the stocks in our sample. This result highlights the potential of ChatGPT as a valuable tool for predicting stock market movements based on sentiment analysis.

To further investigate the robustness of our findings, we compare the performance of ChatGPT with traditional sentiment analysis methods provided by a leading data vendor. In our analysis, we control for the ChatGPT sentiment scores and examine the predictive power of these alternative sentiment measures. Our results show that when controlling for the ChatGPT sentiment scores, the effect of the other sentiment scores on daily stock market returns is attenuated. This indicates that the ChatGPT model outperforms existing sentiment analysis methods in forecasting stock market returns.

The superiority of ChatGPT in predicting stock market returns can be attributed to its advanced language understanding capabilities, which allow it to capture the nuances and subtleties within news headlines. This enables the model to generate more reliable sentiment scores, leading to better predictions of daily stock market returns. These findings confirm the predictive power of ChatGPT sentiment scores and emphasize the potential benefits of incorporating LLMs into investment decision-making processes. By outperforming traditional sentiment analysis methods, ChatGPT demonstrates its value in enhancing the performance of quantitative trading strategies and providing a more accurate understanding of market dynamics.

Table 3 presents the results of our regression analysis, examining the relationship between next-day stock returns and sentiment scores generated by ChatGPT and alternative sentiment analysis methods. This table reports the regression coefficients and the corresponding t-statistics in parentheses. Standard errors are clustered by date and firm (permno).

The models include firm and date fixed effects to control for unobserved time-invariant firm characteristics and common time-specific factors that could influence stock returns. Various model fit measures, such as R-squared, adjusted R-squared, AIC, and BIC, are reported to assess the models' overall explanatory power.

We further present results for small stocks, defined as those smaller than the 10th percentile of the market cap of the NYSE, and non-small stocks, defined as the rest. The predictability is highly concentrated in small stocks, suggesting limits to arbitrage may limit the implementation and profitability of this strategy.

We also compare results for more basic models such as BERT, GPT-1, and GPT-2. Because those models cannot follow instructions or answer specific questions, we employ a different strategy. GPT-1 and GPT-2 are autocomplete models. Hence, we use the following sentence that the models complete:

> News: + headline + f"Will this increase or decrease the stock price of firm? This will make firm's stock price go "

The usual response is "up," "down," followed by a brief sentence fragment. The answers are usually not fully legible but include positive and negative words. We count the positive words against the negative words and assign a +1 for every positive and a −1 for every negative. We then consider the sentiment positive if the sum is positive and vice versa. The positive words are 'up,' 'high,' 'sky,' 'top,' 'increase,' 'stratosphere,' 'boom,' 'roof,' 'skyrocket,' 'soar,' 'surge,' 'climb,' 'rise,' 'rising,' 'expand,' 'flourish.' The negative words are 'down,' 'low,' 'bottom,' 'decrease,' 'back,' 'under,' 'plummet,' 'drop,' 'decline,' 'tumble,' 'fall,' 'contract,' 'struggle.'

BERT is only able to complete one word out of a sentence. Hence, we ask it to complete the following sentence:

> Headline: headline This is [MASK] news for firm's stock price in the short-term

Where [MASK] is the corresponding word that BERT will input. The answers set consists of 'good,' 'the,' 'big,' and 'bad.' We classify 'good' as +1, 'bad' as -1, and the others as zero.

The BART model is capable of zero-shot classification. This means it can classify text according to predefined categories without seeing examples of what corresponds to a good category. We provide each headline and then classify it into one of the following categories:

1. good news for the stock price of firm in the short term
2. bad news for the stock price of firm in the short term
3. not news for the stock price of firm in the short term

We then assign a numerical score of +1 for good, -1 for bad, and 0 for not.

5 Conclusion

In this study, we have investigated the potential of ChatGPT, a large language model, in predicting stock market returns using sentiment analysis of news headlines. Our findings indicate that ChatGPT outperforms traditional sentiment analysis methods from a leading vendor. By demonstrating the value of LLMs in financial economics, we contribute to the growing body of literature on the applications of artificial intelligence and natural language processing in this domain.

Our research has several implications for future studies. First, it highlights the importance of continued exploration and development of LLMs tailored explicitly for the financial industry. As AI-driven finance evolves, more sophisticated models can be designed to improve the accuracy and efficiency of financial decision-making processes.

