AI Infrastructure, Firm Value and Expected Stock Returns*

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Abstract

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JEL classification: G12, G14, O33.
Keywords: AI Infrastructure, Large Language Models (LLMs), Empirical Asset Pricing, Mispricing, Productivity J-Curve, Intangible Investment

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Abstract

This paper examines how AI infrastructure affects asset prices. Using large language models (LLMs) to analyze earnings call transcripts from S&P 500 firms, we construct novel firm-level AI infrastructure measures. Firms with higher AI infrastructure earn quarterly alphas of 0.4% to 0.9% relative to those with lower levels, controlling for risk factors and anomalies. These firms are typically larger, with higher Tobin's Q, more R&D, and lower leverage. The results suggest markets undervalue AI infrastructure, as the expensing of intangible investments suppresses short-term earnings—consistent with the productivity J-curve (Brynjolfsson et al. (2021)).

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1 Introduction

AI infrastructure refers to the integrated ecosystem of hardware, software, and technological resources that enable organizations to develop, deploy, and maintain AI-powered systems. It includes both tangible assets, such as servers, specialized AI chips (e.g., GPUs and TPUs), data centers, and networking equipment, and intangible assets, such as proprietary AI models, training datasets, algorithms, MLOps (Machine Learning Operations) platforms, cloud-based AI services, and intellectual property. While recent research has explored the labor market and productivity effects of AI adoption (e.g., Eisfeldt et al. (2024); Babina et al. (2024)), the financial market implications of AI infrastructure remain relatively unexplored. This paper addresses that gap by investigating how AI infrastructure relates to asset prices and firm fundamentals. We develop a novel, scalable methodology to measure firm-level AI infrastructure using large language models (LLMs) applied to earnings call transcripts. This generative AI-based approach yields interpretable, firm-level insights into AI-related investments. We find that firms with more extensive AI infrastructure earn significantly higher future stock returns and exhibit greater resilience during downturns, suggesting that markets may underprice AI infrastructure. Our results show that AI infrastructure is concentrated among large, high-growth firms with higher Tobin's Q and strong R&D intensity, underscoring its role in supporting innovation, competitiveness, and long-run firm performance.

We contribute to the literature by introducing a structured LLM framework to assess corporate AI investments. We leverage prompt-engineered queries (GPT-3.5/GPT-4) to extract insights from unstructured earnings calls. First, we develop a prompt engineering framework that instructs LLMs to act as domain-specific analysts. Our prompts guide the model to locate references to AI infrastructure, assess their relevance within a firm's broader business strategy, and benchmark these initiatives against industry norms. Second, we implement a Chain of Thought (CoT) reasoning approach that encourages the model to break down its reasoning into logical steps, enhancing interpretability and minimizing spurious noise in its assessments. Third, we utilize zero-shot learning to allow the model to perform these tasks without labeled training data, instead relying on structured prompt templates and internal reasoning to produce firm-level classifications. This enables scalable, repeatable analysis across thousands of firm-quarters.

To demonstrate the value of our methodology, we apply it to S&P 500 firms' earnings calls from 2006 to 2024, accessed via the API Ninjas Earnings Call Transcript API. These transcripts capture executive discussions on strategy, operations, and technology, providing rich context for identifying AI infrastructure investments over time. We link this data to firm fundamentals from COMPUSTAT and stock returns from CRSP to explore how AI infrastructure shapes firm performance and investor outcomes. To ensure comparability and interpretability, we exclude firms in financial, insurance, and real estate sectors, where AI applications tend to be software-driven and sector-specific, often deviating from the physical and computational infrastructure focus of our study.

Our LLM-based framework assigns a binary AI infrastructure classification to each firm-quarter observation, where 1 denotes firms with high AI infrastructure levels and 0 indicates firms with low AI infrastructure levels. To deepen the analysis, we also decompose AI infrastructure into four foundational components: Computing Hardware and Software Ecosystem ($CHSE$), Power and Energy Resources (PER), Data Storage and Management Systems ($DSMS$), and Technical Standards and Specifications (TSS). $CHSE$ refers to the high-performance processors; distributed and edge computing resources; cloud infrastructure; and specialized software tools that enable firms to develop, deploy, and manage AI systems efficiently across operations. PER encompasses energy-efficient architectures; advanced cooling systems; renewable energy integration; and backup solutions, all of which contribute to the sustainability, reliability, and performance of firms' AI infrastructure. $DSMS$ includes secure and scalable storage solutions; data pipelines; caching mechanisms; version control tools; and distributed storage systems, all of which support the effective management of large datasets and ensure low-latency access across industries. TSS covers standardization efforts such as model interchange formats; data structures; API specifications; performance benchmarks; security and privacy protocols; and hardware compatibility metrics, which collectively facilitate efficient, secure, and sustainable AI adoption.

Descriptive patterns indicate that 9.2% of S&P 500 firms qualified as high-AI-infrastructure investors during our sample period, with the rates doubling to 19.1% during the 2022-2024 generative AI boom. Notably, investments were most concentrated in Computing Hardware and Software Ecosystem ($CHSE$) and Power and Energy Resources (PER)–the foundational enablers of advanced AI deployment–reflecting industry prioritization of these capability domains. Firms with higher AI infrastructure scores tend to be larger, more growth-oriented, and hold higher market valuations. These firms also invest more heavily in R&D, rely more on intangible capital, and interestingly, employ more labor–suggesting that AI infrastructure may complement, rather than substitute for, skilled human capital. Case studies of top-scoring firms such as Apple, Microsoft, and NVIDIA reveal concentrated strengths in foundational infrastructure, while low-scoring firms are primarily in traditional, capital-intensive industries with limited AI integration.

We empirically examine whether AI infrastructure is associated with superior stock performance. Using portfolio sorts based on binary classifications derived from ChatGPT, we find that firms with high AI infrastructure consistently outperform their low AI peers. The high-minus-low return spread ranges from 0.435% to 0.930% per quarter and remains significant across CAPM, Carhart, and Fama-French 5-factor models. These results hold even when excluding technology firms, indicating that AI infrastructure provides a generalizable advantage beyond the tech sector. Furthermore, return differentials widen during periods of economic weakness–measured by the Chicago Fed National Activity Index ($CFNAI$), Gross Domestic Product (GDP), the Industrial Production Index ($INDPRO$), and the S&P 500 Index ($S\&P$ 500)–indicating that the mispricing of AI infrastructure intensifies during downturns, when its long-term value is increasingly overlooked by the market. This return premium persists across various model specifications, suggesting that AI infrastructure is a priced firm characteristic not fully captured by traditional asset pricing frameworks. These findings imply that markets may systematically underprice AI infrastructure, potentially overlooking its strategic importance for future firm performance. Specifically, AI infrastructure's intangible investment costs are expensed, suppressing short-term earnings (consistent with the productivity J-curve). This mispricing contributes to persistent alpha, supporting intangible investment models.

Further analysis using Fama-MacBeth regressions shows that AI infrastructure is a strong and robust predictor of next-quarter stock returns. This relationship holds across the full sample (2006-2024) and is particularly pronounced during the recent Generative AI boom (2022-2024). During the full sample period, the regression results show that firms with higher AI infrastructure earn 30-40 basis points higher returns in the following quarter, even after controlling for standard risk factors and anomalies. In the Generative AI boom period, firms with higher AI infrastructure earn 40-110 basis points higher returns, with this premium persisting across different model specifications. This further suggests that AI infrastructure is a priced firm characteristic not fully captured by traditional asset pricing frameworks. These findings imply that markets may systematically underprice AI infrastructure, potentially overlooking its strategic importance for future firm performance. During the Generative AI boom period, when disaggregating AI infrastructure into its four key subcomponents–$CHSE$, PER, $DSMS$, and TSS–we find that $DSMS$ and TSS are the strongest predictors of future returns, suggesting that data readiness and interoperability are especially valued by investors.

Furthermore, we examine whether firms with high AI infrastructure experience distinct changes in corporate fundamentals over time. We find that firms with high AI infrastructure tend to experience faster growth, reduced leverage, higher market valuation (Tobin's Q), and stronger R&D investment. These findings suggest that AI infrastructure drives long-term growth, financial discipline, and innovation, although its benefits are often not reflected in short-term earnings or book values, leading to market underreaction.

Next, we assess how AI infrastructure influences future firm performance during the generative AI boom (2022–2024). Using ChatGPT-generated scores to classify firms by high or low AI infrastructure, the analysis shows that various components, including $CHSE$, PER, $DSMS$, and TSS, impact corporate fundamentals. Results reveal that $CHSE$ and PER positively affect firm growth and market valuation, with $DSMS$ having the strongest impact on *Tobin's Q*, highlighting the market's valuation of robust data management. TSS also influences both valuation and R&D, underscoring the role of technical standards in driving innovation. Overall, firms with strong AI infrastructure, particularly in data management and technical standards, are better positioned for long-term growth, emphasizing the importance of investing in these areas to enhance value creation during the AI boom. Consistent with theories linking imperfect information to resource misallocation (e.g., David et al. (2016)), our findings suggest that firms investing in AI infrastructure–particularly in data storage and technical standards–enhance their internal information processing capabilities, which in turn drives superior productivity, valuation, and stock performance.

Finally, our analysis of AI infrastructure determinants reveals that larger firms, growth-oriented companies (low B/M ratio), and those with higher market valuations (Tobin's Q) are significantly more likely to higher AI infrastructure. R&D-intensive firms also show higher AI infrastructure, whereas traditional intangible assets do not consistently predict AI investment. Notably, AI infrastructure exhibits strong persistence over time. These findings align with prior evidence (McElheran et al. (2024)) that AI adoption concentrates among large firms, innovative startups, and tech hubs, often alongside other advanced technologies.

In the context of AI infrastructure, the "Productivity J-Curve" framework of Brynjolfsson et al. (2021) offers a powerful lens for understanding how investments in new intangible capital can initially depress measured productivity and earnings, yet ultimately generate substantial long-term gains in productivity and value. Because intangible AI investments–such as proprietary models, training datasets, and R&D–are typically expensed rather than capitalized, their costs reduce reported short-term earnings and obscure the underlying value creation. This accounting treatment can cause investors to undervalue such firms in the early phase of the J-curve, when significant resources are devoted to building AI infrastructure but the benefits are not yet evident in financial metrics. As AI systems mature and begin to deliver operational efficiencies, innovation, and future cash flows, the market gradually recognizes their worth, leading to upward valuation adjustments and sustained alpha generation.

A complete understanding of this dynamic requires distinguishing between tangible and intangible AI infrastructure. Tangible investments–such as data centers, servers, and GPUs–are capital expenditures that appear on the balance sheet and provide the essential physical foundation for AI deployment and scale. Intangible investments, by contrast, are expensed immediately, suppressing short-term earnings and creating conditions for market underreaction and return predictability. Our methodology leverages earnings call transcripts to capture signals of both tangible and intangible investment, enabling a comprehensive view of their interplay. While tangible assets signal commitment to AI capabilities, it is often the expensed intangibles that drive the mispricing documented in our results. The decomposition of AI infrastructure components, including computing hardware and software ecosystems, data storage and management systems, and technical standards, reveals that the observed return premium is most strongly linked to intangible-intensive firms, consistent with the Productivity J-Curve.

McElheran et al. (2024) further show that early AI adoption–though still limited to fewer than 6% of firms–is concentrated among large firms and high-growth startups, often clustering with other emerging technologies (e.g., cloud computing) in 'superstar' hubs. As these investments scale and AI capabilities are deployed more broadly, these firms experience stronger fundamentals, including increased R&D intensity, higher Tobin's Q, and greater resilience–particularly during downturns. This delayed return on intangible assets reinforces the notion that high-AI firms are undervalued in the short term but ultimately outperform, as predicted by the J-curve framework. Brynjolfsson et al. (2023) show that generative AI adoption boosts productivity–especially for lower-skilled workers–demonstrating how AI investments create long-term value that may not be immediately captured by standard accounting measures.

Unlike the rational expectations view of investment-driven productivity shocks in Cochrane (1991), our findings suggest systematic mispricing: the market underestimates the lagged payoff of AI intangibles. These dynamics are further supported by Czarnitzki et al. (2023), who find positive and significant associations between AI use and firm productivity. Recently, Babina et al. (2025) measure firm-level AI investment using AI-skilled human capital and document that AI investments increase firms' systematic risk, as reflected in higher market betas, particularly on the upside. Their findings suggest that AI acts as a growth option, making firms more sensitive to market movements. In contrast, our paper takes a mispricing perspective, showing that markets underappreciate the long-term value of AI infrastructure. While their study emphasizes risk reallocation, we highlight return predictability and valuation inefficiencies. Together, these perspectives suggest that AI affects both risk and pricing channels in capital markets.

What's more, this study is the first to develop a scalable and interpretable framework for measuring firm-level AI infrastructure investments using a prompt-engineered, zero-shot LLM-based approach with CoT reasoning, applied to earnings call transcripts. In this context, we contribute to the emerging literature on the revolutionary impact of ChatGPT and other LLMs in extracting signals from financial markets, corporate behavior, and decision-making. Recent research highlights the predictive and analytical power of LLMs across financial domains. Eisfeldt et al. (2024) show that firms more exposed to Generative AI saw stock price gains after ChatGPT's launch, driven by labor-technology substitution. Kim et al. (2024b) find GPT-4 outperforms human analysts in earnings prediction and improves trading performance. Chen et al. (2025) show ChatGPT uniquely predicts stock market and macroeconomic trends from news, outperforming other models. Lopez-Lira and Tang (2023) demonstrate that LLMs predict stock returns from news headlines, particularly for smaller firms and negative news, due to information-processing advantages. Fedyk et al. (2025) show that GPT-4 mirrors human investment preferences but also reveals biases when demographic information is absent. Li et al. (2024) use LLMs to map analysts' views on corporate culture and link them to stock recommendations and firm value. Kim et al. (2024a) find that ChatGPT-generated summaries of corporate disclosures enhance investor understanding and market reactions. Kim and Nikolaev (2024) show that LLMs integrating narrative context into financial metrics improve profitability predictions and asset pricing models. Kim and Nikolaev (2025) demonstrate that combining narrative and numeric data improves forecasts of firm performance, especially when accounting information is noisy. Jha et al. (2024) develop a ChatGPT-based investment score predicting firms' future capex and linking disclosure sentiment to short- and long-term returns. Building on this emerging literature, our study extends the use of LLMs to measure AI infrastructure investments from earnings calls, offering a scalable framework to link AI capabilities to stock returns, firm valuation, and R&D activity, thereby uncovering a new priced intangible asset in financial markets. Notably, our paper does not use LLMs to directly predict stock returns or corporate performance. Instead, we leverage them to construct a measure of AI infrastructure, which in turn predicts future returns and firm performance.

More broadly, our study relates to the expanding literature exploring how broader technological changes reshape firm dynamics, labor markets, and economic inequality. Acemoglu and Restrepoe (2022) document that 50–70% of changes in the U.S. wage structure over the past four decades are driven by automation-induced displacement, particularly among workers specialized in routine tasks. Kogan et al. (2021) show that higher rates of industry innovation increase top workers' earnings while raising labor income risk, with significant welfare losses and hedging demands emerging in response to innovation shocks. Relatedly, Autor et al. (2020) find that the decline in labor's share of GDP is closely linked to the rise of "superstar firms," characterized by high markups, low labor shares, and increasing market concentration, a dynamic further intensified by globalization and technological progress. Complementing these trends, Tambe et al. (2020) highlight that firms' investments in IT-related intangible assets, termed "digital capital," have risen substantially since the 1990s, now accounting for a large share of firm assets and predicting future productivity growth. Similarly, Begenau et al. (2018) show that big data disproportionately benefits large firms by lowering their cost of capital, facilitating further growth and consolidation. Finally, Cockburn et al. (2018) emphasize that AI, particularly deep learning, represents a new general-purpose "method of invention," reshaping R&D activities and creating powerful incentives for firms to race for control over critical datasets and algorithms.

The remainder of the paper is organized as follows: Section 2 outlines the methodology used in this study, including our data sources and the LLM framework employed. Section 3 details the data collection process and provides summary statistics. Section 4 presents the main empirical results. Finally, Section 5 concludes the paper.

