Does AI Engagement Enhance Firm Value?
A Market-based Perspective

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Keywords: Artificial Intelligence (AI), Firm Value, Signaling Theory, Investment, Smart Transformation.
JEL classification: G11; G14; G17

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Abstract

This paper investigates the impact of artificial intelligence (AI) engagement on firm value, using panel data from China's A-share listed companies from 2010 to 2023. We construct a firm-level AI engagement variable based on annual report text mining, and measure firm value using Tobin's Q. The findings show a significant positive relationship between the AI engagement level and contempraneous and subsequent year's firm value, indicating that AI contributes to enhancing firms' market valuation. Further mechanism analysis shows that AI investment promotes firm value primarily through hardware investment. In addition, a comprehensive smart transformation index, integrating software, hardware, and application depth, plays a significant mediating role in the relationship between AI and firm value. Overall, the results suggest that markets reward firms that not only disclose AI engagement but also back it with concrete commitments such as sustained investment and broader digital transformation, consistent with signaling theory.

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1. Introduction

In recent years, artificial intelligence (AI) has emerged as a key driver of corporate innovation. Firms across diverse industries have actively embraced AI technologies to improve efficiency, support decision-making, and create new business opportunities. Despite this growing adoption, a fundamental question remains: Does a firm's AI engagement translate into greater firm value in the market?

A substantial body of research has documented the positive effects of AI on firm-level outcomes such as productivity and operational efficiency.[1] These studies highlight the role of AI as a transformative production technology that improves real economic performance. However, the existing literature has paid relatively little attention to the capital market's perspective. In particular, it remains unclear whether, and through what mechanisms, investors incorporate firms' AI engagement into their valuation assessments.

This study seeks to address this gap by examining whether AI engagement, which is captured through AI-related disclosures in annual reports, translates into higher firm value in the stock market. To capture investors' forward-looking assessment of a firm's tangible and intangible assets, we employ Tobin's Q as the primary measure of firm value. By shifting the focus from internal firm performance to external market evaluation, this study contributes to a more comprehensive understanding of the economic significance of AI engagement.

Furthermore, this study investigates the mechanisms through which AI engagement conveys value to the market. Building on signaling theory, we establish hypotheses that AI-related

[1] For instance, Damioli et al. (2021), Marioni et al. (2024), and Huang and Lin (2025) demonstrate productivity improvements associated with AI adoption in global, European, and U.S. firms, respectively. Similarly, Lei et al. (2025), Xu and Song (2025), Wu and Zhu (2025), Zhong et al. (2024), Zhai and Liu (2023), and Wang et al. (2023), as well as Luo et al. (2024), provide consistent evidence using Chinese data, while Mikalef and Gupta (2021), Czarnitzki et al. (2023), and Gómez-Bengoechea and Jung (2024) offer supporting evidence from survey-based studies. Lui et al. (2022) and Cao et al. (2024) analyze U.S. firms' AI disclosures and provide insights into market reactions and informational value.

disclosures, when perceived as credible, can enhance investor confidence and, in turn, increase firm valuation (Spence, 1973; Connelly et al., 2011). Since AI has emerged as a widely used buzzword, investors face the challenge of distinguishing substantive engagement from "AI washing," in which firms exaggerate or superficially claim AI initiatives without making meaningful investments or operational changes. To address this concern, we examine a set of complementary signals that strengthen the credibility of AI engagement. Such signals include tangible commitments such as AI-related investments, observable productivity improvements, and evidence of strategic alignment through broader digital transformation initiatives. By analyzing these signals in conjunction with AI disclosures, we aim to identify which combinations most effectively convey authentic engagement to the market.

Empirically, this study analyzes annual reports from China's A-share listed firms over the 2010–2023 period. Using text mining techniques, we construct a firm-level measure of AI engagement and examine its relationship with Tobin's Q. China provides a particularly relevant setting for this study. First, the country's shift away from labor-intensive, cost-driven manufacturing toward higher value-added industries has made AI a strategic imperative (Fu, 2023; Gao, 2024). Second, strong policy support such as the New Generation Artificial Intelligence Development Plan 2017, Made in China 2025, and Digital China, has accelerated AI diffusion and elevated its signaling value in the capital markets. Third, estimates suggest that AI will contribute up to 26% of China's GDP by 2030, the highest share among major economies(GSMA, 2024; PwC, 2018), highlighting China as an ideal testbed for investigating the market implications of corporate AI engagement.

Main results are as follows. First, firms' AI engagement is positively associated with Tobin's Q both contemporaneously and with a one-year lag, suggesting that stronger AI involvement enhances market valuation. The effects diminish with two- and three-year lags, becoming statistically insignificant, which indicates a fading valuation impact over time.

Second, the impact of AI investment varies across time and firm characteristics. The effect is significantly positive only during 2016–2023, likely reflecting policy support, technological maturity, and improved organizational capabilities. By valuation group, the relationship is insignificant for low- and medium-valued firms but strongly positive for high-valued firms.

Finally, mechanism analysis shows that firms with high AI investment, especially in hardware, exhibit significantly higher valuations, indicating that firms with substantial investment receive an additional valuation premium. Total factor productivity (TFP), as a measure of productivity, does not significantly mediate the relationship between AI engagement level and Tobin's Q. In contrast, AI-driven smart transformation, proxied by the Smart_index, is significantly and positively associated with both AI engagement and Tobin's Q, supporting its mediating role.

This paper makes the following contributions. First, our study shifts the focus from real economic outcomes to the market's valuation of firms' AI engagement. While prior research has primarily examined the impact of AI adoption on productivity and operational efficiency, evidence consistently documents productivity gains at the global (Damioli et al., 2021), European (Marioni et al., 2024), and U.S. level (Huang & Lin, 2025), as well as in China (Lei et al., 2025; Xu & Song, 2025; Wu & Zhu, 2025; Zhong et al., 2024; Zhai & Liu, 2023; Wang et al., 2023; Luo et al., 2024). Survey-based studies further corroborate these findings (Mikalef & Gupta, 2021; Czarnitzki et al., 2023; Gómez-Bengoechea & Jung, 2024).

By contrast, relatively few studies address the market valuation of AI adoption. Event-based analyses on U.S. firms (Lui et al., 2022; Cao et al., 2024) provide initial insights, and only Huang and Lin (2025) present evidence of valuation effects at the firm level for the US. However, no systematic analysis exists for China. By focusing on A-share listed firms, this study fills this gap and offers distinct implications given China's manufacturing-oriented industrial structure.

Second, this study systematically uncovers the mechanisms through which AI engagement influences firm value, thereby enriching the empirical foundation of general-purpose technology (GPT) theory at the firm level. In particular, it demonstrates that investors do not simply react to symbolic AI disclosures but evaluate the credibility of AI signals. Firms that combine AI-related disclosures with tangible investments and evidence of smart transformation send more credible signals of technological capability and strategic vision. This aligns with signaling theory and highlights that valuation premiums are awarded to firms that align commitment with execution.

Finally, the study offers practical implications. For managers, the findings emphasize the importance of communicating AI strategies transparently and backing them with concrete investments to avoid being perceived as engaging in "AI washing." For investors and regulators, the study highlights the need to critically assess AI-related claims using multiple signals, thereby improving the efficiency of capital allocation and policy design.

2. Literature review and hypothesis

2.1. Theoretical foundations of AI: A GPT and strategic resource perspective

Artificial intelligence (AI) is increasingly recognized as a transformative force in the modern economy. From a theoretical standpoint, AI can be understood both as a general-purpose technology (GPT) and as a strategic organizational resource. These two perspectives jointly provide theoretical foundation for analyzing the economic value of AI and its impact on firm performance.

First, the theory of general-purpose technologies (GPTs) emphasizes that AI possesses broad applicability, continuous evolutionary potential, and strong technological spillover effects (Bresnahan & Trajtenberg, 1995; Trajtenberg, 2018). As a GPT, AI has the capacity to enhance productivity across a wide range of industries like earlier technologies such as electricity and the internet. Although the early adoption of AI may involve learning costs and organizational friction, its long-term economic impact is substantial and far-reaching (Brynjolfsson et al., 2021). This aligns with the theory of disruptive innovation, which highlights how emerging technologies reshape industries over time (Christensen, 2003; Downes & Nunes, 2013).

