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Verba volant, transcripta manent: what corporate earnings calls reveal about the AI stock rally

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Abstract

This paper investigates the economic impact of technological innovation, focusing on generative AI (GenAI) following ChatGPT's release in November 2022. We propose a novel framework leveraging large language models to analyze earnings call transcripts. Our method quantifies firms' GenAI exposure and classifies sentiment as opportunity, adoption, or risk. Using panel econometric techniques, we assess GenAI exposure's impact on S&P 500 firms' financial performance over 2014-2023. We find two main results. First, GenAI exposure rose sharply after ChatGPT's release, particularly in IT, Consumer Services, and Consumer Discretionary sectors, coinciding with sentiment shifts toward adoption. Second, GenAI exposure significantly influenced stock market performance. Firms with early and high GenAI exposure saw stronger returns, though earnings expectations improved modestly. Panel regressions show a 1 percentage point increase in GenAI exposure led to 0.26% rise in quarterly excess returns. Difference-in-Difference estimates indicate 2.4% average quarterly stock price increases following ChatGPT's release.

Keywords: artificial intelligence, generative AI, ChatGPT, earnings call, equity returns

JEL classification: C80, G14, G30, L25, O33

Non-Technical Summary

In today's rapidly evolving global economy, firms face both challenges and opportunities from technological breakthroughs and shifting supply conditions. This paper focuses on one of the most transformative recent developments: the rise of generative AI (GenAI), whose strategic and financial implications became especially clear after the release of ChatGPT in November 2022. While the case study centers on GenAI, the analytical framework we develop can also be applied to other sources of structural change, such as climate regulation, trade tensions, or geopolitical risks.

Our approach relies on recent advances in textual analysis with firm level financial data. We analyze earnings call transcripts, quarterly discussions where executives outline strategy and performance, to understand how firms talk about emerging technologies. We use large language models and a technique called zero-shot classification, which identifies relevant topics in text without relying on keywords, to measure how much attention firms give to GenAI. We also assess whether they frame it as an opportunity, a step toward adoption, or a source of risk.

This paper makes two contributions. First, we introduce a flexible method for measuring firm-level attention to technological change. We show that GenAI-related discussions began gaining traction after 2017, following the introduction of the transformer architecture, and surged after ChatGPT's release. This increase was especially strong in the Information Technology sector, where average exposure nearly quadrupled from 2022 to 2023. Other sectors such as Communication Services, Consumer Discretionary, and Financials also saw notable increases. Firms varied widely in their level of engagement, even within the same sector. Over time, the tone of GenAI discussions shifted from mostly future potential to also concrete implementation, especially in the tech sector.

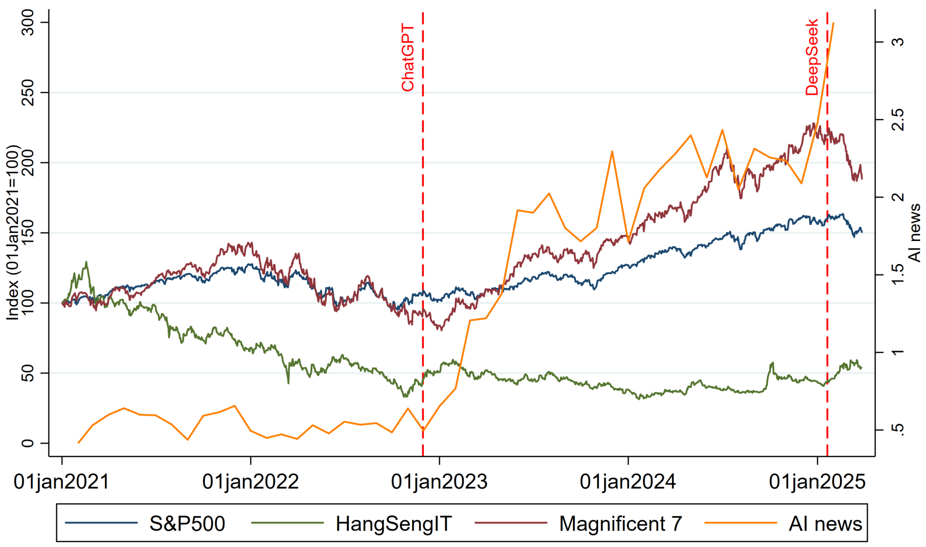
Second, we provide empirical evidence that early engagement with GenAI translated into stronger market performance. Firms that were already discussing GenAI before ChatGPT's release, especially in sectors likely to benefit from AI, experienced higher equity returns in the quarters that followed. For every one percentage point increase in GenAI exposure, early adopters experienced a 0.26 percent rise in quarterly excess returns. On average, their stock prices rose 2.4 percent more per quarter than those of firms slower to engage. These gains appear to reflect investor sentiment more than immediate changes in earnings expectations. Notably, discussions framed around adoption had a stronger market impact than those focused on opportunity alone.

This paper also helps fill an important gap in the existing research by showing how the way firms talk about new technologies relates to their performance in financial markets over the short to medium term. While most studies on artificial intelligence have focused on its potential to boost productivity or reshape the labor market, fewer have examined how firms' strategic communication about AI connects to their stock market outcomes and earnings expectations. Our study highlights the importance of how firms position themselves when facing technological innovation and shows that the market impact of GenAI engagement tends to persist over several quarters.

1 Introduction

In today's rapidly evolving world, firms must constantly adapt to technological innovation and shifting supply conditions, whether through breakthroughs in artificial intelligence (AI), the emergence of climate-related regulation, or evolving trade and geopolitical risks. Understanding how they respond to these changes and how markets react to their strategic decisions is key for evaluating both firm-level resilience and macro-economic outcomes. A salient recent example is the release of ChatGPT in late 2022, which marked a turning point in public and corporate engagement with generative artificial intelligence (GenAI). This event provides a timely and powerful case study to examine the impact of firms' readiness for groundbreaking technologies. Historically, general-purpose innovations, such as the internet and, more recently AI, have triggered waves of investor enthusiasm that have driven significant shifts in market valuations. Following ChatGPT's release, leading U.S. technology firms — commonly known as the Magnificent 7 — saw substantial equity gains, outpacing benchmarks like the S&P 500 and Hong Kong's Hang Seng IT Index (see Figure 1). These gains arguably reflected, at least in part, expectations of GenAI-driven productivity growth. Notably, this surge occurred against a backdrop of steadily rising AI-related media coverage after ChatGPT breakthrough. However, the sudden emergence of DeepSeek, a Chinese GenAI competitor, in early 2025 briefly disrupted this momentum, triggering a decline in U.S. tech stock valuations amid concerns over intensifying global competition. In this context of rapidly shifting investor sentiment and uncertainty over the impact of technological change, our study seeks to address the following research question: "How does the exposure of firms to emerging technologies and recent advancements in GenAI influence their financial performance?".

Figure 1: GenAI Technologies and Stock Market Performance



Note: Vertical dashed red lines indicate key GenAI events: ChatGPT's release (November 2022) and DeepSeek R1's launch (January 2025). Left y-axis shows indexed values (January 2021=100) for S&P500, Hang Seng IT, and Magnificent 7 tech stocks. Right y-axis shows AI media coverage measured as percentage of AI-related articles in top economic publications.

To address this question, we develop a novel framework that combines natural language processing

(NLP) with econometric techniques. This framework quantifies firms' attention to emerging technologies (hereafter referred to as firms' exposure) and assesses its impact on economic outcomes, such as stock market performance, following external shocks like the ChatGPT launch. Our approach contributes to the growing *sentometrics* literature (Algaba, Ardia, Bluteau, Borms, and Boudt, 2020; Borms, 2020), which integrates textual analysis with econometric methods to extract quantifiable insights from qualitative data.

The core idea of our analysis is to use earnings call transcripts to measure firm-level exposure to specific topics. This enables us to systematically link firms' strategic communication about GenAI to their financial performance — an angle that has received limited attention in the literature. As a starting point, we employ a technique called *zero-shot classification* at the paragraph-level to identify topic-specific content without the need for manual labels or training data. This approach offers the key advantage over traditional topic modeling methods of not requiring extensive parameter tuning. Our firms' exposure measures are determined by the proportion of transcript content focused on GenAI. This allows us to monitor how managers perceive these subjects over time and across firms and industries. We then utilize a large language model (LLM), namely GPT-4o (Hurst, Lerer, Goucher, Perelman, Ramesh, Clark, Ostrow, Welihinda, Hayes, Radford, et al., 2024) to decompose GenAI exposure according to the prevailing sentiment in each relevant paragraph. Specifically, we assess whether the sentiment is dominated by *Opportunity, Adoption,* or *Risk*. In our context, *Opportunity* refers to promising paths that firms are exploring; *Adoption* indicates the planned ongoing integration of GenAI into operations and *Risk* highlights the potential negative impact on profits stemming from GenAI-related factors, such as increased competition or implementation costs. This distinction is crucial because firms are often at different phases of adoption, roll-out, or monetization of GenAI, all factors that may have distinct implications for market valuations.

We then apply this framework to the panel of U.S. S&P 500 firms examining their earnings calls over the period 2014-2024 to uncover two distinct sets of empirical findings. The first concerns the evolution of GenAI exposure itself, how it has changed over time, how it varies across sectors, and how firms differ in the way they frame GenAI in their communications. The second focuses on the financial implications of this exposure, examining how different types and timings of engagement with GenAI relate to stock market performance and earnings expectations.

On the descriptive side, we document that GenAI was already being discussed in earning calls before the release of ChatGPT. These discussions began gaining momentum after 2017, following the introduction of the *transformer architecture* (Vaswani, Shazeer, Parmar, Uszkoreit, Jones, Gomez, Kaiser, and Polosukhin, 2017), a breakthrough in artificial intelligence that revolutionized how computational models process and generate natural language. However, the most pronounced increase in GenAI-related discussions occurred only after ChatGPT's release in late 2022, marking a clear break point in corporate attention and strategic engagement with the technology. Industry-level data show that the IT sector experienced the most pronounced increase, with average firm exposure nearly quadrupling from 2022 to 2023. More moderate increases are observed in Consumer Services and Consumer Discretionary, sectors that are naturally position to benefit from GenAI due to their reliance on personalized customer experiences, operational efficiency, and data-driven decision-making. Over time, the tone of GenAI discussions also shifted: mentions of adoption became more frequent in the Post-ChatGPT period, particularly among IT firms, while discussions of risk remained limited throughout the sample. A variance decomposition confirms that GenAI exposure remains highly heterogeneous across firms, even after accounting for firm, time, industry, and time-industry fixed effects.

Turning to the impact on financial markets, we find evidence that early and sustained engagement with GenAI determined a significantly better stock market performance. We define *Early Exposed* firms as those in the top 25% of the GenAI exposure distribution prior to the ChatGPT release, and *Laggards* as all others. Panel regressions exploiting time variation in exposure show that *Early Exposed* firms outperformed *Laggards* by around 0.26% in quarterly excess returns for every one percentage point increase in GenAI exposure. To further assess causality, we implement a Difference-in-Differences (DiD) analysis, which reveals that *Early Exposed* firms experienced stock price increases of 2.4 percentage points more than *Laggards* on average each quarter following the release. We also find that, while there is a clear first-mover advantage, sustained engagement with GenAI technology plays an important role in stock market valuations. These effects persist even after controlling for earnings expectations, suggesting that markets may be responding to positive sentiment or pricing in anticipated productivity gains not yet reflected in fundamentals. The results underscore both a first-mover advantage and the importance of sustained strategic engagement with GenAI.

We also find that *Early Exposed* firms benefited significantly from discussions framed in terms of both *Adoption* and *Opportunity*. Their stock prices outperformed those of *Laggards* by 0.63% and 0.45% respectively, in quarterly excess returns for every one percentage point increase in Adoption or Opportunity-related GenAI exposure. Notably, these gains occurred without a corresponding increase in earnings expectations, suggesting that investor sentiment rather than immediate revisions to fundamentals was the primary driver. The stronger effect of *Adoption* relative to *Opportunity* is consistent with the idea that markets place greater value on concrete implementation signals, which are more likely to yield to near-term profitability. Although the sample size limits statistical power, industry-level DiD estimates provide further support to this pattern. *Early Exposed* firms in the IT sector experienced larger stock price gains than remaining firms. Similar positive effects are observed in the Consumer Services and Consumer Discretionary sectors, industries that are particularly well-positioned to utilize and benefit from GenAI technologies.

Our main empirical findings remain robust across a range of alternative specifications. These include redefining *Early Exposed* firms using a median split of GenAI exposure, excluding the so-called "Magnificent 7" from the sample and incorporating additional firm-level controls into the panel regressions. Across all these tests, the positive link between GenAI engagement and stock market performance holds consistently.

This paper contributes to bridging a key gap in the literature: linking textual indicators of technological engagement to firm-level financial outcomes using NLP tools. While the existing literature on artificial intelligence extensively addresses its potential to boost productivity and economic growth (Cerutti, Pascual, Kido, Li, Melina, Tavares, and Wingender, 2025; Bick, Blandin, and Deming, 2025), our study takes a distinct approach by focusing on firm-level GenAI exposure and its link to stock performance. Previous works, such as Agrawal, Gans, and Goldfarb (2018), have primarily emphasized GenAI's potential and its role as a prediction technology, without delving into its specific financial implications at the firm level. In the realm of financial markets, researches by He, Larkin, and Li (2020); Back, Morana, and Spann (2023) have investigated AI's influence on investor behavior and algorithmic trading, yet these studies do not quantify the effects of AI exposure on individual firms' stock valuations. Our paper seeks to bridge this gap. Closely related to our study is the work by Eisfeldt, Schubert, and Zhang (2023), which also examines the impact of ChatGPT's release on corporate valuations. Their research focuses on firm-level workforce exposure to GenAI and its effects on valuation due to potential labor replacement or productivity enhancements, particularly in the two weeks following the shock. In contrast, we utilize textual analysis of earnings call transcripts to quantify firms' exposure to emerging technologies, enabling us to assess not just the direct impact on stock market performance but also whether this impact is related to sentiment concerning GenAI opportunities, adoption, and risks. Unlike Eisfeldt et al. (2023), who emphasize firms with labor exposure to GenAI, our research highlights the strategic positioning of firms regarding new technology and the associated benefits in terms of stock returns, without taking a stance on the channel of exposure—whether it comes via product or labor markets. Additionally, we explore how exposure influenced earnings expectations and extend our analysis beyond the immediate reactions of financial markets, demonstrating that these effects persist and influence stock prices over several quarters.

The rest of the paper is organized as follows. Section 2 reviews the literature on textual analysis and corporate communication, with a focus on recent advances in NLP. Section 3 introduces our sentometrics methodology, detailing how we construct firm-level exposure and sentiment measures from earning call transcripts and outlines the econometric models used. Section 4 presents our empirical findings, including descriptive trends, regression results, and robustness checks. Section 5 concludes and discusses broader applications of our framework to other structural transformations.

2 Textual Analysis - A Review of Literature and Approaches

To evaluate how firms are exposed to groundbreaking technologies like GenAI, we utilize textual analysis of earnings call transcripts, a high-value source of forward-looking corporate communication. This approach allows us to capture how companies discuss opportunities and adopt these innovations. In this section, we review key advances in the literature that inform our methodological choices. Our aim is not only to build on established techniques, but also emphasize the advantages of recent developments in natural language processing. These advancements allow for more precise, context-aware measurement of firm-level exposure.