2 Methods

2.1 Generative AI Prompt Engineering

This research leverages advanced large language models to evaluate companies' AI infrastructure investments and their impact on stock performance and firm fundamentals. LLMs represent a significant advancement in artificial intelligence, capable of processing and generating human-like text by recognizing patterns in vast training datasets. These models, including GPT-3.5 and GPT-4, have demonstrated remarkable capabilities in understanding context, executing complex instructions with precision, and delivering context-aware, insightful responses across a wide range of specialized fields. Our research methodology employs these language models to analyze corporate earnings transcripts for indicators of a company's AI infrastructure level. This approach builds on recent studies demonstrating the effectiveness of LLMs, such as ChatGPT, in extracting predictive investment signals from conference calls (Jha et al. (2024) and Kim et al. (2024a)), finaical statements (Kim et al. (2024b) and Kim et al. (2024a)), and SEC reports (Kim and Nikolaev (2024)).

Effective prompts serve as the critical interface between users and language models, translating human intent into actionable guidance for the model. In our research, prompts are engineered to transform the language model into a financial analyst–one capable of deciphering complex earnings call transcripts to evaluate companies' AI infrastructure levels. When given a prompt, the model analyzes its structure and intent, generates candidate responses, and selects the output that best balances relevance, coherence, and accuracy. The model's performance hinges on prompt design: vague or ambiguous prompts yield unreliable results, while precise, well-structured prompts produce actionable insights.

2.2 Chain of Thought (CoT) Reasoning

A key innovation in our research is the application of Chain of Thought (CoT) reasoning–a technique that significantly enhances language models' problem-solving capabilities. Unlike simple question-answer formats, CoT prompting instructs the model to break down complex analytical tasks into a series of logical steps before arriving at a conclusion. This approach mirrors how human experts approach multifaceted problems: by decomposing them into manageable components, addressing each component systematically, and then synthesizing the findings into a final assessment. For financial analysis tasks that require complex judgment, CoT provides several advantages. By working through multiple logical steps, the model can handle more complex analytical tasks than would be possible with direct prompting. The explicit reasoning chain makes the model's decision-making process visible and auditable, rather than presenting conclusions as black-box outputs. Breaking analysis into discrete steps helps prevent logical errors and oversight of critical factors. Additionally, the structured approach ensures that all relevant considerations are systematically addressed for each company analyzed.

In our research, we implemented a four-step CoT framework specifically designed for evaluating corporate AI infrastructure level. The first step involves evidence identification, systematically identifying mentions of AI technologies, computational infrastructure, data processing capabilities, and related investments within earnings transcripts. The second step is strategic significance assessment, evaluating whether these AI investments represent core strategic initiatives or peripheral experiments within the company's overall business model. The third step encompasses comparative industry analysis, contextualizing the company's AI investments relative to sector norms and competitive benchmarks. The final step is classification synthesis, integrating insights from the previous steps to make a final "High" or "Low" classification of AI infrastructure investment.

2.3 Zero-Shot Learning Application

Our methodology employs zero-shot learning, wherein the language model makes assessments without receiving explicit training examples. Instead of showing the model examples of companies with "High" versus "Low" AI infrastructure investments, we provide clear evaluation criteria and rely on the model's pre-existing knowledge of corporate finance, technology investments, and industry patterns.

The prompt we developed for this purpose guides the model through a structured analysis:

> *Forget all previous instructions. Pretend you are a financial expert with stock recommendation experience. We'll provide a description of an earnings transcript, and you need to determine whether this company has high AI infrastructure. Follow this structured approach before giving your final answer:*
>
> 1. *Identify AI-related Investments: Scan the earnings transcript for mentions of AI infrastructure, data centers, machine learning applications, or cloud computing.*
> 2. *Assess Significance: Determine whether AI is a core part of the company's business strategy or just a minor component.*
> 3. *Consider Industry Context: Compare this company's AI investments with industry standards.*

4. *Final Decision: Based on the above factors, respond with "High" if AI infrastructure is significant, otherwise "Low."*

For maximum consistency and reproducibility, we set the temperature parameter of our language model queries to 0, ensuring that identical inputs consistently produce the same analytical outputs. This parameter setting is crucial for maintaining methodological rigor in our research.

The integration of zero-shot learning with Chain of Thought reasoning represents a methodological advancement in applying language models to financial analysis. Our approach enables systematic, transparent evaluation of companies' AI infrastructure investments based on their public disclosures, providing valuable insights for investment decision-making and market analysis.

The Apple example demonstrates our methodology in practice. The model first identifies Apple's "Apple Intelligence" initiative and related AI investments, assesses these investments as strategically significant rather than peripheral, evaluates Apple's AI focus relative to industry trends, and finally classifies Apple as having "High" AI infrastructure based on this comprehensive analysis.

For example, consider the following excerpt from Apple's (AAPL) third-quarter 2024 earnings transcript: The transcript mentions "Apple intelligence," which builds on years of innovation and investment in AI and Machine Learning. Apple intelligence is described as a transformative set of capabilities that will enrich customers' lives through features like notification summaries, reduced interruptions, and more.

ChatGPT's CoT reasoning proceeds as follows:

1. *Identify AI-related Investments: The transcript highlights "Apple intelligence," emphasizing significant investments in AI and machine learning, including features like notification summaries.*
2. *Assess Significance: AI is integral to Apple's strategy, with Apple intelligence described as transformative and embedded across products, indicating a core focus.*
3. *Consider Industry Context: Apple's AI investments align with industry trends, where leading tech firms prioritize AI integration, and their scale appears competitive.*
4. *Final Decision: Given the substantial AI investments and strategic emphasis, the AI infrastructure is significant. Response: High.*

The integration of CoT reasoning in the prompt design represents a key methodological advancement. By requiring ChatGPT to follow defined steps—identifying investments, assessing their role, and benchmarking against the industry—the model produces decisions that are both systematic and transparent. This approach mirrors human analytical processes, enhancing the reliability of the classification and making it easier to understand the rationale behind each output.

2.4 Ensuring an Ex-Ante and Non-Overlapping AI Infrastructure Classification

Our AI infrastructure indicator is constructed on an ex-ante basis, without reference to future returns or firm performance. Using LLM, we classify firms solely on the textual content of their earnings calls from the same quarter. The model is only asked to rate the firm's AI infrastructure level, not to forecast stock prices, earnings, or any other forward-looking metric. Because the classification relies exclusively on contemporaneous transcripts and not on any subsequent market or financial data, there is no overlap between the information used for classification and the variables used in the return prediction stage. This procedure could, in principle, be implemented in real time using only the transcripts available at that moment.

This design is fundamentally different from approaches that identify "today's winners" ex-post and then look backward. Instead, our method applies the LLM to noisy and incomplete public disclosures to assign an AI infrastructure intensity score based solely on the language in the earnings call. The subsequent return tests then examine whether this contemporaneous AI intensity measure–constructed without any knowledge of future outcomes–predicts returns in the next quarter, in line with standard predictive-return research designs.

Concerns about lookahead bias are mitigated by the operational nature of LLMs. These models do not "know the future"; they identify linguistic and thematic patterns present in the input text. When analyzing, for example, a 2015 transcript, the model evaluates the significance of language regarding AI infrastructure using contextual cues such as emphasis, repetition, and framing within that same document–not by projecting or recalling future events. The LLM's output reflects its ability to generalize about AI-related content, not to predict future firm performance. Moreover, LLMs do not possess an internal timeline that could align events with subsequent outcomes, further preventing temporal leakage.

In sum, our LLM-based classification serves exclusively as a content-based rating of a firm's AI infrastructure intensity, constructed entirely from contemporaneous disclosures. It is not a return prediction model, and it does not use or have access to any future performance data, ensuring that our research design is free from information overlap and lookahead bias.

2.5 Econometric Modeling

We prompt ChatGPT to evaluate each firm's AI infrastructure capabilities based on its earnings call transcripts. The output of this evaluation is translated into binary indicators: a score of 1 signifies a high level of AI-enabling infrastructure, and 0 otherwise. ChatGPT and similar LLMs perform most reliably on binary classification tasks, particularly when applied to lengthy, unstructured text such as earnings call transcripts. Introducing multiple intermediate categories would require finer semantic distinctions that significantly increase the risk of misclassification and noise. Our priority was to maximize the accuracy of the classification signal, even at the expense of granularity. ChatGPT generates these scores for an aggregate measure, labeled *AI Infrastructure*, as well as for four specific subcomponents representing distinct technological domains: Computing Hardware and Software Ecosystem (*CHSE*), Power and Energy Resources *(PER*), Data Storage and Management Systems (*DSMS*), and Technical Standards and Specifications (*TSS*). These subcomponents capture critical enablers for scalable and efficient AI deployment within firms.

Using these AI-related indicators as inputs, we conduct econometric modeling in two key steps: infrastructure signal extraction and return prediction. In the first step, ChatGPT processes textual information to generate firm-level indicators for both the overall AI infrastructure and its subcomponents. In the second step, we employ these indicators to forecast future firm-level stock returns using a cross-sectional Fama-MacBeth regression framework. We estimate the following general model:

$$Ret_{i,t+1} = \beta_0 + \beta_1 \cdot X_{i,t} + \beta_2 \cdot Ret_{i,t} + \theta_t \cdot RF_t + \gamma_j + \alpha_i + \delta_t + \epsilon_{i,t}, \tag{1}$$

where $Ret_{i,t+1}$ denotes stock i's return in the subsequent quarter, and $X_{i,t}$ is a firm-level AI infrastructure variable–either the aggregate score or one of the four subcomponents (*CHSE, PER, DSMS*, and *TSS*). RF_t represents a vector of risk factors, including the Fama-French five factors and the momentum factor. γ_j is the industry fixed effect, α_i is the firm fixed effect, and δ_t is the year-quarter fixed effect. The error term $\epsilon_{i,t}$ captures firm-level residual variation.

In extended specifications, we augment this model to include a rich set of firm-level controls:

$$Ret_{i,t+1} = \beta_0 + \beta_1 \cdot X_{i,t} + \beta_2 \cdot Ret_{i,t} + \theta_t \cdot RF_t + \gamma' Z_{i,t} + \gamma_j + \alpha_i + \delta_t + \epsilon_{i,t}, \tag{2}$$

where $Z_{i,t}$ includes standard firm characteristics such as firm size ($SIZE$), book-to-market ratio (B/M), Tobin's Q (*Tobin's Q*), leverage (LEV), profitability (ROA), investment ($CAPEX$), R&D intensity ($R\&D$), asset tangibility ($TANG$), intangible assets ($INTANG$), and labor inputs ($LABOR$). This set of controls helps ensure that the estimated relationship between AI infrastructure and future stock returns is not confounded by broader firm-level economic fundamentals.

Standard errors are clustered at the firm level to account for potential autocorrelation and heteroskedasticity in residuals across time within firms. This clustering approach enhances the reliability of inference by acknowledging the panel structure of the data and the non-independence of observations across quarters for the same firm.

3 Data

In this section, we discuss the different datasets we use and the process of variable construction.

3.1 Data Sources and Sample Selection

We utilize multiple data sources. First, we use S&P 500 firms' conference call transcripts as our primary text source to assess their AI infrastructure level. Second, we obtain corporate accounting variables and stock returns from Compustat and CRSP.

Our primary text dataset includes earnings call transcripts from 2006 to 2024, obtained using API Ninjas' Earnings Call Transcript API[1]. This API provides entire transcripts of major firms'

[1]available at https://www.api-ninjas.com/api/earningscalltranscript

quarterly earnings calls, with historical data available from 2006 forward. These earnings call transcripts are the written records of the quarterly conference calls where executives of a publicly traded company—typically the CEO, CFO, and sometimes other senior leaders—discuss financial results, operational highlights, and future outlook with investors, analysts, and media. These calls, held four times a year after quarterly earnings releases, follow a standard structure: opening remarks summarizing key results, detailed financial discussions (revenue, profits, expenses), segment-by-segment performance breakdowns, forward-looking statements (projections and strategic plans), and a Q&A session where analysts pose direct questions. The purpose is to provide transparency into the company's financial health and strategy, equip investors with insights for decision-making, and allow analysts to probe executives on performance and risks. Transcripts are publicly available via SEC filings, investor relations pages, and financial platforms, serving as critical resources for stakeholders to assess a company's trajectory.

This study excludes financial, insurance, real estate, and related industries to ensure the validity and interpretability of our AI infrastructure scoring methodology. This stems from two critical methodological considerations. First, the nature of AI infrastructure demonstrates significant variability across industries. In financial and insurance sectors, AI applications are predominantly specialized, focusing on algorithmic trading, risk assessment, fraud detection, and customer analytics. These applications rely primarily on proprietary models and software rather than the physical AI infrastructure that is the focus of our research. Similarly, real estate industries tend to leverage AI for predictive analytics, automated property valuation, and customer engagement, which do not necessitate the extensive computing hardware, power resources, or communication networks central to our investigation. Second, these industries operate within unique regulatory and technological ecosystems that would complicate our comparative analysis. Financial and insurance firms are governed by strict regulatory frameworks—such as GDPR (General Data Protection Regulation), PSD2 (Revised Payment Services Directive), and Basel III—which profoundly influence their AI adoption patterns in ways that may not be captured by a generalized scoring system. Real estate firms, moreover, frequently employ localized, market-specific AI tools that lack the standardization necessary for meaningful cross-firm comparisons. By excluding these sectors, we aim to develop a more robust, transferable AI infrastructure scoring methodology that can be reliably applied across diverse non-financial industrial contexts.

3.2 Summary Statistics

Table 1 describes the Summary Statistics for the AI infrastructure dataset for S&P 500 firms. It provides a detailed overview of AI infrastructure levels, firm characteristics, and firm performance metrics.

The upper panel of Panel A shows that the mean AI infrastructure score for S&P 500 firms is 0.092, which indicates that 9.2% of firms have a high AI infrastructure level according to the ChatGPT-generated scores. Across the whole sample, relatively few firms have high AI infrastructure. The mean return*Ret* is 1.069%, and the median is slightly higher at 1.256%. The distribution of returns is notably wide, with a standard deviation of 4.561 percentage points, and a 5th percentile of -6.947% and 95th percentile of 8.319%.

The lower panel of Panel A shows the summary statistics for the Generative AI boom subsample, which includes S&P 500 firms from 2022 to 2024. The mean AI infrastructure score for firms during this period is 19.1%, indicating a higher level of AI infrastructure during the Generative AI boom compared to the whole sample period. We also observe that certain technology-related categories, such as the *Computing Hardware and Software Ecosystem (CHSE)* and *Power and Energy Resources (PER)*, have higher mean scores of 32.4% and 42.1%, respectively, compared to other categories. This suggests that during the Generative AI boom, AI infrastructure investments were particularly concentrated in $CHSE$ and PER. In contrast, categories such as $DSMS$ and TSS exhibit significantly lower to AI infrastructure, with mean scores ranging from 6.0% to 6.5%. This disparity highlights a selective focus on specific technology areas during the boom period, potentially reflecting strategic prioritization of critical AI-enabling components over broader infrastructure categories.

Panel B presents summary statistics for firm characteristics. The average firm size ($SIZE$), measured as the natural logarithm of total book assets, is 9.791, corresponding to approximately \$17.9 billion in assets, with a median of 9.819 (about \$18.4 billion). The size range spans from 7.703

to 11.815, representing firms with assets between roughly \$2.2 billion and \$135 billion—covering both relatively small and very large firms. The mean book-to-market ratio (B/M) is 0.329, with a median of 0.277, suggesting that most firms in the sample are growth-oriented (with B/M less than 1), while value-oriented firms are concentrated in the upper percentiles. The mean *Tobin's Q*, defined as the ratio of the market value of assets (market capitalization plus debt minus current assets) to the book value of assets, is 1.849, exceeding the median of 1.348, indicating a right-skewed distribution. The average leverage ratio (LEV), calculated as total debt divided by total debt plus market equity, is 0.206, reflecting moderate leverage across firms. The range (0.023 to 0.489) illustrates substantial variation in capital structure. The mean return on assets (ROA), measured as net income over total assets, is 1.9%, with a relatively narrow range from -0.4% to 5%, indicating generally modest profitability. The capital expenditures-to-sales ratio ($CAPEX$) has a mean of 0.182, significantly above the median of 0.089, reflecting a right-skewed distribution driven by a few firms with substantial physical investments. The research and development (R&D) expenditure to total capital stock ratio averages 3.1%, with a median of 1.6%, suggesting that R&D investment is concentrated among a smaller subset of firms. The mean tangibility ratio ($TANG$), defined as property, plant, and equipment (PP&E) over total assets, is 27.9%, with a median of 19.2%, indicating that most firms maintain a moderate base of tangible assets. Conversely, the mean intangibility ratio ($INTANG$), defined as intangible assets over total assets, is 26.7%, comparable in magnitude to $TANG$ but skewed toward firms with heavier reliance on intangible capital. The average labor intensity ratio ($LABOR$), measured as the natural logarithm of employment to net PP&E, is 2.007, with a wide range from -1.070 to 3.914. Positive values indicate labor intensity exceeding the value of physical capital, while negative values imply the opposite.