Second, the strategic resource perspective further underscores the strategic value of AI. When firms develop proprietary algorithms, customized platforms, or data-driven process systems, these AI capabilities gradually evolve into VRIN (valuable, rare, inimitable, and non-substitutable) resources particularly when deeply embedded in a firm's routines and knowledge structures (Barney, 1991). Moreover, the development of AI capabilities often involves path dependence, causal ambiguity, and social complexity (Nelson & Winter, 1982), which further increase the difficulty of imitation. These characteristics make AI a critical strategic resource for achieving and sustaining competitive advantage (Ritala et al., 2024).

Building on these characteristics, AI has been designated as a national strategic resource by major global economies. China, the United States, and the European Union have all released explicit AI engagement strategies (State Council of China, 2017; White House Office of Science and Technology Policy, 2023; European Commission, 2025). In particular, China's "Digital China" strategy and the New Generation Artificial Intelligence Development Plan (2017–2030) explicitly define AI as a strategic GPT, aiming to drive enterprise innovation, industrial upgrading, and overall economic competitiveness.

In sum, AI functions both as a macro-level engine of economic growth and as a micro-level source of competitive advantage. These dual roles provide a solid theoretical foundation for this study's central hypothesis: firms with a higher level of AI engagement are more likely to achieve higher firm value.

2.2. The Relationship between AI engagement and firm value

A growing body of empirical research confirms that AI exerts a significant positive impact on firm-level real economic outcomes, including labor productivity, total factor productivity (TFP), and employment. Damioli et al. (2021), using data from 5,257 firms worldwide, find that AI-driven innovation proxied by patent activity significantly enhances labor productivity, with particularly strong effects observed in small and medium-sized enterprises (SMEs) and service sectors. Similarly, Mikalef and Gupta (2021), based on interviews with AI experts in the US, provide evidence that AI capability enhances organizational creativity and contributes to improved firm performance. Czarnitzki et al. (2023), drawing on unique firm-level survey data from Germany, identify a positive and statistically significant relationship between AI adoption and productivity. Gómez-Bengoechea and Jung (2024), using survey data from Spanish firms, report that the adoption and widespread use of AI technologies lead to substantial improvements in labor productivity. Finally, Marioni et al. (2024) employ firm-level data from 15 European countries between 2011 and 2019 to examine the productivity effects of AI, measured through patenting activity in AI-related fields, and find that the productivity gains directly attributable to AI are both statistically significant and economically meaningful.

Studies conducted in the Chinese context offer consistent evidence. Several studies demonstrate that AI-related innovation positively influences TFP at the firm level (Lei et al, 2025; Xu & Song, 2025; Wu & Zhu, 2025; Zhong et al., 2024; Zhai & Liu, 2023; Wang et al., 2023) and across provincial panel data (Luo et al., 2024). For example, Wang et al. (2023) find that an increase in the frequency of AI-related terms in annual reports can enhance the TFP of manufacturing firms using listed manufacturing firms, while Wu & Zhu (2025) show a positive relationship between the level of AI application and their TFP in service firms. In Taiwan, Yang(2022) reports that AI technology positively affects productivity and employment using firm-level data.

Beyond productivity, AI also contributes to enhanced risk management capabilities. Zhang et al. (2025) find that AI innovation significantly reduces stock price crash risk (SPCR) among U.S. firms, primarily through improved corporate governance and reduced information asymmetry. Similarly, Li et al. (2024) , using textual analysis of Chinese firms' annual reports, show that AI adoption enhances internal control quality and effectively mitigates corporate risk exposure.

While prior research provides strong evidence that AI adoption enhances firm productivity and economic performance, fewer studies have examined its impact on firm value from a market perspective. Recent empirical findings offer mixed results. Lui et al.(2022), analyzing 119 AI investment announcements by U.S. firms, find that such announcements can trigger short-term negative market reactions in certain contexts. These findings reflect investors' sensitivity to the risks of emerging technologies and their concerns about the uncertain short-term returns of AI investments, particularly in cases where firms lack a clear strategic vision or sufficient market readiness. In contrast, Cao et al. (2024) investigate voluntary AI-related disclosures in annual reports and find that firms' AI revenue and cost disclosures offer predictive insights into future growth, investment, and operational efficiency beyond what is captured by current AI activities. Huang and Lin (2025), using the S&P 500 firms from 2010 to 2017, also empirically demonstrate that AI adoption positively affects both financial performance and market valuation. Building on these theoretical and empirical insights, this study proposes the following hypothesis:

Hypothesis 1: Firms with a higher level of AI engagement exhibit higher firm value, as measured by Tobin's Q.

2.3. Mechanisms linking AI engagement to firm value: A signaling perspective

We investigate the mechanisms through which firm-level AI engagement is translated into greater firm value in the stock market and. Drawing on signaling theory, we posit that firms' AI-related actions act as credible signals that help reduce information asymmetry between firm management and investors (Connelly et al., 2011; Spence, 1973).

In the context of emerging technologies such as AI, voluntary disclosures regarding AI initiatives serve as forward-looking signals intended to influence investor expectations. However, prior research cautions that disclosure alone may not reliably indicate genuine AI capability, as some firms might engage in "AI washing" by exaggerating or overstating their AI efforts without corresponding investments or operational improvements (Anand et al., 2025; Nyilasy & Gangadharbatla, 2025). As a result, the stock market's response likely depends on the credibility of these signals with real economic activity.

Accordingly, we explore which types of AI engagement are positively interpreted by investors as credible signals when assessing firm value. Specifically, we employ three firm-level variables that may serve as mechanisms linking AI engagement to market valuation: (1) real investment in AI-related resources, (2) gains in productivity, and (3) the breadth and depth of AI-driven smart transformation. We argue that these complementary indicators strengthen the signaling value of AI engagement and help investors distinguish between superficial and substantive strategies. In contrast, firms lacking such signals may face muted or even negative market reactions due to investor skepticism.

Real AI Investment as a Signal

First, firm's AI investment is used as signaling variable. Firms engaged in AI are expected to increase investments in both software and hardware. On the software side, typical investments include algorithmic platforms, data hubs, and robotic process automation (RPA) systems to facilitate intelligent business operations (Davenport et al., 2018). Empirical studies find that strong AI governance is associated with higher levels of such investment, which, in turn, enhance organizational efficiency and profit margins (Mikalef & Gupta, 2021; Xiao et al., 2024).

On the hardware side, firms increasingly invest in technologies that form the infrastructure of Industry 4.0 and enable smart manufacturing such as sensors, robotics, and edge computing (Lee et al., 2018). The combined effects of software and hardware investment create a platform synergy that contributes to sustained competitive advantage.

Hypothesis 2-a: The positive association between AI engagement and firm value is stronger for firms that exhibit credible complementary signals of AI investment, such as software and hardware investment.

Productivity Gains as a Signal

Second, firm's productivity gain is employed as signaling variable. Firm-level productivity improvements serve as a credible signal of effective AI engagement, helping investors distinguish genuine technological adoption from superficial claims. Since AI implementation often leads to efficiency gains and enhanced operational performance, observable productivity growth reduces information asymmetry and increases market confidence. Therefore, firms demonstrating stronger productivity gains are more likely to be rewarded with higher market valuations, reinforcing the signaling role of performance outcomes in the AI-firm value relationship.

Furthermore, prior research in the context of digital transformation and general-purpose technologies has demonstrated that firms realizing productivity gains are more likely to sustain innovation-led growth and attract long-term capital (Brynjolfsson & Hitt, 2000). In the case of AI, these gains often stem from enhanced operational efficiency, cost reduction, and highly skilled labor inputs, all of which contribute to higher output per input (Lei et al, 2025; Xu & Song, 2025; Wu & Zhu, 2025; Zhong et al., 2024; Zhai & Liu, 2023; Wang et al., 2023).

However, productivity gains may not emerge immediately due to time lags in realizing the benefits of AI adoption. Since productivity often functions as a lagging indicator, it may not fully capture the mediating effect of AI engagement on firm value in the short term, unlike leading indicators such as investment amounts. This temporal gap suggests that it may underrepresent the immediate market perception of AI efforts.

Hypothesis 2-b: The market valuation premium associated with AI engagement is further amplified for firms demonstrating greater outputs such as productivity, which function as credible signals.

Smart Transformation as a Signal

Finally, we consider the depth and scope of smart transformation, namely the systematic integration of AI across multiple business functions, as a critical signaling mechanism.[2] Prior research shows that firms that embed AI into diverse functional areas such as production, finance, and marketing, benefit from enhanced productivity and organizational resilience (Gómez-Bengoechea & Jung, 2024).