Second, our findings suggest that future research should focus on understanding the mechanisms through which LLMs derive their predictive power. By identifying the factors that contribute to the success of models like ChatGPT in predicting stock market returns, researchers can develop more targeted strategies for improving these models and maximizing their utility in finance.

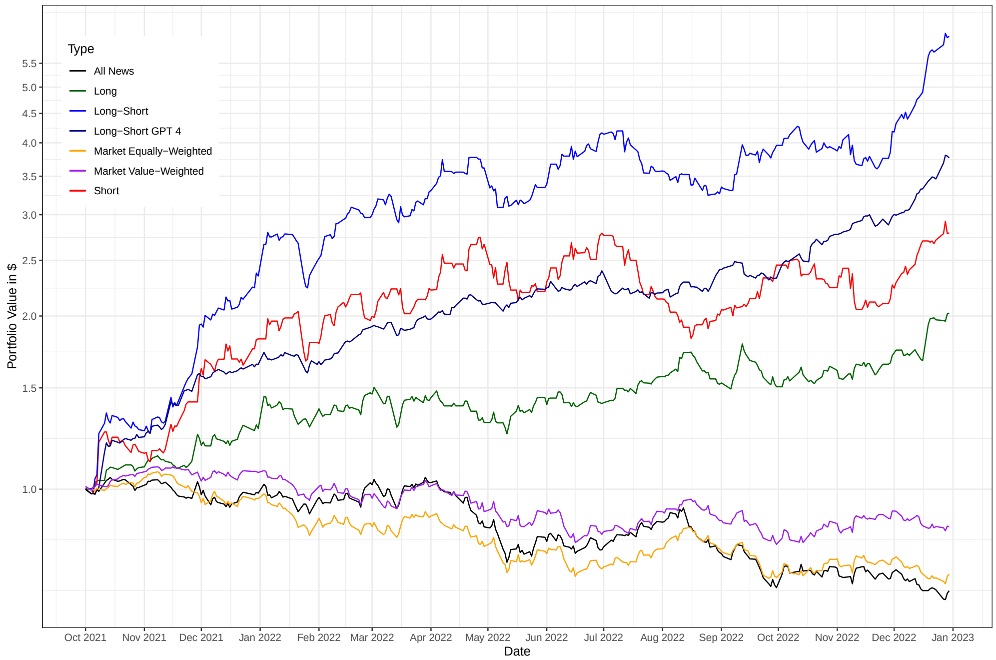
Additionally, as LLMs become more prevalent in the financial industry, it is essential to investigate their potential impact on market dynamics, including price formation, information dissemination, and market stability. Future research can explore the role of LLMs in shaping market behavior and their potential positive and negative consequences for the financial system.

Lastly, future studies could explore the integration of LLMs with other machine learning techniques and quantitative models to create hybrid systems that combine the strengths of different approaches. By leveraging the complementary capabilities of various methods, researchers can further enhance the predictive power of AI-driven models in financial economics.

In short, our study demonstrates the value of ChatGPT in predicting stock market returns and paves the way for future research on the applications and implications of LLMs in the financial industry. As the field of AI-driven finance continues to expand, the insights gleaned from this research can help guide the development of more accurate, efficient, and responsible models that enhance the performance of financial decision-making processes.