Panel C compares firm characteristics between high and low AI infrastructure firms, focusing on mean differences in AI infrastructure scores. High AI infrastructure firms exhibit significantly larger total book assets (9.949, approximately \$20.8 billion) than low AI infrastructure firms (9.776, approximately \$17.6 billion), consistent with economies of scale in AI adoption (t=5.078). Their lower book-to-market ratio (0.250 vs. 0.337, t=-11.021) aligns with a growth-oriented profile, which theory associates with higher intangible investment and innovation-driven valuation premia. The higher Tobin's Q for high AI infrastructure firms (2.763 vs. 1.761, t=22.417) reflects market expectations of future earnings growth, potentially driven by AI-related productivity gains.

High AI infrastructure firms also maintain lower leverage ratios (0.147 vs. 0.212, $t=-16.617$), a pattern consistent with pecking-order theory: firms with higher equity valuations (as implied by Tobin's Q) may prefer equity over debt financing. Their marginally higher return on assets (2.2% vs. 1.9%, t=6.000) suggests potential efficiency gains from AI adoption, though further analysis is needed to establish causality.

Investment patterns differ notably. High AI infrastructure firms allocate a smaller share of sales to capital expenditures (0.153 vs. 0.185, $t=-4.564$), indicating a shift from physical to intangible capital. Their R&D intensity is significantly higher (5.3% vs. 2.7% of total capital stock, t=17.563), supporting the hypothesis that AI adoption correlates with innovation-driven business models.

This is further reflected in asset composition: high AI infrastructure firms hold fewer tangible assets (18.7% vs. 28.8%, $t=-16.326$) and more intangible assets (29.2% vs. 26.5%, t=4.459), consistent with characteristics of technology-intensive firms. Interestingly, these firms also exhibit higher labor intensity (2.356 vs. 1.974, t=9.012), contradicting the hypothesis that AI primarily substitutes for labor. Instead, this supports the view that AI complements skilled labor, particularly in firms reliant on engineers and data scientists.

In summary, high AI infrastructure firms are larger, more growth-oriented, and command higher market valuations. Their financial and operational profiles—lower leverage, higher R&D intensity, and greater reliance on intangible assets—are consistent with innovation-driven firms. The labor intensity findings suggest that AI adoption complements rather than replaces human capital, emphasizing the critical role of skilled labor in implementing AI infrastructure.

Table 2 presents a detailed comparison of S&P 500 firms based on their AI infrastructure capabilities as of September 30, 2024. It focuses on the top 10 firms with the highest and lowest AI infrastructure levels, excluding financial, insurance, real estate, and related industries. The firms are evaluated based on market capitalization (in billions of U.S. dollars) and their performance across six specific categories related to AI infrastructure: *CHSE*, *PER*, *DSMS*, and *TSS*. Each category is scored using ChatGPT, with a value of 1 indicating a high level of capability and 0 indicating a low level. The table is divided into two panels: Panel A for firms with high AI infrastructure levels and Panel B for those with low levels, with each firm's industry classified using the three-digit NAICS (North American Industry Classification System) code.

In Panel A, the top 10 firms with high AI infrastructure levels are showcased, all assigned an overall AI score of 1, reflecting their strong capabilities in this domain. Leading the list is Apple Inc., with a market capitalization of $3,522 billion, operating in the Computer and Electronic Product Manufacturing industry. Apple excels in *CHSE* , *PER* , and *TSS* (scoring 1 in each), but scores 0 in *DSMS*. Microsoft Corporation follows with a market value of $3,199 billion in the Software Publishing Industries, achieving a perfect score of 1 across all six categories, demonstrating its robust AI infrastructure. NVIDIA Corporation, valued at $2,979 billion, also in Computer and Electronic Product Manufacturing, scores highly in *CHSE* , *PER* , and *DSMS* , but falls short in *TSS* . Other notable firms include Amazon.com, Inc. ($1,959 billion, Nonstore Retailers), Meta Platforms, Inc. ($1,248 billion, Other Information Services), and Alphabet Inc. ($929 billion, Data Processing and Hosting), each showing varying strengths across the categories, with Alphabet excelling in five out of six. Tesla, Inc. ($839 billion, Transportation Equipment Manufacturing), Oracle Corporation ($472 billion, Professional Services), Advanced Micro Devices, Inc. ($266 billion), and Salesforce, Inc. ($262 billion) round out the list, with Oracle notably scoring 1 in all categories except *SPS*.

In contrast, Panel B highlights the top 10 firms with low AI infrastructure levels, each assigned an overall AI score of 0, indicating minimal capability across the evaluated categories. Eli Lilly and Company, with a market capitalization of $842 billion in Chemical Manufacturing, leads this group, scoring 1 in *CHSE* and *PER* but 0 elsewhere. Broadcom Inc. ($806 billion, Computer and Electronic Product Manufacturing) and Walmart Inc. ($649 billion, General Merchandise Retailers) follow, both scoring 0 across all categories, suggesting a significant lag in AI infrastructure development. Exxon Mobil Corporation ($521 billion, Petroleum and Coal Manufacturing) scores 1 in *PER* but 0 in all other areas, while The Procter & Gamble Company ($407 billion), The Home Depot, Inc. ($402 billion), Costco Wholesale Corporation ($393 billion), Johnson & Johnson ($390 billion), AbbVie Inc. ($349 billion), and The Coca-Cola Company ($310 billion) all score 0 across every category. These firms, spanning industries like Chemical Manufacturing, Retail, and Food Manufacturing, reflect a broader trend of limited investment or focus on AI infrastructure compared to their Panel A counterparts.

Overall, firms in technology-driven sectors–such as computing, software, and data services–dominate the high AI infrastructure group, leveraging their substantial resources and technical expertise across multiple AI-related domains. In contrast, firms in more traditional industries, including retail, manufacturing, and chemicals, tend to lag behind, often exhibiting limited or no capabilities in the assessed AI infrastructure categories. Notably, market capitalization alone does not determine AI infrastructure: high-value firms like Eli Lilly and Broadcom appear in Panel B with relatively low AI infrastructure scores, highlighting that industry focus and strategic investment play a more decisive role in shaping AI infrastructure .

4 Empirical Results

4.1 Portfolio Sorting Results

Table 3 reports the performance of portfolios constructed based on a binary classification of firms according to their AI infrastructure levels. The AI infrastructure level is a ChatGPT-generated score, denoted as *AI infrastructure*, where a value of 1 represents firms with high AI infrastructure and a value of 0 represents firms with low AI infrastructure. The portfolios are formed using both equal-weighted (Panels A and B) and value-weighted (Panels C and D) methodologies, and their average quarterly returns are evaluated over the period from 2014 to 2024.

Panel A shows that the equal-weighted high AI infrastructure portfolio outperforms the low AI infrastructure portfolio, with an average return differential of 0.512% per quarter, which is statistically significant at the 5% level. This performance gap suggests that firms classified as having high AI infrastructure tend to be systematically rewarded by investors, possibly due to stronger fundamentals, improved operational efficiencies, or forward-looking expectations of technology-driven growth. The outperformance is not merely a result of higher risk: risk-adjusted alphas from various asset pricing models–CAPM (0.448%), Carhart four-factor (0.361%), and Fama-French five-factor (0.377%)–are all positive and statistically significant. This indicates that the return premium associated with high AI infrastructure firms persists even after accounting for traditional sources of systematic risk, implying that AI capabilities may represent a source of excess returns not fully captured by standard risk models.

Panel B explores the robustness of this relationship by excluding firms in traditional tech sectors, thereby focusing on industries where AI is not yet deeply embedded. The high-minus-low return differential declines slightly to 0.435%, though it remains statistically significant at the 5% level. Alphas also remain positive–ranging from 0.278% to 0.354%–and statistically significant. This suggests that the benefits of AI infrastructure are not confined to technology firms alone; rather, firms in non-tech sectors that adopt advanced AI capabilities may also gain a competitive edge. These findings broaden the relevance of AI-related investment considerations to a more diverse set of industries, underscoring the transformative role of AI infrastructure across the economy.

Panel C turns to a value-weighted construction, giving greater influence to larger firms in the portfolio. Here, the high-minus-low return spread increases to 0.875% per quarter, again significant at the 5% level. Risk-adjusted alphas are even stronger in this specification: 0.692% (CAPM), 0.777% (Carhart), and 0.865% (FF-5), with the latter being significant at the 1% level. These results suggest that larger firms with high AI infrastructure capabilities are driving much of the observed return premium. This may reflect economies of scale in AI deployment, more advanced technological capabilities, or the market's recognition of their strategic positioning in AI adoption. The stronger performance in value-weighted portfolios reinforces the economic significance of the AI infrastructure signal among firms with greater market influence.

Panel D again excludes the tech sector in a value-weighted context. Interestingly, the return differential slightly increases to 0.930%, maintaining statistical significance at the 5% level. Alphas remain robust, ranging from 0.768% to 0.921%, with several measures reaching the 1% significance level. This further strengthens the conclusion that AI infrastructure is a meaningful performance driver even outside of technology-centric industries. The ability of non-tech firms with strong AI infrastructure to outperform their peers in terms of stock returns suggests that AI-related capabilities may serve as a source of sustained competitive advantage across a wide range of sectors.

Taken together, the results consistently indicate that firms with higher AI infrastructure levels exhibit superior stock performance, both in raw and risk-adjusted terms, across different portfolio construction methods. The persistence of the high-minus-low differential, even after excluding technology sectors, points to the broader economic importance of AI readiness beyond the traditional boundaries of the tech industry. Furthermore, the statistical significance of alphas across multiple factor models implies that the excess returns associated with AI infrastructure are not fully explained by known risk factors. These results suggest that the market systematically underprices AI infrastructure, likely due to the expensing of intangible investments and the delayed recognition of their value–consistent with the productivity J-curve theory (Brynjolfsson et al. (2021)) .

4.2 Subsample Robustness

Table 4 demonstrates the relationship between AI infrastructure levels and future stock returns during adverse market conditions over the 2014–2024 period. The analysis is based on value-weighted portfolios and is presented separately for the full S&P 500 sample (Panel A) and the non-tech S&P 500 sample (Panel B). The results reveal a consistent pattern: higher AI infrastructure (indicated by column "High") is associated with significantly higher future stock returns compared to lower AI infrastructure (indicated by column "Low"), particularly during periods of economic weakness.

Macroeconomic and market conditions are assessed using four key indicators: the Chicago Fed National Activity Index ($CFNAI$), Gross Domestic Product (GDP), the Industrial Production Index ($INDPRO$), and the S&P 500 Index ($S\&P$ 500). The $CFNAI$ is a composite of 85 monthly indicators tracking production, employment, and consumption. GDP represents the total value of domestic goods and services, while $INDPRO$ measures real output in manufacturing, mining, and utilities. The $S\&P$ 500 Index tracks the performance of 500 leading publicly traded U.S. companies.

In Panel A, when economic conditions are below average, as indicated by these four key indicators ($CFNAI$, GDP, $INDPRO$, and $S\&P$ 500), the return differential between high and low

AI infrastructure firms (H−L) is both economically and statistically significant. During periods of low $CFNAI$, high AI infrastructure firms outperform their low AI counterparts by 1.048 percentage points (t=1.99). Similarly, during low GDP growth, the return differential is 0.752 percentage points (t=2.43). When industrial production ($INDPRO$) is weak, high AI infrastructure firms generate 0.992 percentage points higher returns (t=2.72), and during periods of low $S\&P$ 500 performance, the differential is 1.091 percentage points (t=3.10).

Panel B extends the analysis by excluding technology firms to assess whether the observed effects are driven solely by the tech sector. The pattern holds strongly among non-tech firms as well. During low $CFNAI$, non-tech firms with high AI infrastructure outperform their low-AI counterparts by 1.091 percentage points (t=1.96). The return spreads are similarly notable during low GDP (0.839 points, t=2.64), low $INDPRO$ (0.872 points, t=2.26), and low $S\&P$ 500 performance (1.240 points, t=3.31).

These findings suggest that investments in AI infrastructure enhance firm resilience during economic downturns, enabling firms to sustain stronger financial performance amid broader market challenges, and this effect is not confined to the tech sector. The statistical significance of the return differentials reinforces the robustness of this relationship, underscoring the strategic value of AI as a driver of resilience. Notably, the effect of AI infrastructure on future stock returns is more pronounced when key macroeconomic indicators—$CFNAI$, GDP, $INDPRO$, and $S\&P$ 500—are below their averages over the 2014–2024 period. The consistent pattern across these variables is consistent with the literature (Fama and French (2008), Baker and Wurgler (2007), Ang et al. (2006), and Barberis et al. (1998)) suggesting that mispricing tends to be more severe during market downturns.

The double-sorting analysis of Table 5 reveals significant cross-sectional return predictability based on firm characteristics. First, sorting on firm size ($SIZE$) reveals that among small firms, small stocks exhibit higher average returns than large stocks: the average monthly return increases from 1.22% in the low group to 1.63% in the high group; large firms exhibit a more substantial and statistically significant High−Low spread of 0.74 percentage points (t=2.77), with returns rising from 0.73% to 1.47% across the size spectrum. Sorting by price (PRC), we observe that the return spread is higher among high-price firms, at 0.71 percentage points (t=2.98), compared to 0.37 percentage points among low-price firms, which is statistically insignificant. When firms are sorted based on book-to-market (B/M) ratio, the High−Low spread among small firms is 0.50 percentage points (t=1.70), marginally significant. Leverage-based (LEV) sorting reveals that low-leverage firms experience a significant High−Low return spread of 0.69 percentage points (t=3.19). Return on assets (ROA) sorting shows that both low- and high-ROA firms have significant High−Low spreads of 0.61 (t=2.10) and 0.53 (t=2.21) percentage points, respectively, suggesting that more profitable firms outperform regardless of their baseline profitability level. Finally, sorting by labor intensity *Labor* demonstrates that among low labor cost firms, the return spread is highest at 0.96 percentage points (t=2.99). These results suggest that cross-sectional return predictability is stronger for larger firms, those with higher growth potential, and firms with lower leverage. These findings are consistent with McElheran et al. (2024), who find that AI technology usage is concentrated among large firms, innovative startups, and a few major tech hubs.

4.3 Fama-MacBeth Regressions

Table 6 presents the results of Fama-MacBeth regressions examining the relationship between a firm's AI infrastructure level and its subsequent quarterly stock returns (Ret_{t+1}). The key independent variable, *AI Infrastructure*, is a binary measure generated by ChatGPT, where a score of 1 indicates a high AI infrastructure level and 0 indicates a low level. In Table 6, we also control for the well-established risk factors that explain cross-sectional variation in stock returns to isolate the effect of *AI Infrastructure*. These risk factors include the Fama-French five factors and the momentum factor, collectively represented as $MKTRF$, SMB, HML, RMW, CMA, and UMD. The $MKTRF$ factor, or market risk premium, is the excess return of the market portfolio over the risk-free rate, capturing the overall sensitivity of a stock to market movements. SMB (Small Minus Big) reflects the size effect, measuring the return differential between small-cap and large-cap stocks; a positive loading on SMB implies the stock behaves more like a small-cap firm. HML (High Minus Low) captures the value premium by comparing returns of high book-to-market (value) stocks to low book-to-market (growth) stocks. The RMW (Robust Minus Weak) factor accounts for differences in profitability, distinguishing firms with robust profitability from those with weak profitability. Similarly, CMA (Conservative Minus Aggressive) represents the investment factor, measuring the return spread between firms that invest conservatively and those that invest aggressively, based on the premise that conservative firms tend to outperform. Lastly, UMD (Up Minus Down) is the momentum factor, capturing the tendency of stocks with strong past performance (winners) to continue outperforming those with poor past performance (losers) in the short term. Including these factors in a return regression helps isolate the effect of firm-specific variables, such as AI-related characteristics, by accounting for common sources of risk that drive returns across the market. In Table 6, we also control for firm characteristics ($SIZE$, B/M, *Tobin's Q*, LEV, ROA, $CAPEX$, $R\&D$, $TANG$, $INTANG$, $LABOR$). Standard errors are clustered at the firm level to account for within-firm correlation.