The transformation effect theory posits that the realization of AI value often stems from a holistic upgrade in business processes, organizational structure, and resource allocation (Fosso

[2] Smart transformation refers to the strategic and operational changes in firms or industries driven by the integration of advanced digital technologies such as artificial intelligence, big data, cloud computing, and Internet of Things (IoT), with the aim of enhancing efficiency, innovation, and competitiveness.

Wamba, 2022; Kim et al., 2011). Peters and Taylor (2017) highlight that the development of AI capabilities is typically accompanied by the continuous accumulation of intangible capital such as platforms and data infrastructure, which constitutes a structural reconfiguration that fundamentally drives changes in firm value. Similarly, Matarazzo et al. (2021), using structural equation modeling, find that the performance impact of AI is not attributable to any single input dimension, but rather is jointly driven by the chain of digital orientation process optimization.

Recent studies on manufacturing firms (Chen & Zhang, 2024; Guo & Xu, 2021; Pillai et al., 2022) also suggest that the degree of integration between AI and digital technologies—and particularly the firm's capability to form a coordinated system across multiple dimensions—is a key factor explaining performance heterogeneity. Collectively, these findings reinforce the view that the effectiveness of AI transformation depends not only on the scale of resource input, but also on the firm's ability to construct and implement synergistic capabilities across software, hardware, and process layers. In this paper, degree of smart transformation is proxied by a firm's AI application depth measure (Tech_depth) and smart transformation index (Smart_index).

Hypothesis 2-c: The positive association between AI engagement and firm value is stronger for firms that exhibit AI innovation such as cross-functional smart transformation as credible complementary signals.

3. Data and methodology

Considering that the smart transformation in China began around 2000, this study focuses on A-share listed firms from 1999 to 2023 as research sample. The financial data are obtained from the CSMAR database, while the textual data from annual reports are collected from

CNINFO (巨潮资讯网). To ensure the accuracy of the estimation results, the study excludes ST and *ST firms from the sample and applies a two-sided 1% winsorization to all continuous variables to mitigate the influence of outliers. The following describes the main variables used in the analysis, which are summarized in Table 1.

3.1. Construction of the firm's AI engagement level

The firm-level artificial intelligence engagement variable (AI_eng) used in this study follows the methodological approach of Yao et al. (2024) and is constructed based on the frequency of AI-related keywords appearing in the whole text of annual report texts of listed firms . The AI keyword dictionary is developed with reference to international research by Chen and Srinivasan (2024), Li et al.(2021), and Mikolov et al. (2013). The study applies Word2Vec techniques (Mikolov et al., 2013) to train word embeddings on the full text of annual reports, and integrates a curated set of 73 AI-related keywords drawn from industry reports and academic literature. This dictionary has been widely adopted in recent research measuring AI engagement of Chinese firms. To maintain consistency and replicability with the methodology of Yao et al. (2024), no modifications are made to the original AI keyword dictionary. The complete list of keywords is provided in Appendix A.

The annual report texts of A-share listed companies from 1999 to 2023 are collected from CNINFO, resulting in a panel dataset containing 38000 firm-year observations . During text preprocessing, the full text of each annual report is tokenized using the open-source Python module "jieba" for Chinese word segmentation. To ensure accurate identification of compound AI terms (e.g., "machine learning," "natural language processing"), the AI keyword dictionary is integrated into the segmentation process as a user-defined lexicon. After segmentation, the total number of AI keyword occurrences is counted for each annual report. Finally, the AI engagement of a firm (AI_eng) is defined as the natural logarithm of the count plus one: AI_eng = ln (number of AI keywords + 1)

3.2. Variables and descriptive statistics

Our dependent variable firm value is measured by Tobin's Q, defined as the ratio of a firm's value to its total book assets (Bartlett & Partnoy, 2017; Chung & Pruitt, 1994). The data are obtained from the CSMAR database. Observations with missing, zero, or negative total assets are treated as missing values; Tobin's Q values greater than zero are log-transformed, while non-positive values are excluded. This variable is merged with firm-level measures of AI engagement (AI_eng), investment (AI_inv), total factor productivity (TFP), and the smart transformation index (Smart_index). Firms with complete financial data and annual report texts are retained to construct the final panel dataset for empirical analysis. The control variables include firm size as market capitalization (ln(Size)), book-to-market ratio (BM), return on equity (ROE), asset size (ln(Asset)), and cash-to-asset ratio (Cash). To mitigate the influence of extreme values, all continuous variables except for AI_eng are winsorized at the 1st and 99th percentiles. The variable AI_eng retains its original values, as its zero values carry meaningful economic implications by reflecting the heterogeneity in AI engagement levels across firms. Detailed definition of all variables is explained in Table 1.

Table 2 presents the descriptive statistics of the main variables. The mean of firm value (Tobin's Q) is 0.612, with a median of 0.501, indicating that the overall market valuation of sample firms is generally below the replacement cost of assets. The distribution is moderately right-skewed, with a maximum value of 6.579. The mean of AI engagement level (AI_eng) is 1.054, with a standard deviation of 1.299 and a maximum value of 6.599, suggesting significant variation in AI engagement among firms. Notably, since data coverage begins in 2000, some firms still report zero values, reflecting the absence of substantive AI engagement during the early stages. For control variables, the average market value (Size) is 1.040, while the mean book-to-market ratio (BM) is 0.631. After winsorization, the average return on equity (ROE) is 0.043, total asset (Asset) has a mean of 22.317, and the mean cash-to-asset ratio (Cash) is 0.148, indicating that the sample firms exhibit overall financial stability, with outlier effects effectively controlled.

Panel B of Table 2 presents the correlation matrix of the main variables. The AI engagement level (AI_eng) is positively and significantly correlated with firm value (Tobin's Q), with a correlation coefficient of 0.0835 ($p < 0.01$), providing preliminary support for the hypothesis that AI contributes to enhanced market valuation. The correlations among control variables are generally low, suggesting no immediate concern of multicollinearity. To further verify this, we compute the variance inflation factors (VIFs) for the main explanatory variables. All VIF values are well below the conventional threshold of 10, with an average of 1.87; most variables exhibit VIFs under 5. These results indicate that multicollinearity is not a serious issue in our regression models.

3.3 Mechanism variables

Table 3 reports the descriptive statistics for mechanism variables. AI_inv represents the total AI investment intensity, defined as the sum of the share of AI-related software investment to total assets (Soft_inv) and the share of AI-related hardware investment to total assets (Hard_inv). The average investment in AI is 0.005 with a maximum of 0.068. When investment is divided into software and hardware investment, the average shares of intelligent software investment (Soft_inv) and intelligent hardware investment (Hard_inv) are 0.002 and 0.003, respectively, with both reaching a maximum of 0.034. TFP measures the production efficiency of listed firms and is estimated using the Levinsohn–Petrin (LP) method. The average is 8.353 with a standard deviation of 1.072.

Tech_depth is measured by the frequency of AI-related business application keywords in annual reports, excluding terms used in the construction of the core independent variable (AI_eng) to avoid overlapping interpretation. The full list of keywords used for Tech_depth construction is provided in Appendix B.

The smart transformation index (Smart_index) is designed to measure the level of investment and application in a firm's strategic AI-enabled transformation. It is constructed by integrating financial variables and text analysis results, following the methodologies of Ho et al. (2011), Zhang and Li (2022), and Dou et al. (2023). Specifically, Smart_index comprises three second-level indicators: (1) Soft_inv, (2) Hard_inv, and (3) the depth of AI application across business functions (Tech_depth). The three components are aggregated using the entropy weighting method to form a composite index that captures the overall extent of a firm's AI-driven transformation. Detailed definitions and measurement approaches for index are provided in Panel B of Table 1, and illustrated in Figure 1.

In Table 3, the mean value of the smart transformation index (Smart_index) is 0.017, while the average AI application depth (Tech_depth) is 3.472, with a maximum value of 53. This indicates that some leading firms have achieved a relatively high level of smart transformation. Overall, the distribution of variables is reasonable, and internal sample variation is sufficient for empirical analysis.

4. Empirical Results: AI engagement and firm value

4.1. Baseline Regression

Table 4 reports the baseline regression results on the impact of AI engagement level (AI_eng) on firm value, measured by Tobin's Q. Models (1) through (4) examine the effects of AI engagement at the current period (t) on Tobin's Q, including one-, two-, and three-year lags (t, t+1, t+2, and t+3), respectively.

