AI Sentiment

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We analyze the average sentiment from 1,000 identical questions submitted to ChatGPT on a daily basis and find that this sentiment explains changes in firms' abnormal returns over the past two months. We further show that the effect strengthens following the lifting of Italy's temporary ban on ChatGPT and exhibits several shifts corresponding to three structural breaks in sentiment. In addition, we find that the impact varies with sentiment exposure, as proxied by industry technology intensity, institutional ownership, and firm size.

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1. Introduction

Use of ChatGPT has grown rapidly over time. Active users increased to 179 million in May 2024.[2] As of June 2025, 34% of U.S. adults use ChatGPT, 28% of those user's report using it for work-related tasks.[3] The service is available in most major economies; even in China—where the service is officially restricted—people still use it widely (Figure 1).[4] ChatGPT users cover the vast majority of global financial markets, with notable exceptions including Russia and some countries in the Middle East and Africa (Figure 2).[5]

How the chat AI tool prompt messages affect investor behaviors – as 50% of the chats from professionals in business and management are work-related[6] and that ChatGPT consistently dominates all other AI chat tools in U.S.: since January 2024, its market share has remained above 70%, ahead of Google Gemini, Perplexity, and Claude,[7] it is a unsure question of how the tones in the messages in the prompt responses those professional received affect their investment behaviors. In particular, while current literature on the impact of sentiment on investor choices show that tone in financial news (Tetlock, 2007 & 2010; Tetlock et al., 2008; Garcia, 2013), in financial statements and in social media discussions (Antweiler and Frank, 2004), weather (Hirshleifer and Shumway, 2003; Kamstra, et al., 2003; Cao and Wei, 2005; Novy-Marx, 2014), Friday

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[2] Chatterji et al. (2025).
[3] https://www.pewresearch.org/short-reads/2025/06/25/34-of-us-adults-have-used-chatgpt-about-double-the-share-in-2023/.
[4] Data source: https://borealisdata.ca/dataset.xhtml?persistentId=doi%3A10.5683%2FSP3%2FWCUN0S. We code "Yes" responses to the survey item use_gpt as indicating ChatGPT use and compute the percentage of participants answering "Yes." The survey was conducted in 21 countries in 2023 with approximately 1,000 respondents.
[5] Data source: https://data.worldbank.org/indicator/CM.MKT.LCAP.CD. Market capitalization of listed domestic companies (current US$), 2023.
[6] https://www.pewresearch.org/short-reads/2025/06/25/34-of-us-adults-have-used-chatgpt-about-double-the-share-in-2023/.
[7] Data source: Top Generative AI Chatbots by Market Share – December 2025, FirstPageSage, accessed on Dec 7, 2025 at https://firstpagesage.com/reports/top-generative-ai-chatbots/.

(DellaVigna and Pollet, 2009) affect investor behaviors, no study is conducted on the new source of investor sentiment – the tone in the prompt response, affect investors' decisions.

In this study, we find that the average sentiment in GPT responses—after controlling for prompt content and orthogonalizing sentiment with respect to market-wide sentiment—is associated with movements in abnormal stock returns across many countries from March 2023 to July 2024. We also find that as the GPT model underwent three major structural changes—enabling internet search, introducing personalization, and releasing GPT-4o—the sensitivity of stock prices to sentiment shifts changed significantly. This suggests that features of prompt responses, including model updates, can influence investor behavior.

We analyze the causality of the sentiment-price relationship using two natural experiments: the temporary ban of ChatGPT service in Italy and the permanent ban of ChatGPT service in China. We show that after service was restored in Italy, Italian firms' price responses to sentiment shifts became significantly stronger.

We then test the mechanisms through which the response sentiment effects. First, we show that exposure to the sentiment reinforces the sentiment effect – the firms in the industries that are closely related to artificial intelligence experience a stronger price response when the prompt-response sentiment shifts. Second, we find that the firms with higher institutional ownership experience a milder price response when prompt-response sentiment shifts – this finding suggests that the prices of the firms with higher proportion of noise traders are more sensitive to the response-prompt sentiment moves. Our findings are consistent with (i) limited-attention and visibility-based mechanisms that affect the diffusion and pricing of sentiment-related information (Peng and Xiong, 2006; Fang and Peress, 2009), and (ii) noise-trader risk and limits-to-arbitrage mechanisms that allow sentiment-driven mispricing to persist (De Long et al., 1990; Shleifer and Vishny, 1997).

Lastly, we perform an event study that tests the significance in the price changes of days around one of the significant structural breaks in the prompt-response sentiment – the sentiment jumps on June 28, 2023, as ChatGPT allows Internet searching. We find that from day 0 (the break day) to day 2 (two days after the break), the abnormal returns of firms are negative and significant at 1% significance level when we use the standardized prompt-response sentiment and control for the first-order lag in the abnormal returns. The days before the break only have day -4 that experiences a significant change which could be explained by a global bank policy adjustment on Jun 22, 2023. Second, we show that when using the market-sentiment orthogonalized prompt-response sentiment to replace the standardized sentiment, day 0 – day 4 experience significant price changes.

Our study contributes to the literature on the sentiment effect – by identifying a new source of sentiment as in the AI chat tool prompt responses, on the stock price abnormal returns. Second, we derive a theoretical framework that explains the price response to changes in sentiment due to noise traders' misperception of market signals; Third, this study also contributes to related literature on artificial intelligence by showing the phenomenon in financial markets that investors behaviors are shaped by the features of the AI tools; the tools' generated messages shifts investor decisions and stock abnormal returns. It implicates that we should use the AI tools with caution and the introduction of AI tools introduces new source of exposure to technological advancements. Fourth, Our study also contributes to the literature on the international financial markets by focusing on a comparison among 52 countries, showing that a global information search tool influences stock market performance.

2. Literature Review

2.1 Sentiment Effects

The investor-sentiment literature, including Baker and Wurgler (2006), Lemmon and Portniaguina (2006), and Stambaugh et al. (2012), documents that investor sentiment has a significant influence on stock returns. Researchers employ a variety of measures to capture investor sentiment. Sentiment reflected in the tone of financial news affects stock returns: Tetlock (2007, 2010) and Tetlock et al. (2008) show that sentiment measured using the Loughran–McDonald dictionary explains daily market returns. Alternative measures based on search activity have also been widely used. Da et al. (2011) use Google search frequency for company names and tickers as a proxy for investor attention, while Da et al. (2015) show that investor sentiment measured using Google Search Trends keywords related to financial and economic fears is associated with lower short-term market returns and higher volatility. Antweiler and Frank (2004) use internet message-board activity as a proxy for investor sentiment and document its effect on stock performance. While these studies demonstrate that various sentiment measures are associated with stock price reactions, to our knowledge, no existing study examines the relationship between sentiment generated by AI tools and stock prices.

2.2 Animal Spirits and Investor Behaviors

How the investor sentiment drives investment behaviors and thus stock prices is explained by several hypotheses in related literature. Psychological aspects may help explain how information and affect influence investor decisions. Lerner et al. (2015) discuss how emotions affect decision-making and propose several alternative models for how emotions exert their effects. Edmans et al.

(2007) show that sudden changes in investor mood can influence market returns—for example, they document a significant negative impact of soccer losses on market performance. Clore and Schwarz (1983) show that judgments are affected by mood at the time they are made, suggesting that people's judgments can be influenced by recent events in their lives.

Risk aversion is one of the channels through which sentiment influences investment behaviors. Novy-Marx (2014) finds that "animal spirits"—such as exposure to colder weather—can change investors' risk aversion and investment behavior. Kamstra et al. (2003) show the impact of SAD (seasonal affective disorder), supported by psychological evidence linking depression to increased risk aversion. Relatedly, the seasonal effect on investor mood and market index performance appears to vary cyclically. Cao and Wei (2005) and Hirshleifer and Shumway (2003) also support the idea that weather affects mood and investor risk aversion. Thus, our hypothesis is that investors' risk aversion—and therefore their investment behavior—will be affected by the tone of the responses they receive from ChatGPT, provided they are frequent users of the LLM chatbot. Alternatively, rather than influencing investors' risk aversion, the investors' risk assessment, however, may be affected by moods as well – as Loewenstein, et al. (2001) suggest that, according to their risk-as-feelings hypothesis, behaviors are driven by emotional reactions to risk situations when facing uncertainty. Thus, the responses investors receive, through their daily interactions with the AI tools, may affect their investment decisions facing investment risks and uncertainties. This hypothesis suggests that investors' perception of risk premium varies with prompt responses.

2.3 Limited Attention

The way sentiment affects stock returns may be explained by the limited-attention hypothesis (Barber and Odean, 2008). This hypothesis is also supported by Engelberg and Parsons (2011), who find that local media coverage strongly affects investor trading, even when controlling for the same information event and the timing of reporting. DellaVigna and Pollet (2009) document a "Friday effect", the announcements released on Fridays generate a weaker immediate price response and lower trading volume, consistent with investor inattention late in the week. Garcia (2013) finds that the impact of sentiment on market returns concentrates during recessions.

This study also fits into the literature on the noise traders' demands drive divergence of price from fundamental values, as De Long, et al. (1990) shows how noise traders' traders that divergent from fundamental values and arbitrageurs unable to bet against them. The limits of arbitrage, as suggested by Shleifer and Vishny (1997), driven by capital limits, leads to the long-lasting existence of the price divergence from fundamental values. Kumar and Lee (2006) find return co-movement that they attribute to systematic retail trading, especially during high-sentiment periods.

An alternative explanation for the relationship between the sentiment and stock prices is that sentiment accelerates information processing. As related literature, including Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999), shows investors process and react to the information, and information affects investment behaviors. In particular, Fang and Peress (2009) show that media coverage influences stock returns, and which effect is moderated by firm size and institutional ownership.

3. Theoretical Framework and Hypotheses

We adopt the noise-trader framework of De Long, et al. (1990) to explain how biased beliefs move prices in competitive equilibrium. Consider one risky asset and a risk-free asset with gross rate $1 + r$. There are two trader types: informed investors and noise traders. Noise traders' beliefs about the risky asset's mean payoff are biased by a sentiment term θ_t. In equilibrium, the difference in risky positions across the two types of investors and the resulting price are characterized in De Long et al. (1990, Eq. (14)), and the asset's expected excess return rises with the variance and persistence of sentiment—the "noise-trader risk" result in De Long et al. (1990, Eq. (17)). As in:

$$\Delta R_{n-i} = (X_t^n \; - \; X_t^i)[r + p_{t+1} \; - \; p_t(1 + r)]$$

$$_t(\Delta R_{n-i}) \; = \; \rho_t \; - \; \frac{(1 + r)^2(\rho_t)^2}{(2\gamma)\phi\sigma_\rho^2}$$

Where X is the amount in the risky asset, r is risk-free rate, p_t is the price, ρ is the misperception from noise traders, γ is the coefficient of absolute risk aversion, ϕ is the proportion of noise traders, and σ_ρ^2 is the misperception variance.