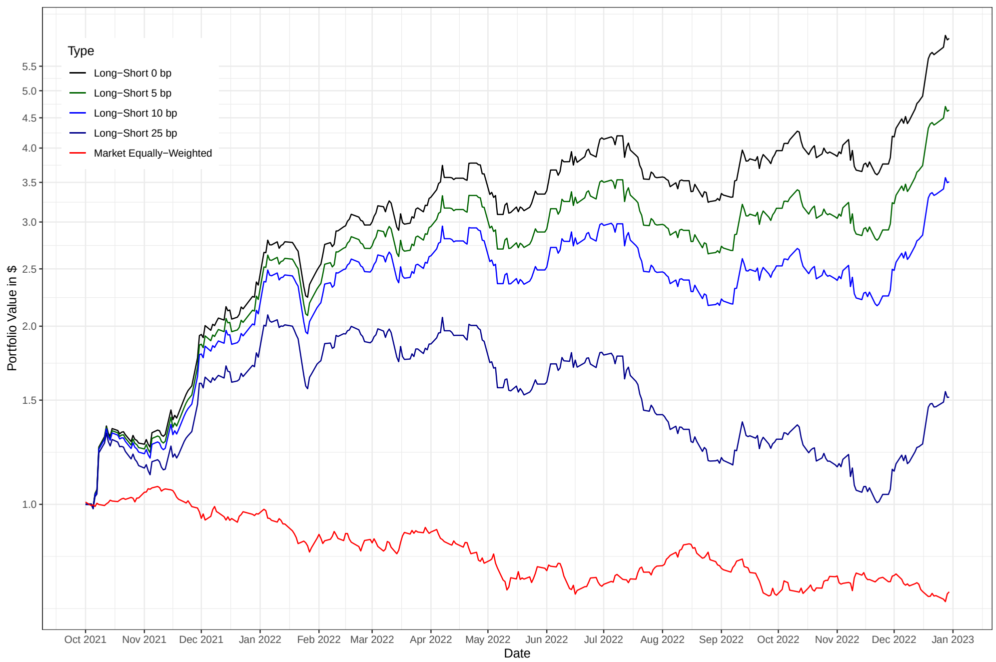
Figures

Figure 1: Cumulative Returns of Investing $1 (Without Transaction Costs)



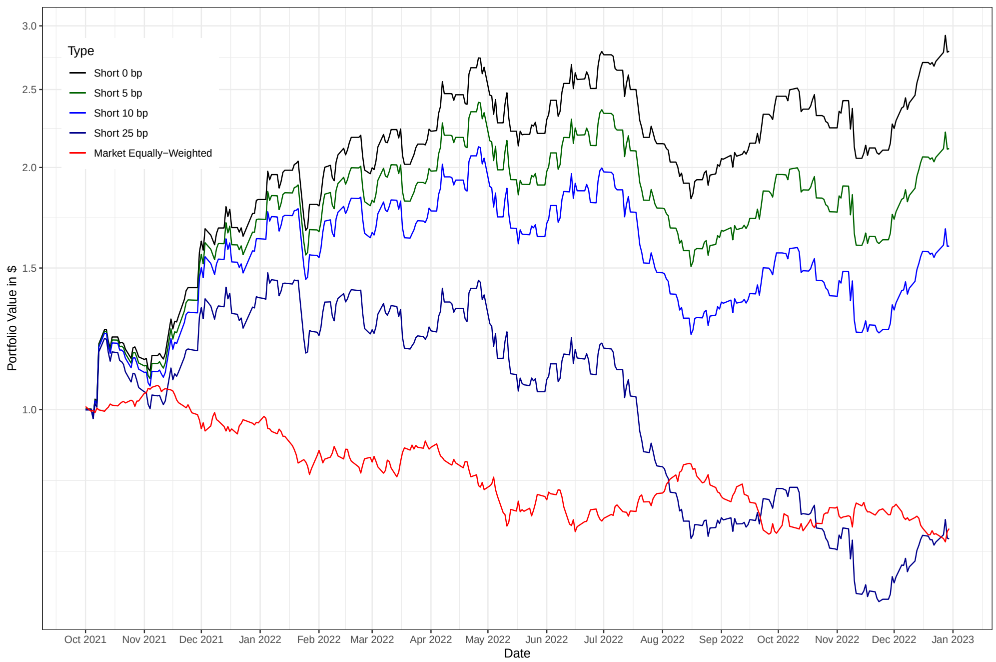
This figure presents the results of different trading strategies without considering transaction costs. We assume that if a piece of news is revealed before the market close, we buy (or short-sell) a position at the market close price. If a piece of news is announced after the market closes, we assume we buy (or short-sell) a position at the next opening price. All the strategies are rebalanced daily. The "All-news" black line corresponds to an equal-weight portfolio in all companies with news the day before. The green line corresponds to an equal-weighted portfolio that buys companies with good news, according to ChatGPT 3.5. The red line corresponds to an equal-weighted portfolio that short-sells companies with bad news, according to ChatGPT 3.5. The light blue line corresponds to an equal-weighted zero-cost portfolio that buys companies with good news and short-sells companies with bad news, according to ChatGPT 3.5. The dark blue line corresponds to an equal-weighted zero-cost portfolio that buys companies with good news and short-sells companies with bad news, according to ChatGPT 4. The yellow line corresponds to an equally weighted market portfolio. The purple line corresponds to a value-weighted market portfolio.