The results show that AI_eng has a significantly positive effect on Tobin’s Q in both the current period and with a one-year lag (coefficients = 0.002, $p < 0.05$; and 0.005, $p < 0.05$, respectively). These findings suggest that more engagement in AI contributes to higher market valuation, with effects that persist but gradually decline over time. The coefficients for the two-year and three-year lags are smaller and become statistically insignificant, indicating a decaying temporal pattern in AI’s valuation impact. Among the control variables, firm size (Size) is positively and significantly associated with firm value, while the book-to-market ratio (BM) is negatively correlated with Tobin’s Q, consistent with theoretical expectations in corporate finance. Firm asset (Asset), profitability (ROE), and cash flow status (Cash) also show expected signs in some model specifications. All regressions include year fixed effects. Most year dummy variables are statistically significant, indicating the presence of strong time effects. Overall, the baseline results support the central hypothesis that AI engagement enhances firm value.

4.2. Time-variation of AI engagement effect

Previous studies suggest that the economic effects of AI technologies typically exhibit dynamic evolution, shaped by policy environments, the stage of technology diffusion, and industry maturity (Comunale & Manera, 2024; Ma & Wang, 2024; Qin et al., 2024). In China, since the release of the “Internet Plus” strategy (State Council of China, 2015) and the New Generation Artificial Intelligence Development Plan (State Council of China, 2017), AI-related policies have been intensively promoted. Together with the “new infrastructure” initiative and the acceleration of industrial digitalization, corporate investment in AI and its impact on market valuation may display distinct temporal patterns.

To examine the time dynamics of AI's impact on firm value, we first employ an interaction model with year fixed effects and plot the marginal effects of AI_eng across years. Figure 2 shows that before 2015, the marginal effects of AI engagement are generally weak and volatile. A significant upward trend emerges after 2015; however, between 2016 and 2019, the effects decline and temporarily turn negative. Starting in 2020, with improved policy support and technological maturity, the marginal effect rebounds and maintains a consistently positive level. This overall pattern indicates that the effect of AI investment evolves through distinct stages and is shaped by the rhythm of policy rollout, technological advancement, and capital market perception (Tambe et al., 2020).

Further, we divide the sample period into three subperiods: 2000–2010, 2011–2015, and 2016–2023, and conduct subsample regressions for each period. Table 5 reveals that the effect of AI investment on firm value is significantly positive only during the 2016–2023 period (coefficient = 0.011, $p < 0.01$), while no significant relationship is found in the earlier periods. These findings further confirm that the value-enhancing effect of AI materializes progressively alongside policy initiatives, technological maturation, and organizational capability development and exhibits clear time heterogeneity (Haefner et al., 2023; Ma & Wang, 2024).

4.3. Robustness Checks

Given that the AI engagement level variable (AI_eng) is constructed using text mining from annual reports and exhibits a right-skewed distribution with long-tail characteristics, we conduct a series of robustness checks by applying alternative data treatment methods to validate the baseline results. Specifically, we implement the following approaches: (1) Winsorizing AI_eng at the 1st and 99th percentiles (denoted as AI_w); (2) Conducting a trimmed regression by excluding observations at the top and bottom 1%; (3) Re-estimating the model using the raw (unprocessed) data. Figure 3 illustrates the distributional differences of the AI_eng variable before and after trimming.

Table 6 presents the regression results under each treatment scenario. The results show that the positive effect of AI_eng on firm value remains statistically significant across all three specifications. Moreover, the coefficient magnitudes are highly consistent with those from the baseline regression. These findings indicate that the conclusion—that AI investment enhances firm value—is not driven by outliers and exhibits strong robustness.

Prior studies suggest that the effect of AI technologies on firm value exhibits significant heterogeneity across firms, particularly with respect to differences in market valuation. Firms with higher valuation levels tend to receive stronger responses from capital markets regarding their AI investments, as market expectations are shaped by perceived innovation capacity . This is consistent with the theory of disruptive innovation , which posits that when underlying technologies are disruptive, innovation can lead to the destruction of existing industry value. While investments in emerging technologies and digital activities may temporarily boost productivity, they may also suppress sales growth in the short term (Chen et al., 2019). Larger and younger firms typically experience greater return volatility and are able to allocate more resources to selling, general, and administrative (SG&A) expenses. Moreover, prior technology investments significantly predict current digital activities, suggesting that digital transformation is an ongoing, cumulative process (Chen & Srinivasan, 2024). Accordingly, high-valuation firms are often equipped with stronger absorptive capacity and innovation capital, making their AI engagements more likely to be interpreted as credible value signals by the market and, thus, to generate positive valuation responses.

To empirically test these theoretical expectations, we first divide the sample into three groups based on Tobin's Q tertiles—low, medium, and high valuation firms—and conduct regressions within each subgroup. Table 7 reports that the coefficient of AI_eng is statistically insignificant in the low and medium valuation groups but becomes significantly positive in the high valuation group (coefficient = 0.002, $p < 0.05$). This finding suggests that the value realization of AI engagement is contingent on the firm's valuation level, and that firms with stronger market recognition are more likely to benefit from AI-enhanced value creation. These results support the heterogeneity hypothesis from the perspective of market expectations and firm-specific capabilities.

To further explore whether there exists a continuous, non-linear relationship between AI investment and firm value, we employ a threshold regression approach that systematically scans different values of Tobin's Q to detect structural shifts in the marginal effect of AI investment. Figure 4 reveals that the marginal effect of AI_eng significantly increases once Tobin's Q exceeds approximately 1.5 and peaks around 2.0. This evidence confirms the presence of a "threshold perception" effect in capital markets, enriching our understanding of how AI investment is evaluated under varying valuation conditions. It also suggests that frictions associated with new technologies may delay or constrain the realization of their economic benefits.

5. Mechanism analysis

Building on the baseline regression results, this section further investigates the mechanisms through which AI engagement affects firm market value.

5.1. AI engagement & AI investment

To examine whether capital markets can differentiate between firms' symbolic and substantive AI strategies, we adopt a two-dimensional classification based on standardized z-scores for AI engagement and AI investment intensity. Compared to a simple median-split method, this approach offers a more precise distinction by identifying firms that exhibit genuinely high AI investment intensity rather than merely large absolute expenditures. Specifically, we construct an AI investment intensity indicator (AI_inv = Soft_inv + Hard_inv) and define a firm as "high AI investor" if its z-score exceeds 1, meaning its investment share is at least one standard deviation above the sample average. This criterion helps eliminate size-driven mechanical bias and better captures real strategic commitment.

Based on this classification, firms are categorized into four groups: High Engagement–High Investment (High-High), High Engagement–Low Investment (High-Low), Low Engagement–High Investment (Low-High), and Low Engagement–Low Investment (Low-Low). We then compare the average Tobin's Q in the following year across these groups to assess how the market values different AI strategy profiles.

Table 8 shows that firms in the High & High group exhibit the highest average Tobin's Q (0.830), indicating a strong market premium for those demonstrating both strategic participation and substantial investment in AI. In contrast, the Low-Low group records the lowest average (0.586), with a large and highly significant valuation gap of 0.213 ($t = 18.379$), suggesting the importance of strategic alignment in AI-related value creation.

Further intra-group comparisons reveal that among firms with high AI engagement, additional investment leads to a substantial valuation uplift (+0.213), whereas among firms with low engagement, investment alone results in only modest gains (+0.100). Similarly, under constant investment conditions, higher engagement boosts valuation by 0.144 in the high-investment group, but only 0.031 in the low-investment group. These patterns indicate that both commitment and action are necessary for firms to fully realize the market value of AI initiatives—underscoring a synergy effect between internal capability and external resource allocation.

To better understand how AI engagement and AI investment jointly influence firm valuation, we construct binary indicators D(AI_eng) and D(AI_inv), which equal 1 if the respective variable exceeds a threshold (z-score > 1), and 0 otherwise. This binary classification helps capture non-linear effects and allows for intuitive interpretation of "high" versus "low" AI strategies.

Table 9 presents the fixed-effects regression results based on this classification. In Model (1), AI engagement remains positively associated with Tobin's Q (coefficient = 0.002, $p < 0.05$), confirming its direct contribution to firm value. In Model (2), firms with high AI investment (D(AI_inv) = 1) exhibit significantly higher valuations (coefficient = 0.006, $p < 0.1$), indicating that capital markets respond more favorably to substantive investment rather than nominal declarations. In Model (3), the interaction term between continuous AI engagement and the high-investment dummy (AI_eng × D(AI_inv)) is significantly positive (coefficient = 0.004, $p < 0.01$), indicating that firms combining strong AI engagements with substantive investment receive an additional valuation premium.