Intuitively, when noise traders are optimistic ($\theta_t > 0$), they take larger positions, pushing prices and creating risk that informed investors are unwilling or unable to fully offset due to limits of arbitrage. Portfolios that load on this risk can earn higher expected returns. We write firm i's return as a standard factor component plus a sentiment-priced component:

$$R_{i,t} = \beta_i' f_t \; + \; \eta_i \, s_t \; + \; \varepsilon_{i,t}$$

where f_t are observed risk factors and s_t is the sentiment observed each day. η_i is the firm i's exposure to the sentiment. We decompose the observed signals into a latent common component g_t and noise ν_t:

$$s_t = g_t + \nu_t$$

$$m_t = \rho \, g_t + \xi_t$$

m_t is a market-sentiment index. This decomposition motivates using both s_t and m_t, when desired, the residual sentiment:

$$e_t \equiv s_t - \Pi(m_t) \text{(orthogonal to } m_t\text{) in estimation.}$$

Consistent with limited attention theory (Peng and Xiong, 2006), suppose a fraction ϕ_t of investors are noise traders, who place weight γ_i on s_t. Their belief shift in expected return for asset i is:

$$\Delta\mathbb{E}_t[R_{i,t+1}] \;=\; \eta_i\, \phi_t\, s_t$$

where η_i captures asset i's exposure to the sentiment s_t. With mean–variance preferences, representative demand is

$$X_{i,t} \;=\; \frac{1}{\gamma\, \sigma_i^2}\, \Delta\mathbb{E}_t[R_{i,t+1}] \;=\; \frac{1}{\gamma\, \sigma_i^2}\, \eta_i\, \phi_t\, s_t,$$

where γ is risk aversion and σ_i^2 is the return variance. Under linear price impact (Kyle, 1985), order-flow from these investors moves prices:

$$\Delta p_{i,t} \;=\; \Lambda\, \Delta X_{i,t}^n \;=\; \Lambda \cdot \frac{1}{\gamma\, \sigma_i^2}\, \eta_i\, \phi_t\, s_t,$$

with $\Lambda > 0$ denoting (inverse) market depth. Collecting terms, same-day returns admit

$$R_{i,t} = \beta_i' f_t + \kappa_i\, \phi_t\, s_t + \varepsilon_{i,t}$$

Where $\kappa_i \equiv \frac{\Lambda\, \eta_i}{\gamma\, \sigma_i^2}$. Subtracting the factor piece yields the abnormal return (alpha):

$$\alpha_{i,t} \equiv R_{i,t} - \beta_i' f_t = \kappa_i \, \phi_t \, s_t + \varepsilon_{i,t}$$

In robustness, replace s_t by the residual $e_t$to isolate sentiment information beyond traditional sentiment:

$$\alpha_{i,t} = \kappa_i \, \phi_t \, e_t + \varepsilon_{i,t}$$

This mapping nests the De Long et al. (1990) insight—biased beliefs held by a nontrivial investor mass ($\phi_t > 0$) move prices—while giving you a clean empirical slope $\kappa_i$that depends on exposure to the signal (s_t), exposure (η_i), market depth (Λ), risk aversion (γ), and return price risk (σ_i^2). We show that the empirical implications of the theoretical models on the relationship between sentiment and alpha is that:

1) The abnormal return increases with the sentiment positivity; A more positive sentiment results in a higher abnormal return on stocks.
2) More exposed firms experience stronger price responses to shifts in sentiment.
3) The firms with shallower market depth, e.g. the less visible firms and smaller firms, tend to experience more sensitive changes in abnormal returns when sentiment changes.
4) A more negative sentiment moves noise traders' moods and increases their risk aversion, thus leading to a lower risk premium and lowering sensitivity of abnormal returns to changes in sentiment.
5) Riskier assets, as indicated by return variance, are less sensitive to changes in sentiment.
6) Firms with higher proportion of noise traders are more sensitive to changes in sentiment.

Hypothesis I: Prompt-response sentiment affects stock prices.

Hypothesis II.a: Because market-wide sentiment effects are reflected in prompt sentiment, the effect is concentrated among smaller and less visible firms.

Hypothesis II.b: The effect of prompt-response sentiment is concentrated among riskier firms.

Hypothesis II.c: Prompt responses accelerate information processing; therefore, the effect of sentiment in the responses is strongest for firms with a higher proportion of noise traders.

Hypothesis II.d: Firms with higher exposure experience larger price responses when sentiment shifts.

4. Methodology and Data

The responses users receive (either through a website portal or an API) depend on the model features. Since ChatGPT is a black-box model, one cannot determine exactly how responses shift after model updates—but ChatLog-Daily (Tu et al., 2024) provides a useful sample of the answers users receive on a daily basis. For instance, when asking the question, "How do jellyfish function without brains or nervous systems?", GPT may provide different answers depending on the model features. Our hypothesis is that investors' moods may be influenced by the responses they receive from ChatGPT if they are frequent users. Specifically, we analyze the sentiment of responses generated for 1,000 identical prompts sent to the OpenAI API (model: gpt-3.5-turbo).[8] The prompts are drawn from the "Explain Like I'm Five"[9] (ELI) question set (Fan et al., 2019), which

[8] Tu et al. (2024) compute daily sentiment as the simple average of three model-generated responses for each of 1,000 ELI5 questions, using a temperature of 1 (which controls the degree of randomness in the model's outputs). In the same paper, they identify statistically significant shifts in ChatGPT's classification performance around March 24, 2023, and June 28, 2023.

[9] One can find example ELI5 questions on the dataset website. The ELI5 dataset pairs long-form questions with human-written answers collected from the r/explainlikeimfive (ELI5) subreddit and includes supporting documents retrieved from web sources, making it useful for comparing LLM-generated responses with human reference answers.

contains roughly 270,000 long-form, open-ended questions that ask for simple explanations of "why," "how," and "what" topics.[10]

$$\alpha lpha\_ff5_{i,t} = \alpha + \beta Sentiment_t + \gamma_t + \delta_i + \varepsilon_{i,t}$$

Where $\alpha lpha\_ff5_{i,t}$ denotes the daily Fama–French five-factor abnormal return (alpha) for firm i.[11] We collect global daily security prices from WRDS (Compustat Global Security Daily) and compute log returns. We obtain the Fama–French five factors from Ken French's data library and use them to estimate daily alphas.[12] $Sentiment_t$ is the daily average relative sentiment, defined as the sentiment of the model's answers minus the sentiment of the corresponding questions, averaged across the 1,000 prompts. Sentiment for both questions and answers is estimated using VADER (Valence Aware Dictionary and sEntiment Reasoner), a widely used lexicon-based sentiment tool (Hutto and Gilbert, 2014). We then compute the difference between answer sentiment and question sentiment to mitigate bias arising from the prompts' own sentiment.[13]

We summarize variables in Table 1. The average daily Fama–French five-factor abnormal return, *alpha_ff5*, is -0.459%, suggesting that global firm alphas tend to be negative from March 2023 to July 2024. Our sentiment measures, *Sentiment_z* (the standardized sentiment ~ N(0,1)). is negatively skewed and the market sentiment - orthogonalized sentiment, *Sentiment_e*, is more symmetric. We graph the daily average raw returns and alphas in Figure 3. Firm and index returns

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[10] A smaller proportion of the ELI5 questions are "if," "is," "when," "can," "where," "in," and "does" questions.
[11] We estimate alphas by regressing excess returns on the market, size, HML, RMW, and CMA risk factors using an estimation window of trading days −45 to −1, requiring a minimum of 30 observations per estimation window.
[12] Daily Fama/French five-factor (2×3) data are from Kenneth R. French's Data Library (U.S. Research Returns: "Fama/French 5 Factors (2×3) [Daily]": https://mba.tuck.dartmouth.edu/pages/faculty/ken.French/index.html
[13] Technical details on VADER are available at: https://github.com/cjhutto/vaderSentiment. VADER is a lexicon- and rule-based sentiment analysis method developed and validated primarily on social media text (Hutto and Gilbert, 2014). It is available in the NLTK toolkit and is commonly used as a baseline sentiment model in LLM-related studies.

are highly correlated; alphas are less volatile but still show positive correlation with the returns. In Table 1, Panel B, we report the distribution of our firm-day observations by country. No single country dominates our sample. The largest share is China with 15.03%, followed by the U.S. (11.7%), and India (10.85%). Japan and Korea account for 9.50% and 7.44% of our sample, respectively. All other countries never dominate with a sizable subsample.

We split sample into four regions based on structural break test, Quandt Likelihood Ratio test, to detect breakpoints in sentiment. Region 0: March 28, 2023 - June 27, 2023; Region 1: June 28, 2023 - February 13, 2023 (since June 28, 2023 GPT enabled Internet browsing to incorporate real-time news into responses); Region 2: February 14, 2023 - May 9, 2024 (GPT enabled personalized responses and push more frequent model updates); Region 3: May 10, 2024 - May 20, 2024 (GPT-4o was released on May 10, 2024).[14] As in Figure 4, GPT sentiments experienced three structural shifts corresponding to the three major model events. As shown in the figure, we extract several representative records from different periods to illustrate changes in response style in Figure 5. The same ELI5 question is asked, but the answer style varies substantially over time. In Panel B, when internet searching is allowed, the answer becomes more colloquial. After personalization is introduced in Panel C, the response contains more details. After the release of o4 in Panel D, the answer becomes more natural but also longer. These patterns mirror the sentiment shifts across the four periods.

In Figure 6, we graph each country's daily average alphas, grouping countries by geographic regions. In Panel A of Figure 6, the European countries returns in the first three groups comove strongly, especially within western Europe. However, with the exception of Turkey, eastern

[14] ChatLog sentiment is available up to May 20, 2024.