We estimate the folllowing models:

$$\begin{aligned} Ret_{i,t+1} = \beta_0 &+ \beta_1 \cdot \text{AI Infrastructure}_{i,t} + \beta_2 \cdot Ret_{i,t} + \beta_3 \cdot MKTRF_t \\ &+ \beta_4 \cdot SMB_t + \beta_5 \cdot HML_t + \beta_6 \cdot RMW_t + \beta_7 \cdot CMA_t + \beta_8 \cdot UMD_t \\ &+ \gamma_j + \alpha_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{3}$$

whereas $\varepsilon_{i,t}$ is the error term, γ_j is the industry fixed effect (Model 2), α_i is the firm fixed effect (included in Model 3), and δ_t is the year-quarter fixed effect (Models 2 and 3).

$$\begin{aligned} Ret_{i,t+1} = \beta_0 &+ \beta_1 \cdot \text{AI Infrastructure}_{i,t} + \beta_2 \cdot Ret_{i,t} + \beta_3 \cdot MKTRF_t \\ &+ \beta_4 \cdot SMB_t + \beta_5 \cdot HML_t + \beta_6 \cdot RMW_t + \beta_7 \cdot CMA_t + \beta_8 \cdot UMD_t \\ &+ \beta_9 \cdot SIZE_{i,t} + \beta_{10} \cdot B/M_{i,t} + \beta_{11} \cdot \text{Tobin's Q}_{i,t} + \beta_{12} \cdot LEV_{i,t} \\ &+ \beta_{13} \cdot ROA_{i,t} + \beta_{14} \cdot CAPEX_{i,t} + \beta_{15} \cdot R\&D_{i,t} + \beta_{16} \cdot TANG_{i,t} \\ &+ \beta_{17} \cdot INTANG_{i,t} + \beta_{18} \cdot LABOR_{i,t} + \alpha_i + \gamma_j + \alpha_i + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{4}$$

whereas $\varepsilon_{i,t}$ is the error term, γ_j is the industry fixed effect (Model 5), α_i is the firm fixed effect (included in Model 6), and δ_t is the year-quarter fixed effect (Models 5 and 6).

Across all six models, *AI Infrastructure* exhibits a statistically significant positive relationship with future returns, with coefficients ranging from 0.003 to 0.006 and significance levels between 5% and 1%. This finding suggests that firms with more advanced AI infrastructure tend to generate higher subsequent returns. The inclusion of additional controls and fixed effects strengthens this result, as evidenced in Models 2 through 6, where the coefficient remains robust even after accounting for firm characteristics.

The control variables yield mixed results. Lagged returns ($Ret_{i,t}$) are negatively associated with future returns in some specifications, consistent with short-term return reversals. Market risk ($MKTRF$) is strongly positive, while value (HML) and momentum (UMD) factors show varying levels of significance. Among firm characteristics, size ($SIZE$) and leverage (LEV) are consistently significant, with $SIZE$ negatively and LEV positively related to returns. Research and development spending ($R\&D$) exhibits a negative association in the most comprehensive model (Model 6).

The models progressively incorporate fixed effects to account for different sources of heterogeneity: Models 2 and 5 add industry and year-quarter (YQ) effects; and Models 3 and 6 include firm fixed effects and YQ effects. The explanatory power (R^2) increases from 13.5% in the baseline model (Model 1) to 35.6% in the most saturated specification (Model 6), highlighting the importance of controlling for both firm-level and time-specific variations. While the sample size decreases in Models 4 through 6 due to limited data on firm characteristics, the results remain both statistically and economically significant.

In particular, Model 6—the most comprehensive specification—shows that firms with high levels of AI infrastructure experience returns approximately 0.5 percentage points higher per quarter than those with lower levels (significant at the 1% level). This effect remains robust even after controlling for momentum effects and firm-specific attributes, suggesting that AI infrastructure is an important factor in explaining cross-sectional variation in stock returns.

Sample sizes differ between the first three models (15,762 observations) and the latter three (8,245 observations), largely due to the availability of firm-level data. The inclusion of firm and YQ fixed effects across several models enhances the robustness of the findings by controlling for unobserved heterogeneity and time-specific effects. Overall, the results indicate that a firm's AI infrastructure level—measured via an AI-generated metric—is a statistically and economically significant predictor of future returns, even after accounting for the established asset pricing factors and firm-specific characteristics.

These findings suggest that markets may systematically underprice AI infrastructure, consistent with recent theories in innovation economics and strategic management. In particular, the positive return predictability of AI infrastructure supports the "productivity J-curve" hypothesis, which posits that the expensing of intangible investments depresses short-term earnings, thereby obscuring their long-term value creation potential (Brynjolfsson et al., 2021). AI infrastructure has a form of intangible capital that is both strategically valuable and difficult to replicate. Because this type of capital is neither fully captured by conventional accounting metrics nor fully internalized by market participants, mispricing may persist until investors gradually revise their expectations about the firm's future profitability.

Table 7 presents the results of Fama-MacBeth return prediction regressions conducted over the Generative AI Boom period, which spans from January 2022 to December 2024. The dependent variable is the firm's return in the quarter following the observation period, denoted as Ret_{t+1}. The key independent variable of interest is a firm-level measure of AI infrastructure, labeled as *AI Infrastructure*, which captures the firm's to AI-enabling technologies. *Computing Hardware and Software Ecosystem (CHSE)*, *Power and Energy Resources (PER)*, *Data Storage and Management Systems (DSMS)*, and *Technical Standards and Specifications (TSS)* are ChatGPT-generated scores, assigned as 1 if ChatGPT determines that the firm has a high level and 0 otherwise.

Computing Hardware and Software Ecosystem (CHSE) encompasses the hardware and software ecosystem that power AI systems. High-performance processors such as GPUs, TPUs, and CPUs, optimized for parallel processing and matrix computations, play a critical role in firm daily operational tasks. Distributed computing systems allow firms to process large-scale datasets across multiple machines, while memory architectures optimized for AI workloads manage computationally intensive tasks. Edge computing resources support real-time analysis closer to where data is generated, and cloud computing infrastructure offers scalable solutions to meet varying computational demands efficiently. Complementing this infrastructure are software tools and platforms that facilitate AI adoption and implementation. Machine learning frameworks such as TensorFlow and PyTorch enable the development of AI models. Machine Learning Operations (MLOps) tools streamline deployment, monitoring, and updating of AI systems across firm operations. Data preprocessing and analysis tools ensure the preparation of high-quality inputs, while model optimization and compression tools enhance computational efficiency.

Power and Energy Resources (PER) underscores the importance of sustainable and reliable energy solutions in *AI Infrastructure*. Energy-efficient computing architectures reduce operational costs and environmental impact while supporting high-performance computing tasks. Advanced cooling systems maintain the reliability of AI hardware under intensive workloads, such as in predictive maintenance or personalized marketing algorithms. Renewable energy integration reflects firms' growing focus on sustainability, and backup power systems ensure continuity of operations in critical scenarios, such as manufacturing or retail during power outages.

Data Storage and Management Systems (DSMS) emphasizes the organization and handling of data, including secure and scalable storage systems, data pipelines, and tools for managing data versions and latency. It focuses on the effective organization and handling of data across diverse industries. Distributed storage systems support the secure and scalable management of large datasets, while data lakes and warehouses enable structured storage and retrieval of both operational and customer data. Caching systems reduce latency in accessing frequently used datasets, such as sales records or sensor data in manufacturing. Version control systems track updates to datasets and AI models, ensuring reproducibility and transparency. Data pipelines streamline data movement and transformation, facilitating tasks like demand prediction, trend analysis, and operational monitoring.

Technical Standards and Specifications (TSS) focus on standardization and interoperability in AI adoption, enabling firms to integrate AI efficiently. This includes standardized model interchange formats and data structures that facilitate cross-platform compatibility, APIspecifications for seamless system communication, and performance benchmarking standards to assess AI capabilities. Additionally, security and privacy standards safeguard proprietary and customer data, while hardware compatibility and energy efficiency metrics support cost-effective and sustainable

AI implementation.

These four components capture the foundational elements necessary for the deployment and scaling of AI technologies. Specifically, they reflect a firm's capabilities in computation, energy efficiency, data handling, and adherence to technical protocols that support AI implementation. The regressions also control for the firm-specific characteristics measured at time t as in Table 6. The decomposition of *AI Infrastructure* into four distinct dimensions reveals heterogeneous effects across technological domains, each contributing uniquely to firms' return predictability during the Generative AI boom.

We estimate the folllowing models for Models 1 to 5:

$$Ret_{i,t+1} = \beta_0 + \beta_1 \cdot \mathrm{X}_{i,t} + \beta_2 \cdot Ret_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t} \tag{5}$$

whereas X is $\textit{AI Infrastructure}_{i,t}$ for Model 1, $CHSE_{i,t}$ for Model 2, $PER_{i,t}$ for Model 3, $DSMS_{i,t}$ for Model 4, and $TSS_{i,t}$ for Model 5, $\varepsilon_{i,t}$ is the error term, γ_j is the industry fixed effect, and δ_t is the year-quarter fixed effect. We estimate the folllowing models for Models 6 to 10:

$$\begin{aligned} Ret_{i,t+1} = {} & \beta_0 + \beta_1 \cdot \mathrm{X}_{i,t} + \beta_2 \cdot Ret_{i,t} + \beta_3 \cdot SIZE_{i,t} + \beta_4 \cdot B/M_{i,t} + \beta_5 \cdot \text{Tobin's Q}_{i,t} \\ & + \beta_6 \cdot LEV_{i,t} + \beta_7 \cdot ROA_{i,t} + \beta_8 \cdot CAPEX_{i,t} + \beta_9 \cdot \mathrm{R\&D}_{i,t} + \beta_{10} \cdot TANG_{i,t} \\ & + \beta_{11} \cdot INTANG_{i,t} + \beta_{12} \cdot LABOR_{i,t} + \gamma_j + \delta_t + \varepsilon_{i,t} \end{aligned} \tag{6}$$

whereas X is $\textit{AI Infrastructure}_{i,t}$ for Model 6, $CHSE_{i,t}$ for Model 7, $PER_{i,t}$ for Model 8, $DSMS_{i,t}$ for Model 9, and $TSS_{i,t}$ for Model 10, $\varepsilon_{i,t}$ is the error term, γ_j is the industry fixed effect, and δ_t is the year-quarter fixed effect[2]. All regressions include industry and year-quarter fixed effects to control for unobserved heterogeneity across sectors and time. Standard errors are clustered at the firm level to account for within-firm correlation in the error terms.

Across specifications, the AI infrastructure variable is positively and significantly associated with future returns, with coefficients of 0.007 and t-statistics of 3.80 and 2.89 in Models 1 and 6, respectively. The categorical AI measures also show statistically significant positive effects on

[2] In unreported robustness checks, we replace the year-quarter fixed effects with standard asset pricing risk factors (as specified in Table 6) to account for cross-sectional variation in returns. The results remain qualitatively and quantitatively similar, suggesting our findings are robust to alternative specifications of systematic risk.

returns: $CHSE$ is significant at the 5% level in Models 2 and 7, while PER is significant at the 1% level in Models 3 and 8; $DSMS$ is significant at the 1% and 5% levels in Models 4 and 9; and TSS is significant at the 5% and 10% levels in Models 5 and 10. Among control variables, book-to-market consistently shows a negative and highly significant relationship with future returns, while firm size has a weakly positive and marginally significant effect in some specifications. Other firm characteristics, including *Tobin's Q*, LEV, ROA, $CAPEX$, $R\&D$, and intangibles, generally do not exhibit statistically significant relationships with returns. However, labor input appears positively associated with returns in some models, reaching significance at the 1% level. The R^2 values across models range from approximately 21.7% to 24.9%, indicating a moderate degree of explanatory power.

The *Computing Hardware & Software Ecosystem (CHSE)* exhibits a coefficient of 0.004–0.006 (p<0.05) in our analysis, indicating that firms specializing in AI-optimized processors–such as GPUs (e.g., NVIDIA, AMD) and TPUs (e.g., Google's custom accelerators)–or foundational software frameworks (e.g., PyTorch, TensorFlow, CUDA) realize 40–60 basis points higher quarterly returns, on average, compared to peers. *CHSE* companies possess significant competitive advantages through both hardware specialization and software ecosystem development. The integrated nature of AI computing platforms creates natural barriers to entry, as competitors must excel in both specialized hardware design and complex software framework development. This dual expertise requirement limits the competitive landscape and enhances the strategic positioning of established players. The risk-adjusted returns of *CHSE* firms reflect their pivotal influence within a market environment characterized by constrained computational capacity and heightened demand for AI infrastructure. Empirical evidence from Huang (2025) and Huang (2024) identifies a scarcity premium associated with advanced computational resources, particularly during periods of intensified training for LLMs.

The *Power & Energy Resources (PER)* shows a coefficient of 0.004–0.005 (p<0.05), reflecting the growing capital intensity of AI operations. As Le Monde (2024) documents, training a single frontier model now requires approximately 50 GWh of electricity–an amount comparable to the annual electricity consumption of 4,000 average U.S. households. Meta's LLaMA 3 model was trained over 50 days consuming an estimated 41.67 GWh. These figures underscore the substantial energy demands of training large-scale AI models, which indeed approach the annual electricity consumption of some small countries. Firms with proprietary energy infrastructure or renewable portfolios (e.g., hyperscale data center operators) thus command valuation premiums, particularly during periods of grid capacity constraints (International Energy Agency (2024)).

The *Data Storage & Management Systems (DSMS)* demonstrates the largest effect size (a coefficient of 0.010–0.011, $p<0.01$). Firms with petabyte-scale curated datasets or distributed storage architectures (e.g., vector databases) appear to be especially well-positioned to generate alpha in the Generative AI era. This finding underscores the critical role of data infrastructure as a strategic asset: high-quality, scalable, and efficiently managed data systems are not only essential for training and fine-tuning large AI models but also serve as a source of durable competitive advantage. $DSMS$ enables firms to leverage advanced AI workflows–such as retrieval-augmented generation (RAG), real-time analytics, and multi-modal inference–which in turn may enhance productivity, innovation capacity, and ultimately, market valuation. The strong positive association between $DSMS$ and future returns suggests that investors reward firms that invest in robust data capabilities, recognizing them as foundational to long-term AI-driven value creation[3].

The *Technical Standards & Specifications (TSS)* shows a coefficient of 0.008 ($p<0.10$), with weaker statistical robustness. Firms that actively contribute to technical standardization processes–such as developing or aligning with API standards, interoperability protocols, or obtaining certifications like those aligned with the $NIST$ (National Institute of Standards and Technology), AI Risk Management Framework (RMF)–benefit from network effects. These effects arise when standard participation enhances compatibility, trust, and scalability, encouraging broader adoption and ecosystem participation.

The results provide compelling evidence that firms with stronger AI infrastructure are more likely to experience higher stock returns in the subsequent quarter during the Generative AI Boom period (2022–2024). The consistently positive and statistically significant coefficients on the AI

[3]We thank Professor William Gropp at the National Center for Supercomputing Applications ($NCSA$) and UIUC for in-depth discussion about this.

infrastructure variable suggest that the market may be rewarding firms that are strategically positioned within the AI infrastructure level. This finding supports the view that AI capabilities represent a new form of intangible capital that is increasingly being priced by investors. Moreover, the binary indicators for subcomponents of AI infrastructure–$CHSE$, PER, $DSMS$, and TSS–further reinforce this conclusion. These components highlight the diverse channels through which AI readiness can enhance firm value. For instance, firms with robust computing ecosystems ($CHSE$) or superior data management systems ($DSMS$) appear to command a return premium, which could reflect either higher expected growth, competitive advantage, or investor enthusiasm for AI-aligned assets.

The evidence continues to suggest systematic market underpricing of firms with strong AI infrastructure. Specifically, the positive return predictability of AI infrastructure aligns with the "productivity J-curve" hypothesis, which posits that intangible investments–such as advanced computing ecosystems ($CHSE$) and data management platforms ($DSMS$)–are expensed rather than capitalized, thereby suppressing short-term earnings and concealing long-term value creation (Brynjolfsson et al. (2021)). $CHSE$ captures firms' control over specialized AI chips and proprietary software frameworks–assets that create deep integration and high switching costs–while $DSMS$ reflects scalable data architectures critical to differentiated AI capabilities. Although power and energy resources (PER) represent tangible infrastructure, they are increasingly scarce and strategically valuable in the context of AI's rising energy demands, making them a source of competitive advantage as well. Finally, participation in technical standards and specification development (TSS) enhances interoperability, trust, and ecosystem influence, reinforcing network effects and further entrenching firms' strategic positions. Because these capabilities are often overlooked by conventional financial metrics, mispricing may persist until investors gradually update expectations about the firm's future profitability.