2.1 Earnings Call Transcripts in Firm-Level Analysis

Earnings calls are a particularly valuable setting for sentometric analysis of economic shocks. During these quarterly events, executives communicate not only about past performance but also outline forward-looking strategies and responses to emerging trends. The language used in these transcripts reflects a carefully crafted message, shaped by internal priorities and external expectations, providing a rich and standardized source of qualitative data across firms and over time.

Prior research has demonstrated the predictive power of earnings call content in domains ranging from political risk (Chin and Fan, 2023) to economic shock response (Hassan, Hollander, Kalyani, Schwedeler, Tahoun, and van Lent, 2024; Adolfsen, Heissel, Manu, and Vinci, 2024). These studies underscore the value of viewing earnings calls as more than mere reporting tools: they are strategic documents that can reveal firms' evolving orientations toward key themes, such as technological innovation, climate risks, or trade policy.

2.2 Textual Analysis in Economic Research

Textual analysis has become an essential tool in economic and financial research, particularly for extracting insights from qualitative sources such as central bank communications (Iglesias, Ortiz, and Rodrigo, 2017; Bailliu, Han, Sadaba, and Kruger, 2021; Armelius, Bertsch, Hull, and Zhang, 2020; Aruoba and

Drechsel, 2024), news media (Baker, Bloom, and Davis, 2016; Caldara and Iacoviello, 2022) and corporate disclosures (Loughran and McDonald, 2011) and to quantify broader sources of uncertainty and geopolitical risk (Baker et al., 2016; Caldara and Iacoviello, 2022). However, many early applications rely on keyword frequencies or sentiment dictionaries (Hassan et al., 2024), which, while useful, often fall short in capturing the nuanced and strategic nature of corporate language. As firms use implicit or coded phrasing to manage stakeholder perceptions, more sophisticated tools are needed to uncover underlying priorities and themes. Recent advances in NLP, particularly with the transformer architecture (Vaswani et al., 2017) and large language models (LLMs), have revolutionized economic and financial textual analysis. Domain-specific models like FinBERT (Araci, 2019) now detect nuanced language patterns in earnings calls and policy communications that dictionary-based approaches miss entirely. These technologies excel through three key capabilities: contextual understanding of financial terminology, few-shot learning that reduces dependence on labeled data (Brown, Mann, Ryder, Subbiah, Kaplan, Dhariwal, Neelakantan, Shyam, Sastry, Askell, et al., 2020), and multi-level text processing from syntax to discourse. The result is significantly enhanced ability to quantify previously elusive factors—strategic positioning, policy uncertainty, and market sentiment—providing economists with more precise measurements of qualitative information (Gentzkow, Kelly, and Taddy, 2019).

2.3 Topic Modeling and Sentiment Analysis

To extract latent topics from text, traditionally, researchers have turned to methods like Latent Semantic Analysis (LSA) (Deerwester, Dumais, Furnas, Landauer, and Harshman, 1990) and Latent Dirichlet Allocation (LDA) (Blei, Ng, and Jordan, 2003). While these approaches have proven useful in identifying broad thematic patterns, they face several limitations: they require manual interpretation of topics, have difficulty with context-dependent meanings, and often perform poorly on short or noisy text segments—issues particularly relevant for corporate communication.

Transformer-based models (Wu, Nguyen, and Luu, 2024) offer improved scalability, with BERTopic (Grootendorst, 2022) combining transformer embeddings (Devlin, Chang, Lee, and Toutanova, 2019) with clustering for coherent representations and enabling trend detection (Boutaleb, Picault, and Grosjean, 2024). These methods capture richer meaning and produce more coherent topic clusters, thereby improving accuracy. However, operating in an unsupervised setting can limit their effectiveness when classifying documents into pre-defined, economically meaningful categories. For supervised topic classification, researchers have explored keyword matching (Hassan et al., 2024), machine learning classifiers, and LLM-based evaluation. Hybrid methods like dictionary-learning (Sautner, Van Lent, Vilkov, and Zhang, 2023) and specialized classifiers (Johnson, Gerlach, and Sáez-Trumper, 2021) show promise, but require substantial labeled data.

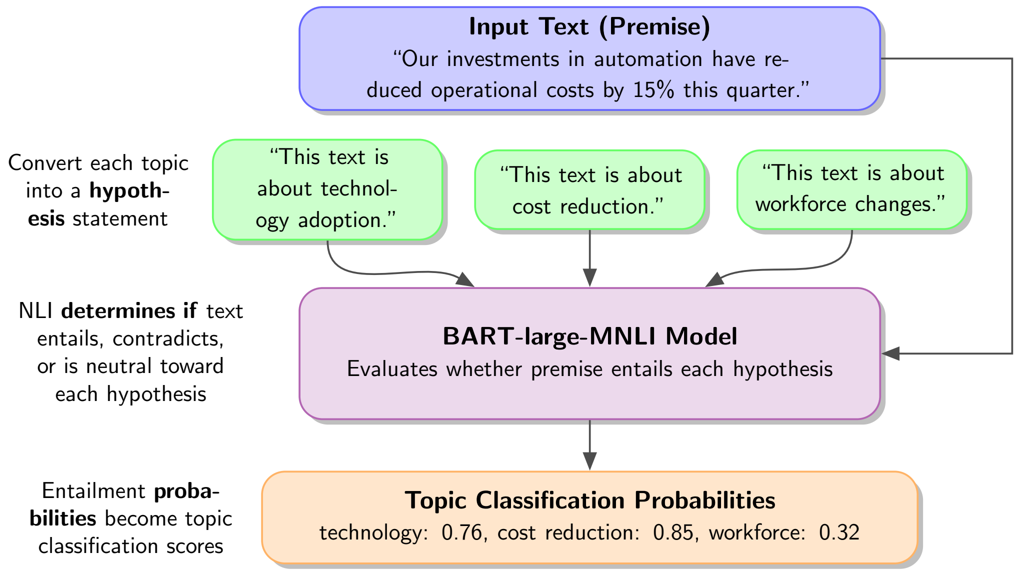
In contrast, LLMs offer powerful economic text analysis tools with superior contextual understanding. Context-driven deep learning models outperform traditional bag-of-words approaches for sentiment analysis (Chin and Fan, 2023), while generative AI tools like ChatGPT better predict firm-level volatility from earnings calls (Kim, Muhn, and Nikolaev, 2023). Though these methods may reduce explainability (Bell, Solano-Kamaiko, Nov, and Stoyanovich, 2022), various solutions exist (Lundberg and Lee, 2017; Lopardo, Precioso, and Garreau, 2023, 2024; Lopardo, 2024). The advantage of using these methods, which leverage LLMs, lies in their ability to capture the full semantic context of a text rather than relying solely on surface-level word occurrences.

3 Methodology

The innovation of this paper lies in the deployment of two state-of-the-art Natural Language Processing models to analyze firm-level discussions. We utilize zero-shot classification (ZSC) to detect topic exposure without requiring labeled training data. Additionally, we employ an LLM for sentiment analysis to assess the tone and polarity of these exposures in detail. This dual approach is particularly well suited to our context, where executives may discuss relevant issues such as AI adoption using non-standardized or unpredictable language. By doing so, we can capture both the presence and sentiment of strategic communications.

Specifically, we employ the BART-large-MNLI model[1] (Yin, Hay, and Roth, 2019; Lewis, Liu, Goyal, Ghazvininejad, Mohamed, Levy, Stoyanov, and Zettlemoyer, 2019) for topic modeling: it uses a transformer architecture trained on Natural Language Inference (NLI) tasks. The model assesses whether a given sentence (the premise) logically entails a set of hypotheses, which we define to correspond to specific research topics (*e.g.*, "This text is about artificial intelligence"). As shown in Figure 2, the model assigns a probability score to each topic based on entailment strength. Sentiment analysis is conducted exclusively on those transcript segments identified as GenAI-related, ensuring that the sentiment scores reflect only the tone of discussions specifically focused on generative AI. This allows us to classify content even when firms use indirect or domain-specific terminology—something keyword or dictionary methods often miss.

Figure 2: Zero-Shot Classification Framework



Note: The framework uses natural language inference to classify text by evaluating whether input text (premise) entails statements about predefined topics (hypotheses). Higher entailment probabilities indicate stronger topic relevance without requiring labeled training data.

For sentiment analysis, we utilize GPT-4o (Hurst et al., 2024), employing prompt engineering techniques to detect specific dimensions of tone in topic-relevant discussions. Once topic-relevant content is identified, we analyze its tone using sentiment classification. This approach allows researchers to customize exactly what they want to measure—such as risk perception versus adoption enthusiasm for new

[1] Publicly available at `https://huggingface.co/facebook/bart-large-mnli`

technologies—rather than relying on generic positive/negative classifications. By analyzing text segments already identified by BART-large-MNLI, this method reveals nuanced insights about corporate positioning that conventional sentiment analysis would miss.

As detailed in the Appendix, this flexibility of our approach allows us to apply the same classification logic across firms and industries, identifying meaningful themes and events in earnings call transcripts with high accuracy and without the need for topic-specific training data.

Measuring Exposures and their Economic Impact. In the following we discuss specific steps of our methodology for constructing firm-level exposure measures from earnings call transcripts and evaluating their economic impact. The approach consists of four main steps:

1. **Transcript Segmentation**: dividing earnings call transcripts into meaningful segments for granular analysis.
2. **Topic Modeling via zero-shot classification**: identify segments related to the topic of interest.
3. **Sentiment Analysis via prompt engineering**: utilize LLM with prompt engineering to detect specific sentiment dimensions in topic-related segments.
4. **Exposure Calculation**: compute transcript-level metrics including topic exposure (proportion of transcript dedicated to the topic) and corresponding sentiment measures.
5. **Econometric Analysis**: assess the impact of firm-level exposure and its sentiment on financial outcomes (*e.g.*, stock returns, earnings expectations) using econometric techniques such as panel regressions and difference-in-differences analysis.

3.1 Transcript segmentation

The first step involves segmenting earnings call transcripts to isolate meaningful units of analysis. Our goal is to measure topic exposure as the proportion of the transcript dedicated to a given topic. While one might consider counting individual topic-related words or sentences, we contend that analyzing at the paragraph level provides a more suitable unit. Upon reviewing the transcripts, we found that these corporate presentations are meticulously prepared and professionally transcribed documents with a deliberate structure that reflects thematic shifts. The transcription process deliberately preserves both the speakers' tones and the natural thematic shifts in the discussion. The paragraph-level organization is a deliberate feature of how companies convey information to investors and analysts. Therefore, analyzing transcripts at this level allows us to preserve and utilize this inherent thematic organization, avoiding the risks of over-fragmentation with sentence-level analysis or excessive aggregation at the full-text level. Figure 3 illustrates this point with two example snippets related to artificial intelligence. Sentence-level classification tends to underestimate the extent of the topic's discussion, whereas paragraph-level classification accurately captures that both snippets are fully related to artificial intelligence.

Figure 3: Comparison of Text Segmentation Levels

Segment	**# AI-related sentences**	**# Total sentences**	**Relative AI Exposure**
First, a robust AI infrastructure that includes data centers, chips and a global fiber network.	1	1	100%
We recently moved the Gemini app team to Google DeepMind to speed up deployment of new models, and streamline post-training work. This is all helping us move faster. For instance, it was a small, dedicated team that built NotebookLM, an incredibly popular product that has so much promise. We're also using AI internally to improve our coding processes, which is boosting productivity and efficiency. Today, more than a quarter of all new code at Google is generated by AI, then reviewed and accepted by engineers. This helps our engineers do more and move faster.	2	6	33.33%

Note: Comparison of AI exposure measurement between sentence-level and paragraph-level analysis for two text examples. Paragraph-level analysis better captures thematic coherence, while sentence-level classification tends to underestimate topic exposure.

In the rest of the paper, we refer to a segment as any paragraph extracted from the transcripts.

3.2 Topic detection via zero-shot classification

The second step of the methodology involves identifying the segments of text that relate to the topic of interest. As mentioned before, we rely on a state-of-the-art zero-shot classification (ZSC) model to perform this task. Specifically, we employ the `BART-large-MNLI` model[2] developed by Facebook/Meta, which we refer to as *ZSC* throughout the paper.

The framework is grounded in a natural language inference (NLI) task: given a segment of text (the *premise*) and an hypothesis (*e.g.*, "This text is about artificial intelligence"), the model determines whether the premise entails, contradicts, or is neutral with respect to the hypothesis. As shown in Figure 2, the model returns a probability score that reflects the strength of entailment. A higher score indicates a stronger semantic match between the segment and the hypothesized topic.

This model has demonstrated high accuracy in detecting relevant content without requiring any topic-specific training data or fine-tuning.

3.3 Sentiment analysis via prompt engineering

The third step of our methodology analyzes sentiment characteristics of topic-relevant segments using GPT-4o, a state-of-the-art large language model. We utilize prompt engineering techniques to evaluate sentiment dimensions tailored to our research interest. For GenAI discussions specifically, we prompt the model to evaluate three distinct sentiment aspects: *Opportunity* (perceived competitive advantages or revenue potential), *Adoption* (attitudes toward implementation timelines and integration) and *Risk* (concerns about implementation challenges or regulatory issues). This allows us to distinguish, for example,

[2] Publicly available at `https://huggingface.co/facebook/bart-large-mnli`

between firms discussing GenAI primarily as a future opportunity versus those actively implementing solutions.

3.4 Firm-level exposure and sentiment

The fourth step in the analysis involves computing the firm-level exposure and sentiments to a specific topic. Let $D_i(t)$ denote the earnings call transcript of company i at quarter t, and let $D_{i,j}(t)$ represent the j-th segment in $D_i(t)$. Let τ denote the specific topic of interest.

We define a topic detector for topic τ as the function $\delta^{(\tau)}(z)$, which takes any text segment z and outputs:

$$\delta^{(\tau)}(z) := \begin{cases} 1, & \text{if } z \text{ is } \tau\text{-related}\,, \\ 0, & \text{otherwise}\,. \end{cases} \tag{1}$$

Let $|z|$ represent the number of sentences in the text z. The exposure $E_i^{(\tau)}(t)$ of company i to the topic τ at quarter t is computed using the following equation:

$$E_i^{(\tau)}(t) := \frac{\sum_j \delta^{(\tau)}(D_{i,j}(t)) \cdot |D_{i,j}(t)|}{|D_i(t)|}\,. \tag{2}$$

This formulation ensures that each segment contributes to the exposure measure in proportion to its length, accounting for the fact that some topics may be discussed in greater detail than others. Although topic detection is conducted at the paragraph level (see Section 3.1), exposure is computed at the sentence level to better reflect the relative emphasis placed on each topic.

Figure 3 illustrates the importance of this weighting: if exposure were calculated purely at the paragraph level, short and long topic-related segments would be treated equally. Equation (2), by contrast, ensures that longer discussions carry more weight in the exposure score, thereby more accurately capturing the time and attention devoted to a topic during the earnings call.

As described in Section 3.2, we implement the detector $\delta^{(\tau)}$ using our zero-shot classification model, which identifies whether a given paragraph pertains to the topic τ without requiring labeled training data.