European returns appear less correlated with those of other European groups. In Panel B of Figure 5, we graph the returns for Asian countries and Oceania (Australia and New Zealand). We find that eastern Asian countries also closely comove with each other, but Chinese firms deviate from other countries around December 2023 to May 2024. We find less correlation among the south Asian or the southeastern Asian countries; in particular, Thailand's returns are more volatile than those of others in the same group. In Oceania, the two countries' returns comove closely with each other but do not appear to be strongly related to European countries' returns. Overall, we find that Asian countries' return patterns differ from European ones. In Panel C of Figure 6, we depict the returns for American countries, the Middle East, and Africa. We find that countries in the American group (except Argentina) tend to comove. Middle Eastern and African countries, by contrast, appear to have their own patterns and do not seem to correlate strongly with any other geographical groups.

5. *The Impact of GPT Sentiment on Firm Alphas*

In Column (2) of Table 2 shows a one unit increase in the GPT sentiment is associated with a 0.111% decline in the firm daily alpha, significant at 1%. We find that the structural shifts in sentiment is associated with significant differences in the sentiment effects; the impact is smaller when GPT enables Internet browsing (as in Region 1); becomes stronger during personalized responses and frequent update window (as in Region 2); and is slight smaller when 4o released (as in Region 3), compared with the benchmark window (as in Region 0).

5.1. Natural Experiments – The Temporary and the Permanent Bans of ChatGPT Service

Although the sentiment should be isolating from world news influences, as the prompt questions are based on ELI5 dataset ("Explain Like I'm five"), such as "How can different animals perceive different colors?" But one may argue that the sentiment effect, however, may be driven by the market sentiments, especially after Internet browsing was enabled on June 28, 2023. Italy temporarily banned ChatGPT service from March 31 to April 27, 2023, allowing us to isolate the impact of sentiment. Second, ChatGPT service is not available in China – so Chinese firms have limited exposure to GPT sentiment influence. In Column (1) of Table 3, while higher sentiment significantly lowers alphas by 0.108% daily (significant at 1%), the three-way interaction of *Treated* (=1 for Italian firms), *Ban* (=1 during ban window), and sentiment is not significant. In Column (2), we find the three way interaction of *Treated*, *Restore* (=1 after restoration of service), and sentiment suggests a reinforced effect of sentiment on Italian firms after the service is restored on April 28, 2023. The finding that the ban itself does not lead to significant shifts in sentiment impact, but that the subsequent restoration has a significantly stronger effect, may be explained by traffic patterns as depicted in Figure 7: ChatGPT visit volume appears to have been relatively limited from March to April 2023 worldwide, but increased substantially afterward. While we do not have Italy-specific visit data, Cloudflare's monthly traffic statistics for ChatGPT indicate that volumes rose sharply only after October 2023 (see Figure 7). Chinese firms, on average, experience a 70% smaller effect (0.0852, significant at the 1% level) of sentiment, consistent with their more limited access to the service.

5.2. The Orthogonalized Sentiment from Market Sentiment Indices

To isolate the impact of model-level sentiment on firm alphas, we recognize that after February 2024 GPT can browse online, while before that date it is possible that the data used to train the model already incorporate specific information about news and important economic events. We therefore orthogonalize GPT sentiment from market-level sentiments by using the residuals from a regression of sentiment on a set of market sentiment indices. These include Google search trends for "recession", "inflation", "bankruptcy", "layoff", and "stock market crash"; economic policy uncertainty (EPU) indices from Baker et al. (2016); the global EPU index; and the VIX. The regression also includes day-of-week dummies to control for important market updates or announcements scheduled on fixed dates. This residual measure removes the impact of market sentiment, i.e., the impact of market news/events, and focuses on the model's sentiment changes and their impact on firm alphas.

We report the results in Table 4. In column (1), we run a regression similar to Table 2, column (2). The coefficient on *Sentiment_e* remains significant and negative (-0.710 at the 1% level), suggesting that a 1% increase in the negativity of the tone in GPT responses is associated with a 0.710% decrease in firm alphas. To test whether jumps in the average sentiment of GPT change the impact of sentiment on alphas, in column (2) we add the dummies for the three regions (periods) defined in Table 2, which mirror the three stages of sentiment depicted in Figure 2, and interact them with *Sentiment_e*. We find that all of the region dummies and their interaction terms are significant at the 1% level.

5.3. The Mechanisms of Sentiment Effect on Alphas

Several mechanisms may explain the sentiment effect. First, investors exposed to GPT-generated sentiment are more likely to concentrate on technology firms. Firms with higher AI exposure tend to have investor bases that are more likely to use ChatGPT. Second, retail investors are more likely to be influenced by sentiment. Higher institutional ownership is negatively related to the size of the retail investor base. Edmans et al. (2007) show that the impact of investor mood on market performance is stronger for small stocks. Da et al. (2011) find that short-term price increases and higher volatility associated with elevated investor sentiment—proxied by search volume for company names—are concentrated among retail investors. Consistent with these mechanisms, Column (1) of Table 5 shows that firms in AI-related industries experience approximately a 15% stronger alpha effect when GPT sentiment changes. Column (2) of Table 5 shows that the impact of GPT sentiment nearly disappears when a firm is predominantly held by financial institutions (for a one-unit increase in the exposure measure). Overall, firms with investor bases concentrated in technology industries and dominated by retail investors exhibit stronger sentiment effects on alphas.

In column (3) of table, we present the results of the country-level ChatGPT website traffic volume on the prompt sentiment effect. We obtain the traffic volume for www.chatgpt.com from CloudFlare. The country-month level traffic does not seem to moderate the effect of the prompt sentiment on firm alphas. This result indicates that the impact of the prompt sentiment does not vary with the number of visits to the service.

In column (4) and (5) we test whether the size of the firm, a proxy for the visibility of the firms, affects impact of the prompt sentiment, which is a direct test of our *Hypothesis II.a*. In column (4), we split our sample into two groups: small and large firms, based on their capitalization (as close price multiples by number of shares outstanding) daily median in the same country. In column (5), we use the capitalization (scaled down by 10^{11}). In both columns results we find that firm size significantly moderates the prompt sentiment effect - smaller firms, which are typically less visible, tend to experience stronger price responses when prompt sentiment changes. We find that the coefficient on *Small* × *Sentiment_e* is -4.309 and significant at 10%, and that the coefficient on

Size × *Sentiment_e* is 0.0381 and significant at 1%. Thus, the results in column (4) and (5) suggest that the less visible firms are more sensitive to the influence from the prompt sentiment, validating our *Hypothesis II.a*.

In column (6) of Table 5, we test whether the prompt sentiment affects the risky firms more, testifying our *Hypothesis II.b*, that risky firms are more sensitive to prompt sentiment. We define Risk = 1 for firms with Fama-French five factor return residual standard deviation greater than 75th percentile in the country-year distribution.[15] The result in column (6) shows that riskier firms tend to have higher average abnormal returns (0.0802, means 0.008% daily abnormal return, significant at 5%).

5.4 The Event Study of the Major Structural Shift in Sentiment

Finally, we conduct an event study on the significant change in average AI sentiment around June 28, 2023, using *Sentiment_z* or *Sentiment_e t*o proxy for AI sentiment in the event window. We focus on the 11 trading days around the event (from five trading days before to five trading days after June 28, 2023, the date with the most significant shift in the sentiment). We compute abnormal returns on these dates and use day 6 as the benchmark to test the impact of sentiment on firm alphas. In columns (1) and (2) of Table 6, we find that around the event days (day 0, day 1, day 2) changes in firms' abnormal returns are significant and negative. When we use residual sentiment, the effect disappears around day 5. Before the event, we do not find significant returns from day -3 to day -1 or on day -5, but we do observe a significant return change on day -4 (June 22, 2023). In Figure 8 , we depict changes in alphas around the event days. We find that around

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[15] We run a regression for each firm of excess return on Fama-French five factors with estimation window day – 45 to day -1 with at least 30 trading days. The residuals are estimated and summarized for standard deviation on firm-year basis. Then country-year level 75th percentile is used to split sample into Risk = 1 risky firms and Risk = 0 non-risky firms.

the event date, June 28, 2023, abnormal returns experience significant declines, and the standard deviations of alphas in this window are much larger than on days further away from the event date.

6. Conclusion

In this study, we construct a sentiment index using the average sentiment (tone) from responses to 1,000 identical questions submitted to ChatGPT on a daily basis. We find that this “AI sentiment” significantly affects firms’ alphas over 45 days, and that changes in alphas correspond to three structural breaks in AI sentiment. In addition, we conduct several natural experiments, including Italy’s temporary ban on ChatGPT services and China’s permanent ban on ChatGPT services. We show that an orthogonalized sentiment index, relative to common market sentiment indices, continues to significantly affect firm alphas. Furthermore, an event study around the most important structural break in AI sentiment shows significant abnormal returns over the following five days.

We also find that firms in the technology industry, firms with lower institutional ownership, and smaller firms exhibit stronger responses to AI sentiment. These results suggest that latent sentiment embedded in widely used AI tools by financial professionals can influence asset prices.

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Table 1 Summary Statistics

This table reports summary statistics for all variables. *Return* is the firm-level daily stock return across 52 countries. *Alpha_ff5* is the daily Fama–French five-factor abnormal return. *Sentiment* is the raw AI sentiment extracted from ChatGPT responses to 1,000 identical prompts per day (Tu et al., 2023). *Sentiment_z* is the standardized sentiment; *Sentiment_e* is the residual from regressing *Sentiment* on standardized market-sentiment indices (Google Trends for "recession," "inflation," "bankruptcy," "layoff," and "stock market crash"; the 12 EPU indices and the Global EPU; and the VIX), with day-of-week and month fixed effects. Event indicators are Ban (=1 during Italy's ban, Mar 31–Apr 27, 2023), Restore (=1 on/after Apr 28, 2023), Treated (=1 for Italian firms), and Forbid (=1 for Chinese firms).