4.4 Further Robustness Check

Table 8 presents the results of Fama-MacBeth return prediction regressions over the full sample period from January 2006 to December 2024. The regressions include an extensive set of controls for well-established return predictors and anomaly variables, including measures of financial distress (DRP and OOS), equity issuance (NSI and CEI), operating efficiency (NOA, $Prof$, ROA), firm investment behavior (AG, $ItoA$), and other standard firm characteristics. Model 1 includes no fixed effects, Model 2 controls for time-varying macroeconomic shocks through year-quarter fixed effects, Model 3 incorporates industry fixed effects to account for sector-specific differences, and Model 4 includes both year-quarter and industry fixed effects for a fully saturated specification.

Across all four model specifications, the coefficient on the AI infrastructure variable is positive and statistically significant at the 5% level, with point estimates ranging from 0.003 to 0.004. This suggests that firms classified as having high AI infrastructure levels earn, on average, between 30 and 40 basis points higher returns in the following quarter, relative to their counterparts with lower AI infrastructure scores. Importantly, this return premium persists even after controlling for a broad array of anomaly variables and risk factors, indicating that AI infrastructure not fully accounted for in traditional asset pricing frameworks.

The explanatory power of the models increases substantially with the inclusion of fixed effects: while Models 1 and 3 have R^2 values below 2%, Models 2 and 4 reach over 30%, reflecting the significant role of time and industry variation in explaining return dynamics. The persistence of the AI infrastructure effect across these varying specifications demonstrates its robustness to alternative modeling choices.

The explanatory power of the models increases substantially with the inclusion of time fixed effects. Model 1, which includes no fixed effects, and Model 3, which controls for industry fixed effects, both show R^2 values below 2%. However, Model 2, which controls for time-varying macroeconomic shocks through year-quarter fixed effects, achieves an R^2 of over 30%. The inclusion of both year-quarter and industry fixed effects in Model 4 does not lead to a significant increase in R^2 , indicating that time variation, rather than industry variation, plays the key role in explaining return dynamics. Despite these variations, the persistence of the AI infrastructure effect across all models underscores its robustness.

Among control variables, several findings are noteworthy. The DRP is strongly and negatively associated with future returns across all models ($p < 0.01$), consistent with prior evidence that distress-prone firms earn lower subsequent returns due to default risk and investor aversion Campbell et al. (2008). NOA also shows a robust negative relationship with future returns, echoing the findings of Hirshleifer et al. (2004) that asset bloat can signal inefficient investment or earnings management. $Prof$, ROA, and $ItoA$ show weaker and less consistent effects, with significance depending on the model specification.

Overall, these results provide compelling empirical support for the view that AI infrastructure constitutes a priced firm characteristic that is not fully captured by existing return predictors. The consistent significance of this variable, even after accounting for standard anomalies and firm fundamentals, suggests that AI-related capabilities introduce a distinct dimension of economic value that traditional asset pricing models may overlook–particularly due to their intangible, forward-looking, and often firm-specific nature. This persistent return premium implies that markets may be systematically underestimating the strategic importance of AI infrastructure in driving future firm performance.

4.5 Firm Performance

Table 9 reports the results of Fama-MacBeth regressions examining whether firms identified as having high AI infrastructure exhibit systematically different changes in key corporate fundamentals in the subsequent period. The analysis spans the full sample period from January 2006 to December 2024, and includes firm-level controls, industry fixed effects, and year-quarter (YQ) fixed effects to account for sector-specific and temporal variations. The AI infrastructure variable is based on a ChatGPT-generated binary score, equal to 1 if the firm is assessed as having high AI infrastructure capabilities at time t, and 0 otherwise. The dependent variables reflect the change in corporate fundamentals from t to $t + 1$, allowing us to assess the forward-looking impact of AI infrastructure.

In Model 1, the dependent variable is the change in firm size ($\Delta SIZE$), measured as the log difference in market capitalization. The coefficient on AI infrastructure is positive and statistically significant at the 1% level (0.015, $t = 3.77$), indicating that firms with high AI infrastructure tend to grow more rapidly in size over the subsequent period.

Model 2 uses the change in leverage (ΔLEV) as the dependent variable. Here, the coefficient on AI infrastructure is negative and significant at the 10% level (-0.002, $t = -1.78$), implying that high-AI firms reduce their leverage more than their low-AI counterparts.

Model 3, the dependent variable is the change in *Tobin's Q* (Δ *Tobin's Q*), a forward-looking valuation ratio capturing market expectations of future profitability. The coefficient on AI infrastructure is again positive and statistically significant at the 5% level (0.077, $t = 2.53$), suggesting that the market progressively prices in the long-term advantages associated with AI infrastructure. The increase in Tobin's Q further indicates a reassessment of firm value, consistent with the hypothesis that AI functions as an intangible growth driver that is gradually recognized over time.

Model 4 focuses on the change in *R&D* intensity ($\Delta R\&D$), with a highly significant and positive coefficient on AI infrastructure (0.006, $t = 3.37$). This finding provides direct evidence that AI infrastructure complements rather than substitutes for innovation: firms with advanced AI capabilities continue to invest in research and development, potentially leveraging AI to enhance the efficiency and success rate of R&D initiatives. Rather than crowding out innovation, AI appears to reinforce the firm's commitment to technological progress.

Taken together, the results across all four models paint a coherent picture: firms with high AI infrastructure systematically outperform in dimensions central to long-term value creation–growth, financial discipline, market valuation, and innovation. These improvements, however, are not necessarily reflected in contemporaneous earnings or book values, which can cause markets to underreact in the short term. This underreaction aligns with recent theories emphasizing the mispricing of intangible capital. The fact that AI infrastructure predicts changes in fundamentals rather than simply correlating with their levels further strengthens the interpretation that markets gradually update their beliefs about the value implications of AI over time.

These results provide micro-level validation for the idea that AI infrastructure serves as a forward-looking signal of firm quality that is not immediately incorporated into market prices. In this sense, AI infrastructure functions not only as a technological asset, but as a predictive indicator of future corporate health–reinforcing the broader narrative that markets may systematically underprice AI-intensive firms, particularly when their value stems from intangible, non-rival, and hard-to-measure sources.

Table 10 presents the Fama-MacBeth regression results examining the relationship between AI infrastructure levels and various corporate fundamentals during the Generative AI boom period. The analysis measures AI infrastructure using ChatGPT-generated scores, which classify firms as having high (1) or low (0) AI infrastructure. This includes key subcomponents: Computing Hardware and Software Ecosystem (*CHSE*), Power and Energy Resources (*PER*), Data Storage and Management Systems (*DSMS*), and Technical Standards and Specifications (*TSS*). The regressions control for firm characteristics at time t, with standard errors clustered at the firm level and year-quarter fixed effects included. The dependent variables are measured as period-over-period changes in firm size ($\Delta SIZE$), leverage (ΔLEV), profitability (ΔROA), market valuation ($\Delta Tobin's$ Q), capital expenditures ($\Delta CAPEX$), and R&D intensity ($\Delta R\&D$). Each model includes firm-level controls defined in Table 1, as well as industry and year–quarter fixed effects. Standard errors are clustered at the firm level to account for within-firm correlation over time. The sample spans from January 2022 to December 2024.

The primary explanatory variable in Panel A is the Computing Hardware and Software Ecosystem ($CHSE$) indicator, a binary measure equal to one if the firm is classified as having a high AI infrastructure level in this dimension and zero otherwise. All specifications control for firm-level characteristics, as defined in Table 1, and include both industry and year–quarter fixed effects. Standard errors are clustered at the firm level. The results indicate that a high $CHSE$ score is associated with statistically significant improvements in multiple dimensions of future corporate performance. Firms with strong AI computing hardware and software capabilities tend to experience greater subsequent growth in size (0.010, t=3.38), higher profitability (0.002, t=2.08), larger increases in market valuation (0.058, t=2.41), and greater R&D intensity (0.004, t=2.13). In contrast, $CHSE$ is negatively related to changes in leverage (-0.003, $t=-2.54$), suggesting that high-infrastructure firms reduce debt ratios over time. The economic effects are nontrivial, given that the dependent variables are expressed as period-over-period changes, and the statistical significance levels ($p<0.05$ in most cases) indicate robustness. During the Generative AI boom period, having strong AI computing hardware/software infrastructure appears to be a leading indicator of better future fundamentals (growth, profitability, market value, R&D investment) and lower leverage–even after controlling for firm size, leverage, profitability, and other characteristics.

Panel B focuses on the Power and Energy Resources (PER) measure, which equals one for firms with substantial AI-relevant energy capacity and zero otherwise. High-PER firms exhibit significantly faster future growth in size (0.008, t=3.00), larger gains in market valuation (0.082, t=2.65), increased capital expenditures (0.030, t=3.63), and higher R&D intensity (0.002, t=2.12), while also reducing leverage (−0.002, t=−2.09). The combination of stronger growth, greater investment, and lower debt levels points to an expansionary strategy that may be supported by internal financing or equity issuance, consistent with the capital-intensive nature of AI-related infrastructure development.

Panel C examines Data Storage and Management Systems ($DSMS$), another core infrastructure component. Firms with high $DSMS$ capability demonstrate even stronger size growth than those in the $CHSE$ and PER categories (0.018, t=2.03), reductions in leverage (−0.004, t=−2.25), notable improvements in market valuation (0.264, t=1.92), and higher R&D intensity (0.004, t=3.12). These results suggest that robust data storage and management capabilities not only support immediate operational needs but also signal a commitment to innovation and long-term technological positioning.

Panel D addresses Technical Standards and Specifications (TSS), measured as one for firms adhering to or setting high-level technical AI standards. High-TSS firms experience the largest relative size gains among the four components examined (0.023, t=2.64), significant improvements in market valuation (0.152, t=1.96), and increased R&D intensity (0.006, t=2.52). These results highlight the potential strategic value of leadership in technical standard-setting, which may confer competitive advantages in market perception and innovation trajectories.

During the Generative AI boom period, across all panels, the direction of effects is remarkably consistent: firms with stronger AI infrastructure–whether in computing capabilities, power and energy resources, data systems, or technical standards–tend to grow faster, increase investment and innovation, and reduce leverage in subsequent periods. The magnitudes are economically meaningful, particularly given the dependent variables measure changes rather than levels, and the robustness of the statistical significance reinforces the conclusion that AI infrastructure serves as a forward-looking indicator of corporate expansion and innovation investment during periods of rapid technological adoption.

4.6 The Determinants of AI Infrastructure Level

Table 11 reports the results of Fama-MacBeth regressions that examine the determinants of a firm's AI infrastructure level at time $t+1$. The dependent variable, *AI infrastructure*, is a binary indicator generated by ChatGPT, where a value of 1 indicates a high level of AI infrastructure and 0 otherwise. The independent variables include a set of corporate fundamentals measured at time t, firm fixed effects, and year-quarter fixed effects. Model 2 additionally controls for the firm's AI infrastructure score at time t, allowing the analysis to isolate changes over time. Standard errors are clustered at the firm level to correct for within-firm correlation, and the analysis spans a broad sample from January 2006 to December 2024. In both specifications, $SIZE$ is positively and significantly associated with AI infrastructure, suggesting that larger firms are more likely to have advanced AI infrastructure. Book-to-market ratio (B/M) has a statistically significant negative coefficient, indicating that growth-oriented firms (i.e., firms with low B/M ratios) are more likely to adopt or invest in AI infrastructure. *Tobin's Q* also enters with a positive and statistically significant coefficient, implying that firms with higher market valuations relative to their assets tend to exhibit greater AI infrastructure readiness. Among investment-related variables, *R&D* is positively and significantly associated with AI infrastructure, consistent with the notion that innovation-driven firms are more inclined to build AI capabilities. Conversely, $INTANG$ has a negative and highly significant relationship with AI infrastructure, suggesting that not all intangible-heavy firms invest in AI, or that traditional measures of intangibility may not capture AI-specific capabilities. Other firm characteristics—such as leverage (LEV), return on assets (ROA), capital expenditures ($CAPEX$), asset tangibility ($TANG$), and labor intensity ($LABOR$)—do not appear to be robust predictors, as their coefficients are statistically insignificant across both models. Model 2 incorporates lagged AI infrastructure as a control variable, which enters positively and significantly, with a coefficient of 0.281 (t=9.58), suggesting strong persistence in AI infrastructure levels over time. The inclusion of this lagged variable increases the model's explanatory power, as indicated by the rise in R^2 from 19.9% in Model 1 to 26.1% in Model 2. Overall, the results indicate that firm size, market-based valuation metrics, and R&D investments are key predictors of future AI infrastructure, while there is persistence in infrastructure levels across time. These results are consistent with McElheran et al. (2024), who find that AI adoption is more prevalent among large enterprises, highly innovative startups, and firms located in major technology hubs. Moreover, AI integration often accompanies the use of advanced technologies and firm characteristics indicative of strong growth potential.

5 Conclusion

This study introduces several key innovations in understanding the role of AI infrastructure in firm performance and stock valuation. We develop a novel, scalable methodology for measuring firm-level AI investments, providing granular insights into their economic implications. Leveraging LLMs, we analyze earnings call transcripts to construct a structured, interpretable framework for assessing AI infrastructure across firms and sectors. Our approach integrates prompt-engineered queries, Chain-of-Thought (CoT) reasoning, and zero-shot learning to create a repeatable classification system of firm-level AI infrastructure investments. Unlike prior research that focuses primarily on AI's labor market effects, our work emphasizes the strategic significance of AI infrastructure within the firm. We show that such infrastructure is a critical driver of growth, competitiveness, and financial performance. Firms with high levels of AI infrastructure consistently outperform their peers, generating higher stock returns. We also document strong associations between AI infrastructure and key firm fundamentals, including market valuation, size, R&D intensity, and growth. Firms with robust AI infrastructure tend to be larger, more innovative, and more reliant on intangible capital. To unpack these dynamics further, we decompose AI infrastructure into four core components: (1) computing hardware and software ecosystems, (2) power and energy resources, (3) data storage and management systems, and (4) technical standards and specifications. This decomposition enables a deeper understanding of the specific technological foundations that drive firm-level outcomes and value creation. The underpricing of AI infrastructure in financial markets is because its intangible benefits–such as innovation potential and long-term growth–are not fully reflected in conventional accounting metrics or short-term earnings, markets tend to undervalue these investments. This mispricing results in persistent alpha, aligning with the resource-based view of the firm, whereby AI infrastructure serves as a forward-looking signal of firm quality and long-run competitiveness.

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Table 1: **Summary Statistics**

This table presents the summary statistics. Panel A reports the summary statistics of AI infrastructure levels for S&P 500 firms[4] with quarterly earnings call transcripts. The AI infrastructure dataset covers quarterly earnings transcripts from S&P 500 firms from 2006 to 2024, while the dataset for the six categories focuses on the Generative AI boom period, spanning quarterly earnings transcripts from 2022 to 2024. The *AI Infrastructure* is a ChatGPT-generated score, assigned as 1 if ChatGPT determines that the firm has a high AI infrastructure level, and 0 if it determines that the firm has a low AI infrastructure level. Similarly, ChatGPT generates scores for four additional categories: *Computing Hardware and Software Ecosystem (CHSE)*, *Power and Energy Resources (PER)*, *Data Storage and Management Systems (DSMS)*, *Technical Standards and Specifications (TSS)*. Each category-specific score is assigned as 1 if ChatGPT determines that the firm has a high level in that category and 0 otherwise. *Ret* represents the quarterly return in the percentage format of each firm in the S&P 500 index. Panel B reports the summary statistics for firm characteristics. $SIZE$ represents the natural logarithm of total book assets. B/M represents the book-to-market ratio. *Tobin's Q* is defined as the ratio of a firm's market value of assets to its book value of assets. The market value of assets is calculated as the sum of the firm's market capitalization and the book value of debt, minus current assets. LEV is the ratio of a firm's total debt to the sum of its total debt and market equity value. ROA represents the return on assets, defined as net income divided by total assets. $CAPEX$ is capital expenditures scaled by sales. *R&D* is the ratio of Research and Development (R&D) expenditures to Total Capital Stock. Total Capital Stock represents the value of a firm's long-term investments and assets used for production. $TANG$ is defined as the ratio of Property, Plant, and Equipment (PP&E) to Total Assets, representing asset tangibility. $INTANG$ is defined as the ratio of intangible asset to Total Assets, representing asset intangibility. $LABOR$ is defined as the natural logarithm of the ratio of employment to the net value of PP&E, following Eisfeldt et al. (2024) and Donangelo (2014). Panel C reports the mean differences for each firm characteristic across two subsamples, categorized by the ChatGPT *AI Infrastructure* score. The low (high) subsample consists of earnings call transcripts with a ChatGPT *AI Infrastructure* score of 0 (1). The sample includes S&P 500 firms with earnings conference call transcripts and non-missing financial variables from 2006 to 2024. All continuous variables are winsorized at the 1% and 99% levels to limit the influence of outliers.