Model (4), which includes only D(AI_eng), yields statistically insignificant results, suggesting that symbolic engagement alone may not be sufficient to generate valuation premiums. However, Model (5) further reinforces our result: the interaction between the two dummy variables (D(AI_eng) × D(AI_inv)) also yields a significantly positive coefficient (0.008, $p < 0.05$), highlighting that strategic alignment—i.e., the match between internal engagement and external resource commitment—is particularly well received by capital markets.

The evidence indicates that investors do not merely respond to symbolic AI disclosures or isolated investment figures. Instead, capital markets are capable of distinguishing firms that authentically align strategic intent with execution in their AI transformation. This pattern aligns closely with the predictions of signaling theory: firms that exhibit both strong AI commitment and actual resource allocation are more likely to convey credible signals of technological capability and long-term vision, thereby earning valuation premiums from investors.

Table 10 reports the mediation regression results for AI investment when dividing it into software-based and hardware-based investment. The result of Model (1) shows that AI_eng is significantly positively associated with Soft_inv. However, in Model (2), the coefficient of Soft_inv on Tobin's Q is negative (–19.664, $p < 0.1$), indicating that although AI_eng drives software investment, the market valuation effect of such investment may be limited or even negative in the short term. This result suggests a potential misalignment between resource allocation and value realization—firms may increase investments in algorithm platforms and data systems, but if these are not accompanied by simultaneous improvements in organizational structure, process design, or workforce capabilities, the impact on firm performance remains constrained. Moreover, the impact of intangible software investments often manifests with a delay and may not be immediately reflected in valuation metrics like Tobin's Q. Therefore, this path shows a partial mediation effect: AI engagement does encourage greater investment in software, but value conversion depends heavily on integration capacity and organizational learning cycles. This finding is consistent with the literature on IT investment lag effects (Aboody & Lev, 2000; Brynjolfsson et al., 2021).

Model (3) and (4) report the mediation effects via hardware intelligent investment (Hard_inv). The results indicate that while AI_eng does not significantly affect Hard_inv, the latter has a strong positive effect on Tobin's Q (coefficient = 24.983, $p < 0.01$). In other words, AI engagement does not automatically lead to hardware upgrades, which are more likely driven by firm-specific strategy and execution capacity. However, once smart hardware infrastructure is in place, it significantly boosts business agility and operational efficiency, thereby enhancing firm value. This aligns with the theory of technology–organization co-evolution (Tanriverdi et al., 2010), suggesting that the coupling of computing power and business processes plays a crucial role in generating market-recognized value. Prior studies have also shown that in manufacturing sectors, managers are more willing to invest in hardware when they anticipate substantial operational improvements from advanced technologies like AI (Chen et al., 2023; Pillai et al., 2022).

5.2. AI engagement & Productivity

We examine whether AI engagement enhances firm market value through improvements in total productivity (TFP), a commonly used measure of resource efficiency and technological progress. However, the empirical results presented in Table 11 suggest that TFP does not significantly mediate the relationship between AI engagement level and Tobin's Q. This finding does not contradict prior research showing that AI adoption improves firm productivity. In fact, Model (1) supports a positive association between AI engagement and TFP, consistent with earlier studies. Rather, the evidence from Model (2) suggests that TFP does not serve as a mediating channel linking AI engagement to market valuation.

Several explanations are plausible. One possible explanation is a perception lag: even if AI engagement enhances productivity, such improvements are difficult for investors to observe and may take time to be reflected in market expectations. By contrast, more immediate signals such as reported investment amounts are readily recognized and incorporated into investors' valuation assessments. This suggests that while productivity gains may indeed exist, they are less salient in shaping short-term market responses compared to direct and tangible signals of AI commitment.

Second, this finding aligns with the well-known "productivity paradox" articulated by Solow (1987): "You can see the computer age everywhere but in the productivity statistics." As a general-purpose technology, AI requires substantial complementary investments in intangible assets and organizational redesign before its full economic benefits can be realized (Bresnahan

& Trajtenberg, 1995). These adjustments, including re-engineering business processes, accumulating digital capabilities, retraining employees, and updating internal systems, are difficult to capture in conventional financial statements or productivity metrics (Brynjolfsson et al., 2021).

Second, while TFP remains an important indicator of firm performance, it may not fully capture the real impact of AI on firm value in emerging market contexts, especially in the early diffusion phase of such technologies. The absence of a significant TFP effect suggests that we need to consider alternative mechanisms that can better reflect firms' strategic transformation driven by AI, particularly those involving intangible assets and deep technological integration.

5.3. AI engagement & Smart transformation

Given the limitations of traditional productivity measures, we shift our focus to the firm-level strategic transformation process enabled by AI. Prior studies highlight that the organizational value of AI depends not only on the amount of investment, but also on how deeply AI is embedded in core business operations. The adoption of AI typically involves ongoing upgrades in both software systems and hardware infrastructure, reshaping the structure of firms' digital capital (Gómez-Bengoechea & Jung, 2024; Fosso Wamba, 2022; Bharadwaj, 2000).

Based on this, we identify three key transformation dimensions:(1) Soft_investment, the share of intelligent software investment, (2) Hard_investment, the share of intelligent hardware investment, and (3) Tech_depth, the depth of AI application across business functions. To capture the integrated effect of these dimensions, we construct a composite Smart Transformation Index (Smart_Index) using the entropy weighting method. This index reflects the extent to which firms undergo structural transformation supported by AI technologies.

To test the mediating effect of these pathways, we follow the three-step regression approach proposed by Baron and Kenny (1986), examining both the direct and indirect effects of AI level on Tobin's Q via the above mechanisms. Table 12 reports the mediation regression results for AI-driven smart transformation mechanisms affecting firm value. In Model (1) and (2), a composite index of Tech_depth is significantly and positively associated with AI_eng and Tobin Q, supporting the mediating role. Model (3) and (4) present the regression results using the Smart_index. The results reveal that AI_eng significantly increases Smart_index (coefficient = 0.033, $p < 0.01$), and Smart_index positively affects Tobin's Q (coefficient = 6.305, $p < 0.1$). Moreover, the direct effect of AI_eng decreases slightly but remains significant, suggesting a stable partial mediation through this integrated transformation mechanism. These findings highlight a multi-dimensional coordination mechanism in the process of value creation. Rather than relying on a single input (e.g., software or hardware), firms tend to achieve value through synchronized development in digital capabilities and embedded technology applications.

6. Conclusion

This study reveals a complex and nonlinear relationship between the level of artificial intelligence (AI) engagement and firm value. The mechanism analysis further indicates that AI enhances firm value primarily through sustained investment and the deep integration of technology. The smart transformation index, which integrates software, hardware, and AI application depth, exhibits a significant positive mediating effect, reflecting the integrative nature of AI capability. These findings not only enrich the theoretical framework of general-purpose technologies (GPTs) but also provide a conceptual basis for explaining the underlying mechanisms behind the observed effects.

The findings of this study provide practical implications for both policy design and corporate strategy. On the policy side, the realization of AI's value is conditional and context-dependent, implying that a universal-access approach to AI promotion may generate inefficiencies. Rather than providing indiscriminate support, policymakers should focus resources on industries and firms with high integration potential, strong organizational resilience, and long-term strategic vision, where AI adoption is most likely to generate significant economic and strategic benefits. For corporate managers, it is essential to move beyond blindly following AI trends and instead pursue sustainable strategies that emphasize long-term value creation. This requires investing in infrastructure, enhancing data governance, strengthening talent systems, and redesigning business processes, rather than relying on short-term speculative initiatives.