Panel A: Summary Statistics (N, Mean, P25, P50, P75, SD)

Variable	Obs (In millions)	Mean	p25	p50	p75	SD
Returns						
Return	12.8	0.000	-0.009	0.000	0.008	0.047
alpha_ff5	9.51	-0.459	-2.793	-0.239	1.742	8.155
Sentiments						
Sentiment	12.8	-0.026	-0.161	0.031	0.040	0.106
Sentiment_z	12.8	0.000	-1.268	0.531	0.620	1.000
Sentiment_e	12.8	0.001	-0.017	0.000	0.017	0.049
Events						
Ban	12.8	0.065	0.000	0.000	0.000	0.246
Restore	12.8	0.874	1.000	1.000	1.000	0.332
Treated	12.8	0.01	0.000	0.000	0.000	0.097
Breakdown	12.8	0.003	0.000	0.000	0.000	0.059
Forbid	12.8	0.150	0.000	0.000	0.000	0.357

Panel B. Distribution of Firm-Day Observations by Country (Counts And Percentages)

LOC	Country/Region	Freq.	Percent	LOC	Country/Region	Freq.	Percent
ARG	Argentina	15,942	0.12	KOR	South Korea	949,547	7.44
AUS	Australia	597,331	4.68	LKA	Sri Lanka	79,964	0.63
AUT	Austria	20,926	0.16	LUX	Luxembourg	66,899	0.52
BEL	Belgium	43,406	0.34	MAR	Morocco	20,973	0.16
BGD	Bangladesh	84,982	0.67	MEX	Mexico	39,857	0.31
BRA	Brazil	151,069	1.18	MLT	Malta	11,839	0.09
CHE	Switzerland	75,732	0.59	MOZ	Mozambique	290	<0.01
CHL	Chile	55,849	0.44	MYS	Malaysia	295,920	2.32
CHN	China	1,919,248	15.03	NGA	Nigeria	47,394	0.37
CZE	Czech Republic	7,151	0.06	NLD	Netherlands	37,873	0.30
DEU	Germany	239,539	1.88	NOR	Norway	84,275	0.66
DNK	Denmark	76,096	0.60	NZL	New Zealand	43,631	0.34
ESP	Spain	92,865	0.73	PAK	Pakistan	134,285	1.05
EST	Estonia	10,055	0.08	PHL	Philippines	69,046	0.54
FRA	France	216,717	1.70	POL	Poland	200,418	1.57
GBR	United Kingdom	478,356	3.75	PRT	Portugal	12,756	0.10
GRC	Greece	44,402	0.35	ROU	Romania	67,218	0.53
HKG	Hong Kong SAR	457,701	3.58	SAU	Saudi Arabia	70,344	0.55
HRV	Croatia	24,239	0.19	SGP	Singapore	168,734	1.32
HUN	Hungary	16,196	0.13	SVK	Slovakia	2,320	0.02
IND	India	1,384,851	10.85	SWE	Sweden	261,600	2.05
ISL	Iceland	6,804	0.05	THA	Thailand	239,746	1.88
ISR	Israel	187,069	1.47	TUR	Turkey	150,528	1.18
ITA	Italy	121,396	0.95	TWN	Taiwan	646,308	5.06
JAM	Jamaica	22,190	0.17	USA	United States	1,494,080	11.7
JPN	Japan	1,212,898	9.50	VEN	Venezuela	8,501	0.07
				Total		12,767,356	

Table 2. Firm Alpha Responses To Daily AI Sentiment

This table reports the relation between firm-level alpha and the average daily AI sentiment. The dependent variable is the daily Fama–French five-factor alpha (*alpha_ff5*) for firms across 52 economies worldwide. *Sentiment_z* is the standardized daily average sentiment derived from ChatGPT conversation logs, measured as the average tone in responses to 1,000 identical prompts issued each day (Tu et al., 2023). *Region* equals 1 on and after June 28, 2023, equals 2 after Feb 14, 2024, and equals 3 after May 10, 2024, when the sentiment series exhibits a level shift associated with model updates. **p < 0.01, *p < 0.05, p < 0.10.

	(1)	(2)	(3)
VARIABLES	alpha_ff5	alpha_ff5	alpha_ff5
Sentiment_z	0.00110	-0.111***	-0.0518*
	(0.0101)	(0.00677)	(0.0304)
1.Region			-0.274***
			(0.0482)
2.Region			-0.399***
			(0.0570)
3.Region			-0.968***
			(0.0685)
1.Region × Sntiment_z			0.434***
			(0.0348)
2.Region × Sentiment_z			-0.269***
			(0.0327)
3.Region × Sentiment_z			0.0907***
			(0.0314)
Constant	-0.459***	-0.458***	-0.329***
	(0.0117)	(2.02e-05)	(0.0444)
Firm FE		Yes	Yes
Monthly Date FE		Yes	Yes
Cluster S.E.	Firm	Firm	Firm
Observations	9,508,235	9,508,226	9,508,226
R-squared	0.000	0.102	0.102
RMSE	7.747	7.747	7.747
Adj R-squared	0.0975	0.0975	0.0975

Table 3. AI Sentiment And Firm Alpha During Ban Events

This table reports the impact of AI sentiment on firm-level abnormal returns during two major ChatGPT ban events. The dependent variable is the daily Fama–French five-factor alpha (*alpha_ff5*) for firms across 52 economies worldwide. Key regressors are defined as follows. *Sentiment_z* is the standardized daily average sentiment from ChatGPT chat logs, measured as the average tone in responses to 1,000 identical prompts each day (Tu et al., 2023). *Ban* equals 1 for March 31-April 27, 2023 (the period when Italy temporarily banned ChatGPT). *Treated* equals 1 for Italian firms. *Restore* equals 1 on and after April 28, 2023 (the date service was restored in Italy). *Forbid* equals 1 for Chinese firms. ∗∗∗p < 0.01, ∗∗ p < 0.05, ∗p < 0.1.

	(1)	(2)	(3)
VARIABLES	alpha_ff5	alpha_ff5	alpha_ff5
Sentiment_z	-0.108***	-0.445***	-0.124***
	(0.00686)	(0.0416)	(0.00786)
Ban	-1.227***		
	(0.137)		
Treated × Ban	0.305		
	(0.787)		
Treated × Sentiment_z	-0.100	2.519***	
	(0.102)	(0.616)	
Ban × Sentiment_z	-0.742***		
	(0.0889)		
Treated × Ban × Sentiment_z	0.188		
	(0.528)		
Restore		0.553***	
		(0.0765)	
Treated × Restore		-4.214***	
		(0.837)	
Restore × Sentiment_z		0.336***	
		(0.0421)	
Treated × Restore × Sentiment_z		-2.490***	
		(0.628)	
Forbid × Sentiment_z			0.0852***
			(0.0216)
Constant	-0.446***	-0.960***	-0.458***
	(0.00120)	(0.0728)	(3.49e-05)
Firm FE	Yes	Yes	Yes
Monthly Date FE	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm
Observations	9,508,226	9,508,226	9,508,226
R-squared	0.102	0.102	0.102
RMSE	8.665	8.665	8.665
Adj R-squared	0.00606	0.00606	0.00606

Table 4. Residual AI Sentiment

Table 4 examines the effect of the residual component of AI sentiment on firm-level abnormal returns (alphas). The dependent variable is the daily Fama–French five-factor alpha (*alpha_ff5*) for firms across 52 economies worldwide. Residual AI Sentiment, *Sentiment_e*, is defined as the daily residual from regressing AI sentiment, the standardized average tone of ChatGPT's responses to 1,000 identical prompts (Tu et al., 2023), on a set of standardized market-sentiment proxies: U.S. Google search trends for "recession," "inflation," "bankruptcy," "layoff," and "stock market crash"; the 12 Economic Policy Uncertainty (EPU) indices of Baker, Bloom, and Davis (2016); the Global EPU index; and the VIX. The residualizing regression includes day-of-week fixed effects. The dependent variable is each firm's Fama-French five-factor abnormal return. The coefficient on *Sentiment_e* therefore captures variation in AI sentiment orthogonal to contemporaneous market sentiment. We control for policy/outage events as in Table 2: *Region* (=0 for dates before Jun 27, 2023; =1 for dates after Jun 28, 2023; =2 for dates after Feb 14, 2024; and =3 for dates after May 10, 2024). ∗∗∗p < 0.01, ∗∗ p < 0.05, ∗p < 0.1.

	(1)	(2)
VARIABLES	alpha_ff5	alpha_ff5
Sentiment_e	-0.710***	2.837***
	(0.0669)	(0.190)
1.Region		-0.764***
		(0.0357)
2.Region		-0.824***
		(0.0453)
3.Region		-0.988***
		(0.0523)
1.Region × Sentiment_e		2.001***
		(0.247)
2.Region × Sentiment_e		-5.951***
		(0.220)
3.Region × Sentiment_e		-2.466***
		(0.204)
Constant	-0.452***	0.126***
	(0.000108)	(0.0262)
Firm FE	Yes	Yes
Monthly Date FE	Yes	Yes
Cluster S.E.	Firm	Firm
Observations	9,469,825	9,469,825
R-squared	0.102	0.102
RMSE	8.665	8.665
Adj R-squared	0.00606	0.00606

Table 5. AI Sentiment Mechanisms

Table 5 examines how firm FF5 alphas respond to AI sentiment through two channels: (i) AI industries and (ii) institutional ownership. The dependent variable is *alpha_ff5* (Fama–French five-factor alpha). *Sentiment_e* denotes residual AI sentiment (as defined in Table 4). Column (1): AI Industries: is a standardized industry-level proxy for sensitivity to AI, constructed from GSU industry codes that identify industries closely associated with AI (see Appendix A for the industry list). Column (2): Institutional ownership. Institutional ownership is the total percent of shares held by institutions (LSEG), winsorized at the 1st and 99th percentiles and standardized. Each specification assesses whether the sensitivity of alphas to AI sentiment varies with the relevant channel (via interaction terms between *Sentiment_e* and the channel proxy). We control for model updates and ban events as in Table 2: *Region* (=0 for dates before Jun 27, 2023; =1 for dates after Jun 28, 2023; =2 for dates after Feb 14, 2024; =3 for dates after May 10, 2024); *Ban* (Italy's temporary ban, Mar 31-Apr 27, 2023), *Treated* (=1 for Italian firms), and *Breakdown* (=1 on Nov 8, 2023, the U.S. outage). ∗∗∗$p < 0.01$, ∗∗ $p < 0.05$, ∗$p < 0.1$.