For the sentiment analysis of the identified topic-relevant segments τ (*i.e.*, $\delta^{(\tau)}(D_{i,j}(t)) = 1$), we employ GPT-4o to evaluate the sentiment along three distinct axes: *Opportunity, Adoption,* and *Risk.* The model assigns probability scores to each sentiment category based on our prompt engineering framework (detailed in Appendix A.2), creating a probability distribution across these dimensions. We then aggregate these segment-level scores to the transcript level by measuring the weighted share of each sentiment dimension. Formally, the topic sentiment index $S_i^{(\tau)}(t)$ representing the average tone of a company i at time t for topic τ is computed as

$$S_i^{(\tau)}(t) := \frac{\sum_j \delta^{(\tau)}(D_{i,j}(t)) \cdot s_{i,j}(t)}{\sum_j \delta^{(\tau)}(D_{i,j}(t))}\,, \tag{3}$$

where $s_{i,j}(t)$ is the sentiment score assigned by the classifier to the j-th segment. This approach allows us to quantify not just overall exposure to a topic, but also the proportion of that exposure reflecting specific sentiment dimensions that may drive market reactions.

The sentiment score $s_{i,j}(t)$ in Equation (3) takes the form of a vector containing these three sentiment dimensions, enabling the calculation of separate topic sentiment indices $S^{(\tau)}_{i,\text{Opportunity}}(t)$, $S^{(\tau)}_{i,\text{Adoption}}(t)$, and $S^{(\tau)}_{i,\text{Risk}}(t)$. As shown in Figure 4(b), this approach reveals meaningful temporal shifts in sentiment that would be missed by purely quantitative exposure measures.

3.5 Econometric analysis

The fifth step in the methodology involves evaluating the economic consequences of firm-level exposure using econometric techniques. Once the relevant exogenous shock and exposure measure are identified, the impact can be assessed using two complementary approaches: panel regressions, which explore time variation in exposure, and difference-in-differences (DiD) analysis, which compares outcomes between firms with high and low exposure before and after the shock. In the DiD framework, firms are classified into treatment and control groups based on their exposure levels prior to the shock, ensuring that group assignment is not influenced by the shock itself.

The analysis can be applied to multiple outcome variables, such as stock returns, earnings, or other performance metrics. We formalize our analytical framework using the following panel regression specifications:

$$Y_{i,t} = \beta_1 \cdot \text{Exposure}_{i,t} + \gamma F_{i,t} + \alpha_t + \lambda_i + \varepsilon_{i,t} \tag{4}$$

$$+ \beta_2 \cdot \text{Exposure}_{i,t} \cdot \text{EarlyExposed}_i \tag{5}$$

$$+ \beta_3 \cdot \text{Exposure}_{i,t} \cdot \text{PostShockDummy}_t \tag{6}$$

Equation (4) estimates the baseline effect of exposure on the outcome variable $Y_{i,t}$, controlling for firm-level characteristics ($F_{i,t}$), time fixed effects (α_t), and firm or sector fixed effects (λ_i). Equation (5) adds an interaction term to capture differential effects for firms that were early adopters of the technology. Equation (6) further includes an interaction with a post-shock dummy variable, allowing us to estimate how the effect of exposure changes after the shock. To complement this approach, we also estimate a standard difference-in-differences model:

$$Y_{i,t} = \beta_1 \cdot \text{EarlyExposed}_i \cdot \text{PostShockDummy}_t + \gamma F_{i,t} + \alpha_t + \lambda_i + \varepsilon_{i,t} \tag{7}$$

The standard DiD model isolates the shock's effect by interacting the early exposure indicator with the post-shock dummy variable. This specification captures the difference in outcomes between the treated and control firms after the shock, adjusting for firm-specific and time-specific effects.

4 Empirical Application: GenAI Exposure and Firm Performance

We now apply the general econometric framework introduced in Section 3.5 to assess the impact of generative AI (GenAI) exposure on firm performance following the release of ChatGPT in November 2022. The key elements of the empirical setup are summarized below.

Table 1: Summary of Empirical Design

Component	Description
Dependent Variable	Financial variable at firm level $Y_{i,t}^{QoQ}$.
Stock Price	Quarterly % change in market capitalization.
Expected EPS	Quarterly % change in expected EPS one year ahead.
Impact of GenAI	
GenAI Exposure	Firm-level exposure derived from earnings call transcripts.
Early Exposed	Firms in the top 25% of GenAI exposure prior to ChatGPT.
PostChatGPT	Post-treatment dummy for the ChatGPT release.
Controls	
Firm Controls	Return on assets, log of total assets, capital expenditure, and long- and short-term debt ratios (from *Compustat*).
Macro Controls	U.S. GDP growth forecast (1-year ahead) and 10-year U.S. bond yield (from *Consensus Economics* and *Refinitiv*).
Fixed Effects	Various fixed effects (e.g., time, sector, firm, time-sector interaction.)

Note: Summary of key variables and methodology used in the empirical analysis. *Early Exposed* firms are classified based on pre-ChatGPT GenAI exposure levels (top 25th percentile) to ensure treatment assignment is not influenced by the shock itself.

These include panel regressions with firm and time fixed effects, as well as a Difference-in-Differences (DiD) approach. Specifically, we adapt the general model to the GenAI setting using the following specifications:

$$Y_{i,t}^{QoQ} = \beta_1 \cdot \textbf{GenAI Exposure}_{i,t} + \gamma F_{i,t} + \alpha_t + \lambda_i + \varepsilon_{i,t} \tag{8}$$

$$+ \beta_2 \cdot \textbf{GenAI Exposure}_{i,t} \cdot \text{EarlyExposed}_i \tag{9}$$

$$+ \beta_3 \cdot \textbf{GenAI Exposure}_{i,t} \cdot \text{PostChatGPT}_t \tag{10}$$

Equation (8) estimates the baseline effect of GenAI exposure on quarterly outcomes, controlling for firm-level characteristics, time fixed effects, and sector fixed effects. Equation (9) adds an interaction term to capture whether early adopters of GenAI experienced different effects. Equation (10) further includes an interaction with a Post-ChatGPT dummy variable to estimate how the effect of exposure changed after the release of ChatGPT.

We also estimate a standard DiD specification to isolate the effect of the shock:

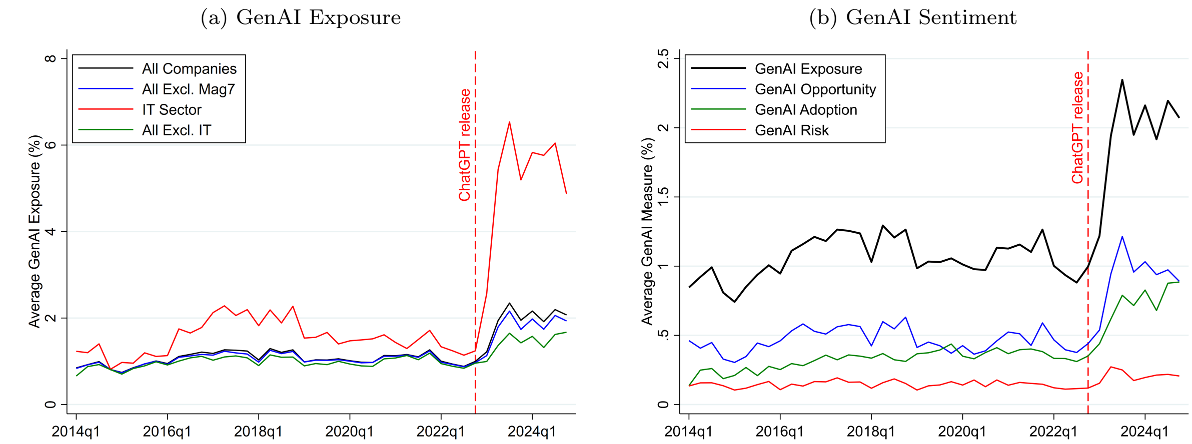
$$Y^{QoQ}_{i,t} = \beta_1 \cdot \text{EarlyExposed}_i \cdot \text{PostChatGPT}_t + \gamma F_{i,t} + \alpha_t + \lambda_i + \varepsilon_{i,t} \tag{11}$$

We apply the econometric framework to a panel of 480 S&P 500 firms over the period 2014–2024. The GenAI exposure measure is constructed from 22,590 quarterly earnings call transcripts, as detailed earlier. All estimations include different fixed effects and use clustered standard errors at the firm-level and account for within-firm correlation in the error terms.

4.1 Stylised facts

In this section, we examine the properties of our GenAI exposure measures, which quantify the emphasis placed on GenAI in corporate quarterly communications. As described in Section 3.4, this metric captures the importance that both management and stakeholders attribute to GenAI related technologies.

Figure 4: GenAI Exposure and Sentiment Trends



Note: Panel (a) shows average GenAI exposure across the sample; Panel (b) displays sentiment analysis breakdown. The vertical dashed red line indicates ChatGPT's release in Q4 2022, which coincides with substantial increases in exposure, particularly in technology-focused companies.

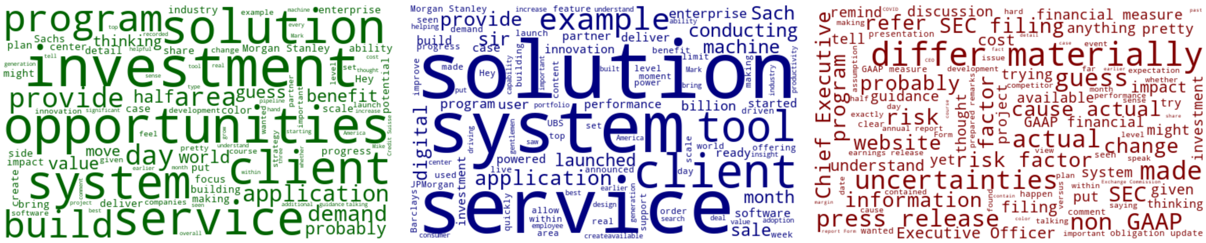
Figure 4 (a) shows the evolution of average GenAI exposure across the full S&P 500 and the separate trends for the Information Technology sector and S&P 500 excluding either IT or the Magnificent 7 firms. These trends reveal that discussions around GenAI were already underway before the release of ChatGPT, as indicated by non-zero exposure levels. Some acceleration in exposure begins after 2017, coinciding with the publication of the seminal paper "Attention Is All You Need" (Vaswani et al., 2017), which introduced the transformer architecture and spurred a strong commercial interest in GenAI technologies. However, the most pronounced increase follows the release of ChatGPT in late 2022. Information Technology firms led this trend, with average exposure rising from 1.3% in 2022 to 5% in 2023— a nearly fourfold increase. The ChatGPT release broadened discussions about GenAI also beyond the traditional tech sectors, as firms outside the IT and Big Tech domains registered a meaningful increase in AI-related exposure.

Figure 4 (b) provides more detailed information by reporting GenAI exposure for the average firm, along with sentiment decomposition into three categories *Opportunity*, *Adoption*, and *Risk*. Prior to ChatGPT, discussions were primarily centered on *Opportunity* rather than *Adoption*-related themes. Discussions about *Risk* were instead relatively rare. Post-ChatGPT, *Opportunity*-related discussions spiked sharply but tapered off shortly thereafter. In contrast, *Adoption*-related discussions increased steadily and eventually reached the same level as the ones *Opportunity*-related by the end of the sample.

To further illustrate the distinction between these three sentiment categories, Figure 5 presents word clouds of the most frequent terms associated with each sentiment dimension. After filtering out common terms, the visualization confirms that each category is characterized by distinct and coherent vocabulary, validating the effectiveness of the sentiment classification approach.

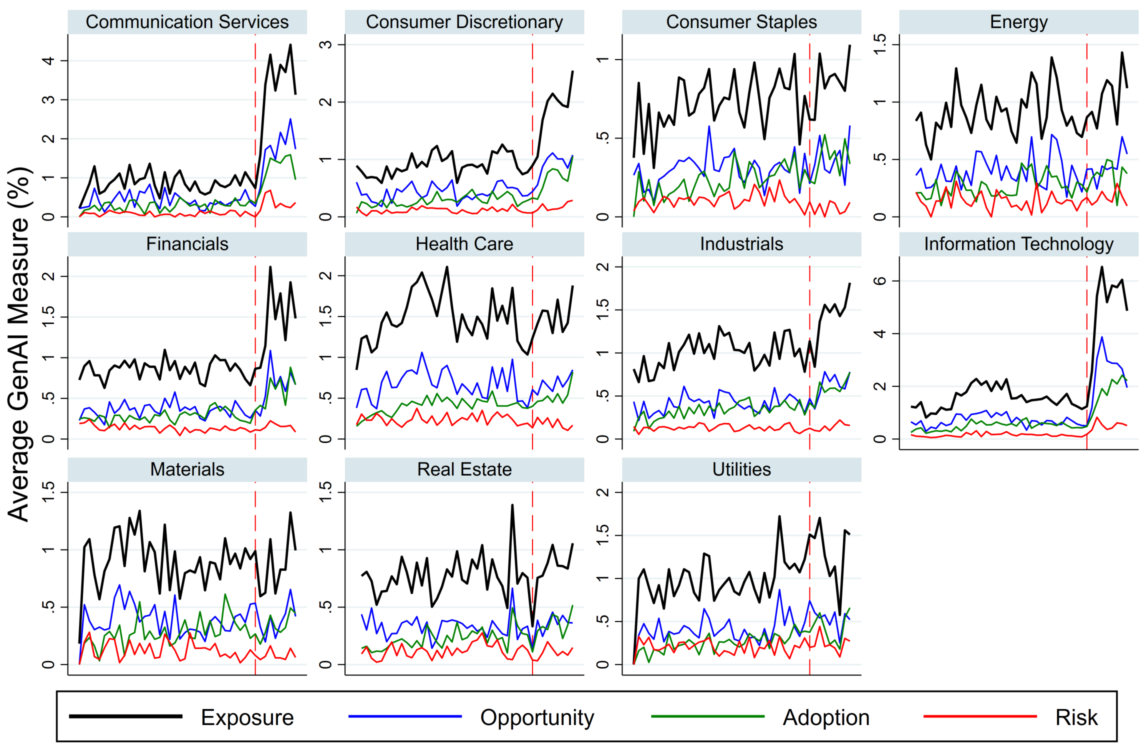
Figure 5: GenAI Sentiment-Driven Word Clouds

(a) GenAI Opportunity (b) GenAI Adoption (c) GenAI Risk



Note: Word size indicates frequency within each sentiment dimension (Opportunity, Adoption, Risk). Frequent common terms across all categories were removed to highlight terminology distinct to each sentiment category.

Figure 6: GenAI Discussion Patterns Across Sectors



Note: GenAI exposure and sentiment trends by sector from 2014 to 2024. The vertical dashed red line marks ChatGPT's release (Q4 2022), after which most sectors show increased discussion of both opportunities and adoption.

Figure 6 highlights sectoral differences in GenAI exposure. Beyond Information Technology, Communication Services firm saw a rise in exposure from 0.9% in 2022 to 3% in 2023. Consumer Discretionary and Financials also experienced notable increases. These sectors are naturally positioned to benefit from GenAI exposure due to their reliance on technology and consumer interaction positioning them to capitalize on the advantages GenAI can provide. In contrast, other sectors exhibited more gradual or flat trends, reflecting a slower pace of adoption.

Table 2 highlights the substantial heterogeneity in GenAI firms' exposure within the same and across sectors both before and after the introduction of ChatGPT.