Statement: During the preparation of this work the author used DeepL service and ChatGPT in order to check grammatic errors and improve our writing in English. After using this service, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

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Figure 1. Conceptual framework of AI-driven smart transformation mechanisms affecting firm value

This figure illustrates the mediating mechanism through which AI engagement level influences firm value (measured by Tobin's Q). The mechanism operates via three distinct transformation pathways—software investment, hardware investment, and AI application depth—each of which function as an individual mediator. These three dimensions are further integrated into a composite indicator (Smart Index), representing an aggregated mediating effect. The model accounts for both direct and indirect pathways from AI level to firm value

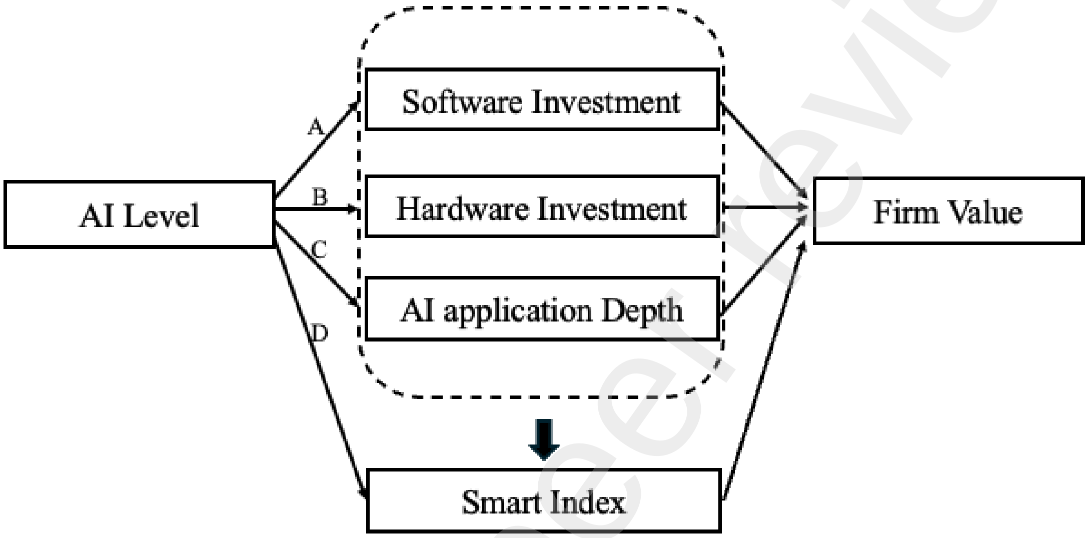

Figure 2. Marginal effect of AI engagement by year

This figure illustrates the estimated marginal effect of AI engagement level on firm value (Tobin's Q) for each year from 2010 to 2023, based on interaction regressions. Dots represent point estimates, and bars indicate 95% confidence intervals.

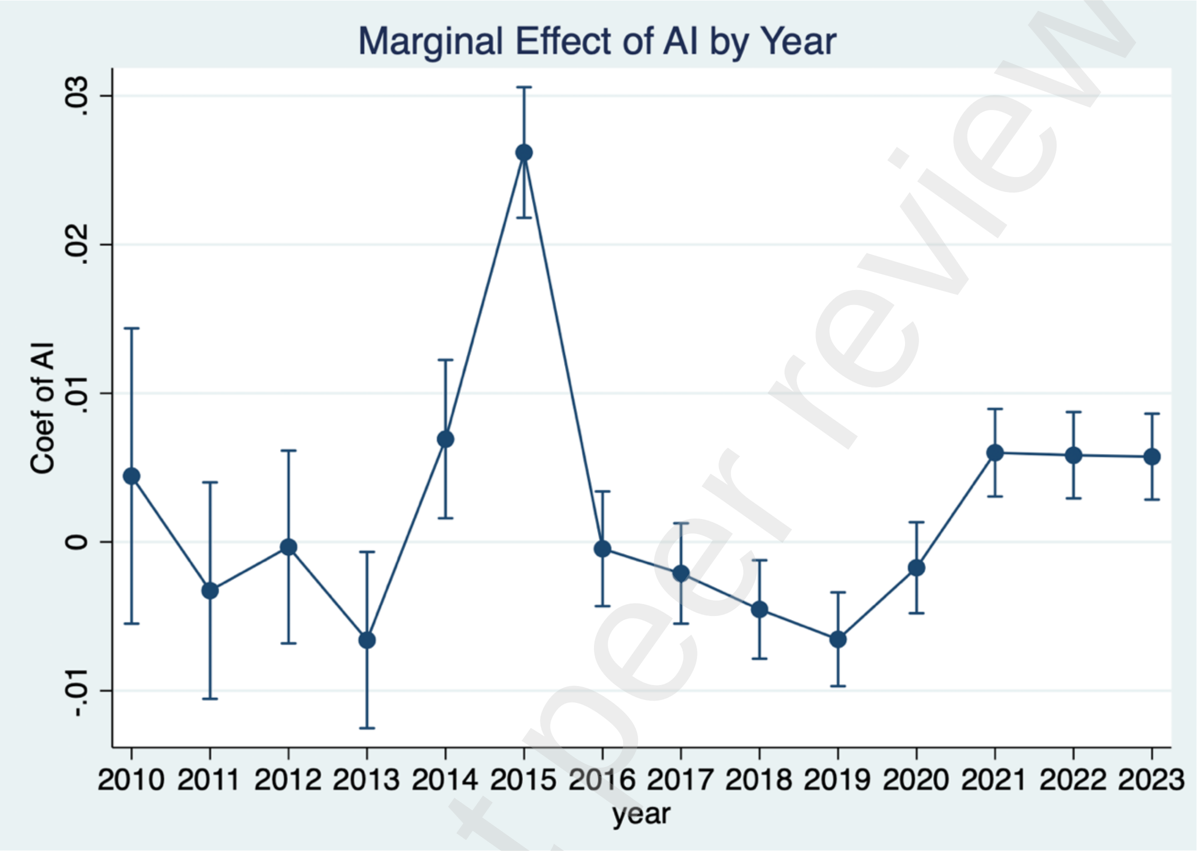

Figure 3. Distribution of AI engagement variable: Raw vs. Trimmed vs. Winsorized

This figure compares the kernel density distributions of the AI engagement level (AI_eng) under three data processing methods: raw (original values), trimmed (1%–99% percentile exclusion), and winsorized (1%–99% percentile compression).

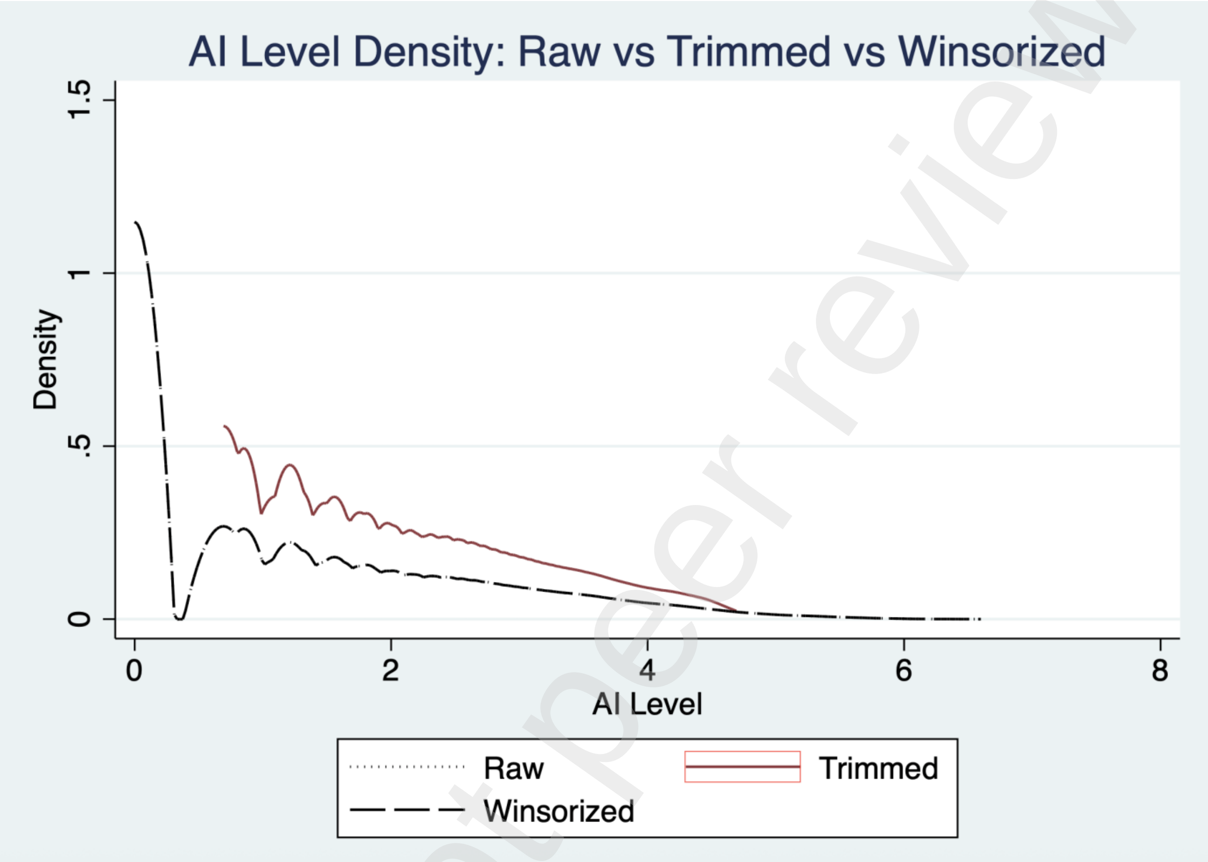

Figure 4. Marginal Effect of AI across Different Tobin's Q Thresholds

This figure illustrates the marginal effect of AI engagement level on firm value (Tobin's Q) across varying Tobin's Q thresholds. The solid line (ai_high) represents the estimated marginal effect for firms above each Tobin's Q threshold, while the dashed line (ai_low) depicts the effect for firms below the threshold.