VARIABLES	(1) AI Industries	(2) Institutional Ownership	(3) Traffic	(4) Small	(5) Size	(6) Risk
Sentiment_e	-5.427***	-2.859***	-1.908	0.658	-1.509	-1.277
	(0.263)	(0.0271)	(1.861)	(2.310)	(2.074)	(2.285)
Exposure	-0.271***	0.0640***	-4.105	-0.915***	0.0126***	0.0802**
	(0.0190)	(0.00596)	(8.136)	(0.132)	(0.00323)	(0.0353)
Exposure × Sentiment_e	-0.844***	2.394***	0.0887	-4.309*	0.0381***	0.535
	(0.142)	(0.0784)	(1.277)	(2.217)	(0.0136)	(0.646)
Constant	-0.0944	0.0385	0.114	0.633***	0.165	0.326***
	(0.0710)	(0.0237)	(1.491)	(0.193)	(0.151)	(0.141)
Control For Model Updates & Ban Events?	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Monthly Date FE	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E.	Firm	Firm	Firm	Firm	Firm	Firm
Observations	988,862	814,758	8,938,433	7,701,242	7,706,400	10,446,746
R-squared	0.004	0.006	0.011	0.015	0.013	0.012
RMSE	8.665	8.665	8.137	8.041	8.041	8.253
Adj R-squared	0.00606	0.00606	0.0109	0.0126	0.0126	0.0115

Table 6. Event study on the sentiment shift.

This table reports firm-level responses of alpha to an important event, the ChatGPT model update to allow Internet access on June 28, 2023. The dependent variable is the daily Fama–French five-factor alpha, *alpha_ff5*. Day is the number of trading days relative to the update date (Day = 0 on June 28, 2023). *Sentiment_z* is defined in Table 2 and *Sentiment_e* as defined in Table 4. We also control for the first-order lag of the dependent variable. ∗∗∗p < 0.01, ∗∗ p < 0.05, ∗p < 0.1.

	(1)	(2)
VARIABLES	alpha_ff5	alpha_ff5
L.alpha_ff5	0.948***	0.948***
	(0.00103)	(0.00103)
Sentiment_e	2.778***	
	(0.0934)	
Day 6 × Sentiment_e	-2.109***	
	(0.0952)	
Day -5	0.105	0.108
	(0.0755)	(0.0753)
Day -4	-0.336***	-0.326***
	(0.0172)	(0.0172)
Day -3	0.00940	0.0110
	(0.0104)	(0.0107)
Day -2	-0.0686	-0.110
	(0.196)	(0.196)
Day -1	0.162	0.0692
	(0.134)	(0.134)
Day 0	-0.199**	-0.330***
	(0.0983)	(0.105)
Day 1	-0.517***	-0.458***
	(0.0217)	(0.0480)
Day 2	-0.343***	-0.549***
	(0.0170)	(0.0491)
Day 3	0.336**	0.0957
	(0.145)	(0.145)
Day 4	0.261***	0.0196
	(0.0957)	(0.0967)
Day 5	0.174	-0.0480
	(0.119)	(0.119)
Sentiment_z		0.246***
		(0.0229)
Day 6 × Sentiment_z		-0.180***
		(0.0230)
Constant	-0.0150***	0.0504***
	(0.000563)	(0.00896)
Firm FE	Yes	Yes
Monthly Date FE	Yes	Yes
Cluster S.E.	Firm	Firm
Observations	7,239,660	7,278,055
R-squared	0.917	0.917
RMSE	2.323	2.323
Adj R-squared	0.917	0.917

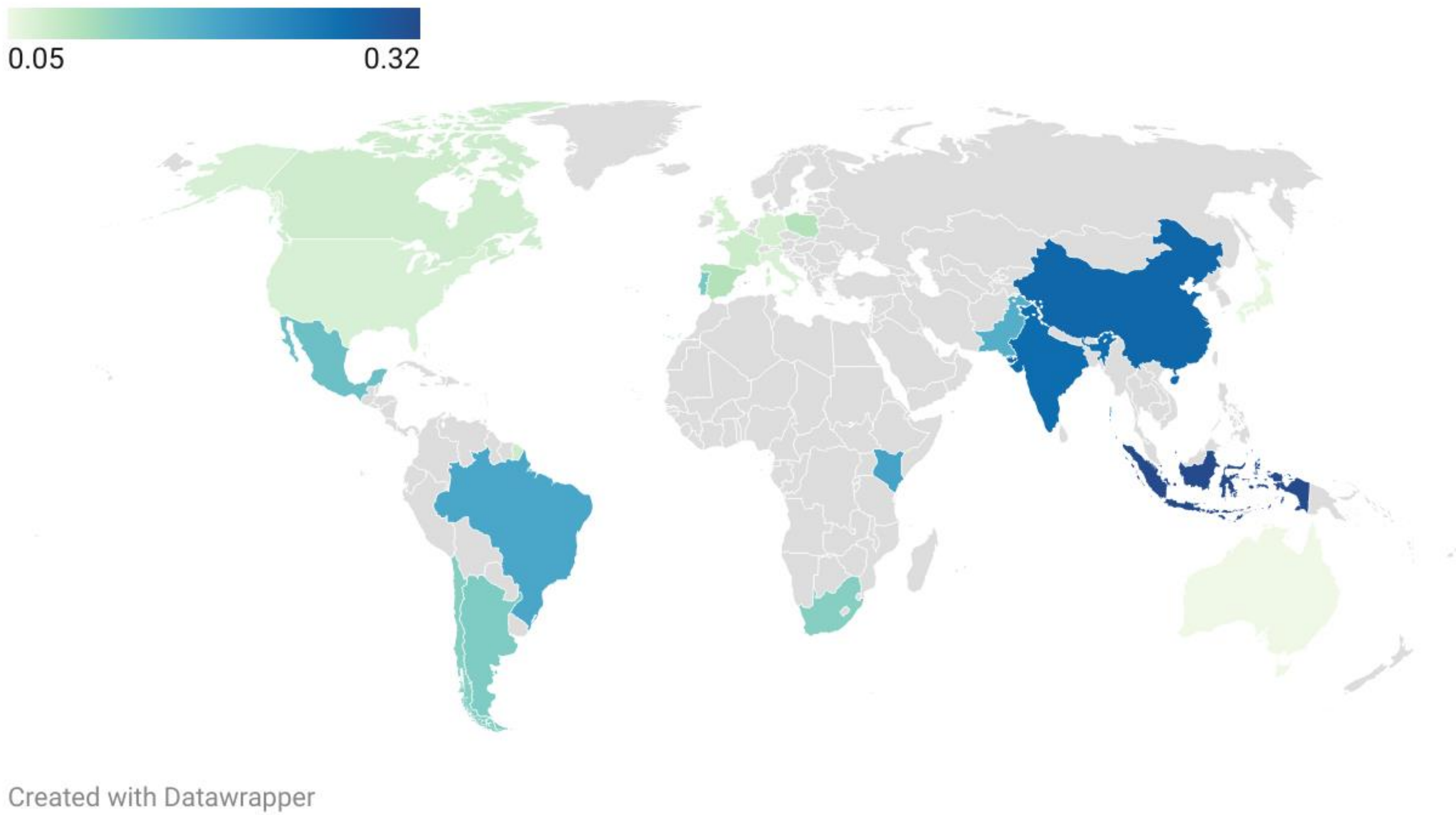


Figure 1. Percentage of ChatGPT Users Among Internet Users

Figure 1 plots, at the country level, the percentage of internet users who answered "yes" to the question of whether they use ChatGPT. The original data were obtained from the Borealis dataset (DOI: 10.5683/SP3/WCUN0S). The figure is created using Datawrapper.

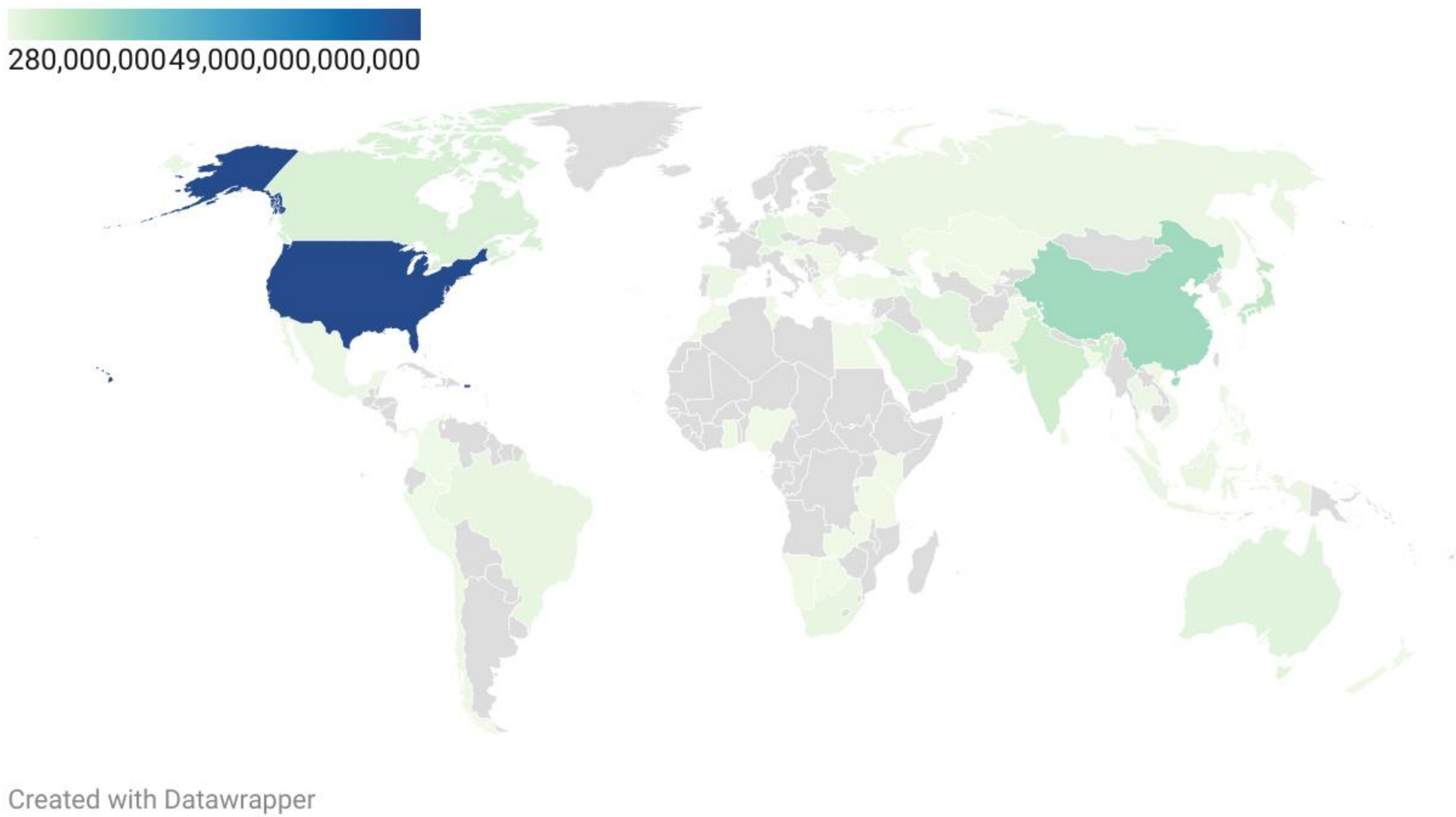


Figure 2. Market Capitalization of Listed Domestic Companies

Figure 2 plots the size of financial markets across countries, measured by the total market capitalization of listed domestic companies. The data are obtained from the World Bank (indicator: CM.MKT.LCAP.CD) and are reported in current U.S. dollars. The figure is created using Datawrapper.