Figure 2: Cumulative Returns of Investing $1 in the Long-Short Strategy for Different Transaction Costs



This figure presents the results of different trading strategies for different transaction costs. We assume that if a piece of news is revealed before the market close, we buy (or short-sell) a position at the market close price. If a piece of news is announced after the market closes, we assume we buy (or short-sell) a position at the next opening price. All the strategies are rebalanced daily. The black line corresponds to an equal-weighted zero-cost portfolio that buys companies with good news and short-sells companies with bad news, according to ChatGPT 3.5, with zero transaction costs. The dark green line corresponds to the same equal-weighted zero-cost portfolio with a cost of 5 basis points per transaction. The light blue line corresponds to the same equal-weighted zero-cost portfolio with a cost of 10 basis points per transaction. The dark blue line corresponds to the same equal-weighted zero-cost portfolio with a cost of 25 basis points per transaction. The red line corresponds to an equally weighted market portfolio.

Figure 3: Cumulative Returns of Investing $1 in the Short Strategy for Different Transaction Costs



This figure presents the results of different trading strategies for different transaction costs. We assume that if a piece of news is revealed before the market close, we buy (or short-sell) a position at the market close price. If a piece of news is announced after the market closes, we assume we buy (or short-sell) a position at the next opening price. All the strategies are rebalanced daily. The black line corresponds to an equal-weighted short portfolio that buys companies with good news and short-sells companies with bad news, according to ChatGPT 3.5, with zero transaction costs. The dark green line corresponds to the same equal-weighted short portfolio with a cost of 5 basis points per transaction. The light blue line corresponds to the same equal-weighted short portfolio with a cost of 10 basis points per transaction. The dark blue line corresponds to the same equal-weighted short portfolio with a cost of 25 basis points per transaction. The red line corresponds to an equally weighted market portfolio.

Tables

Table 1: Descriptive Statistics

This table reports selected descriptive statistics of the daily stock returns in percentage points, the headline length, the response length, the GPT score (1 if ChatGPT says YES, 0 if UNKNOWN, and -1 if NO), and the event sentiment score provided by the data vendor.

	Mean	SD	min	P25	Median	P75	Max	N
Daily Return (%)	0	5.26	−64.97	−2.04	−0.02	1.89	237.11	60755
Headline Length	76.36	28.65	21	56	70	90	395	60755
ChatGPT Response Length	153.31	38.04	0	124	151	179	303	60755
GPT Score	0.24	0.47	−1	0	0	1	1	60755
Event Sentiment Score	0.18	0.49	−1	0	0	0	1	60755

Table 2: Correlations

This table reports the correlation between daily stock returns in percentage points, the headline length, the response length, the GPT score (1 if ChatGPT says YES, 0 if UNKNOWN, and -1 if NO), and the event sentiment score provided by the data vendor.

	Daily Return (%)	Headline Length	ChatGPT Response Length	GPT Score	Event Sentiment Score
Daily Return (%)	1	.	.	.	.
Headline Length	−0.002	1	.	.	.
ChatGPT Response Length	−0.001	0.261	1	.	.
GPT Score	0.018	0.081	0.441	1	.
Event Sentiment Score	0.005	−0.071	0.091	0.279	1