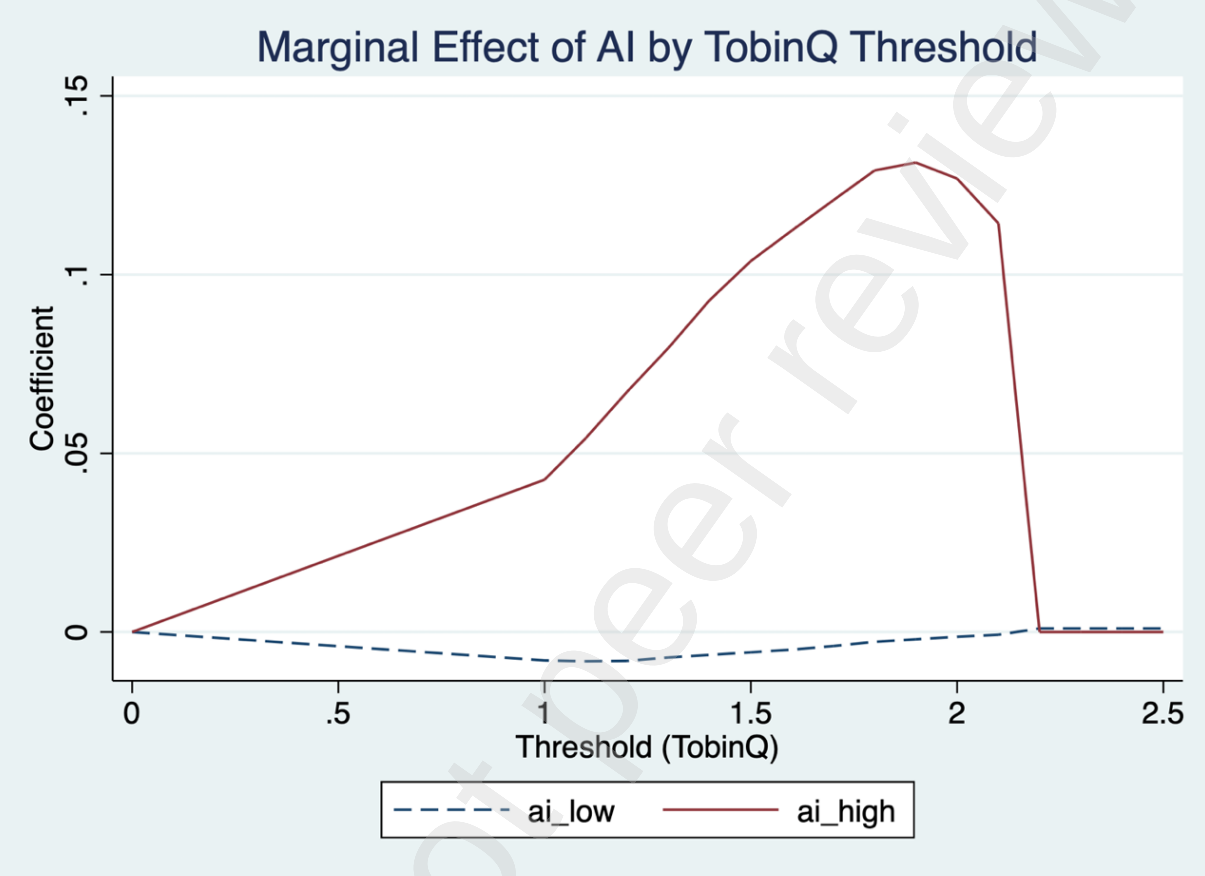

Table 1. Definition of variables

This table describes the definition of variables used in the analysis.

Panel A. Variables definition

Variable	Acronym	Definition
Tobin's Q	Tobin Q	The ratio of the market value of equity to total assets
AI engagement	AI_eng	ln (number of AI keywords + 1)
AI investment	AI_inv	AI_inv= Soft_inv+ Hard_inv
Total factor productivity	TFP	Firm-level total factor productivity, estimated using the Levinsohn–Petrin (LP) method.
Firm size	Size	Log of market capitalization of equity at the end of the previous year.
Book-to-market	BM	The book value of equity divided by the market value of equity, as of the previous year end.
Asset size	Asset	Log of total assets (ln(Asset))
Return on equity	ROE	Net profit divided by shareholders' equity
Cash-to-asset ratio	Cash	Cash and cash equivalents divided by total assets, measured at the end of the fiscal year.

Panel B. Smart transformation index construction

Main Index	Sub-index	Measurement Method
Smart Transformation Index (Smart_index)	Software-based intelligent investment (Soft_inv)	Ratio of intangible assets related to "intelligent," "software," "system," "information platform," and "data" to total assets (extracted from financial reports)
	Hardware-based intelligent investment (Hard_inv)	Ratio of fixed assets related to "electronic equipment," "computers," and "data equipment" to total assets (extracted from financial reports)
	AI application depth (Tech_depth)	Frequency of keywords related to "intelligent business applications" in the full text of annual reports (Appendix B)

Table 2. Descriptive Statistics of Variables

This table presents the descriptive statistics for the main variables used in this study, including firm value (Tobin's Q), AI engagement level (AI_eng), control variables (firm size, ROE, book-to-market ratio, cash ratio), and mechanism variables (Soft_inv, Hard_inv, Tech_depth, Smart_index)

Pane A. Main variables

	Mean	SD	p25	p50	p75	Min	Max
Tobin Q	0.612	0.477	0.258	0.501	0.851	0	6.579
AI_eng	1.054	1.299	0	0.693	1.792	0	6.599
Size	1.04	0.532	0.648	0.989	1.368	0.08	2.551
BM	0.631	0.251	0.442	0.632	0.815	0.001	1.964
Asset	22.317	1.48	21.312	22.062	23.036	17.757	31.431
ROE	0.043	0.172	0.025	0.067	0.111	-1.083	0.316
Cash	0.148	0.136	0.052	0.106	0.199	0	0.655

Panel B. Correlation

	Tobin Q	AI_eng	Size	BM	Asset	ROE	Cash
Tobin Q	1.000						
AI_eng	0.084*	1.000					
	0.000						
Size	0.830*	0.103*	1.000				
	0.000	0.000					
BM	-0.953*	-0.096*	-0.836*	1.000			
	0.000	0.000	0.000				
Asset	-0.397*	0.018*	-0.598*	0.538*	1.000		
	0.000	0.000	0.000	0.000			
ROE	-0.009	-0.002	0.014*	0.008	0.016*	1.000	
	-0.091	-0.639	-0.004	-0.121	-0.001		
Cash	0.083*	0.044*	0.259*	-0.134*	-0.204*	0.033*	1.000
	0.000	0.000	0.000	0.000	0.000	0.000	

Table 3. Descriptive Statistics of Total Factor Productivity, AI Investment Intensity, and AI-Driven Transformation Mechanism Variables

This table reports descriptive statistics for firm-level total factor productivity (TFP), AI investment intensity (AI_inv), and variables capturing AI-driven transformation mechanisms. TFP measures the production efficiency of listed firms. AI_inv is defined as the sum of the share of AI-related software investment to total assets (Soft_inv) and the share of AI-related hardware investment to total assets (Hard_inv). The depth of intelligent technology application (Tech_depth) is measured by the frequency of relevant keywords in annual reports. The smart transformation index (Smart_index) reflects the overall extent of a firm's AI-enabled transformation and is calculated using the entropy weighting method based on Hard_inv, Soft_inv, and Tech_depth.