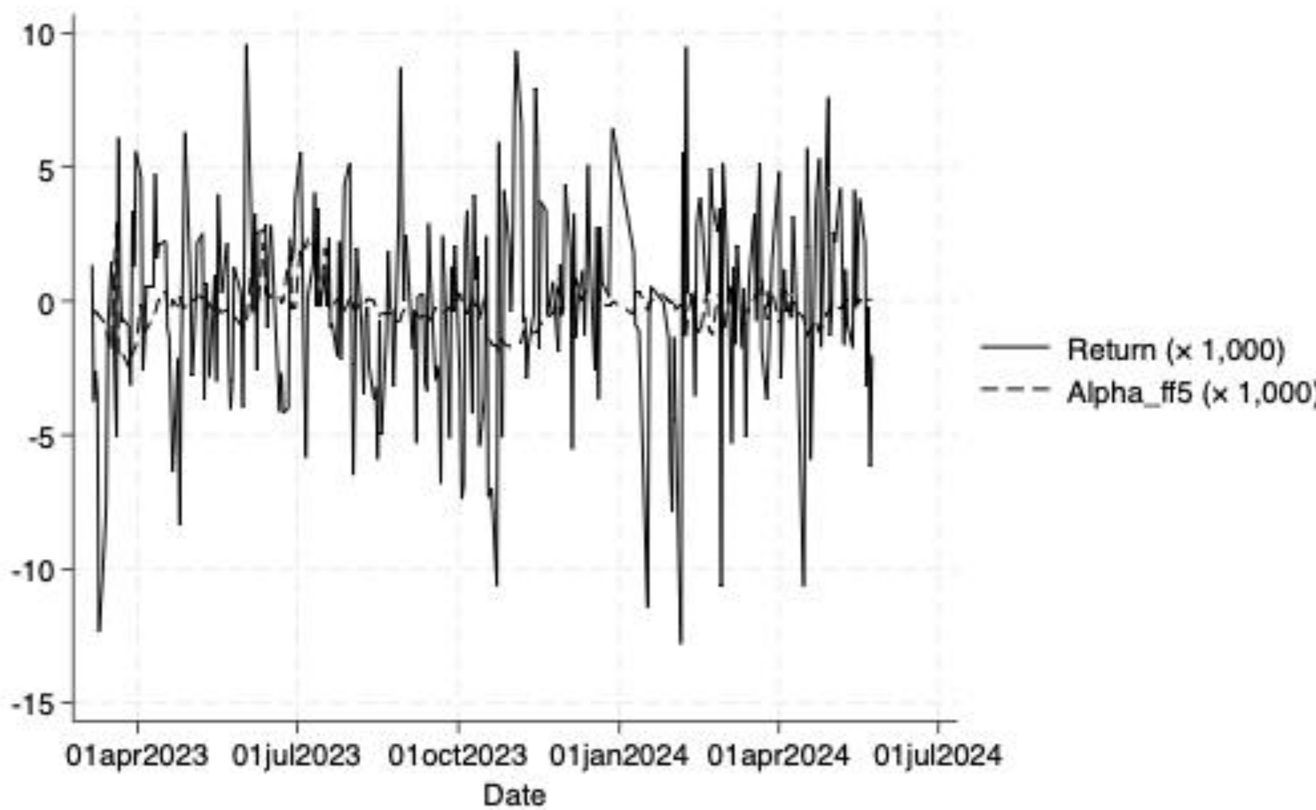


Figure 3. Raw Returns, Abnormal Returns, and Market Index Returns Over Time

Figure 3 plots, for each country, the daily average raw returns and the daily average abnormal returns over time. Abnormal returns are measured as Fama–French five-factor alphas estimated using the five-factor model from Ken French's data library. The model is estimated over trading days −45 to −1 relative to the event date, requiring at least 30 trading days in the estimation window.

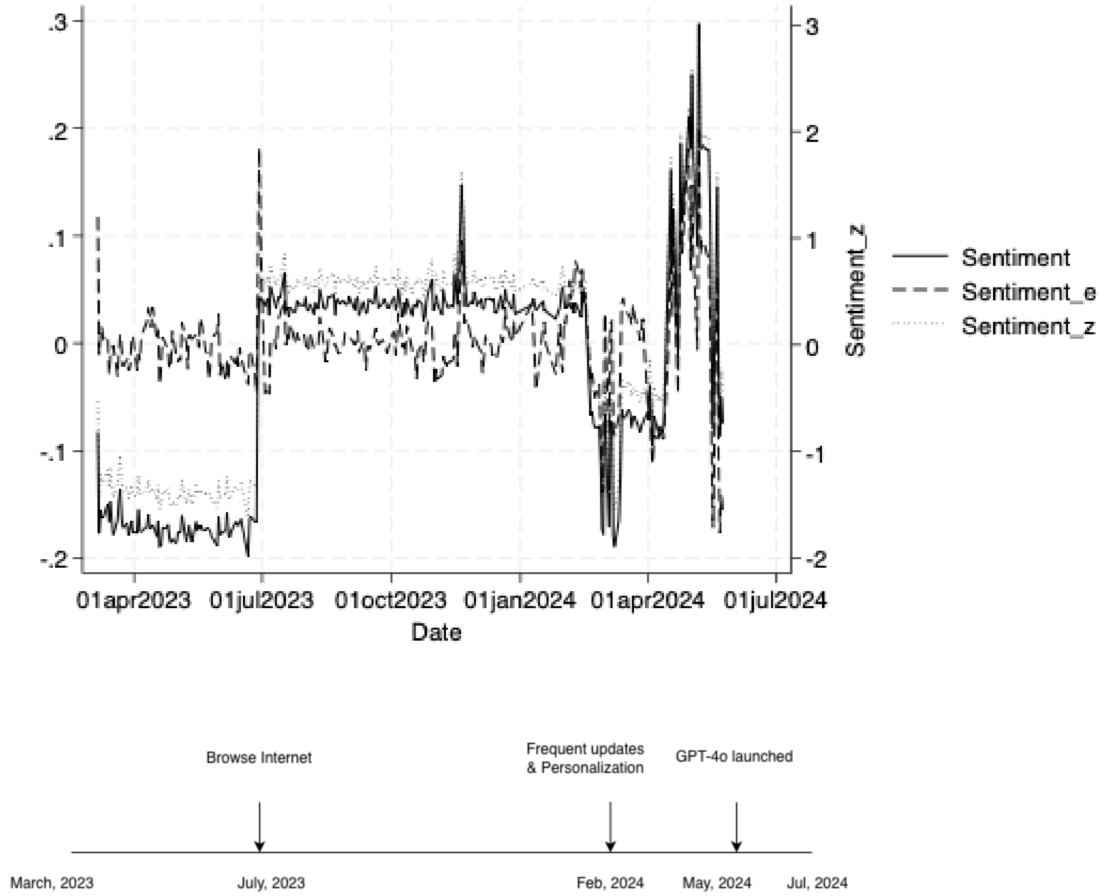


Figure 4. Daily Average AI Sentiment in ChatGPT Responses

Figure 4 plots the daily average sentiment of ChatGPT responses over time. The responses come from ChatLog (Tu et al., 2023) and consist of 1,000 answers per day to 1,000 identical prompts submitted via the API with temperature set to 0, using the same model (GPT-3.5-turbo). Sentiment is measured using VADER, a widely used lexicon-based tool for sentiment analysis. *Sentiment* is the raw daily average VADER score. *Sentiment_e* is the residual ("orthogonalized") sentiment obtained by regressing Sentiment on common market-sentiment proxies—U.S. Google Trends for "recession," "inflation," "bankruptcy," "layoff," and "stock market crash"; the 12 Economic Policy Uncertainty (EPU) indices and the Global EPU index (Baker, Bloom, and Davis, 2016); and the VIX. *Sentiment_z* is the standardized sentiment series (mean 0, standard deviation 1).

Panel A: Chat Date	3/25/23
Question	
Why do multistory office buildings and skyscraper like buildings keep their lights on all the time ? Can someone explain why we aren't saving tons of money by cutting these damn office lights off at night ? Please explain like I'm five.	
Response	
Multistory office buildings and skyscrapers keep their lights on all the time because they have many offices and rooms that need to be illuminated. Even if everyone has left for the day, there may be security personnel or cleaners who need the lights on to do their work. Additionally, some buildings have lights on for safety reasons to prevent accidents or criminal activity in dark areas.	

Panel B: Chat Date	8/6/23
Question	
Why do multistory office buildings and skyscraper like buildings keep their lights on all the time ? Can someone explain why we aren't saving tons of money by cutting these damn office lights off at night ? Please explain like I'm five.	
Response	
Multistory office buildings and skyscrapers often keep their lights on all the time for a few reasons. First of all, it helps with safety and security. By keeping the lights on, people can see and move around the building more easily, especially during nighttime. It also helps security personnel to monitor the building and identify any potential risks or intruders.	

Figure 5. Shifts in Response Content Over Time

Figure 5 illustrates how the content of responses to an identical prompt evolve over time in ChatGPT. The responses are collected in ChatLog (Tu et al., 2023). Because the average sentiment of the responses—measured by VADER—exhibits three major shifts, we select one representative response from each subperiod, defined by the three breakpoints.