Table 2: GenAI Exposure by Sector (One Year Before and After ChatGPT)

Panel A: Pre-ChatGPT (2021Q4-2022Q3)

	Mean	Std. Dev.	Median	75%	Max	N
Information Technology	1.359	1.400	0.989	1.951	9.630	272
Health Care	1.293	1.177	0.955	1.961	6.273	235
Utilities	1.144	1.254	0.815	1.757	7.859	116
Industrials	1.016	1.060	0.770	1.527	5.896	288
Communication Services	0.988	1.191	0.681	1.527	4.752	76
Materials	0.934	0.905	0.739	1.436	6.122	107
Real Estate	0.912	1.016	0.617	1.318	6.226	124
Consumer Discretionary	0.880	0.948	0.565	1.411	5.187	194
Financials	0.794	0.855	0.637	1.255	5.587	278
Energy	0.772	0.727	0.690	1.285	2.885	79
Consumer Staples	0.767	0.830	0.627	1.075	4.110	134
Total	1.020	1.093	0.768	1.524	9.630	1,903

Panel B: Post-ChatGPT (2023Q1-2023Q4)

	Mean	Std. Dev.	Median	75%	Max	N
Information Technology	4.932	6.469	2.494	6.157	38.215	271
Communication Services	3.091	5.050	1.395	2.711	21.635	76
Consumer Discretionary	1.726	3.039	0.917	1.894	29.870	193
Health Care	1.462	1.316	1.205	2.193	6.132	240
Financials	1.406	2.116	0.791	1.739	17.989	283
Utilities	1.367	1.347	1.064	2.208	6.840	120
Industrials	1.310	1.751	0.872	1.508	12.127	293
Energy	0.988	1.082	0.741	1.479	6.432	79
Real Estate	0.861	0.893	0.680	1.376	5.328	122
Consumer Staples	0.839	1.097	0.577	1.075	6.526	134
Materials	0.733	0.929	0.433	1.077	5.283	108
Total	1.863	3.353	0.973	1.990	38.215	1,919

Note: Panel A shows pre-ChatGPT (2021Q4-2022Q3) GenAI exposure metrics across sectors; Panel B shows Post-ChatGPT (2023Q1-2023Q4) metrics. Information Technology has the highest average exposure, more than tripling from 1.36% to 4.93% after ChatGPT's release, with the highest maximum values in both periods.

Table 3 presents a variance decomposition of GenAI exposure, breaking down the sources of variation and their respective contributions to differences in exposure levels reporting the incremental R^2 from adding a specific fixed effect.

Table 3: Variance Analysis of GenAI Exposure Components

	R^2 (% of Total)			
Source of Variation	GenAI Exposure	GenAI Opportunity	GenAI Adoption	GenAI Risk
Fixed Effects				
Time Effects	0.0376 (3.8%)	0.0313 (3.1%)	0.0320 (3.2%)	0.0074 (0.7%)
Sector Effects	0.0525 (5.3%)	0.0367 (3.7%)	0.0268 (2.7%)	0.0124 (1.2%)
Sector × Time	0.0705 (7.1%)	0.0685 (6.8%)	0.0360 (3.6%)	0.0305 (3.1%)
Firm Controls	0.0037 (0.4%)	0.0018 (0.2%)	0.0035 (0.4%)	0.0004 (0.0%)
Firm Effects				
Firm Fixed Effects	0.1528 (15.3%)	0.1309 (13.1%)	0.1036 (10.4%)	0.0756 (7.6%)
Unexplained Variation	0.6865 (68.6%)	0.7327 (73.3%)	0.8016 (80.2%)	0.8741 (87.4%)

Note: R^2 values showing contribution of different factors to GenAI exposure variation. Firm-specific effects (15.3%) are the largest identifiable source, followed by sector-time interactions (7.1%). Substantial unexplained variation (68.6%) indicates economic significance of firm-level heterogeneity beyond sector and time trends.

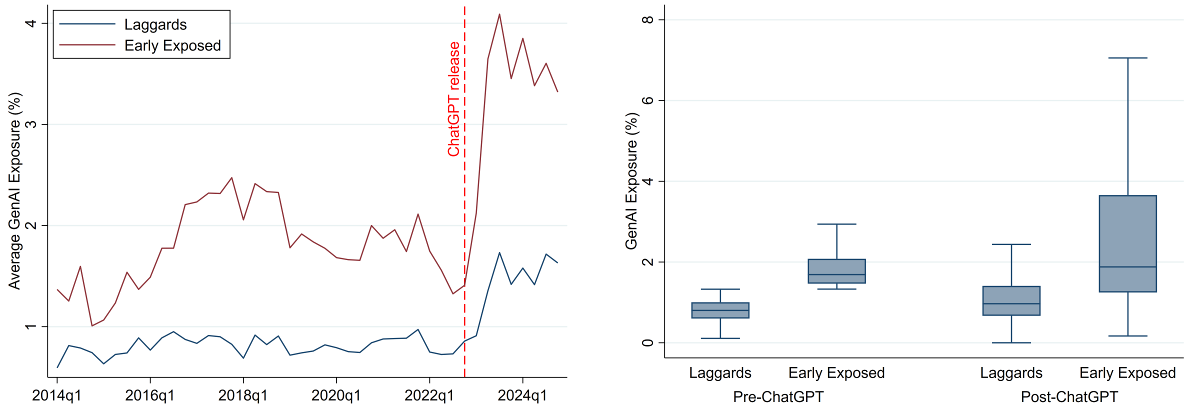
Time Effects account for 3.8% of the variation, indicating that changes over time have a modest impact on GenAI exposure. Sector effects contribute an additional 5.3%, showing that intersectoral differences play some role in the variation. Sector × Time Interactions explain a further 7.1%, suggesting that the combination of sector and time factors provides more insight into changes in exposure. Firm Controls contribute minimally, *i.e.*, 0.4%, indicating limited explanatory power in this context. Firm Fixed Effects are much more significant, accounting for 15.3% of the variation, highlighting that differences at the firm level are a key source of variation in GenAI exposure. Nonetheless, unexplained variation of GenAI exposure remains high at 68.6%. We interpret the substantial share of variance within the firm-quarter as indicative of economically meaningful heterogeneity. Unexplained variation is even slightly higher once we re-do the analysis for GenAI sentiment components. Consequently, this firm-level variation offers critical identification power for our empirical strategy.

Treatment *vs.* control firms. We categorize firms into treatment and control groups based on their average exposure from the fourth quarter of 2017 to the third quarter of 2022, which constitutes the five-year period leading up to the release of ChatGPT. This categorization is necessary for implementing a difference-in-differences approach (see the next section), allowing us to assess the causal impact of GenAI exposure by comparing changes over time between firms with different levels of initial exposure.

Firms with exposure levels at or above the 75th percentile (top 25%) are classified as *Early Exposed*, while those below this threshold are categorized as *Laggards*.

Figure 7 illustrates the trends in GenAI exposure for companies categorized as *Early Exposed* and *Laggards*. The boxplot displays the average GenAI exposure for these two groups both before and after the release of ChatGPT. Both groups of firms show increased attention to GenAI in the Post-ChatGPT period. Notably, the most significant increase in GenAI exposure is observed among firms that were already early adopters of GenAI.

Figure 7: Comparison of Early GenAI Exposed *vs.* Laggards



Note: Firms are classified based on GenAI exposure prior to ChatGPT's release. Early exposed (above 75th percentile exposure) show greater increases in GenAI discussion Post-ChatGPT compared to the remaining firms, suggesting first-mover advantage.

4.2 Empirical Econometric Results

This section examines the empirical findings based on Equations (8) and (10) for panel regressions and Equation (11) for the DiD model.

Panel regression results. Our baseline panel regression results in Table 4 show a considerable impact of GenAI exposure on stock price returns (columns 1 to 3) and expected earnings per share (columns 4 to 6). Specifically, our analysis indicates that a one percentage point increase in time devoted to discussing GenAI leads to a 0.62% rise in quarterly stock prices (column 1). Investors appear eager to allocate funds toward firms that view AI as crucial for maintaining a competitive edge and fostering future growth. Further refining these estimates suggests that early AI exposure is a significant determinant of equity prices, with a positive interaction coefficient of 0.26 (column 2). The results indicate that firms with early AI exposure attracted investor interest and were rewarded for both early and sustained engagement with GenAI technology. Additionally, there is evidence that in the Post-ChatGPT period, all firms with GenAI exposure experienced a surge in market interest, leading to a positive impact on stock prices (column 3).

Examining expected earnings per share reveals that changes in GenAI exposure measures influenced projected earnings per share during the Post-ChatGPT period (column 6) but had no significant impact on *Early Exposed* firms (columns 5 and 6). This suggests that investors' enthusiasm, rather than a corresponding revision of earnings projections, largely drove the rise of equity prices for such firms. However, for the overall sample of companies in the Post-ChatGPT period, our results suggest that stock prices gains were driven by a combination of improved sentiment and heightened expectations about firm fundamentals, as evidenced by higher expected earnings per share. This latter effect may be related to both increased profits and earnings for companies developing AI tools, or the reduced input costs and enhanced productivity for firms employing AI tools.

Figure 8 illustrates the estimated impact of GenAI on stock prices, using coefficients from Equation (10) and cumulative changes in GenAI exposure in 2023 across four distinct groups. This approach suggests that *Early Exposed* firms significantly outperformed the broader market in equity returns. Nearly one third of their gains can be directly attributed to their exposure to GenAI discussion, convincing

Table 4: GenAI Exposure Effects on QoQ Financial Performance

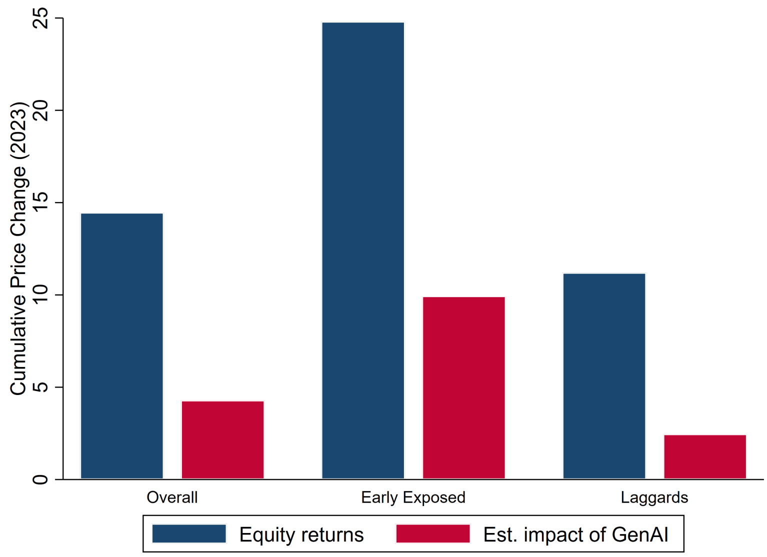
	Stock Price			Expected EPS		
	(1)	(2)	(3)	(4)	(5)	(6)
GenAI Exposure	0.620**	0.352**	0.103	0.189***	0.156*	-0.027
	(2.886)	(2.309)	(0.988)	(3.261)	(1.831)	(-0.339)
GenAI Exposure × Early Exposed		0.260***	0.272***		0.101	0.119
		(5.790)	(5.863)		(0.827)	(1.044)
GenAI Exposure × Post-ChatGPT			0.360***			0.384***
			(3.294)			(14.176)
Expected EPS	0.033	0.057	0.061			
	(0.669)	(1.360)	(1.495)			
Return on Assets	14.824	12.895	8.590	52.706***	48.966***	40.706***
	(0.893)	(1.076)	(0.907)	(3.699)	(3.774)	(4.526)
Log(Assets)	-0.630**	-0.731***	-0.747***	-0.239	-0.298	-0.318*
	(-2.822)	(-3.862)	(-3.928)	(-1.195)	(-1.632)	(-1.814)
GDP Growth Forecast	2.440			1.944***		
	(1.016)			(3.835)		
10Y Interest Rates	0.442			1.961**		
	(0.141)			(2.598)		
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Sector-Time FE	No	No	Yes	No	No	Yes
R^2	0.033	0.264	0.352	0.044	0.097	0.191
N	17,180	17,175	17,173	17,213	17,208	17,206

Note: Regression results showing impact of GenAI exposure on quarterly stock prices and 12-month forward EPS. A one percentage point increase in GenAI exposure associates with 0.62% higher stock prices, with additional premiums for *Early Exposed* (0.26%) and Post-ChatGPT discussions (0.36%). T-statistics in parentheses;* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

investors that firms discussing GenAI sooner were better positioned to capitalize on the technological advancements in 2023.

To provide a more nuanced understanding of these results, Table 5 presents regression results for Equation 9, focusing on the sub-components of the GenAI exposure measure: *Opportunity, Adoption,* and *Risk*. Our results show that *Early Exposed* firms benefited from discussions about both *Adoption* and *Opportunity* as their stock prices outperformed "Laggards" firms by 0.63% and 0.45% in quarterly excess returns for every 1% increase in *Adoption*/*Opportunity* GenAI exposure, while their earnings expectations did not statistically significantly increase. Note that the coefficient of *Adoption* is substantially higher than that of *Opportunity* , suggesting that investor sentiment is more strongly influenced by discussions of GenAI *Adoption*, likely because adoption is expected to yield productivity benefits sooner. In the Post-ChatGPT period, all firms benefited from the anticipation of improved firm fundamentals as well, as shown by the positive and significant reaction of expected earnings per share to both *Opportunity* and *Adoption*. The regression table reveals an unexpected finding: during the Post-ChatGPT period, higher exposure to GenAI *Risk* was associated with stock price gains. A priori, we expected that a stronger emphasis on risks would have an insignificant or even negative impact on stock prices. This outcome can be partly explained by the presence of confounding effects. Specifically, while sentiment measures are uncorrelated at the paragraph level, they exhibit a high correlation at the transcript level in the Post-

Figure 8: GenAI Impact on Company Stock Performance



Note: Blue bars show actual 2023 equity returns; red bars indicate estimated GenAI contribution based on regression coefficients and exposure changes. *Early Exposed* companies show the strongest effects, with GenAI accounting for approximately 40% of their returns.

ChatGPT period (as shown in Table 13). Firms that frequently discuss *Opportunity* and *Adoption* also tend to address potential risks, as these topics especially arise in analysts' Q&A sessions. This interplay suggests that discussions of risk may be perceived as part of a holistic strategy, thereby not necessarily undermining investor confidence.

DiD results. To further validate the impact of GenAI, Table 6 presents the results from the DiD approach. The interaction term *Early Exposed* × *Post-ChatGPT* shows significant positive coefficients for both quarterly stock prices and expected earning per share. It shows that *Early Exposed* firms experienced stock price increases of 2.4 percentage points more than *Laggards* on average each quarter following the release. The DiD analysis hinges crucially on the parallel trends assumption to ensure the reliability of our estimators. This assumption, in economic terms, implies that, in the absence of the ChatGPT shock, the trajectories of changes in stock prices and earnings per share for both *Early Exposed* firms and *Laggards* would have mirrored each other over time. To check this assumption, we re-estimated our model, substituting the Post-ChatGPT indicator with a series of time dummies. We then graphically traced the predicted trends in stock prices and expected earnings per share changes for both groups of firms before the widespread adoption of GenAI. Figure 9 displays these predicted trajectories, revealing no significant divergence between the groups during the pre-ChatGPT era. Both sets of firms exhibit parallel movements in stock prices and expected earnings per share, pointing to the validity of the parallel trends assumption. Moreover, the figure draws attention to a distinct shift in both metrics following the introduction of ChatGPT.