Panel A: Full Sample (2006–2024)

Variable	Mean	Median	Std. Dev.	5%	25%	75%	95%	Obs.
AI Infrastructure	0.092	0	0.289	0	0	0	1	19,596
Ret	1.069	1.256	4.561	−6.947	−1.641	4.002	8.319	19,596

Generative AI Boom Subsample (2022–2024)

Variable	Mean	Med.	Std. Dev.	5%	25%	75%	95%	Obs.
AI Infrastructure	0.191	0	0.393	0	0	0	1	3,676
Comput. Hard. and Soft. Eco. (CHSE)	0.324	0	0.468	0	0	1	1	3,676
Power and Energy Res. (PER)	0.421	0	0.494	0	0	1	1	3,676
Data Stor. and Mgmt Sys. (DSMS)	0.065	0	0.246	0	0	0	1	3,676
Technical Stand. and Spec. (TSS)	0.060	0	0.238	0	0	0	1	3,676

Panel B: The Summary Statistics for Firm Characteristics

Variable	Mean	Med.	Std. Dev.	5%	25%	75%	95%	Obs.
$SIZE$	9.791	9.819	1.213	7.703	8.921	10.646	11.815	15,785
B/M	0.329	0.277	0.286	0.011	0.145	0.436	0.852	15,433
$Tobin'sQ$	1.849	1.348	1.602	0.401	0.847	2.255	5.127	15,432
LEV	0.206	0.176	0.142	0.023	0.101	0.287	0.489	15,785
ROA	0.019	0.017	0.017	−0.004	0.009	0.028	0.050	15,786
$CAPEX$	0.182	0.089	0.249	0.016	0.043	0.196	0.737	15,782
$R\&D$	0.031	0.016	0.045	0.000	0.004	0.037	0.114	8,560
$TANG$	0.279	0.192	0.224	0.045	0.101	0.433	0.739	15,786
$INTANG$	0.267	0.220	0.220	0.000	0.071	0.441	0.672	15,947
$LABOR$	2.007	2.414	1.495	−1.070	1.221	3.079	3.914	15,696

Panel C: The Firm-Level Comparison bt. High *AI Infrastructure* and Low *AI Infrastructure* Firms

Variable	High *AI Infrastructure*	Low *AI Infrastructure*	Difference	*t*-statistics
$SIZE$	9.949	9.776	0.174	5.078
B/M	0.250	0.337	−0.088	−11.021
$Tobin'sQ$	2.763	1.761	1.002	22.417
LEV	0.147	0.212	−0.065	−16.617
ROA	0.022	0.019	0.003	6.000
$CAPEX$	0.153	0.185	− 0.032	−4.564
$R\&D$	0.053	0.027	0.026	17.563
$TANG$	0.187	0.288	−0.101	−16.326
$INTANG$	0.292	0.265	0.027	4.459
$LABOR$	2.356	1.974	0.382	9.012

Table 2: **Firms with High and Low AI Infrastructure Level**

This table presents the 10 firms with the highest and lowest AI infrastructure levels among S&P 500 firms,[a] based on their market capitalization as of September 30, 2024. Panel A lists firms with the highest AI infrastructure levels, while Panel B lists those with the lowest levels. Firms are also evaluated across the following categories: *Computing Hardware and Software Ecosystem (CHSE)*, *Power and Energy Resources (PER)*, *Data Storage and Management Systems (DSMS)*, and *Technical Standards and Specifications (TSS)*. Each category-specific score is generated by ChatGPT and assigned a value of 1 if the firm is determined to have a high level in that category and 0 otherwise. MktVal represents the firm's market capitalization in billions of U.S. dollars. NAICS Industry is classified at the three-digit NAICS level.

Panel A: Top 10 large firms with the high AI infrastructure level

Company Name	MktVal	NAICS 3-Digit Industry	**AI**	*CHSE*	*PER*	*DSMS*	*TSS*
Apple Inc.	3,522	Computer and Electronic Product Mfg.	**1**	1	1	0	1
Microsoft Corporation	3,199	Software Publishing Industries	**1**	1	1	1	1
NVIDIA Corporation	2,979	Computer and Electronic Product Mfg.	**1**	1	1	1	0
Amazon.com, Inc.	1,959	Nonstore Retailers	**1**	1	1	0	0
Meta Platforms, Inc.	1,248	Other Information Svcs	**1**	1	1	0	1
Alphabet Inc.	929	Data Processing, Hosting, & Related Svcs	**1**	1	1	1	1
Tesla, Inc.	839	Transportation Equipment Mfg.	**1**	1	1	0	0
Oracle Corporation	472	Professional, Scientific, and Technical Svcs	**1**	1	1	1	1
Advanced Micro Devices, Inc.	266	Computer and Electronic Product Mfg.	**1**	1	1	1	0
Salesforce, Inc.	262	Software Publishing Industries	**1**	1	0	1	0

Panel B: Top 10 large firms with the low AI infrastructure level

Company Name	MktVal	NAICS 3-Digit Industry	**AI**	*CHSE*	*PER*	*DSMS*	*TSS*
Eli Lilly and Company	842	Chemical Manufacturing	**0**	1	1	0	0
Broadcom Inc.	806	Computer and Electronic Product Mfg.	**0**	0	0	0	0
Walmart Inc.	649	General Merchandise Retailers	**0**	0	0	0	0
Exxon Mobil Corporation	521	Petroleum & Coal Mfg.	**0**	0	1	0	0
The Procter & Gamble Company	407	Chemical Manufacturing	**0**	0	0	0	0
The Home Depot, Inc.	402	Build. Mat., Gard. Equip., Supplies Dealers	**0**	0	0	0	0
Costco Wholesale Corporation	393	General Merchandise Retailers	**0**	0	0	0	0
Johnson & Johnson	390	Chemical Manufacturing	**0**	0	0	0	0
AbbVie Inc.	349	Chemical Manufacturing	**0**	0	0	0	0
The Coca-Cola Company	310	Food Manufacturing	**0**	0	0	0	0

[a] Excluding financial and insurance firms, real estate companies, and other related industries.

Table 3: **Equal-weighted and Value-weighted Portfolios Sorted by AI Infrastrucure Levels**

This table presents the average quarterly returns of equal-weighted and value-weighted binary portfolios sorted by AI infrastructure level. The AI infrastructure level is measured by *AI Infrastructure*, a ChatGPT-generated score where 1 indicates firms with high AI infrastructure levels and 0 indicates firms with low AI infrastructure levels. We report average raw returns, Capital Asset Pricing Model (CAPM) alphas, Carhart four-factor (Carhart) alphas, and Fama-French five-factor (FF-5) alphas for each portfolio. Panel A (Panel C) reports equal (value) weight portfolio results for S&P 500 firms with earnings conference call transcripts and complete financial variables from 2014 to 2024. Panel B (Panel D) reports equal (value) weight portfolio results results for the sample that excludes firms in tech sectors, specifically NAICS 51 (Information) and NAICS 54 (Business Services), following the approach of Acemoglu et al. (2022) and Eisfeldt et al. (2024). The sample period is from January 2014 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Panel A: Equal-weighted Full S&P 500 Sample

	Low	High	High−Low
Average Return	1.019	1.531	0.514**
	(2.44)	(3.43)	(2.61)
CAPM Alpha	0.125	0.573	0.448**
	(0.76)	(3.87)	(2.42)
Carhart Alpha	0.210	0.571	0.361**
	(1.69)	(4.78)	(2.54)
FF5 Alpha	0.170	0.547	0.377**
	(1.48)	(4.47)	(2.54)

Panel B: Equal-weighted Non-Tech S&P 500 Sample

	Low	High	High−Low
Average Return Excluding Tech	1.018	1.453	0.435**
	(2.40)	(3.15)	(2.19)
CAPM Alpha Excluding Tech	0.117	0.471	0.354**
	(0.62)	(3.00)	(1.96)
Carhart Alpha Excluding Tech	0.198	0.480	0.282**
	(1.42)	(3.16)	(1.96)
FF5 Alpha Excluding Tech	0.151	0.429	0.278**
	(1.18)	(3.17)	(1.96)

Panel C: Value-weighted Full S&P 500 Sample

	Low	High	High−Low
Average Return	0.870	1.745	0.875**
	(2.26)	(3.64)	(2.42)
CAPM Alpha	0.036	0.901	0.865**
	(0.31)	(2.45)	(1.98)
Carhart Alpha	-0.031	0.661	0.692**
	(-0.28)	(3.21)	(2.58)
FF5 ALPHA	-0.069	0.663	0.732***
	(-0.80)	(3.16)	(2.85)

Panel D: Value-weighted Non-Tech S&P 500 Sample

	Low	High	High−Low
Average Return Excluding Tech	0.880	1.810	0.930**
	(2.22)	(3.49)	(2.22)
CAPM Alpha Excluding Tech	0.029	0.950	0.921**
	(0.23)	(2.20)	(2.53)
Carhart Alpha Excluding Tech	−0.041	0.727	0.768**
	(−0.36)	(2.97)	(2.05)
FF5 Alpha Excluding Tech	−0.078	0.731	0.809***
	(−0.75)	(3.20)	(2.97)

Table 4: **Value-weighted Portfolios Sorted by AI Infrastrucure Levels During the Adverse Market Conditions**

This table presents the average quarterly returns of value-weighted binary portfolios sorted by AI infrastructure level during adverse market conditions. Macroeconomic and market conditions are characterized by the Chicago Fed National Activity Index ($CFNAI$), Gross Domestic Product (GDP), the Industrial Production Index ($INDPRO$), and the S&P 500 Index ($S\&P$ 500). The $CFNAI$ is a composite measure derived from 85 monthly indicators encompassing production, employment, and consumption. GDP represents the total monetary value of all goods and services produced within a country. $INDPRO$ measures the real output of the manufacturing, mining, and utilities sectors. The $S\&P$ 500 Index reflects the market capitalization-weighted performance of 500 leading publicly traded U.S. companies. In Panels A and B, the $CFNAI$, GDP, $INDPRO$, and $S\&P$ 500 are below their respective means during the sample period. Panel A reports value weight portfolio results for S&P 500 firms with earnings conference call transcripts and complete financial variables from 2014 to 2024. Panel B reports value weight portfolio results results for the sample that excludes firms in tech sectors, specifically NAICS 51 (Information) and NAICS 54 (Business Services), following the approach of Acemoglu et al. (2022) and Eisfeldt et al. (2024). The AI infrastructure level is measured by *AI Infrastructure*, a ChatGPT-generated score where 1 denotes firms with high AI infrastructure levels and 0 denotes firms with low AI infrastructure levels. Average raw returns are reported. The sample period is from January 2014 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Panel A: Value-weighted Full $S\&P$ 500 Sample

	Low	High	High−Low
Low $CFNAI$	0.052	1.100	1.048**
	(0.40)	(2.21)	(1.99)
Low GDP	0.972	1.724	0.752**
	(2.53)	(3.63)	(2.43)
Low $INDPRO$	1.750	2.742	0.992**
	(3.64)	(4.93)	(2.72)
Low $S\&P$ 500	0.479	1.570	1.091***
	(1.00)	(3.18)	(3.10)

Panel B: Value-weighted Non-Tech $S\&P$ 500 Sample

	Low	High	High−Low
Low $CFNAI$ Excluding Tech	0.031	1.122	1.091**
	(0.22)	(1.98)	(1.96)
Low GDP Excluding Tech	0.943	1.782	0.839**
	(2.40)	(3.53)	(2.64)
Low$INDPRO$ Excluding Tech	1.799	2.671	0.872**
	(3.55)	(4.52)	(2.26)
Low $S\&P$ 500 Excluding Tech	0.428	1.668	1.240***
	(0.87)	(3.18)	(3.31)

Table 5: **Equal-Weighted Portfolios Double-Sorted by Firm Characteristics and AI Infrastructure Levels**

This table presents the average quarterly returns of equal-weighted binary portfolios double-sorted by firm characteristics and AI infrastructure levels. $SIZE$ represents the natural logarithm of total book assets. PRC represents the price of the stock. B/M represents the book-to-market ratio. LEV is the ratio of a firm's total debt to the sum of its total debt and market equity value. ROA represents the return on assets, defined as net income divided by total assets. $LABOR$ is defined as the natural logarithm of the ratio of employment to the net value of PP&E, following Eisfeldt et al. (2024) and Donangelo (2014). The AI infrastructure level is measured by *AI Infrastructure*, a ChatGPT-generated score where 1 denotes firms with high AI infrastructure levels and 0 denotes firms with low AI infrastructure levels. Average raw returns are reported. The sample period is from January 2014 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

$SIZE$	Low	High	High−Low
Small	1.220	1.630	0.41
	(2.69)	(2.87)	(1.53)
Large	0.730	1.470	0.74***
	(1.89)	(3.40)	(2.77)

PRC	Low	High	High−Low
Low	1.090	1.460	0.37
	(2.38)	(2.94)	(1.57)
High	0.940	1.650	0.71***
	(2.35)	(3.54)	(2.98)

B/M	Low	High	High−Low
Small	1.120	1.620	0.50*
	(2.70)	(3.07)	(1.70)
Large	0.840	1.170	0.33
	(1.91)	(2.40)	(1.44)

LEV	Low	High	High−Low
Low	1.030	1.730	0.69***
	(2.48)	(3.44)	(3.19)
High	0.940	1.130	0.19
	(2.11)	(2.36)	(0.79)

ROA	Low	High	High−Low
Low	0.830	1.430	0.61**
	(1.84)	(3.00)	(2.10)
High	1.150	1.680	0.53**
	(2.83)	(3.43)	(2.21)

$LABOR$	Low	High	High−Low
Low	0.840	1.800	0.96***
	(2.04)	(4.05)	(2.99)
High	1.140	1.350	0.21
	(2.50)	(2.61)	(0.94)

Table 6: **Fama-MacBeth Return Prediction Regression for the Full Sample Period**

This table presents the Fama-MacBeth regression results from regressing Ret_{t+1} on the AI infrastructure level measure, *AI Infrastructure*, at time t, controlling for asset pricing factors and firm characteristics at time t. Ret_{t+1} represents the firm's return in the first quarter following the observation of the quarterly return Ret_t. *AI Infrastructure* is a ChatGPT-generated score, assigned as 1 if ChatGPT determines that the firm has a high AI infrastructure level, and 0 if it determines that the firm has a low AI infrastructure level. The asset pricing factors are defined in Section 4.3. The firm characteristics are defined in Table 1. Standard errors are clustered at the firm level to account for potential within-firm correlation. The sample period is from January 2006 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
AI Infrastructure	0.003**	0.004***	0.003**	0.005***	0.006***	0.005***
	(2.10)	(2.93)	(2.43)	(2.99)	(3.79)	(2.79)
Ret_t	−0.072***	−0.010	−0.029***	−0.068***	−0.009	−0.022
	(−8.06)	(−1.02)	(−3.03)	(−5.38)	(−0.65)	(−1.53)
$MKTRF$	0.681***	2.164	4.262*	0.748***	9.185***	6.375***
	(33.02)	(0.97)	(1.85)	(25.77)	(32.75)	(20.66)
SMB	0.157***	4.201	7.734	0.171***	−12.407***	−7.575***
	(6.04)	(0.82)	(1.51)	(4.96)	(−26.26)	(−14.95)
HML	−0.305***	5.161	10.621	−0.373***	15.247***	12.249***
	(−12.46)	(0.70)	(1.50)	(−10.38)	(42.82)	(24.28)
RMW	0.115***	5.397	8.480*	0.195***	−0.734***	0.492**
	(3.99)	(1.07)	(1.70)	(4.65)	(−3.28)	(2.13)
CMA	0.456***	−3.967	−9.99	0.406***	−2.232***	−2.340***
	(12.28)	(−0.57)	(−1.47)	(7.24)	(−11.87)	(−10.46)
UMD	−0.130***	3.536	7.626	−0.174***		
	(−8.98)	(0.72)	(1.54)	(−7.56)		
$SIZE$				−0.002***	−0.002***	−0.007***
				(−4.51)	(−3.94)	(−3.61)
B/M				−0.001*	0.001	0.001
				(−1.80)	(0.83)	(0.69)
Tobin's Q				0.001	0.001	−0.002***
				(0.61)	(0.25)	(−3.21)
LEV				0.015**	0.011*	0.043***
				(2.32)	(1.70)	(3.75)
ROA				0.034	0.024	0.059*
				(0.99)	(0.73)	(1.94)
$CAPEX$				0.001	−0.010**	−0.009**
				(0.08)	(−2.42)	(−2.31)
R&D				−0.003	−0.004	−0.008***
				(−0.75)	(−1.09)	(−5.84)
$TANG$				−0.005	0.002	0.022*
				(−1.36)	(0.44)	(1.77)
$INTANG$				−0.008***	−0.006*	−0.006
				(−2.79)	(−1.94)	(−0.84)
$LABOR$				0.001	0.000	0.005*
				(1.30)	(0.36)	(1.87)
Constant	0.004***	0.104	0.218	0.022***	−0.172***	−0.074***
	(11.34)	(0.74)	(1.57)	(4.16)	(−15.94)	(−2.97)
N	15,762	15,762	15,762	8,245	8,245	8,245
R^2	13.5%	30.8%	32.4%	15.3%	32.9%	35.6%
Firm FE	No	No	Yes	No	No	Yes
Industry FE	No	Yes	No	No	Yes	No
YQ FE	No	Yes	Yes	No	Yes	Yes