Panel C: Chat Date	2/20/24
Question	
Why do multistory office buildings and skyscraper like buildings keep their lights on all the time ? Can someone explain why we aren't saving tons of money by cutting these damn office lights off at night ? Please explain like I'm five.	
Response	
The lights in multistory office buildings and skyscrapers are often kept on all the time for safety and security reasons. It helps people see where they are going and makes it easier for emergency services to respond in case of a problem. Additionally, some buildings use automated systems that turn off lights in unoccupied areas to save energy and money. However, keeping some lights on all the time is important for the safety of the people who work in the building.	

Panel D: Chat Date	5/23/24
Question	
Why do multistory office buildings and skyscraper like buildings keep their lights on all the time ? Can someone explain why we aren't saving tons of money by cutting these damn office lights off at night ? Please explain like I'm five.	
Response	
Multistory office buildings and skyscrapers often keep their lights on all the time for safety and security reasons. It helps to deter potential intruders and allows security personnel to monitor the building more easily. Additionally, some buildings have automated lighting systems that are programmed to stay on for specific periods of time for maintenance and cleaning purposes.	

Figure 5. Shifts in Response Content Over Time (Continued)

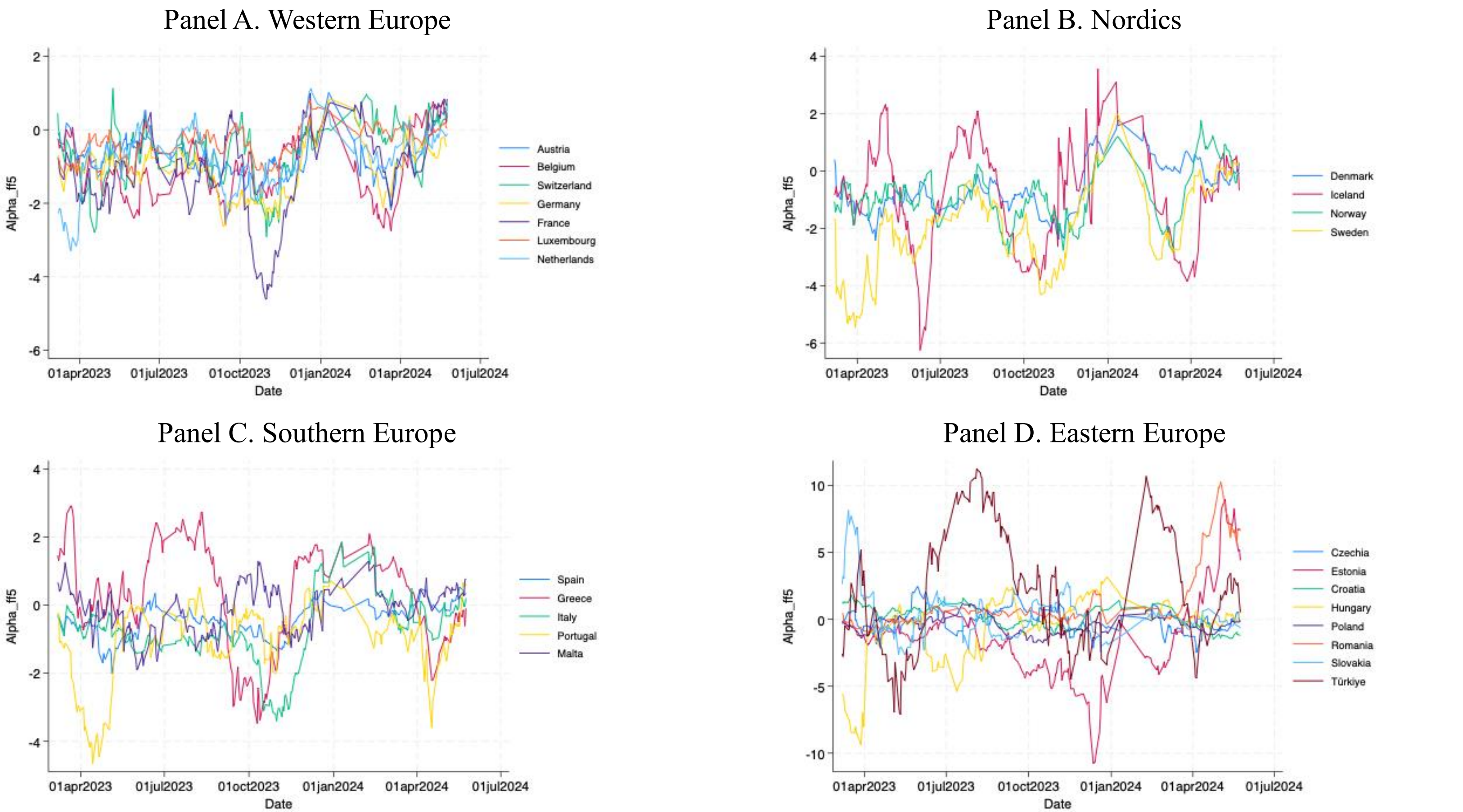
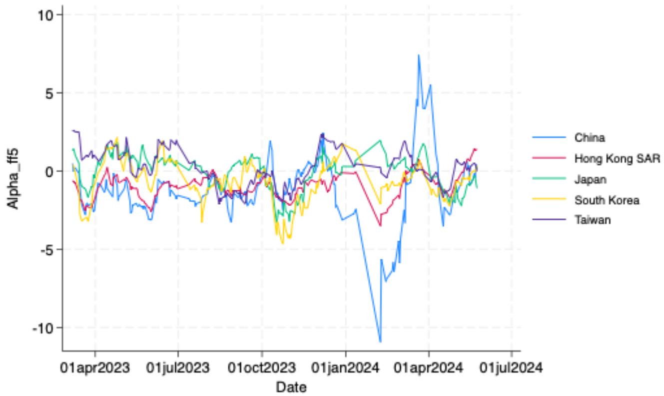


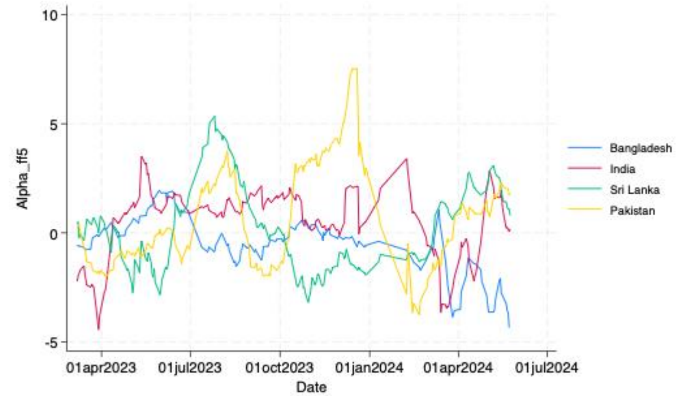
Figure 6. Average Abnormal Returns Across Countries

Our sample includes 52 countries worldwide. This figure plots the daily average abnormal returns (Fama–French five-factor alphas) for each country over time. Countries are grouped by geographic region. The legends show the country code (LOC). The Fama–French five-factor alphas are estimated using the five-factor model from Ken French's data library, with an estimation window of trading days −45 to −1 relative to the event date and requiring at least 30 trading days.

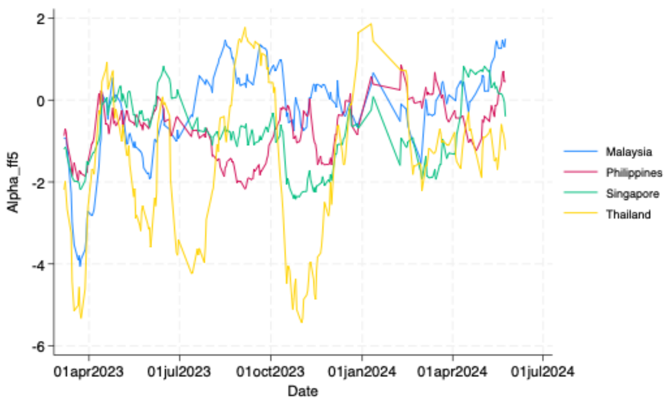
Panel E: East Asia



Panel F: South Asia



Panel G: Southeast Asia



Panel H: Middle East

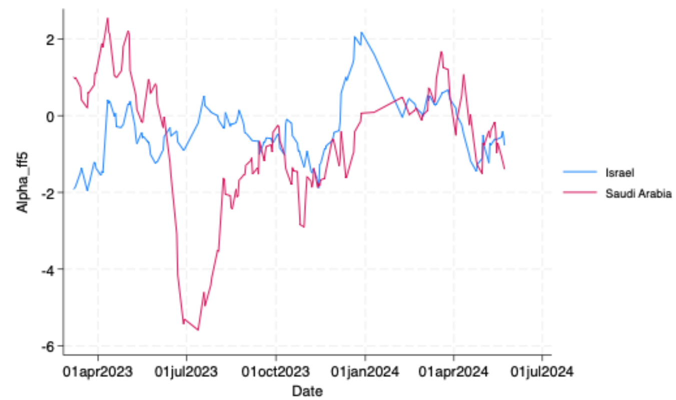


Figure 6. Average Abnormal Returns Across Countries (continued)