We next replicated the DiD method at sectoral level because the incentives driven by GenAI are likely unique to specific industries, particularly those where business models are closely linked to technological innovation and digital transformation. Within each industry, we categorize firms based on their GenAI exposure and calculate the effect of ChatGPT on stock price changes (see Table 7). We can then compare

Table 5: Sentiment-Specific GenAI Impact on QoQ Financial Performance

	Stock Price			Expected EPS		
	(1)	(2)	(3)	(4)	(5)	(6)
Opportunity	0.172			0.049		
	(0.980)			(0.316)		
Adoption		0.229			0.070	
		(1.472)			(0.247)	
Risk			-0.779*			-0.601*
			(-2.214)			(-1.929)
Opportunity × Early Exposed	0.454***			0.088		
	(4.767)			(0.716)		
Adoption × Early Exposed		0.629***			0.357	
		(3.759)			(1.036)	
Risk × Early Exposed			1.172			0.847
			(1.092)			(1.598)
Opportunity × Post-ChatGPT	0.342*			0.539**		
	(1.865)			(2.641)		
Adoption × Post-ChatGPT		0.524			0.425***	
		(1.440)			(6.324)	
Risk × Post-ChatGPT			3.995**			1.322**
			(2.993)			(2.456)
Expected EPS	0.062	0.062	0.062			
	(1.503)	(1.483)	(1.519)			
Return on Assets	8.753	9.093	9.630	40.797***	41.284***	41.654***
	(0.931)	(0.980)	(1.023)	(3.744)	(3.870)	(3.927)
Log(Assets)	-0.748***	-0.745***	-0.745***	-0.329	-0.322	-0.319
	(-3.932)	(-3.954)	(-3.950)	(-1.744)	(-1.744)	(-1.769)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.351	0.351	0.352	0.182	0.181	0.181
N	17,173	17,173	17,173	17,203	17,203	17,203

Note: Regression results showing differential effects of GenAI sentiment dimensions. Opportunity and adoption discussions show positive stock price effects for *Early Exposed*, while risk discussions unexpectedly show positive effects Post-ChatGPT. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

the magnitude of GenAI's impact on stock returns across industries, subject to the caveat of having fewer data points at the sectoral level.

Figure 10 shows, more specifically, the estimated coefficient (β_1), representing the relative impact of the ChatGPT release for *Early Exposed* firms *vs. Laggards* for each sector. The results are significant for the IT sector, indicating that *Early Exposed* firms have experienced a more pronounced surge in stock prices since the ChatGPT's release. The coefficients are also positive and large for Consumer Services and Consumer Discretionary, two sectors which are more inclined to utilize and benefit from AI. In contrast, sectors less likely to benefit for now, such as Utilities, show a negative coefficient.

4.2.1 Robustness

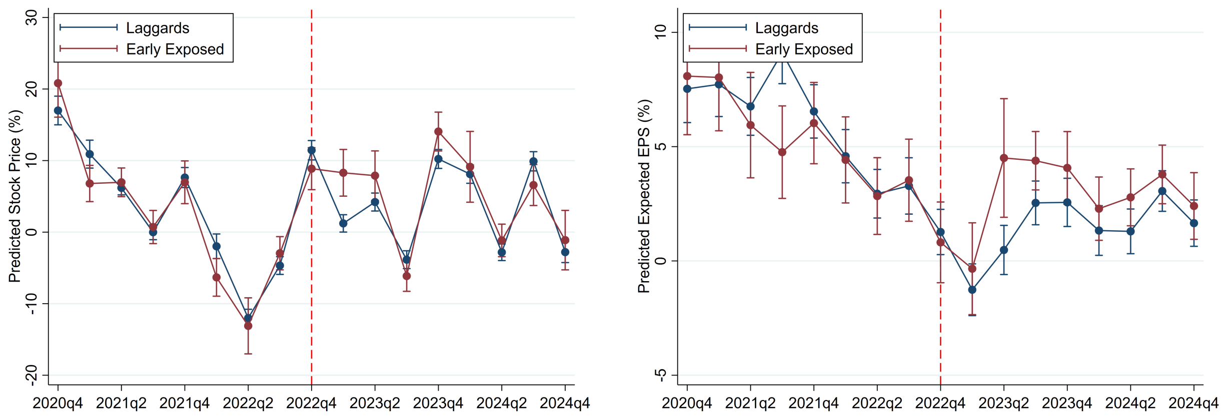
To test the robustness of our findings, we alter our baseline regressions in two ways. The first way involves revisiting the selection criteria for distinguishing between treatment and control firms. The second way

Table 6: Difference-in-Differences Results for GenAI Effects

	Stock Price				Expected EPS			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Early Exposed × Post-ChatGPT	2.17**	2.45***	2.52***	2.53***	1.62**	1.55**	1.21	1.49*
	(2.33)	(2.67)	(2.71)	(2.74)	(2.07)	(2.03)	(1.57)	(1.94)
Early Exposed	1.18***	0.68**			0.64**	0.48*		
	(3.20)	(2.31)			(2.26)	(1.75)		
Post-ChatGPT	-0.41	5.85***	5.55***		-2.17***	-3.94***	-4.37***	
	(-1.21)	(12.36)	(10.90)		(-6.96)	(-9.33)	(-9.75)	
Expected EPS		0.05***	0.01	0.03*				
		(2.77)	(0.68)	(1.69)				
Return on Assets		16.10**	25.80***	24.56***		54.02***	71.89***	66.76***
		(2.35)	(2.97)	(3.49)		(7.53)	(8.03)	(7.33)
Log(Assets)		-0.70***	-0.60	-0.97*		-0.16**	0.70*	-0.78
		(-7.31)	(-1.46)	(-1.78)		(-2.04)	(1.88)	(-1.53)
GDP Growth Forecast		2.51***	2.58***			1.92***	1.96***	
		(15.50)	(15.38)			(13.46)	(13.82)	
10Y Interest Rates		-0.84***	-0.75***			2.78***	2.81***	
		(-3.89)	(-3.42)			(14.64)	(14.89)	
Time FE	No	No	No	Yes	No	No	No	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.002	0.037	0.064	0.286	0.005	0.047	0.107	0.151
N	17,594	17,175	17,175	17,175	17,213	17,208	17,208	17,208

Note: DiD analysis comparing *Early Exposed vs. Laggards* before and after ChatGPT's release. *Early Exposed* firms show 2.17-2.53% higher quarterly stock returns and 1.21-1.62% higher EPS growth Post-ChatGPT. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 9: Parallel Trends in Stock Prices and Earnings Expectations



Note: Predicted values from regression model interacting early GenAI exposure with quarterly time dummies. Parallel pre-ChatGPT trends support causal identification, with divergence occurring after ChatGPT's release (vertical dashed red line).

involves expanding the set of firm-level controls in our panel regressions

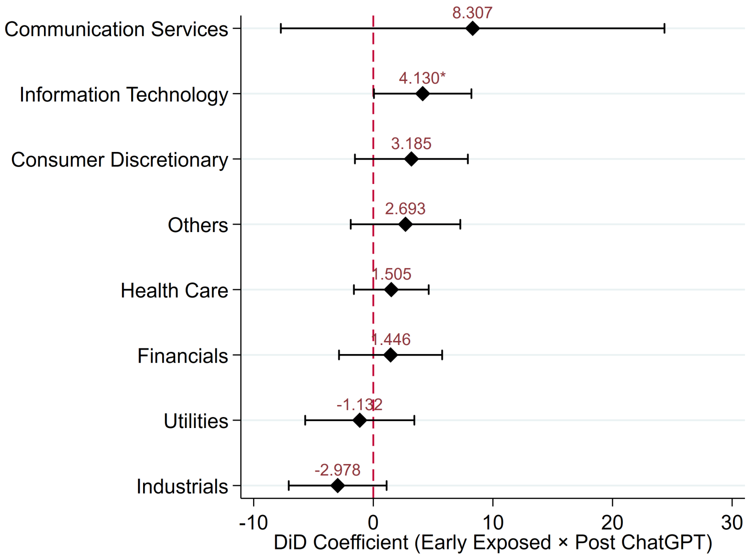
Revising Treatment *vs.* Control Firms. To refine how we define treatment *vs.* control firms, we take a more agnostic approach by ranking all firms based on their early exposure to GenAI and using

Table 7: Pre-ChatGPT GenAI Exposure by Sector

Sector	Mean	Median	Std. Dev.	#Early Exposed	Total	%Early Exposed
Information Technology	1.617	1.416	0.930	40	68	58.8%
Health Care	1.484	1.329	0.725	32	61	52.5%
Consumer Discretionary	0.982	0.832	0.480	11	49	22.4%
Communication Services	0.834	0.822	0.501	4	19	21.1%
Industrials	1.047	0.938	0.504	16	76	21.1%
Utilities	1.027	0.951	0.340	5	30	16.7%
Financials	0.855	0.831	0.373	10	71	14.1%
Materials	0.859	0.775	0.358	3	27	11.1%
Consumer Staples	0.767	0.752	0.440	4	37	10.8%
Energy	0.924	0.927	0.285	2	21	9.5%
Real Estate	0.789	0.802	0.315	1	31	3.2%

Note: Sector-level GenAI exposure statistics during pre-ChatGPT period (2017Q4-2022Q3). Information Technology (58.8%) and Health Care (52.5%) have the highest percentage of firms classified as early GenAI exposed, while Real Estate (3.2%) has the lowest.

Figure 10: Sector-Specific GenAI Effects on Stock Price



Note: Difference-in-Differences (DiD) coefficient estimates by sector, showing *Early Exposed vs. Laggards* performance differences after ChatGPT's release. Communication Services, Information Technology, and Consumer Discretionary show strongest positive effects.

the median exposure to split the sample into two groups. Under this alternative specification, a firm is considered *Early Exposed* if it has spent at least 0.78% of its discussions on GenAI, as opposed to 1.5% as in our benchmark specification As shown in Table 7, the distribution of GenAI exposure prior to ChatGPT is right-skewed, with the mean exceeding the median across all sectors. This skew indicates that a small subset of firms displayed disproportionately high exposure, while the majority had relatively low levels. Consequently, using a median split this results in an *Early Exposed* set that includes several firms with minimal interest in GenAI prior to the launch of ChatGPT, potentially weakening our findings.

Table 8 reports the panel regression results based on this alternative split between treatment and control firm, confirming our hypothesis. The estimates remain qualitatively consistent with the baseline, indicating that higher GenAI exposure leads to higher stock prices and earnings per share, especially in the Post-ChatGPT period. However, the coefficient on the interaction between GenAI exposure and being *Early Exposed* in column (3) is no longer statistically significant, reflecting the blurred distinction between treatment and control groups. We also repeat the difference-in-differences (DiD) analysis under this alternative split (see Table 11 in the Appendix). The DiD results continue to show a positive and statistically significant effect of GenAI exposure on stock prices. However, the effect on earnings per share is no longer statistically significant, supporting our earlier interpretation that the main effects are likely driven by improved sentiment rather than higher future earnings per share.

Table 8: Robustness Analysis: Median Split Approach

	Stock Price			Expected EPS		
	(1)	(2)	(3)	(4)	(5)	(6)
GenAI Exposure	0.620**	0.376*	0.173	0.189***	0.256*	0.081
	(2.886)	(2.027)	(1.303)	(3.261)	(2.189)	(0.774)
GenAI Exposure × Early Exposed		0.165*	0.129		-0.040	-0.035
		(1.888)	(1.633)		(-0.281)	(-0.274)
GenAI Exposure × Post-ChatGPT			0.343**			0.382***
			(3.065)			(12.329)
Expected EPS	0.033	0.057	0.061			
	(0.669)	(1.363)	(1.496)			
Return on Assets	14.824	12.685	8.367	52.706***	48.910***	40.627***
	(0.893)	(1.057)	(0.868)	(3.699)	(3.762)	(4.522)
Log(Assets)	-0.630**	-0.731***	-0.747***	-0.239	-0.300	-0.320*
	(-2.822)	(-3.838)	(-3.910)	(-1.195)	(-1.639)	(-1.825)
GDP Growth Forecast	2.440			1.944***		
	(1.016)			(3.835)		
10Y Interest Rates	0.442			1.961**		
	(0.141)			(2.598)		
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Sector-Time FE	No	No	Yes	No	No	Yes
R^2	0.033	0.263	0.352	0.044	0.097	0.191
N	17,180	17,175	17,173	17,213	17,208	17,206

Note: Alternative specification using median rather than 75th percentile to classify *Early Exposed*. Results remain consistent but with smaller coefficient magnitudes, confirming that firms with the highest early GenAI exposure benefited the most. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Additionally, we alter the selection of firms into a treatment and control groups by excluding the "Magnificent 7" companies from the baseline sample of firms. The rationale is that five of these companies were in the treated group and strongly benefited from the Post-ChatGPT boom, potentially playing a major role in the results. Table 9 presents the results and confirms our results hold even excluding the influence of these dominant players. While the coefficient indicating the additional benefits for *Early Exposed* firms to GenAI declines slightly after excluding the "Magnificent 7," it remains statistically significant.

Table 9: Robustness Analysis: Excluding Magnificent 7

	Stock Price			Expected EPS		
	(1)	(2)	(3)	(4)	(5)	(6)
GenAI Exposure	0.507**	0.320*	0.091	0.154**	0.038	-0.064
	(2.376)	(1.965)	(1.127)	(2.538)	(0.576)	(-0.803)
GenAI Exposure × Early Exposed		0.153**	0.159***		0.135	0.147
		(2.665)	(4.030)		(1.411)	(1.539)
GenAI Exposure × Post-ChatGPT			0.324**			0.268**
			(2.533)			(2.340)
Expected EPS	0.034	0.057	0.062			
	(0.706)	(1.437)	(1.621)			
Return on Assets	12.796	10.970	6.397	54.204**	48.179**	39.387***
	(0.743)	(0.874)	(0.655)	(2.883)	(2.852)	(3.531)
Log(Assets)	-0.696**	-0.804***	-0.821***	-0.265	-0.347	-0.363*
	(-2.697)	(-3.489)	(-3.511)	(-1.207)	(-1.699)	(-1.876)
GDP Growth Forecast	2.488			1.924***		
	(1.031)			(3.469)		
10Y Interest Rates	0.549			1.787*		
	(0.174)			(2.155)		
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Sector-Time FE	No	No	Yes	No	No	Yes
R^2	0.031	0.265	0.354	0.035	0.092	0.183
N	16,923	16,918	16,916	16,953	16,948	16,946

Note: This table compares firms with low versus high GenAI exposure. The split is determined by the average *GenAIExp* per firm over the five-year period preceding ChatGPT's release, up to 2017Q4. Firms with low (high) exposure are those below (above) the 25th percentile of exposure.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Expanding Firm-Level Controls. The second way we test robustness involves the set of firm-level controls in our panel regressions. We include additional variables such as the log of capital expenditure and short- and long-term debt ratios, while keeping all other specifications unchanged. The results in Table 10 show that our main conclusions remain broadly unchanged compared to our baseline specification.