Table 7: **Fama-MacBeth Return Prediction Regression for the Generative AI Boom Period**

This table presents the Fama-MacBeth regression results from regressing Ret_{t+1} on the AI infrastructure level measure, *AI Infrastructure*, at time t, controlling for asset pricing factors and firm characteristics at time t. Ret_{t+1} represents the firm's return in the first quarter following the observation of the quarterly return Ret_t. *Computing Hardware and Software Ecosystem (CHSE)*, *Power and Energy Resources (PER)*, *Data Storage and Management Systems (DSMS)*, and *Technical Standards and Specifications (TSS)* are ChatGPT-generated scores, assigned as 1 if ChatGPT determines that the firm has a high level and 0 otherwise. The firm characteristics are defined in Table 1. Standard errors are clustered at the firm level to account for potential within-firm correlation. The sample period is from January 2022 to December 2024 for the Generative AI Boom Period. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8	Model 9	Model 10
AI Infrastructure	0.007***					0.007***				
	(3.80)					(2.89)				
$CHSE$		0.004**					0.006***			
		(2.34)					(2.61)			
PER			0.004***					0.005**		
			(2.85)					(2.24)		
$DSMS$				0.010***					0.011**	
				(3.25)					(2.57)	
TSS					0.008**					0.008*
					(2.14)					(1.83)
Ret_t	−0.032	−0.033	−0.033	−0.034	−0.033	−0.015	0.006	−0.017	−0.017	0.008
	(−1.35)	(−1.40)	(−1.37)	(−1.41)	(−1.35)	(−0.46)	(0.20)	(−0.54)	(−0.53)	(0.25)
$SIZE$						0.002	0.001	0.002*	0.002*	0.001
						(1.57)	(1.28)	(1.87)	(1.66)	(1.21)
B/M						−0.004***	−0.004***	−0.004***	−0.004***	−0.004***
						(−6.59)	(−6.35)	(−6.95)	(−6.35)	(−5.69)
Tobin's Q						0.001	0.001	0.001	0.001	0.001
						(0.68)	(0.46)	(0.51)	(0.66)	(0.41)
LEV						0.009	0.001	0.009	0.007	0.000
						(0.84)	(0.13)	(0.88)	(0.71)	(0.04)
ROA						0.06	0.052	0.059	0.051	0.053
						(1.26)	(1.14)	(1.22)	(1.06)	(1.16)
$CAPEX$						−0.004	0.001	−0.004	−0.003	0.004
						(−0.33)	(0.18)	(−0.38)	(−0.31)	(0.49)
R&D						0.003	0.002	0.007	0.006	−0.004
						(0.15)	(0.10)	(0.43)	(0.35)	(−0.22)
$TANG$						0.006	−0.005	0.005	0.004	−0.007
						(0.39)	(−0.44)	(0.36)	(0.26)	(−0.71)
$INTANG$						−0.007	−0.011	−0.007	−0.008	−0.012
						(−0.89)	(−1.47)	(−0.83)	(−0.99)	(−1.54)
$LABOR$						0.002	0.004***	0.002	0.002	0.004***
						(1.06)	(2.63)	(1.13)	(1.10)	(2.81)
Constant	−0.027***	−0.024***	−0.026***	−0.024***	−0.025***	−0.045***	−0.037***	−0.048***	−0.042***	−0.035**
	(−10.39)	(−9.82)	(−10.14)	(−9.68)	(−9.79)	(−3.22)	(−2.73)	(−3.48)	(−3.14)	(−2.48)
N	3,019	3,019	3,019	3,019	3,019	1,608	1,608	1,608	1,608	1,608
R^2	24.9%	24.7%	24.7%	24.8%	24.7%	24.4%	21.8%	24.3%	24.4%	21.7%
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: **Fama-MacBeth Regression Results: Return Prediction Controlling for Standard Anomalies**

This table presents the Fama-MacBeth regression results from regressing Ret_{t+1} on the AI infrastructure level measure, *AI Infrastructure*, at time t, controlling for asset pricing factors and firm characteristics at time t. Ret_{t+1} represents the firm's return in the first quarter following the observation of the quarterly return Ret_t. *AI Infrastructure* is a ChatGPT-generated score, assigned as 1 if ChatGPT determines that the firm has a high AI infrastructure level, and 0 if it determines that the firm has a low AI infrastructure level. *DRP* (Distress Risk Probability) as introduced by Campbell et al. (2008) quantifies a firm's likelihood of failure as a percentage, derived through a dynamic logistic regression model. This model integrates both financial accounting measures and market-based indicators, including stock price behavior, the book-to-market ratio, return volatility, firm size relative to the S&P 500 Index, and cumulative abnormal returns over the same benchmark. In contrast, *OOS* (Ohlson's O-score) (Griffin and Lemmon (2002); Dichev (1998)) is based on a static framework relying solely on accounting ratios such as net income over total assets, working capital relative to market-valued assets, and the ratio of current liabilities to current assets. *NSI* (Net stock issuance) (Ritter (1991); Loughran and Ritter (1995)) is computed as the annual logarithmic change in the number of outstanding shares, adjusted for corporate actions like stock splits, following the methodology of Fama and French (2008). Similarly, *CEI* (Composite equity issuance) (Daniel and Titman (2006)) reflects the difference between the 12-month change in market capitalization and the firm's stock return over the same period. *NOA* (Net operating assets) (Hirshleifer et al. (2004)) represent the difference between a firm's operating assets and liabilities, normalized by lagged total assets. Regarding profitability, both *ROA* (Return on Assets) (Fama and French (2006); Chen et al. (2014))—net income divided by total assets—and *Prof* (Profitability) (Novy-Marx (2013))—gross profits over current assets—serve as common indicators. *AG* (Asset growth), as discussed by Cooper et al. (2008), captures the year-over-year percentage change in total assets. Finally, *ItoA* (Investment-to-assets) (Titman et al. (2004); Xing (2008)) measures annual investment activity by computing the change in gross property, plant, and equipment plus inventory, scaled by prior-period total assets. The sample period is from January 2006 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Model 1	Model 2	Model 3	Model 4
AI Infrastructure	0.004**	0.003**	0.004**	0.003**
	(2.05)	(2.22)	(2.00)	(2.01)
DRP	−0.024***	−0.024***	−0.024***	−0.024***
	(−6.58)	(−7.75)	(−6.62)	(−7.80)
OOS	0.001	0.001	0.001	0.002
	(1.55)	(1.49)	(1.54)	(1.51)
NSI	0.002	0.001	0.004	0.002
	(0.97)	(0.42)	(1.50)	(0.83)
CEI	0.003	0.001	0.003	0.001
	(0.90)	(0.51)	(0.89)	(0.44)
NOA	−0.009***	−0.008***	−0.009***	−0.008***
	(3.35)	(3.49)	(2.84)	(3.00)
Prof	0.003	0.005**	0.000	0.004
	(1.11)	(2.12)	(0.01)	(1.37)
AG	0.005	0.004	0.005	0.005
	(1.17)	(1.18)	(1.04)	(1.41)
ROA	0.001	0.011*	0.001	0.011*
	(0.09)	(1.82)	(0.19)	(1.69)
ItoA	−0.010*	−0.003	−0.012*	−0.006
	(−1.78)	(−0.59)	(−1.96)	(−1.19)
Constant	0.027***	0.037***	0.034***	0.045***
	(5.76)	(5.00)	(2.87)	(3.81)
N	9,648	9,648	9,648	9,648
R^2	0.8%	30.6%	1.4%	31.1%
Industry FE	No	No	Yes	Yes
YQ FE	No	Yes	No	Yes

Table 9: **AI Infrastructure Level as a Predictor of Corporate Fundamentals for the Full Sample Period**

This table presents the Fama-MacBeth regression results from regressing the change in corporate fundamental variables from time t to $t+1$ on the level of AI infrastructure., *AI Infrastructure*, at time t, controlling for firm characteristics at time t. *AI Infrastructure* at t is a ChatGPT-generated score, assigned as 1 if ChatGPT determines that the firm has a high AI infrastructure level, and 0 if it determines that the firm has a low AI infrastructure level. The firm characteristics are defined in Table 1. Standard errors are clustered at the firm level to account for potential within-firm correlation. The sample period is from January 2006 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

	Model 1	Model 2	Model 3	Model 4
	$\Delta SIZE$	Δ *LEV*	Δ *Tobin's Q*	Δ *R&D*
AI Infrastructure	0.015***	−0.002*	0.077**	0.006***
	(3.77)	(−1.78)	(2.53)	(3.37)
SIZE	−0.015***			
	(−10.30)			
LEV		−0.081***		
		(−16.94)		
Tobin's Q			−0.035***	
			(−3.59)	
R&D				−0.264***
				(−16.44)
Constant	0.162***	0.003	−0.120**	0.009***
	(8.53)	(0.26)	(−2.44)	(2.73)
N	15,762	14,584	15,408	7,639
R^2	4.2%	12.9%	4.9%	29.5%
Industry FE	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes

Table 10: **AI Infrastructure Level as a Predictor of Corporate Fundamentals for the Generative AI Boom Period**

This table presents the Fama-MacBeth regression results from regressing corporate fundamental variables at $t+1$ on the AI infrastructure level measure, *AI Infrastructure*, at time t, controlling for firm characteristics at time t. *AI Infrastructure* at t is a ChatGPT-generated score, assigned as 1 if ChatGPT determines that the firm has a high AI infrastructure level, and 0 if it determines that the firm has a low AI infrastructure level. *Computing Hardware and Software Ecosystem (CHSE)*, *Power and Energy Resources (PER)*, *Data Storage and Management Systems (DSMS)*, and *Technical Standards and Specifications (TSS)* are ChatGPT-generated scores, assigned as 1 if ChatGPT determines that the firm has a high level and 0 otherwise. The firm characteristics are defined in Table 1. Standard errors are clustered at the firm level to account for potential within-firm correlation. The sample period is from January 2022 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$.

Panel A	Model 1	Model 2	Model 3	Model 4	Model 5
	Δ *SIZE*	Δ *LEV*	Δ *ROA*	Δ *Tobin's Q*	Δ *R&D*
CHSE	0.010***	−0.003**	0.002**	0.058**	0.004**
	(3.38)	(−2.54)	(2.08)	(2.41)	(2.13)
SIZE	−0.005***				
	(−3.86)				
LEV		−0.005			
		(−1.62)			
ROA			−0.321***		
			(−6.34)		
Tobin's Q				0.034	
				(1.45)	
R&D					−0.141**
					(−2.31)
CAPEX					
Constant	0.048***	0.015***	0.007***	−0.286***	0.002*
	(3.79)	(10.06)	(4.91)	(−4.46)	(1.73)
N	3,019	3,019	2,988	2,947	1,523
R^2	1.9%	8.3%	16.0%	5.8%	26.9%
Industry FE	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes

Panel B	Model 1	Model 2	Model 3	Model 4	Model 5
	Δ *SIZE*	Δ *LEV*	Δ *Tobin's Q*	Δ *CAPEX*	Δ *R&D*
PER	0.008***	−0.002**	0.082***	0.030***	0.002**
	(3.00)	(−2.09)	(2.65)	(3.63)	(2.12)
SIZE	−0.005***				
	(−4.02)				
LEV		−0.009***			
		(−2.68)			
ROA					
Tobin's Q			0.037		
			(1.54)		
R&D					−0.203***
					(−4.17)
CAPEX				−0.295***	
				(−4.52)	
Constant	0.052***	0.014***	−0.307***	0.079***	0.003**
	(3.99)	(10.65)	(−4.34)	(10.16)	(2.26)
N	3,019	2,965	2,947	2,987	1,389
R^2	1.7%	9.4%	6.1%	42.1%	45.1%
Industry FE	Yes	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes	Yes

Panel C	Model 1	Model 2	Model 3	Model 4
	Δ *SIZE*	Δ *LEV*	Δ *Tobin's Q*	Δ *R&D*
DSMS	0.018**	−0.004**	0.264*	0.004***
	(2.03)	(−2.25)	(1.92)	(3.12)
SIZE	−0.005***			
	(−4.04)			
LEV		−0.009***		
		(−2.85)		
Tobin's Q			0.089***	
			(5.12)	
R&D				−0.187***
				(−3.71)
Constant	0.053***	0.013***	−0.281***	0.004**
	(4.16)	(10.78)	(−6.40)	(2.55)
N	3,019	2,965	2,828	1,466
R^2	1.8%	9.4%	17.0%	40.3%
Industry FE	Yes	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes	Yes

Panel D	Model 1	Model 2	Model 3
	Δ *SIZE*	Δ *Tobin's Q*	Δ *R&D*
TSS	0.023***	0.152*	0.006**
	(2.64)	(1.96)	(2.52)
SIZE	−0.005***		
	(−4.03)		
Tobin's Q		0.090***	
		(4.72)	
R&D			−0.189***
			(−3.75)
Constant	0.054***	−0.271***	0.004***
	(4.13)	(−6.49)	(2.68)
N	3,019	2,828	1,466
R^2	2.0%	16.0%	40.7%
Industry FE	Yes	Yes	Yes
YQ FE	Yes	Yes	Yes

Table 11: **Determinants of AI Infrastructure Level**

This table presents the Fama-MacBeth regression results from regressing AI infrastructure level measure, *AI Infrastructure*, at time $t+1$ on corporate fundamental variables at t , controlling for *AI Infrastructure*, at time t and firm characteristics at time t. *AI Infrastructure* is a ChatGPT-generated score, assigned as 1 if ChatGPT determines that the firm has a high AI Infrastructure level, and 0 if it determines that the firm has a low AI Infrastructure level. The firm characteristics are defined in Table 1. Standard errors are clustered at the firm level to account for potential within-firm correlation. The sample period is from January 2006 to December 2024. t-statistics are shown in parentheses. $*p < 0.1; **p < 0.05; ***p < 0.01$..

	Model 1	Model 2
AI Infrastructure		0.281***
		(9.58)
$SIZE$	0.035***	0.025***
	(4.02)	(4.20)
B/M	−0.001***	−0.001***
	(−2.74)	(−2.67)
Tobin's Q	0.014**	0.010**
	(2.45)	(2.35)
LEV	−0.108	−0.071
	(−1.43)	(−1.25)
ROA	−0.304	−0.188
	(−1.43)	(−1.15)
$CAPEX$	0.051	0.038
	(1.06)	(1.01)
R&D	0.058**	0.054**
	(2.01)	(2.57)
$TANG$	−0.141	−0.112
	(−1.39)	(−1.48)
$INTANG$	−0.150***	−0.113***
	(−3.55)	(−3.70)
$LABOR$	−0.004	−0.003
	(−0.26)	(−0.29)
Constant	−0.325***	−0.231***
	(−2.61)	(−2.66)
N	8,273	8,273
R^2	19.9%	26.1%
Industry FE	Yes	Yes
YQ FE	Yes	Yes

Appendix

Appendix A: Classifying Technology infrastructure Components Using APICalls and Chain of Thought (CoT)

0. API Call and CoT Examples for Classifying AI Infrastructure Level

API Call for Classifying AI Infrastructure Level

We make an API call to OpenAI's GPT model to classify a company's *AI Infrastructure* level based on its third-quarter 2024 earnings transcript. First, We initialize a request to GPT-3.5-turbo, specifying a temperature of 0, which ensures the response is as deterministic and consistent as possible. Then, We define the system role by using the system message to instruct the AI to act as a financial expert with experience in stock recommendations. The prompt tells the model to evaluate the earnings transcript and classify the company's *AI Infrastructure* level.