Table 3: Regression of Next Day Returns on the Prediction Score

This table reports the results of running regressions of the form $r_{i,t+1} = a_i + b_t + \gamma' x_t + \varepsilon_{i,t+1}$. Where $r_{i,t+1}$ is the next day's return in percentage points, a_i, b_t are firm and time fixed effects. x_t corresponds to the vector containing the ChatGPT or data vendor score. The corresponding t-statistics are in parentheses. Standard errors are clustered by date and firm. All models include firm and time fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GPT-score	0.259***	0.243***										
	(5.259)	(4.980)										
event-sentiment-score		0.058		0.038			0.118*					
		(1.122)		(0.683)			(2.272)					
GPT-4-score			0.176***	0.167***								
			(5.382)	(4.768)								
bart-large-score					0.142***							
					(4.653)							
distilbart-mnli-12-1-score						0.150***						
						(4.919)						
GPT-2-large-score								0.035				
								(1.051)				
GPT-2-score									0.001			
									(0.025)			
GPT-1-score										0.034		
										(1.304)		
bert-score											−0.226***	
											(−3.703)	
bert-large-score												0.001
												(0.020)
Num.Obs.	60 755	60 755	60 755	60 755	60 176	60 755	60 755	60 176	60 176	60 755	60 176	60 176
R2	0.184	0.184	0.184	0.184	0.185	0.184	0.184	0.185	0.185	0.184	0.185	0.185
R2 Adj.	0.121	0.121	0.121	0.121	0.121	0.121	0.121	0.121	0.121	0.121	0.121	0.121
R2 Within	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
R2 Within Adj.	0.001	0.001	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AIC	370 534.7	370 534.9	370 534.8	370 536.1	367 175.7	370 547.3	370 560.5	367 194.8	367 195.9	370 566.9	367 180.1	367 195.9
BIC	409 811.3	409 820.5	409 811.4	409 821.7	406 374.6	409 823.9	409 837.2	406 393.7	406 394.8	409 843.5	406 379.0	406 394.8
RMSE	4.75	4.75	4.75	4.75	4.76	4.75	4.75	4.76	4.76	4.75	4.76	4.76
Std.Errors	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno
FE: date	X	X	X	X	X	X	X	X	X	X	X	X
FE: permno	X	X	X	X	X	X	X	X	X	X	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 4: Regression of Next Day Returns on the Prediction Score (Small Stocks)

This table reports the results of running regressions of the form $r_{i,t+1} = a_i + b_t + \gamma' x_t + \varepsilon_{i,t+1}$. Where $r_{i,t+1}$ is the next day's return in percentage points, a_i, b_t are firm and time fixed effects. x_t corresponds to the vector containing the ChatGPT or data vendor score. The corresponding t-statistics are in parentheses. Standard errors are clustered by date and firm. All models include firm and time fixed effects. Small stocks are defined as those whose market capitalization is less than the 10th percentile NYSE market capitalization.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GPT-score	0.653***	0.542***										
	(5.145)	(4.028)										
event-sentiment-score		0.277*		0.256+			0.435***					
		(2.117)		(1.876)			(3.567)					
GPT-4-score			0.501***	0.419***								
			(4.830)	(3.645)								
bart-large-score					0.165							
					(1.504)							
distilbart-mnli-12-1-score						0.207+						
						(1.895)						
GPT-2-large-score								0.019				
								(0.216)				
GPT-2-score									0.064			
									(0.765)			
GPT-1-score										0.008		
										(0.098)		
bert-score											−0.492**	
											(−2.598)	
bert-large-score												0.018
												(0.096)
Num.Obs.	14 343	14 343	14 343	14 343	14 238	14 343	14 343	14 238	14 238	14 343	14 238	14 238
R2	0.201	0.201	0.201	0.201	0.201	0.200	0.200	0.201	0.201	0.200	0.202	0.201
R2 Adj.	0.086	0.086	0.086	0.086	0.086	0.084	0.085	0.085	0.085	0.084	0.086	0.085
R2 Within	0.002	0.002	0.002	0.002	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000
R2 Within Adj.	0.002	0.002	0.002	0.002	0.000	0.000	0.001	0.000	0.000	0.000	0.001	0.000
AIC	98 043.0	98 039.8	98 041.0	98 038.7	97 320.5	98 063.3	98 052.1	97 322.6	97 322.0	98 066.4	97 314.2	97 322.6
BIC	111 731.4	111 735.8	111 729.4	111 734.7	110 957.8	111 751.7	111 740.5	110 959.9	110 959.3	111 754.8	110 951.5	110 959.9
RMSE	6.51	6.51	6.51	6.51	6.50	6.51	6.51	6.50	6.50	6.51	6.50	6.50
Std.Errors	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno
FE: date	X	X	X	X	X	X	X	X	X	X	X	X
FE: permno	X	X	X	X	X	X	X	X	X	X	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5: Regression of Next Day Returns on Prediction Score (Non-Small Stocks)