Table 10: Robustness Analysis: Additional Control Variables

	Stock Price			Expected EPS		
	(1)	(2)	(3)	(4)	(5)	(6)
GenAI Exposure	0.673***	0.427**	0.183	0.233***	0.193*	0.009
	(3.337)	(2.840)	(1.719)	(4.702)	(1.937)	(0.076)
GenAI Exposure × Early Exposed		0.220**	0.226***		0.099	0.129
		(2.672)	(5.102)		(0.802)	(1.067)
GenAI Exposure × Post-ChatGPT			0.339***			0.354***
			(4.112)			(7.528)
Expected EPS	0.035	0.062	0.064			
	(0.588)	(1.252)	(1.279)			
Return on Assets	12.408	14.549	7.025	55.191***	50.771***	41.653***
	(0.803)	(1.221)	(0.798)	(3.611)	(3.708)	(4.775)
Log(Assets)	-0.493	-0.325	-0.442*	-0.245	-0.489**	-0.515**
	(-0.822)	(-1.441)	(-2.024)	(-0.836)	(-2.384)	(-2.665)
GDP Growth Forecast	2.131			1.976***		
	(0.925)			(4.178)		
10Y Interest Rates	0.057			1.792**		
	(0.019)			(2.499)		
Log(Capital Expenditure)	-0.226	-0.511***	-0.395***	-0.075	0.097	0.114
	(-0.412)	(-3.938)	(-3.318)	(-0.304)	(0.540)	(0.611)
Long-Term Debt Ratio	-0.458	-0.732**	-0.762**	-0.651	-0.719	-0.726
	(-1.233)	(-2.320)	(-2.350)	(-1.273)	(-1.307)	(-1.388)
Short-Term Debt Ratio	-0.181	0.185	-0.021	3.896***	3.999***	3.625***
	(-0.166)	(0.219)	(-0.028)	(5.044)	(5.985)	(5.747)
Sector FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	No	Yes	Yes	No	Yes	Yes
Sector-Time FE	No	No	Yes	No	No	Yes
R^2	0.032	0.259	0.338	0.049	0.098	0.194
N	13,211	13,208	13,169	13,240	13,237	13,198

Note: Extended specifications including capital expenditure and debt ratios as controls. Results remain consistent with main findings, with slightly stronger coefficients for GenAI exposure, confirming robustness to additional firm-level controls. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5 Conclusions

In this paper we have presented a versatile framework for measuring firm-level exposure to generative artificial intelligence (GenAI). By segmenting earnings call transcripts and quantifying exposure based on the share of discussions devoted to GenAI, we provide a robust tool for analyzing AI's integration into corporate strategies. Central to this approach is the effective use of advanced natural language processing (NLP) techniques, particularly the application of large language models (LLMs) for both topic modeling and sentiment analysis. This approach allows us to measure AI discussions without relying on predefined keywords, significantly improving the precision of exposure measurement while also disentangling multiple dimensions of sentiment (opportunities, adoption, and risk) that characterize firms' strategic responses. Our empirical analysis shows that firms engaging early and significantly with GenAI exposure tended to experience stronger market performance and generally smaller improvements in earnings expectations. These effects appear to be driven by investor sentiment, particularly when firms communicated concrete steps toward implementation. Discussions centered on adoption—rather than abstract potential—tended to elicit stronger market reactions, suggesting that investors respond not just to optimism, but to credible signals of execution and strategic intent.

While our study centers on GenAI in the context of earnings calls and valuation effects, this methodology is equally well-suited for assessing other emerging technologies and external influences, such as climate regulations, trade policies, or geopolitical disruptions and other sources of textual communication. The framework's versatility allows researchers to systematically observe how firms respond to shifting market conditions, providing a robust tool for evaluating the financial impacts of both technological innovations and policy-driven changes.

References

Adolfsen, J. F., Heissel, M., Manu, A.-S., and Vinci, F. Burn Now or Never? Climate Change Exposure and Investment of Fossil Fuel Firms. *ECB Working Paper*, 2024.

Agrawal, A., Gans, J., and Goldfarb, A. Economic Policy for Artificial Intelligence. In *Innovation Policy and the Economy, Volume 19*, pages 139–159. National Bureau of Economic Research, Inc, 2018. URL `https://ideas.repec.org/h/nbr/nberch/14098.html`.

Algaba, A., Ardia, D., Bluteau, K., Borms, S., and Boudt, K. Econometrics Meets Sentiment: An Overview of Methodology and Applications. *Journal of Economic Surveys*, 34(3):512–547, 2020.

Araci, D. FinBERT: Financial Sentiment Analysis with Pre-Trained Language Models. *arXiv preprint arXiv:1908.10063*, 2019.

Armelius, H., Bertsch, C., Hull, I., and Zhang, X. Spread the Word: International Spillovers from Central Bank Communication. *Journal of International Money and Finance*, 103:102116, 2020.

Aruoba, S. B. and Drechsel, T. Identifying Monetary Policy Shocks: A Natural Language Approach. *National Bureau of Economic Research*, 2024.

Back, C., Morana, S., and Spann, M. When do robo-advisors make us better investors? The impact of social design elements on investor behavior. *Journal of Behavioral and Experimental Economics*, 103: 101984, 2023.

Bailliu, J. N., Han, X., Sadaba, B., and Kruger, M. Chinese Monetary Policy and Text Analytics: Connecting Words and Deeds. *Bank of Canada Staff Working Paper*, 2021.

Baker, S. R., Bloom, N., and Davis, S. J. Measuring Economic Policy Uncertainty. *The Quarterly Journal of Economics*, 131(4):1593–1636, 2016.

Bell, A., Solano-Kamaiko, I., Nov, O., and Stoyanovich, J. It's Just Not That Simple: An Empirical Study of the Accuracy-Explainability Trade-off in Machine Learning for Public Policy. In *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*, pages 248–266, 2022.

Bick, A., Blandin, A., and Deming, D. The impact of generative ai on work productivity. Technical report, Federal Reserve Bank of St. Louis, 2025.

Blei, D. M., Ng, A. Y., and Jordan, M. I. Latent Dirichlet Allocation. *The Journal of Machine Learning Research*, 3:993–1022, 2003.

Borms, S. *Sentiment and Econometrics: Toward A Unified Framework of Textual Sentiment Analysis for Economic and Financial Applications.* PhD thesis, Université de Neuchâtel, 2020.

Boutaleb, A., Picault, J., and Grosjean, G. BERTrend: Neural Topic Modeling for Emerging Trends Detection. In *Proceedings of the Workshop on the Future of Event Detection (FuturED)*, pages 1–17, 2024.

Brown, T., Mann, B., Ryder, N., Subbiah, M., Kaplan, J. D., Dhariwal, P., Neelakantan, A., Shyam, P., Sastry, G., Askell, A., et al. Language Models Are Few-Shot Learners. *Advances in Neural Information Processing Systems*, 33:1877–1901, 2020.

Caldara, D. and Iacoviello, M. Measuring Geopolitical Risk. *American Economic Review*, 112(4):1194–1225, 2022.

Cerutti, E. M., Pascual, A. I. G., Kido, Y., Li, L., Melina, G., Tavares, M. M., and Wingender, P. The Global Impact of AI–Mind the Gap. *IMF Working Papers*, 2025(076), 2025.

Chin, A. and Fan, Y. Leveraging Text Mining to Extract Insights from Earnings Call Transcripts. *Journal of Investment Management*, 21(1):81–102, 2023.

Deerwester, S., Dumais, S. T., Furnas, G. W., Landauer, T. K., and Harshman, R. Indexing by Latent Semantic Analysis. *Journal of the American Society for Information Science*, 41(6):391–407, 1990.

Devlin, J., Chang, M.-W., Lee, K., and Toutanova, K. BERT: Pre-training of Deep Bidirectional Transformers for Language Understanding. In *Proceedings of the 2019 Conference of the North American Chapter of the Association for Computational Linguistics: Human Language Technologies, Volume 1 (Long and Short Papers)*, pages 4171–4186, 2019.

Eisfeldt, A. L., Schubert, G., and Zhang, M. B. Generative AI and Firm Values. *National Bureau of Economic Research*, 2023.

Gentzkow, M., Kelly, B., and Taddy, M. Text as Data. *Journal of Economic Literature*, 57(3):535–574, 2019.

Grootendorst, M. BERTopic: Neural Topic Modeling with a Class-Based TF-IDF Procedure. *arXiv preprint arXiv:2203.05794*, 2022.

Hassan, T. A., Hollander, S., Kalyani, A., Schwedeler, M., Tahoun, A., and van Lent, L. Economic Surveillance Using Corporate Text. *Federal Reserve Bank of St. Louis*, 2024.

He, L., Larkin, S., and Li, X. Algorithmic Trading and the Role of AI. *Journal of Financial Markets*, 47:100–123, 2020.

Hurst, A., Lerer, A., Goucher, A. P., Perelman, A., Ramesh, A., Clark, A., Ostrow, A., Welihinda, A., Hayes, A., Radford, A., et al. GPT-4o System Card. *arXiv preprint arXiv:2410.21276*, 2024.

Iglesias, J., Ortiz, A., and Rodrigo, T. How Do the Emerging Markets Central Bank Talk? A Big Data Approach to the Central Bank of Turkey. *BBVA Research*, 2017.

Johnson, I., Gerlach, M., and Sáez-Trumper, D. Language-Agnostic Topic Classification for Wikipedia. In *Companion Proceedings of the Web Conference 2021*, pages 594–601, 2021.

Kim, A. G., Muhn, M., and Nikolaev, V. V. From Transcripts to Insights: Uncovering Corporate Risks Using Generative AI. *Chicago Booth Research Paper*, 2023.

Lewis, M., Liu, Y., Goyal, N., Ghazvininejad, M., Mohamed, A., Levy, O., Stoyanov, V., and Zettlemoyer, L. BART: Denoising Sequence-to-Sequence Pre-training for Natural Language Generation, Translation, and Comprehension. *arXiv preprint arXiv:1910.13461*, 2019.

Lopardo, G. *Foundations of Machine Learning Interpretability*. PhD thesis, Université Côte d'Azur, 2024.

Lopardo, G., Precioso, F., and Garreau, D. Faithful and Robust Local Interpretability for Textual Predictions. *arXiv preprint arXiv:2311.01605*, 2023.

Lopardo, G., Precioso, F., and Garreau, D. Attention Meets Post-hoc Interpretability: A Mathematical Perspective. In *International Conference on Machine Learning (ICML)*. PMLR, 2024.

Loughran, T. and McDonald, B. When Is a Liability Not a Liability? Textual Analysis, Dictionaries, and 10-Ks. *The Journal of Finance*, 66(1):35–65, 2011.

Lundberg, S. M. and Lee, S.-I. A Unified Approach to Interpreting Model Predictions. *Advances in Neural Information Processing Systems (NeurIPS)*, 30:4765–4774, 2017.

Sautner, Z., Van Lent, L., Vilkov, G., and Zhang, R. Firm-Level Climate Change Exposure. *The Journal of Finance*, 78(3):1449–1498, 2023.

Vaswani, A., Shazeer, N., Parmar, N., Uszkoreit, J., Jones, L., Gomez, A. N., Kaiser, Ł., and Polosukhin, I. Attention Is All You Need. *Advances in Neural Information Processing Systems*, 30, 2017.

Wu, X., Nguyen, T., and Luu, A. T. A Survey on Neural Topic Models: Methods, Applications, and Challenges. *Artificial Intelligence Review*, 57(2):18, 2024.

Yin, W., Hay, J., and Roth, D. Benchmarking Zero-Shot Text Classification: Datasets, Evaluation and Entailment Approach. In *2019 Conference on Empirical Methods in Natural Language Processing and 9th International Joint Conference on Natural Language Processing, EMNLP-IJCNLP 2019*, pages 3914–3923. Association for Computational Linguistics, 2019.

Appendix

The Appendix is organized as follows. Section A provides additional details on our textual analysis, including the topic-agnostic classification approach and the prompt engineering framework used for sentiment analysis. Section B presents additional stylized facts on GenAI exposure and sentiment distributions across sectors. Finally, Section C, reports supplementary empirical results and robustness checks.

A Transcripts Analysis

A.1 Topic(-agnostic) modeling

Our zero-shot classification approach enables flexible exposure measurement of topic exposure across any textual data source. Figure 11 illustrates exposure to major topics among US companies from 2014 to 2024. The methodology successfully identifies key historical inflection points, including Brexit, the COVID-19 pandemic, rising inflation, and the recent surge in interest around GenAI. While our analysis in this paper focuses on GenAI, the underlying analytical framework is general and can be applied to a wide range of themes such as climate change, geopolitical risk, or supply chain disruptions.

A.2 Sentiment Analysis via Prompt Engineering

To classify sentiment in GenAI-related earnings call discussions, we employed a structured prompt engineering approach with a large language model (GPT-4o), optimized for consistent classification. Our method utilized explicit categorical definitions to distinguish between three key sentiment dimensions: "ADOPTION," "RISK," and "OPPORTUNITY." Figure 12 presents the full prompt used for classification.

B Stylised Facts

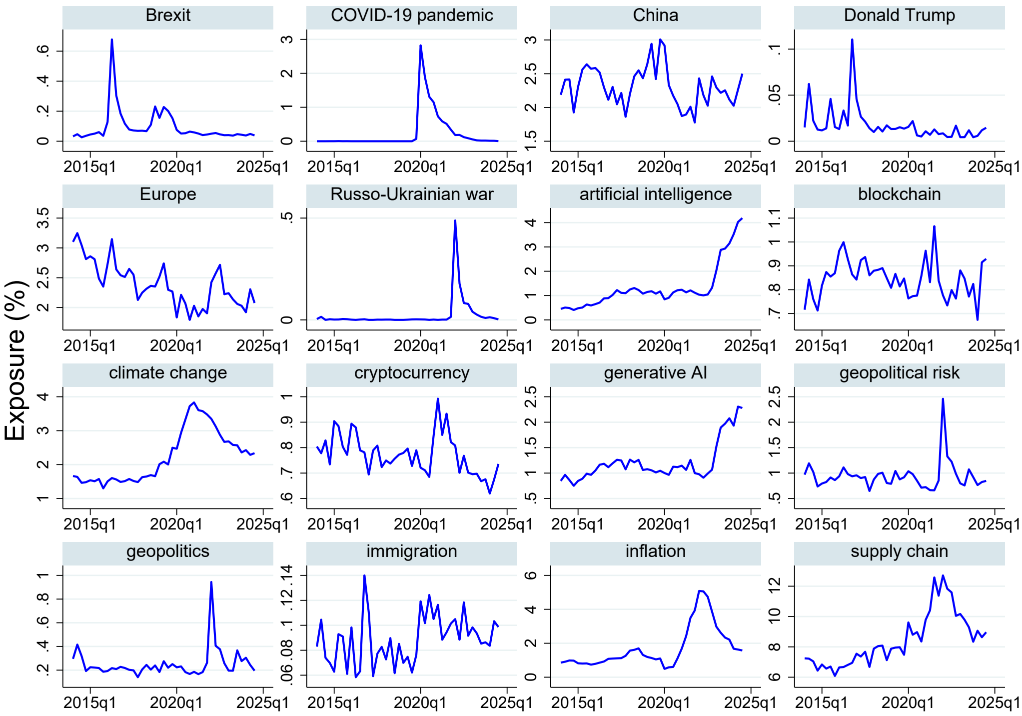
In this section, we provide additional stylised facts on our GenAI exposure measures, which quantify the emphasis placed on GenAI in firms' quarterly earnings calls.

Table 11 compares firms classified as *Early Exposed* (top 25% of GenAI exposure between 2017Q4 and 2022Q3) with *Laggards* (the remaining firms). Early Exposed firms exhibit significantly higher stock price growth, earnings expectations, and notably different balance sheet ratios.

Table 12 presents a detailed breakdown of GenAI exposure across sectors. The data spans the full sample period (2014Q1-2024Q4) as well as the pre-ChatGPT (2021Q4-2022Q3), and Post-ChatGPT (2023Q1-2023Q4) sub-periods. These table confirm a sharp increase in GenAI exposure following ChatGPT's release, particularly in the Information Technology sector.

Table 13 shows the correlation between different GenAI sentiment dimensions (exposure, opportunity, adoption, and risk) before and after ChatGPT's release. Correlations are significantly stronger in the Post-ChatGPT period, especially between overall exposure and opportunity sentiment (0.93), suggesting that firms increasingly framed their GenAI discussions in terms of opportunities rather than risks.