We use zero-shot prompting combined with Chain of Thought (CoT) reasoning to improve the model's decision-making process. The prompt reads as follows:

> Forget all previous instructions. Pretend you are a financial expert with stock recommendation experience. We'll provide a description of an earnings transcript, and you need to determine whether this company has high *AI Infrastructure*. Follow this structured approach before giving your final answer:
>
> 1. Identify AI-related Investments: Look for mentions of *AI Infrastructure*, data centers, machine learning applications, or cloud computing.
> 2. Assess Significance: Determine whether AI is a core part of the company's business strategy or just a minor component.
> 3. Consider Industry Context: Compare this company's AI investments with industry standards.
> 4. Final Decision: Based on the above factors, respond with "High" if *AI Infrastructure* is significant, otherwise "Low."
>
> The AI is guided to follow these logical steps before making a decision.

AI Infrastructure CoT Classification for Apple (AAPL)

Identify AI-related Investments:

- The transcript mentions "Apple intelligence," which builds on years of innovation and investment in AI and Machine Learning.

- Apple intelligence is described as a transformative set of capabilities that will enrich customers' lives through features like notification summaries, reduced interruptions, and more.

Assess Significance:

- AI is a core part of Apple's business strategy, as they have made significant investments in AI and Machine Learning over the years.
- The rollout of Apple intelligence is a major focus, with features designed to enhance user experiences across various apps and services.

Consider Industry Context:

- Apple's focus on AI aligns with industry trends where tech companies are increasingly integrating AI into their products and services.
- The level of investment and emphasis on AI at Apple is significant compared to industry standards, showcasing a strong commitment to *AI Infrastructure*.

Final Decision: Based on the above analysis, We would classify Apple as having **High** *AI Infrastructure*. The significant investments in AI, the core integration of Apple intelligence into various products, and the strategic importance placed on AI technology indicate a strong commitment to *AI Infrastructure* within the company.

1. API Call and CoT Examples for Classifying *Computing Hardware and Software Ecosystem (CHSE)* Level

API Call for Classifying *CHSE* Level

We make an API call to OpenAI's GPT model to classify a company's *CHSE* level based on its third-quarter 2024 earnings transcript. First, We initialize a request to GPT-3.5-turbo, specifying a temperature of 0, which ensures the response is as deterministic and consistent as possible. We then define the system role by using the system message to instruct the AI to act as a financial expert with experience in stock recommendations. The prompt tells the model to evaluate the earnings transcript and classify the company's *Computing Hardware and Software Ecosystem* level.

We use zero-shot prompting combined with Chain of Thought (CoT) reasoning to guide the model's decision-making process. The prompt is structured as follows:

Forget all previous instructions. Pretend you are a financial expert with stock recommendation experience. We'll provide a description of an earnings transcript, and you need to determine whether this company has high CHSE. Follow this structured approach before giving your final answer:

1. Identify Key Components of CHSE: The AI is instructed to look for mentions of high-performance processors such as GPUs, TPUs, and CPUs optimized for parallel processing and matrix computations. It is also told to check for references to distributed computing systems, memory architectures designed for AI workloads, edge computing resources, or cloud computing infrastructure.
2. Evaluate AI-Related Software: The AI is asked to look for software tools and platforms that facilitate AI, such as machine learning frameworks (e.g., TensorFlow, PyTorch) and MLOps tools that streamline the deployment and monitoring of AI systems. It should also check for mentions of data preprocessing and analysis tools, along with model optimization and compression tools designed to enhance computational efficiency.
3. Assess Significance: The model is guided to determine whether these hardware and software systems are critical to the company's operations or if they represent only a small part of the company's overall technology stack. The AI must consider whether these systems are central to the company's strategic direction or not.
4. Industry Context: The AI is prompted to compare the company's investments in computing hardware and software with industry standards. The model should assess whether the company is keeping pace with industry trends or leading in its sector when it comes to computing infrastructure.
5. Final Decision: Based on the above steps, the model is instructed to make its final decision. It should respond with "High" if the company's Computing Hardware and Software Ecosystem is significant and advanced, and "Low" if the infrastructure does not meet the required standard.

Through this structured Chain of Thought approach, the AI is guided to logically analyze and make a well-informed decision before providing the final classification.

CHSE CoT Classification for Apple (AAPL)

Identify Key Components of CHSE:

- The transcript mentions Apple's significant investments in AI and Machine Learning, referred to as Apple intelligence.
- Apple highlights the transformative capabilities of Apple intelligence across various platforms, emphasizing on-device processing and private cloud compute.
- The company discusses the integration of ChatGPT into experiences within iPhone, Mac, and iPad, showcasing a broad base of world knowledge.

Evaluate AI-Related Software:

- Apple emphasizes the rollout of Apple intelligence features, such as notification summaries and reduced interruptions, which are positively received by developers.
- The company plans a staggered launch of Apple intelligence features, starting with US English in the fall and expanding to more functionalities over the next year.

Assess Significance:

- Apple's focus on Apple intelligence and AI-related software tools is a core part of their operations, with significant investments and a commitment to innovation in AI and Machine Learning.
- The company's dedication to enhancing user experiences through AI and machine learning technologies indicates the importance of these systems in their ecosystem.

Industry Context:

- Apple's investments in AI and Machine Learning technologies align with industry trends where companies are increasingly leveraging AI to enhance user experiences and drive innovation.
- The company's focus on AI and Machine Learning is in line with the tech industry's emphasis on developing intelligent systems to improve products and services.

Final Decision: Based on the analysis of the earnings transcript, Apple demonstrates a high level of commitment and investment in $CHSE$. The significant focus on Apple intelligence, AI-related software tools, and the integration of AI capabilities across various devices indicate that Computing Hardware and Software Ecosystem is significant and advanced for Apple.

Therefore, the classification for Apple based on the provided earnings transcript is **High** for $CHSE$. Apple's strategic emphasis on AI and Machine Learning technologies positions them as a leader in this space within the industry.

2. API Call and CoT Examples for Classifying *Power and Energy Resources (PER)* Level

API Call for Classifying *PER* Level

We make an API call to OpenAI's GPT model to classify a company's *PER* level based on its third-quarter 2024 earnings transcript. First, We initialize a request to GPT-3.5-turbo, specifying a temperature of 0, which ensures the response is as deterministic and consistent as possible. We then define the system role by using the system message to instruct the AI to act as a financial expert with experience in stock recommendations. The prompt tells the model to evaluate the earnings transcript and classify the company's *Power and Energy Resources* level.

We use zero-shot prompting combined with Chain of Thought (CoT) reasoning to guide the model's decision-making process. The prompt is structured as follows:

> Forget all previous instructions. Pretend you are a financial expert with stock recommendation experience. We'll provide a description of an earnings transcript, and you need to determine whether this company has high PER. Follow this structured approach before giving your final answer:
>
> 1. Identify Key Components of PER: Look for mentions of energy-efficient computing architectures that reduce operational costs and environmental impact. Check for references to power-efficient hardware designs, optimized data center energy usage, and innovative power management solutions.
> 2. Evaluate Cooling and Power infrastructure: Determine whether the company implements advanced cooling systems to maintain AI hardware reliability under intensive workloads. Look for mentions of liquid cooling, immersion cooling, or other energy-saving temperature regulation methods.
> 3. Assess Renewable Energy Integration: Identify whether the company integrates renewable energy sources such as solar, wind, or hydroelectric power into its *AI Infrastructure*. Analyze if they use battery storage or grid-balancing strategies to enhance sustainability.

4. Examine Backup and Resilience Systems: Check whether the company has robust backup power solutions, such as uninterruptible power supplies (UPS) or on-site energy storage, to ensure operational continuity during outages.
5. Industry Context: Compare the company's investment in PER to industry benchmarks. Wes the company leading in sustainable *AI Infrastructure*, or is it lagging behind competitors?
6. Final Decision: Based on the above factors, respond with "High" if the company's Power and Energy Resources (PER) are significant and advanced, otherwise "Low".

Through this structured Chain of Thought approach, the AI is guided to logically analyze and make a well-informed decision before providing the final classification.

PER CoT Classification for Apple (AAPL)

Identify Key Components of PER: The transcript does not contain specific mentions of energy-efficient computing architectures, power-efficient hardware designs, or innovative power management solutions related to PER.

Evaluate Cooling and Power infrastructure: There is no information provided regarding advanced cooling systems like liquid cooling or immersion cooling that could indicate a focus on energy-saving temperature regulation methods.

Assess Renewable Energy Integration: The transcript mentions Apple's commitment to operating all data centers on 100% renewable energy, which aligns with renewable energy integration practices in PER.

Examine Backup and Resilience Systems: There is no explicit mention of backup power solutions like uninterruptible power supplies (UPS) or on-site energy storage in the transcript.

Industry Context: Apple's dedication to using 100% renewable energy in its data centers is in line with industry benchmarks for sustainable AI Infrastructure.

Final Decision: Based on the analysis, Apple demonstrates a significant commitment to renewable energy integration. While specific details on power-efficient hardware designs and backup power solutions are lacking, the emphasis on renewable energy usage in data centers positions Apple at a high level of PER).

Therefore, the final classification is **High** for Apple's PER. Apple's strong focus on renewable energy integration sets it apart as a leader in sustainable.

3. API Call and CoT Examples for Classifying *Data Storage and Management Systems (DSMS)* Level

API Call for Classifying *DSMS* Level

We make an API call to OpenAI's GPT model to classify a company's *DSMS* level based on its third-quarter 2024 earnings transcript. First, We initialize a request to GPT-3.5-turbo, specifying a temperature of 0, which ensures the response is as deterministic and consistent as possible. We then define the system role by using the system message to instruct the AI to act as a financial expert with experience in stock recommendations. The prompt tells the model to evaluate the earnings transcript and classify the company's *Data Storage and Management Systems* level.

We use zero-shot prompting combined with Chain of Thought (CoT) reasoning to guide the model's decision-making process. The prompt is structured as follows:

> Forget all previous instructions. Pretend you are a financial expert with stock recommendation experience. We'll provide a description of an earnings transcript, and you need to determine whether this company has high DSMS. Follow this structured approach before giving your final answer:
>
> 1. Identify Key Components of DSMS: Look for mentions of secure and scalable storage systems, including distributed storage solutions, cloud storage, and on-premise data centers.
> 2. Evaluate Data Processing and Management: Determine whether the company uses data lakes, data warehouses, or caching systems to optimize data retrieval and latency.
> 3. Assess Version Control and Data Integrity: Identify whether the company implements version control systems to track dataset and AI model updates, ensuring transparency and reproducibility.
> 4. Examine Data Pipelines and Transformation: Check whether the company has automated data pipelines that streamline data movement, transformation, and integration for tasks like trend analysis, demand forecasting, and operational monitoring.
> 5. Industry Context: Compare the company's investment in DSMS to industry benchmarks. Wes the company leading in efficient data storage and management, or is it lagging behind competitors?

6. Final Decision: Based on the above factors, respond with "High" if the company's Data Storage and Management Systems (DSMS) are significant and advanced, otherwise "Low".

Through this structured Chain of Thought approach, the AI is guided to logically analyze and make a well-informed decision before providing the final classification.

DSMS CoT Classification for Apple (AAPL)

Identify Key Components of DSMS: The transcript does not contain explicit mentions of secure and scalable storage systems, distributed storage solutions, cloud storage, or on-premise data centers.

Evaluate Data Processing and Management:The focus of the transcript is on the launch of Apple intelligence, which leverages AI and Machine Learning to enhance user interactions with technology. However, there is no specific mention of data lakes, data warehouses, or caching systems for optimizing data retrieval and latency.

Assess Version Control and Data Integrity: There is no direct mention of version control systems to track dataset and AI model updates for ensuring transparency and reproducibility.

Examine Data Pipelines and Transformation: The transcript does not discuss automated data pipelines for streamlining data movement, transformation, and integration for tasks like trend analysis, demand forecasting, or operational monitoring.

Industry Context: The focus of the discussion is on Apple's financial results, product launches, and services growth. There is no comparison of Apple's investment in DSMS to industry benchmarks related to efficient data storage and management.

Final Decision: Based on the analysis of the earnings transcript, it is evident that the discussion primarily revolves around Apple's financial performance, product launches, and services growth, with minimal emphasis on the key components of Data Storage and Management Systems (DSMS). Therefore, the company's Data Storage and Management Systems (DSMS) do not appear to be significant and advanced based on the provided transcript.

Final Classification: Low. Reasoning: The lack of specific mentions related to DSMS components and industry benchmarks indicates that Apple's focus in the earnings transcript is not on highlighting advanced data storage and management systems.

4. API Call and CoT Examples for Classifying *Technical Standards and Specifications (TSS)* Level

API Call for Classifying *TSS* Level

We make an API call to OpenAI's GPT model to classify a company's *TSS* level based on its third-quarter 2024 earnings transcript. First, We initialize a request to GPT-3.5-turbo, specifying a temperature of 0, which ensures the response is as deterministic and consistent as possible. We then define the system role by using the system message to instruct the AI to act as a financial expert with experience in stock recommendations. The prompt tells the model to evaluate the earnings transcript and classify the company's *Technical Standards and Specifications* level.

We use zero-shot prompting combined with Chain of Thought (CoT) reasoning to guide the model's decision-making process. The prompt is structured as follows:

> Forget all previous instructions. Pretend you are a financial expert with stock recommendation experience. We'll provide a description of an earnings transcript, and you need to determine whether this company has high TSS. Follow this structured approach before giving your final answer:
>
> 1. Identify Key Components of TSS: Look for mentions of standardized model interchange formats and data structures that enable cross-platform AI compatibility. Check for references to APIspecifications that facilitate seamless system integration and interoperability.
> 2. Evaluate Performance and Benchmarking Standards: Determine if the company follows industry-standard benchmarks to assess AI model performance, accuracy, and efficiency. Look for mentions of compliance with widely accepted AI evaluation metrics or regulatory standards.
> 3. Assess Security and Privacy Standards: Identify whether the company adheres to established security and privacy protocols in AI applications. Check for references to encryption standards, data protection measures, or AI governance frameworks ensuring compliance with industry regulations.
> 4. Examine Hardware Compatibility and Energy Efficiency: Look for the company's commitment to hardware standardization and energy-efficient AI deployment. Determine if they follow energy efficiency metrics and design AI systems that are cost-effective and sustainable.

5. Industry Context: Compare the company's adherence to TSS against industry benchmarks. Wes the company a leader in AI standardization and interoperability, or does it struggle with compatibility and compliance?
6. Final Decision: Based on the above factors, respond with "High" if the company's Technical Standards and Specifications (TSS) are significant and advanced, otherwise "Low". Provide a short reasoning followed by your final classification."

Through this structured Chain of Thought approach, the AI is guided to logically analyze and make a well-informed decision before providing the final classification.

TSS CoT Classification for Apple (AAPL)

Identify Key Components of TSS:

- The transcript does not explicitly mention data encryption methods for securing data at rest and in transit.
- There is a mention of "on-device processing that does not collect users' data" which indicates a focus on privacy.

Identify Key Components of TSS:

- The company mentions the rollout of "Apple intelligence" which builds on years of innovation and investment in AI and Machine Learning.
- References to on-device processing, private cloud compute, and integration with ChatGPT across various platforms like iPhone, Mac, and iPad.

Evaluate Performance and Benchmarking Standards:

- The company emphasizes the transformative capabilities of Apple intelligence, indicating a focus on enhancing user experience through AI.
- While specific industry benchmarks are not mentioned, the company highlights the positive reception and potential value of Apple intelligence for users.

Assess Security and Privacy Standards: The company emphasizes privacy through on-device processing and private cloud compute, aligning with established security and privacy protocols in AI applications.

Examine Hardware Compatibility and Energy Efficiency:

- The company highlights the use of Apple silicon in devices like iPhone 15 Pro and Pro Max, Macs, and iPads to leverage AI capabilities efficiently.
- References to energy-efficient AI deployment are not explicitly mentioned in the transcript.

Industry Context:

- Apple is known for its high standards in technology and innovation, often setting industry benchmarks for user experience and product integration.
- The company's focus on AI innovation and privacy aligns with its reputation for leading technological advancements.

Final Decision: Based on the evaluation, the company demonstrates a high level of Technical Standards and Specifications (TSS). The emphasis on privacy, on-device processing, and integration of AI across platforms showcases a commitment to advanced AI technology standards and user experience. Therefore, the classification for this company would be **High** in terms of Technical Standards and Specifications (TSS).