This table reports the results of running regressions of the form $r_{i,t+1} = a_i + b_t + \gamma' x_t + \varepsilon_{i,t+1}$. Where $r_{i,t+1}$ is the next day's return in percentage points, a_i, b_t are firm and time fixed effects. x_t corresponds to the vector containing the ChatGPT or data vendor score. The corresponding t-statistics are in parentheses. Standard errors are clustered by date and firm. All models include firm and time fixed effects. Non-small stocks are defined as those whose market cap is greater than the 10th percentile NYSE market capitalization.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
GPT-score	0.148**	0.158**										
	(3.084)	(3.280)										
event-sentiment-score		−0.041		−0.060			−0.005					
		(−0.830)		(−1.163)			(−0.112)					
GPT-4-score			0.097**	0.111***								
			(3.252)	(3.491)								
bart-large-score					0.144***							
					(4.695)							
distilbart-mnli-12-1-score						0.146***						
						(4.894)						
GPT-2-large-score								0.030				
								(0.947)				
GPT-2-score									−0.014			
									(−0.539)			
GPT-1-score										0.056*		
										(2.332)		
bert-score											−0.165**	
											(−2.795)	
bert-large-score												−0.011
												(−0.200)
Num.Obs.	46 402	46 402	46 402	46 402	45 928	46 402	46 402	45 928	45 928	46 402	45 928	45 928
R2	0.218	0.218	0.218	0.218	0.219	0.218	0.218	0.219	0.219	0.218	0.219	0.219
R2 Adj.	0.159	0.159	0.159	0.159	0.159	0.159	0.158	0.158	0.158	0.158	0.159	0.158
R2 Within	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
R2 Within Adj.	0.000	0.000	0.000	0.000	0.001	0.001	0.000	0.000	0.000	0.000	0.000	0.000
AIC	265 328.7	265 329.8	265 329.2	265 329.3	262 823.9	265 316.8	265 341.2	262 848.3	262 848.9	265 336.7	262 839.8	262 849.1
BIC	294 082.6	294 092.4	294 083.1	294 091.9	291 517.9	294 070.7	294 095.1	291 542.3	291 542.8	294 090.6	291 533.7	291 543.1
RMSE	3.93	3.93	3.93	3.93	3.94	3.93	3.93	3.94	3.94	3.93	3.94	3.94
Std.Errors	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno	by: date & permno
FE: date	X	X	X	X	X	X	X	X	X	X	X	X
FE: permno	X	X	X	X	X	X	X	X	X	X	X	X

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

Table 6: Descriptive Statistics of Portfolios

	Long-Short	Long-Short GPT 4	Long	Short	Market Equally-Weighted	Market Value-Weighted	All News
Sharpe Ratio	3.09	3.80	1.72	1.86	-0.99	-0.39	-0.98
Daily Mean (%)	0.63	0.44	0.25	0.38	-0.10	-0.04	-0.11
Daily Std. Dev. (%)	3.25	1.84	2.32	3.26	1.55	1.49	1.83
Max Drawdown (%)	-22.79	-10.40	-16.94	-34.39	-36.12	-26.68	-38.70

Table 7: Selected Metrics

This table reports selected accuracy, prediction, recall, specificity, and F1 score metrics. The table considers whether the firm's stock market return is positive or negative. We only include observations where the model's response is YES or NO (excluding UNKWON). The numbers are rounded to two decimals. Naive corresponds to predicting always the majority class.

Metric	GPT	Data Vendor	GPT-1	GPT-2	BERT-large	BERT	naive
Accuracy	0.5110	0.5089	0.5117	0.5018	0.5073	0.5071	0.5072
Precision	0.5097	0.5084	0.5101	0.5052	0.5073	0.5071	0.5072
Recall	0.9408	0.9566	0.9383	0.8673	0.9862	0.9985	1.0000
Specificity	0.0686	0.0480	0.0726	0.1257	0.0146	0.0015	0.0000
F1 Score	0.6612	0.6639	0.6609	0.6384	0.6700	0.6726	0.6730

Table 8: Average Next Day's Return by Prediction Score

This table reports the average daily returns in percentage points (0.1 corresponds to 0.1%) by the different model scores.

score	ChatGPT 3.5	GPT-1	GPT-2	BERT	Data Vendor
0	-0.0470	0.0067	-0.0755	0.0451	-0.0016
-1	-0.3562	-0.2845	0.0568	-0.4379	-0.1800
1	0.1390	0.0538	0.0218	-0.1938	0.0217

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