Figure 11: Exposure Analysis Across Major Topics (2014-2024)



Note: Our topic exposure measures effectively capture firms' responses to major global events. The analysis reveals distinct patterns corresponding to the Brexit referendum, the onset of the COVID-19 pandemic (late 2019), inflation surge (early 2021), and the sharp increase in "artificial intelligence" and "generative AI" mentions following ChatGPT's release.

Figure 13 provides a direct comparison of GenAI exposure before and after ChatGPT's release. Figure 13 shows that Information Technology and Communication Services experienced the largest percentage increases.

Figure 12: Prompt used for GenAI-sentiment classification

```
You are an expert financial analyst specializing in technology and corporate and firm's strategy related
to innovation.  Your task is to analyze AI-related snippets from U.S. corporate earnings call transcripts
related to Generative AI and classify them into one of the following three categories:

1.  ''ADOPTION'' - Statements describing specific Generative AI systems or tools or applications that
are currently being used or deployed or any completed integration of AI into products, services, or
operations.  These statements focus on what the company is actually doing with AI right now or has
recently accomplished about incorporating AI into their workflows.

2.  ''RISK'' - Statements highlighting challenges, potential downsides, concerns, or negative impacts
related to Generative AI. These include implementation difficulties, competitive threats, cost overruns,
performance issues, ethical concerns, regulatory hurdles, workforce disruptions associated with AI or
AI-related risk to harm firm's reputation and market acceptance.

3.  ''OPPORTUNITY'' - Statements expressing optimistic outlooks about future applications and potential
benefits of Generative AI, or anticipated positive impacts that have not yet been fully realized.  Rather
than focusing on current adoption, these statements explore the transformative potential and innovative
uses of Generative AI that could create new value.

Guidelines:
1.  Focus on the AI-related message and intent of the statement within its earnings call context.
2.  Pay special attention to timeframes - present/past tense typically indicates adoption, while future
tense often signals opportunity.
3.  Look for emotional tone - cautionary language suggests risk, while enthusiastic language often
indicates opportunity.

Examples:
- Statement:  ''We've deployed our AI-powered pricing algorithm across all retail channels, which is now
handling over 70% of our dynamic pricing decisions.''
Classification:  ADOPTION (Describes specific AI technology already implemented)

- Statement:  ''While AI offers potential, we're finding the integration costs higher than anticipated,
and retraining our workforce has been more challenging than expected.''
Classification:  RISK (Highlights negative aspects and implementation difficulties)

- Statement:  ''We believe AI will transform our customer service capabilities next year, potentially
reducing wait times while increasing resolution rates.''
Classification:  OPPORTUNITY (Describes future benefits not yet realized)

Output only the category label for each transcript snippet.
```

C Empirical Analysis

In this section, we report additional analyses and robustness checks to validate our findings. We first present core financial response analyses examining quarterly performance metrics (Table 14), followed by forward-looking valuation measures including expected P/E ratios through both difference-in-differences and regression frameworks (Tables 15 and 16). We then analyze year-over-year stock price responses using complementary regression and DiD approaches (Tables 17 and 18). To examine sectoral heterogeneity, we provide sector-specific analyses focusing on the Information Technology sector (Table 19). Our robustness analyses include specifications excluding Magnificent 7 companies across multiple outcome variables (Tables 20, 21, 22, and 23), models incorporating additional control variables (Tables 24, 25, and 26), firm fixed effects specifications (Table 27), and alternative exposure classifications using median splits (Table 28). Finally, we present comprehensive sector-level coefficient estimates with confidence intervals (Figure 14).

Table 11: Differences in Firms by GenAI Exposure

	Laggards		Early Exposed		T-Test
Main					
Stock Price	3.2195	2.8785	4.6309	3.6766	-1.4114***
Price YoY	12.9623	8.2636	20.2105	12.3595	-7.2482***
Expected EPS	2.5993	2.4854	3.4149	3.0590	-0.8157***
Balance-Sheet Ratios					
Return on Assets	0.0168	0.0134	0.0180	0.0158	-0.0012**
Debt to Equity	2.8078	1.7806	3.3032	1.3836	-0.4954
Asset Tangibility	0.2670	0.1708	0.1693	0.1017	0.0977***
Sales over Assets	0.1845	0.1360	0.1533	0.1363	0.0312***
Firm Investment Ratio	0.0214	0.0123	0.0201	0.0123	0.0012**
Log(Assets)	10.0909	9.9768	9.6426	9.6860	0.4483***
Exposure Measure					
GenAI Exposure	0.8691	0.6356	1.9642	1.4749	-1.0950***

Note: This table compares firms with *Early Exposed* versus *Laggards*. The split is determined by the average GenAI Exposure per firm over the five-year period preceding ChatGPT's release, up to 2017Q4. *Laggards* (*Early Exposed*) are those below (above) the 75th percentile of exposure. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Sector Distribution of GenAI Exposure

Panel A: Full sample

	Mean	Std. Dev.	Median	75%	Max	N
Communication Services	1.353	2.562	0.748	1.527	21.635	789
Consumer Discretionary	1.091	1.752	0.717	1.480	29.870	2,037
Consumer Staples	0.751	0.897	0.544	1.119	6.526	1,466
Energy	0.931	0.945	0.721	1.377	6.583	845
Financials	0.982	1.312	0.708	1.406	21.273	2,949
Health Care	1.492	1.427	1.153	2.149	10.056	2,511
Industrials	1.094	1.275	0.789	1.497	12.791	3,013
Information Technology	2.221	3.419	1.290	2.614	38.215	2,845
Materials	0.911	1.003	0.648	1.361	7.061	1,101
Real Estate	0.782	0.867	0.589	1.226	6.867	1,302
Utilities	1.060	1.145	0.816	1.592	7.859	1,215
Total	1.233	1.860	0.809	1.624	38.215	20,073

Panel B: Pre-ChatGPT

	Mean	Std. Dev.	Median	75%	Max	N
Communication Services	0.988	1.191	0.681	1.527	4.752	76
Consumer Discretionary	0.880	0.948	0.565	1.411	5.187	194
Consumer Staples	0.767	0.830	0.627	1.075	4.110	134
Energy	0.772	0.727	0.690	1.285	2.885	79
Financials	0.794	0.855	0.637	1.255	5.587	278
Health Care	1.293	1.177	0.955	1.961	6.273	235
Industrials	1.016	1.060	0.770	1.527	5.896	288
Information Technology	1.359	1.400	0.989	1.951	9.630	272
Materials	0.934	0.905	0.739	1.436	6.122	107
Real Estate	0.912	1.016	0.617	1.318	6.226	124
Utilities	1.144	1.254	0.815	1.757	7.859	116
Total	1.020	1.093	0.768	1.524	9.630	1,903

Panel C: Post-ChatGPT

	Mean	Std. Dev.	Median	75%	Max	N
Communication Services	3.091	5.050	1.395	2.711	21.635	76
Consumer Discretionary	1.726	3.039	0.917	1.894	29.870	193
Consumer Staples	0.839	1.097	0.577	1.075	6.526	134
Energy	0.988	1.082	0.741	1.479	6.432	79
Financials	1.406	2.116	0.791	1.739	17.989	283
Health Care	1.462	1.316	1.205	2.193	6.132	240
Industrials	1.310	1.751	0.872	1.508	12.127	293
Information Technology	4.932	6.469	2.494	6.157	38.215	271
Materials	0.733	0.929	0.433	1.077	5.283	108
Real Estate	0.861	0.893	0.680	1.376	5.328	122
Utilities	1.367	1.347	1.064	2.208	6.840	120
Total	1.863	3.353	0.973	1.990	38.215	1,919

Note: Full sample (2014Q1-2024Q4). Pre-ChatGPT (2021Q4-2022Q3). Post-ChatGPT (2023Q1-2023Q4).

Table 13: GenAI Measure Correlations Before/After ChatGPT

(a) Pre-ChatGPT Period

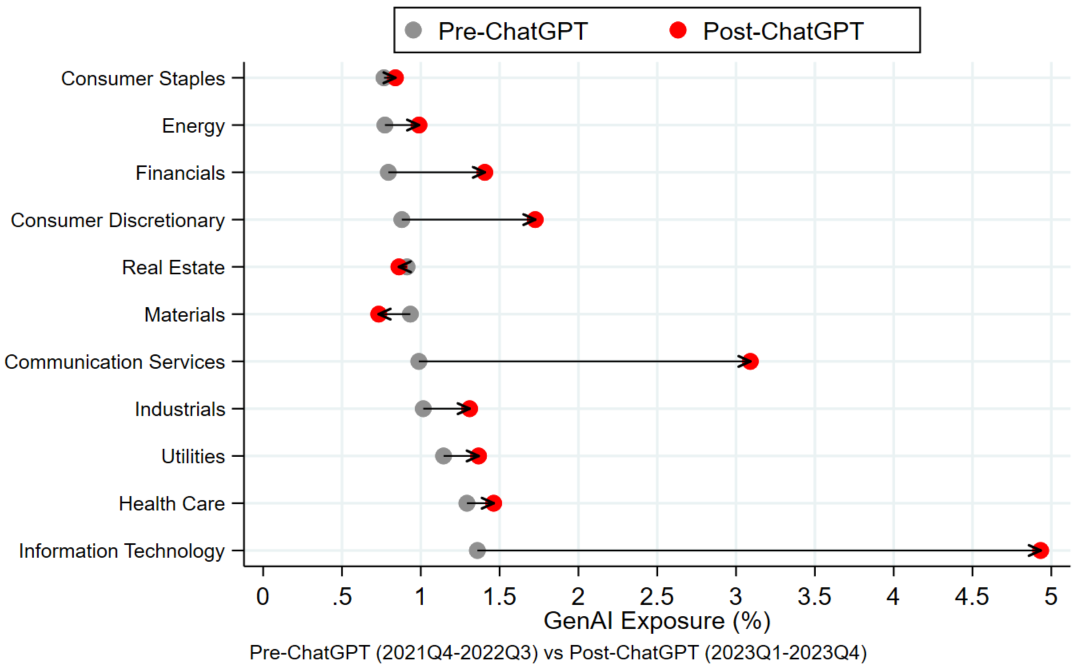
	Exposure	Opport.	Adopt.	Risk
Exposure	1.0000			
Opportunity	0.7636	1.0000		
Adoption	0.5990	0.1603	1.0000	
Risk	0.4256	0.1133	0.0658	1.0000

(b) Post-ChatGPT Period

	Exposure	Opport.	Adopt.	Risk
Exposure	1.0000	1.0000		
Opportunity	0.9335	1.0000	1.0000	
Adoption	0.8038	0.5982	1.0000	1.0000
Risk	0.5097	0.3606	0.2830	1.0000

Note: Correlation coefficients between GenAI exposure measures. Pre-ChatGPT (Panel A) correlations are moderate, while Post-ChatGPT (Panel B) shows substantially stronger correlations, particularly between overall exposure and opportunity (0.93), suggesting more comprehensive GenAI discussions after ChatGPT's release.

Figure 13: Change in GenAI Exposure Pre/Post ChatGPT Across Sectors



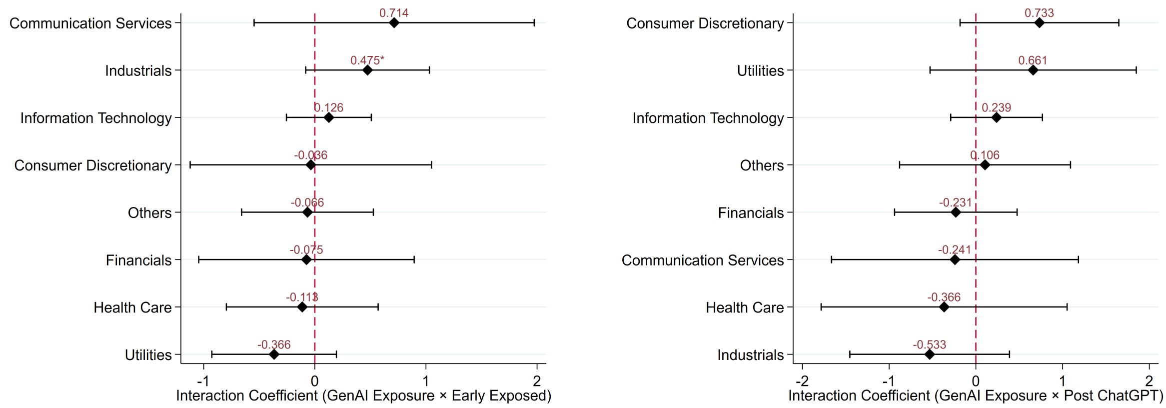
Note: This figure compares the average GenAI exposure across sectors before ChatGPT (2021Q4-2022Q3) and after ChatGPT (2023Q1-2023Q4), showing the most dramatic increases in Information Technology and Communication Services sectors.

Table 14: GenAI Exposure Effects on QoQ Financial Performance

	(1) Stock Price	(2) Expected EPS	(3) Expected P/E
GenAI Exposure	0.620**	0.227***	0.465***
	(2.886)	(3.480)	(3.752)
EPS 12M forw. QoQ	0.033		-0.662***
	(0.669)		(-7.934)
Return on Assets	14.824	55.418**	22.686**
	(0.893)	(3.033)	(2.600)
Log(Assets)	-0.630**	-0.235	-0.351**
	(-2.822)	(-1.087)	(-2.875)
GDP Growth Forecast	2.440	1.927***	0.167
	(1.016)	(3.491)	(0.158)
10Y Interest Rates	0.442	1.757*	-1.237
	(0.141)	(2.105)	(-0.885)
Sector FE	Yes	Yes	Yes
Time FE	No	No	No
Sector-Time FE	No	No	No
R^2	0.033	0.037	0.180
N	17,180	17,210	16,872

Note: Regression results examining the effect of GenAI exposure on quarterly financial performance. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 14: Sector-Level Stock Price Response to GenAI Exposure: Regression Analysis



Panel A: Early Exposed Effect **Panel B:** Post ChatGPT Effect

Note: Sector-level coefficient estimates with 95% confidence intervals. Panel A shows early exposed firm effects (GenAI Exposure × Early Exposed), Panel B shows post-ChatGPT effects (GenAI Exposure × Post ChatGPT). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15: DiD Analysis: Expected P/E Response to GenAI Exposure

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	-0.408	0.672	0.788	0.875
	(-0.469)	(0.902)	(1.016)	(1.134)
Early Exposed	-0.121	0.171		
	(-0.493)	(0.773)		
Post-ChatGPT	0.977**	3.517***	3.643***	
	(2.458)	(7.719)	(7.638)	
EPS 12M forw. QoQ		-0.653***	-0.674***	-0.668***
		(-35.361)	(-35.278)	(-34.669)
Return on Assets		23.691***	27.306***	18.243**
		(4.148)	(3.517)	(2.517)
Log(Assets)		-0.415***	-0.876***	-1.112***
		(-6.501)	(-2.903)	(-2.854)
GDP Growth Forecast		0.212	0.238	
		(1.350)	(1.479)	
10Y Interest Rates		-1.942***	-1.959***	
		(-9.884)	(-9.845)	
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.000	0.180	0.195	0.333
N	17,014	16,867	16,867	16,867

Note: DiD results examining the effect of GenAI exposure on forward P/E ratios. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16: Regression Analysis: Expected P/E Response to GenAI Exposure