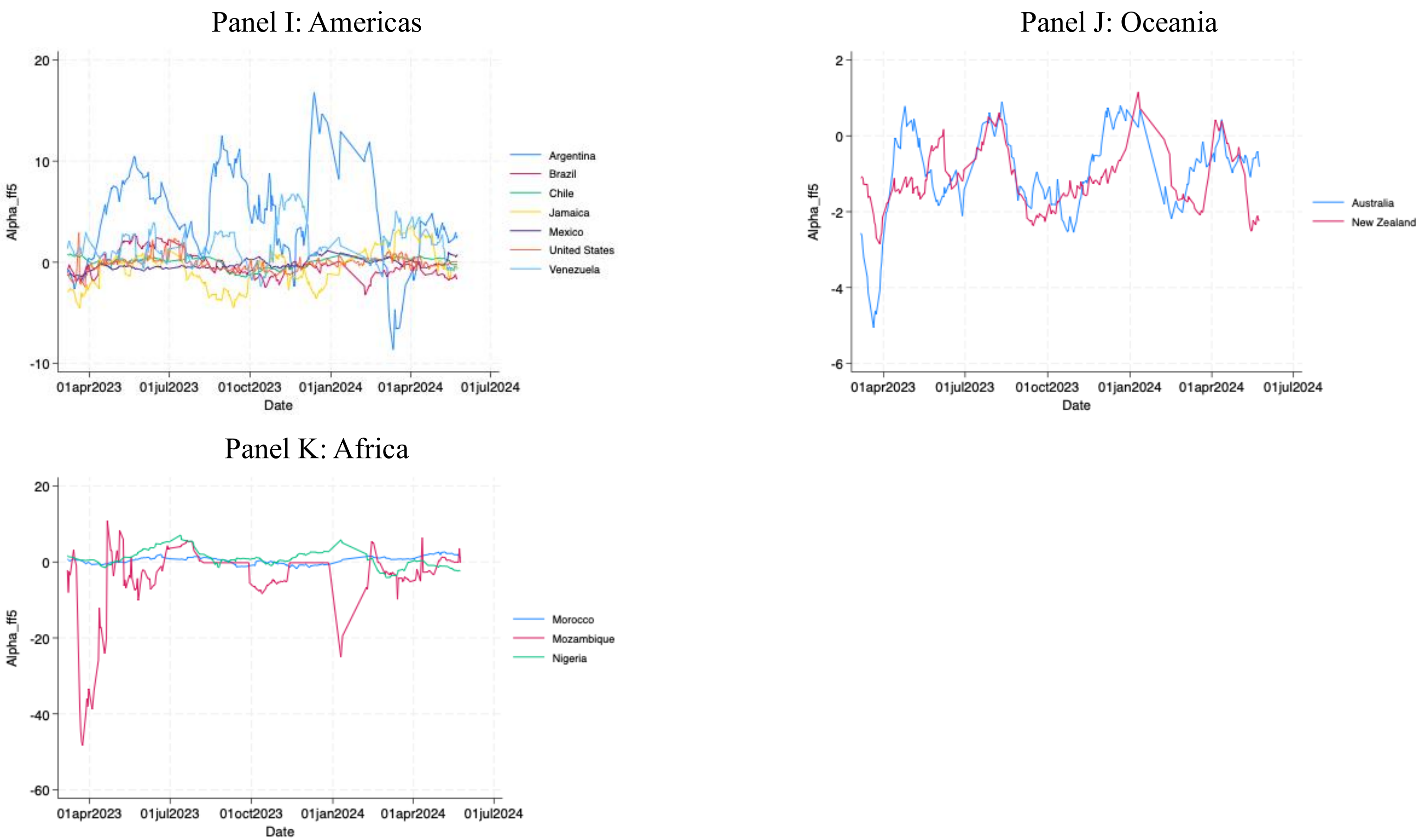


Figure 6. Average Abnormal Returns Across Countries (continued)

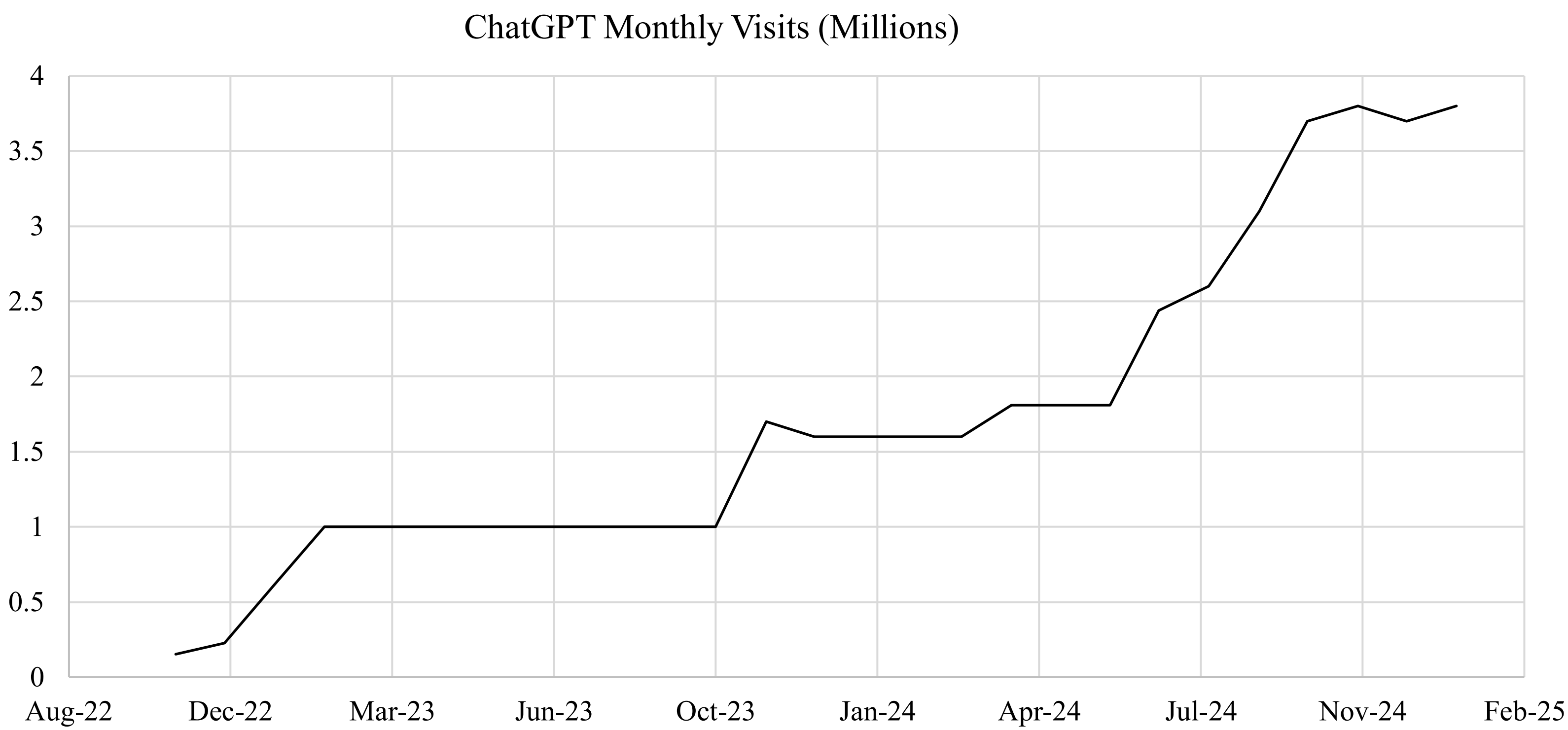


Figure 7. ChatGPT Monthly Visits (Millions)

Figure 7 shows the monthly visits (volume) to ChatGPT services collected from Cloudflare in the U.S.

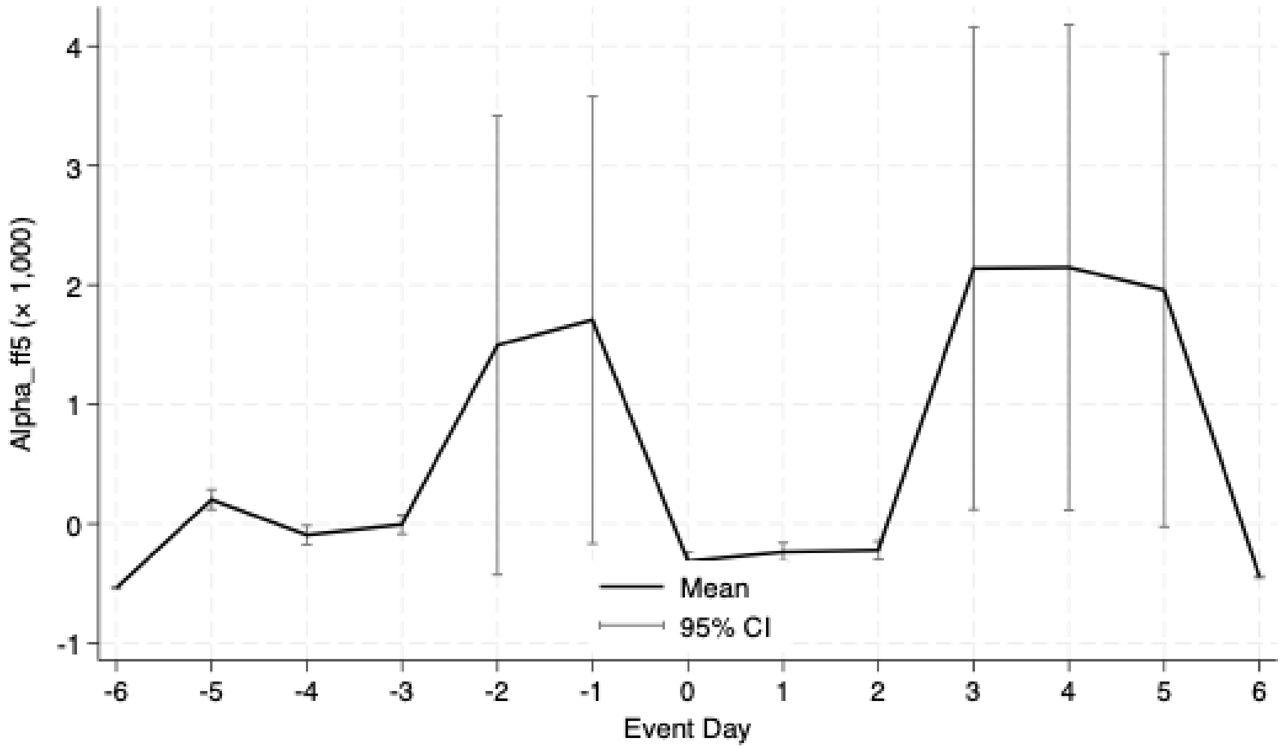


Figure 8. Average Abnormal Returns Around the ChatGPT Sentiment Shift

Figure 8 plots daily average abnormal returns around June 28, 2023, the date on which the average sentiment of ChatGPT responses exhibits a pronounced level shift. Day 0 corresponds to June 28, 2023. Abnormal returns are measured as Fama–French five-factor alphas estimated using the five-factor model from Ken French's data library. The model is estimated over trading days −45 to −1 relative to the event date, requiring at least 30 trading days in the estimation window.

Appendix A. Industry Codes and Exposure Index

In Table 5, we use industry classification as a proxy for exposure to AI-related influences. This appendix defines the mapping between GSUBIND industry codes and the exposure index used in Table 5.

Industry Codes (GSUBIND)	Exposure Index
45301010, 45301020, 45102020, 45103010, 45103020	1
45102010, 60101010	0.7
45201020, 45203015, 45203020, 50202010, 50202020	0.6
45202030, 25504010	0.4
other	0