	(1)	(2)	(3)
GenAI Exposure	0.465***	0.330**	0.132
	(3.752)	(2.474)	(1.133)
GenAI Exposure × Early Exposed		0.064	0.097
		(0.670)	(1.029)
GenAI Exposure × Post-ChatGPT			0.187*
			(2.032)
EPS 12M forw. QoQ	-0.662***	-0.651***	-0.658***
	(-7.934)	(-11.342)	(-10.867)
Return on Assets	22.686**	16.315***	11.897*
	(2.600)	(3.219)	(2.156)
Log(Assets)	-0.351**	-0.388***	-0.421***
	(-2.875)	(-3.727)	(-4.059)
GDP Growth Forecast	0.167		
	(0.158)		
10Y Interest Rates	-1.237		
	(-0.885)		
Sector FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
Sector-Time FE	No	No	Yes
R^2	0.180	0.321	0.387
N	16,872	16,867	16,864

Note: Regression results examining the effect of GenAI exposure on forward P/E ratios. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17: Regression Analysis: Stock Price YoY Response to GenAI Exposure

	(1)	(2)	(3)
GenAI Exposure	2.094***	0.266	0.036
	(3.908)	(0.752)	(0.091)
GenAI Exposure × Early Exposed		2.103***	2.078***
		(4.413)	(4.914)
GenAI Exposure × Post-ChatGPT			0.019
			(0.029)
EPS 12M forw. QoQ	0.923***	0.846***	0.761***
	(5.978)	(6.422)	(4.757)
Return on Assets	101.659**	83.371*	65.085
	(2.338)	(1.860)	(1.657)
Log(Assets)	-2.303***	-2.681***	-2.784***
	(-3.651)	(-4.576)	(-4.859)
GDP Growth Forecast	10.541**		
	(2.627)		
10Y Interest Rates	3.232		
	(0.841)		
Sector FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
Sector-Time FE	No	No	Yes
R^2	0.160	0.257	0.331
N	15,775	15,775	15,773

Note: Regression results examining the effect of GenAI exposure on year-over-year stock price changes. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 18: DiD Analysis: Stock Price YoY Response to GenAI Exposure

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	4.022	3.133	2.407	2.483
	(0.941)	(0.846)	(0.624)	(0.641)
Early Exposed	6.780***	4.217***		
	(3.018)	(2.700)		
Post-ChatGPT	-6.436***	13.551***	10.908***	
	(-5.206)	(8.475)	(6.275)	
EPS 12M forw. QoQ		0.963***	0.838***	0.740***
		(15.938)	(15.782)	(14.122)
Return on Assets		108.901***	177.245***	157.720***
		(3.900)	(5.322)	(4.782)
Log(Assets)		-2.447***	3.003	3.706
		(-6.737)	(1.216)	(1.126)
GDP Growth Forecast		10.553***	10.711***	
		(15.297)	(15.313)	
10Y Interest Rates		0.385	0.647	
		(0.529)	(0.893)	
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.007	0.158	0.252	0.342
N	16,147	15,775	15,775	15,775

Note: DiD results examining the effect of GenAI exposure on year-over-year stock price changes. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19: DiD Analysis: Stock Price Response to GenAI Exposure (Information Technology Sector)

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	2.833	4.045*	4.397**	4.130*
	(1.281)	(1.927)	(2.044)	(1.987)
Early Exposed	1.509*	0.743		
	(1.684)	(1.128)		
Post-ChatGPT	3.318***	11.072***	11.092***	
	(2.756)	(6.848)	(6.579)	
EPS 12M forw. QoQ		0.266***	0.212***	0.200***
		(5.036)	(3.566)	(3.407)
Return on Assets		16.364	17.087	18.617
		(1.128)	(1.041)	(1.305)
Log(Assets)		-0.932***	-1.708**	-1.679
		(-2.939)	(-2.175)	(-1.579)
GDP Growth Forecast		2.232***	2.279***	
		(5.106)	(5.046)	
10Y Interest Rates		-2.117***	-2.104***	
		(-3.391)	(-3.313)	
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.010	0.082	0.110	0.327
N	2,507	2,453	2,453	2,453

Note: DiD results examining the effect of GenAI exposure on quarterly stock price changes within the Information Technology sector. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20: Regression Analysis: Financial Metrics QoQ Response to GenAI Exposure (Excluding Magnificent 7)

	(1) Stock Price	(2) Expected EPS	(3) Expected P/E
GenAI Exposure	0.507**	0.154**	0.400***
	(2.376)	(2.538)	(3.197)
EPS 12M forw. QoQ	0.034		-0.665***
	(0.706)		(-7.907)
Return on Assets	12.796	54.204**	22.220**
	(0.743)	(2.883)	(2.632)
Log(Assets)	-0.696**	-0.265	-0.399**
	(-2.697)	(-1.207)	(-2.750)
GDP Growth Forecast	2.488	1.924***	0.207
	(1.031)	(3.469)	(0.194)
10Y Interest Rates	0.549	1.787*	-1.171
	(0.174)	(2.155)	(-0.847)
Sector FE	Yes	Yes	Yes
Time FE	No	No	No
Sector-Time FE	No	No	No
R^2	0.031	0.035	0.180
N	16,923	16,953	16,623

Note: Regression results examining the effect of GenAI exposure on quarterly financial performance excluding Magnificent 7 companies. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 21: Regression Analysis: Expected EPS Response to GenAI Exposure (Excluding Magnificent 7)

	(1)	(2)	(3)
GenAI Exposure	0.154**	0.038	-0.064
	(2.538)	(0.576)	(-0.803)
GenAI Exposure × Early Exposed		0.135	0.147
		(1.411)	(1.539)
GenAI Exposure × Post-ChatGPT			0.268**
			(2.340)
Return on Assets	54.204**	48.179**	39.387***
	(2.883)	(2.852)	(3.531)
Log(Assets)	-0.265	-0.347	-0.363*
	(-1.207)	(-1.699)	(-1.876)
GDP Growth Forecast	1.924***		
	(3.469)		
10Y Interest Rates	1.787*		
	(2.155)		
Sector FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
Sector-Time FE	No	No	Yes
R^2	0.035	0.092	0.183
N	16,953	16,948	16,946

Note: Regression results examining the effect of GenAI exposure on 12-month forward EPS excluding Magnificent 7 companies. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 22: DiD Analysis: Stock Price Response to GenAI Exposure (Excluding Magnificent 7)

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	1.638*	1.886**	1.938**	1.958**
	(1.791)	(2.106)	(2.144)	(2.177)
Early Exposed	1.035***	0.534*		
	(2.850)	(1.844)		
Post-ChatGPT	-0.451	5.616***	5.280***	
	(-1.350)	(12.040)	(10.517)	
EPS 12M forw. QoQ		0.045***	0.012	0.028*
		(2.733)	(0.691)	(1.690)
Return on Assets		12.016*	25.423***	24.385***
		(1.804)	(2.878)	(3.409)
Log(Assets)		-0.764***	-0.532	-0.981*
		(-7.890)	(-1.265)	(-1.751)
GDP Growth Forecast		2.543***	2.626***	
		(15.806)	(15.720)	
10Y Interest Rates		-0.694***	-0.601***	
		(-3.377)	(-2.874)	
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.001	0.036	0.062	0.288
N	17,325	16,918	16,918	16,918

Note: DiD results examining the effect of GenAI exposure on quarterly stock price changes excluding Magnificent 7 companies. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 23: DiD Analysis: Expected EPS Response to GenAI Exposure (Excluding Magnificent 7)

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	1.529*	1.515**	1.202	1.458*
	(1.952)	(1.976)	(1.557)	(1.901)
Early Exposed	0.512*	0.359		
	(1.806)	(1.314)		
Post-ChatGPT	-2.182***	-4.011***	-4.433***	
	(-6.986)	(-9.441)	(-9.810)	
Return on Assets		51.440***	71.158***	66.044***
		(7.003)	(7.790)	(7.091)
Log(Assets)		-0.201**	0.649*	-0.853
		(-2.422)	(1.715)	(-1.638)
GDP Growth Forecast		1.895***	1.929***	
		(13.577)	(14.008)	
10Y Interest Rates		2.795***	2.822***	
		(14.899)	(15.144)	
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.005	0.047	0.106	0.151
N	16,955	16,950	16,950	16,950

Note: DiD results examining the effect of GenAI exposure on 12-month forward EPS excluding Magnificent 7 companies. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 24: Regression Analysis: Expected EPS Response to GenAI Exposure (with Additional Controls)

	(1)	(2)	(3)
GenAI Exposure	0.233***	0.193*	0.009
	(4.702)	(1.937)	(0.076)
GenAI Exposure × Early Exposed		0.099	0.129
		(0.802)	(1.067)
GenAI Exposure × Post-ChatGPT			0.354***
			(7.528)
Return on Assets	55.191***	50.771***	41.653***
	(3.611)	(3.708)	(4.775)
Log(Assets)	-0.245	-0.489**	-0.515**
	(-0.836)	(-2.384)	(-2.665)
GDP Growth Forecast	1.976***		
	(4.178)		
10Y Interest Rates	1.792**		
	(2.499)		
Log(Capital Expenditure)	-0.075	0.097	0.114
	(-0.304)	(0.540)	(0.611)
Long-Term Debt Ratio	-0.651	-0.719	-0.726
	(-1.273)	(-1.307)	(-1.388)
Short-Term Debt Ratio	3.896***	3.999***	3.625***
	(5.044)	(5.985)	(5.747)
Sector FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
Sector-Time FE	No	No	Yes
R^2	0.049	0.098	0.194
N	13,240	13,237	13,198

Note: Regression results examining the effect of GenAI exposure on 12-month forward EPS with additional control variables. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 25: DiD Analysis: Stock Price Response to GenAI Exposure (with Additional Controls)

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	2.171**	2.634***	2.639***	2.532**
	(2.329)	(2.673)	(2.644)	(2.564)
Early Exposed	1.175***	0.645**		
	(3.197)	(2.019)		
Post-ChatGPT	-0.405	6.245***	6.025***	
	(-1.214)	(10.903)	(9.840)	
EPS 12M forw. QoQ		0.047**	0.013	0.031
		(2.411)	(0.623)	(1.557)
Return on Assets		14.057*	24.523***	26.516***
		(1.940)	(2.676)	(3.566)
Log(Assets)		-0.696***	-0.744	0.061
		(-4.152)	(-1.523)	(0.090)
GDP Growth Forecast		2.204***	2.304***	
		(11.761)	(11.804)	
10Y Interest Rates		-1.316***	-1.135***	
		(-5.252)	(-4.463)	
Log(Capital Expenditure)		-0.182	-0.371*	-1.758***
		(-1.408)	(-1.698)	(-6.594)
Long-Term Debt Ratio		-0.813**	2.279*	0.262
		(-2.217)	(1.782)	(0.208)
Short-Term Debt Ratio		0.082	-3.747	0.931
		(0.091)	(-1.166)	(0.305)
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.002	0.037	0.064	0.284
N	17,594	13,208	13,208	13,208

Note: DiD results examining the effect of GenAI exposure on quarterly stock price changes with additional control variables. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 26: DiD Analysis: Expected EPS Response to GenAI Exposure (with Additional Controls)

	(1)	(2)	(3)	(4)
Early Exposed × Post-ChatGPT	1.624**	1.705**	1.313	1.523*
	(2.067)	(2.059)	(1.578)	(1.831)
Early Exposed	0.641**	0.546*		
	(2.262)	(1.887)		
Post-ChatGPT	-2.165***	-3.870***	-4.542***	
	(-6.958)	(-7.496)	(-8.186)	
Return on Assets		54.162***	73.913***	68.733***
		(7.014)	(7.843)	(7.193)
Log(Assets)		-0.150	1.444***	-0.037
		(-0.984)	(3.238)	(-0.060)
GDP Growth Forecast		1.963***	2.051***	
		(11.774)	(12.377)	
10Y Interest Rates		2.600***	2.733***	
		(11.746)	(12.420)	
Log(Capital Expenditure)		-0.078	-0.641***	-0.481**
		(-0.720)	(-4.417)	(-2.557)
Long-Term Debt Ratio		-0.654	1.808	0.490
		(-1.388)	(1.372)	(0.350)
Short-Term Debt Ratio		3.125***	12.194***	9.250***
		(3.234)	(4.727)	(3.759)
Time FE	No	No	No	Yes
Firm FE	No	No	Yes	Yes
R^2	0.005	0.050	0.115	0.152
N	17,213	13,237	13,237	13,237

Note: DiD results examining the effect of GenAI exposure on 12-month forward EPS with additional control variables. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 27: Regression Analysis: Stock Price Response to GenAI Exposure (with Firm Fixed Effects)

	(1)	(2)	(3)
GenAI Exposure	0.541**	0.327**	0.072
	(2.550)	(2.245)	(0.909)
GenAI Exposure × Early Exposed		0.229***	0.170***
		(11.039)	(3.400)
GenAI Exposure × Post-ChatGPT			0.387**
			(3.112)
EPS 12M forw. QoQ	0.003	0.028	0.030
	(0.067)	(0.725)	(0.843)
Return on Assets	25.913	24.000*	18.252
	(1.342)	(2.020)	(1.798)
Log(Assets)	0.510	-0.959	-0.705
	(0.287)	(-1.036)	(-0.891)
GDP Growth Forecast	2.554		
	(1.068)		
10Y Interest Rates	0.449		
	(0.143)		
Firm FE	Yes	Yes	Yes
Time FE	No	Yes	Yes
Sector-Time FE	No	No	Yes
R^2	0.059	0.287	0.374
N	17,179	17,175	17,173

Note: Regression results examining the effect of GenAI exposure on quarterly stock price changes with firm fixed effects. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 28: DiD Results for GenAI Effects (with Median Split)

	Stock Price (1)	Stock Price (2)	Stock Price (3)	Stock Price (4)	Expected EPS (1)	Expected EPS (2)	Expected EPS (3)	Expected EPS (4)
Early Exposed	0.95	1.13*	1.18*	1.25*	0.25	0.22	0.04	0.22
× Post-ChatGPT	(1.42)	(1.75)	(1.80)	(1.91)	(0.42)	(0.37)	(0.07)	(0.37)
Early Exposed	0.76***	0.31			0.31	0.15		
	(2.86)	(1.37)			(1.47)	(0.73)		
Post-ChatGPT	-0.33	5.91***	5.58***		-1.87***	-3.64***	-4.10***	
	(-0.83)	(11.67)	(10.15)		(-4.93)	(-8.40)	(-8.84)	
EPS 12M forw. QoQ		0.05***	0.01	0.03*				
		(2.85)	(0.70)	(1.71)				
Return on Assets		16.10**	25.96***	24.79***		54.10***	72.02***	66.96***
		(2.34)	(2.99)	(3.53)		(7.46)	(8.03)	(7.34)
Log(Assets)		-0.71***	-0.56	-0.90*		-0.18**	0.73**	-0.72
		(-7.30)	(-1.37)	(-1.67)		(-2.17)	(1.97)	(-1.42)
GDP Growth		2.50***	2.58***			1.92***	1.96***	
Forecast		(15.48)	(15.38)			(13.46)	(13.83)	
10Y Interest Rates		-0.84***	-0.75***			2.78***	2.81***	
		(-3.90)	(-3.42)			(14.65)	(14.89)	
Time FE	No	No	No	Yes	No	No	No	Yes
Firm FE	No	No	Yes	Yes	No	No	Yes	Yes
R^2	0.001	0.036	0.064	0.286	0.003	0.046	0.107	0.151
N	17,594	17,175	17,175	17,175	17,213	17,208	17,208	17,208

Note: DiD results examining the effect of GenAI exposure on stock prices and forward EPS using median split classification. T-statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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