	Mean	SD	p25	p50	p75	Min	Max
AI_inv	0.005	0.008	0.001	0.002	0.006	0.000	0.068
Soft_inv	0.002	0.005	0.000	0.001	0.002	0.000	0.034
Hard_inv	0.003	0.005	0.000	0.001	0.003	0.000	0.034
TFP	8.353	1.072	7.629	8.253	8.969	4.065	13.106
Tech_depth	3.472	8.289	0.000	0.000	3.000	0.000	53.000
Smart_index	0.017	0.026	0.006	0.009	0.016	0.001	0.616

Table 4. AI engagement and Tobin Q

This table reports the results of fixed effects panel regressions examining the effect of AI engagement level (AI_eng) on firm value (measured by Tobin's Q) across current and extended lag periods. Columns (1) to (4) correspond to contemporaneous (t) and lagged effects at t+1, t+2, and t+3, respectively. All models control for firm fixed effects and year fixed effects. The control variables include firm asset size (Asset), market value (Size), book-to-market ratio (BM), return on equity (ROE), and cash ratio (Cash). Robust standard errors are reported in parentheses. Asterisks denote significance levels: ***p < 0.01, **p < 0.05, *p < 0.1.

	(1)	(2)	(3)	(4)
	TobinQ(t)	TobinQ(t+1)	TobinQ(t+2)	TobinQ(t+3)
AI_eng	0.002**	0.005**	0.003	-0.005
	(0.001)	(0.002)	(0.003)	(0.003)
Size	0.261***	0.104***	-0.099***	-0.070***
	(0.003)	(0.008)	(0.009)	(0.010)
BM	-1.679***	-0.736***	-0.444***	0.112***
	(0.006)	(0.015)	(0.018)	(0.020)
Asset	0.014***	-0.115***	-0.135***	-0.114***
	(0.002)	(0.004)	(0.005)	(0.006)
ROE	-0.000*	-0.002***	-0.001	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)
Cash	-0.070***	-0.083***	-0.010	0.033*
	(0.005)	(0.014)	(0.017)	(0.018)
Constant	0.966***	3.223***	3.742***	3.099***
	(0.033)	(0.088)	(0.108)	(0.121)
Year FE	Yes	Yes	Yes	Yes
Observations	38,197	32,000	27,192	23,019
R2	0.903	0.417	0.301	0.298
Number of firms	5,312	4,903	4,426	3,862

Table 5. AI investment and firm value across different periods

This table presents fixed effects regression results examining the relationship between AI engagement level (AI_eng) and firm value (Tobin's Q) across three sub-periods: 2000–2010, 2011–2015, and 2016–2023. All models include firm and year fixed effects. Robust standard errors are reported in parentheses. Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1) 2011 ~2015 TobinQ(t+1)	(2) 2016~2023 TobinQ(t+1)
AI_eng	0.002	0.011***
	(0.007)	(0.003)
Size	0.109***	0.041***
	(0.019)	(0.010)
BM	-0.460***	-0.519***
	(0.040)	(0.020)
Asset	-0.207***	-0.185***
	(0.012)	(0.006)
ROE	0.003	-0.001
	(0.010)	(0.001)
Cash	-0.192***	-0.088***
	(0.029)	(0.021)
Constant	5.150***	4.911***
	(0.251)	(0.141)
Year FE	Yes	Yes
Observations	9,121	21,484
R2	0.481	0.255
Number of firms	2,528	4,748

Table 6. Robustness check: Different data treatments for Tobin Q

This table presents the regression results examining the impact of AI engagement level on firm value (Tobin's Q) under three data treatment approaches: winsorized at 1% and 99% (Column 1), trimmed at 1% and 99% (Column 2), and raw data without processing (Column 3). The results confirm the robustness of the positive effect of AI level across all specifications. Standard errors are clustered at the firm level and reported in parentheses. Asterisks denote significance levels:* p < 0.01, ** p < 0.05, * p < 0.1.

	(1) Winsorized TobinQ(t+1)	(2) Trimmed TobinQ(t+1)	(3) Raw TobinQ(t+1)
AI_eng	0.002**	0.004**	0.002**
	(0.001)	(0.002)	(0.001)
Size	0.261***	0.260***	0.261***
	(0.003)	(0.004)	(0.003)
BM	-1.679***	-1.715***	-1.679***
	(0.006)	(0.009)	(0.006)
Asset	0.014***	0.009***	0.014***
	(0.002)	(0.003)	(0.002)
ROE	-0.000*	-0.000	-0.000*
	(0.000)	(0.000)	(0.000)
Cash	-0.070***	-0.055***	-0.070***
	(0.005)	(0.008)	(0.005)
Constant	0.966***	1.046***	0.966***
	(0.033)	(0.055)	(0.033)
Year FE	Yes	Yes	Yes
Observations	38,197	19,436	38,197
R2	0.903	0.903	0.903
Number of firms	5,312	4,320	5,312

Table 7. Robustness check: AI Effect by TobinQ Groups

This table reports the regression results examining the heterogeneity in the effect of AI engagement level (AI_eng) on firm value (Tobin's Q) across three subsamples divided by Tobin's Q tertiles: low, medium, and high valuation firms. The dependent variable is the one-period-ahead firm value (TobinQ(t+1)). Column (1) includes firms in the bottom tertile of Tobin's Q, Column (2) the middle tertile, and Column (3) the top tertile. All models control for firm size (Size), book-to-market ratio (BM), total assets (Asset), return on equity (ROE), and cash ratio (Cash), and include year fixed effects. Standard errors clustered at the firm level are reported in parentheses. Asterisks denote significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

	(1)	(2)	(3)
	Low	Medium	High
VARIABLES	TobinQ(t+1)	TobinQ(t+1)	TobinQ(t+1)
AI_eng	-0.000	-0.000	0.002**
	(0.000)	(0.000)	(0.001)
Size	0.001***	0.001**	0.075***
	(0.000)	(0.000)	(0.003)
BM	-1.178***	-1.668***	-3.177***
	(0.001)	(0.001)	(0.010)
Asset	0.001***	0.000	-0.000
	(0.000)	(0.000)	(0.002)
ROE	0.000*	0.000	0.000
	(0.000)	(0.000)	(0.000)
Cash	-0.001	0.000	-0.011**
	(0.001)	(0.001)	(0.005)
Constant	1.151***	1.515***	2.080***
	(0.003)	(0.004)	(0.035)
Year FE	Yes	Yes	Yes
Observations	12,757	12,741	12,699
R-squared	0.997	0.997	0.963
Number of firms	3,614	4,069	3,133

Table 8. The next year's Tobin Q for firms sorted by AI engagement and AI investment

This table reports the average Tobin's Q in the following year for firms grouped by two dimensions: AI engagement and AI investment intensity. Firms are categorized into High or Low groups based on standardized z-scores (threshold = 1). The last column and last row present group differences, with corresponding t-values reported in parentheses.

		AI investment		
		High	Low	High-Low
AI engagement	High	0.830	0.617	0.213 (18.379)
	Low	0.686	0.586	0.100 (5.073)
	High-Low	0.144 (6.081)	0.031 (8.531)	

Table 9. AI engagement and Tobin Q: Mediation of AI investment

This table presents the results of fixed effects panel regressions examining how AI engagement and AI investment jointly affect firm valuation (Tobin's Q). Columns (1)–(5) gradually introduce dummy variables and interaction terms to identify whether real investment enhances the valuation impact of AI engagement. D(AI_eng) and D(AI_inv) equal 1 if the firm's z-score of AI engagement or investment intensity exceeds 1. Robust standard errors are reported in parentheses. Asterisks indicate significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

	(1)	(2)	(3)	(4)	(5)
AI_eng	0.002**		0.001		
	(0.001)		(0.001)		
D(AI_inv)		0.006*	-0.004		0.001*
		(0.003)	(0.005)		(0.005)
AI_eng*D(AI_inv)			0.005***		
			(0.002)		
D(AI_eng)				0.002	0.001
				(0.002)	(0.002)
D(AI_eng)*D(AI_inv)					0.010**
					(0.006)
Size	0.261***	0.261***	0.261***	0.261***	0.261***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
BM	-1.679***	-1.679***	-1.679***	-1.680***	-1.679***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Asset	0.014***	0.014***	0.014***	0.014***	0.014***
	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)
ROE	-0.000*	-0.000*	-0.000*	-0.000*	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Cash	-0.070***	-0.070***	-0.070***	-0.071***	-0.070***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Constant	0.966***	0.956***	0.967***	0.960***	0.966***
	(0.033)	(0.033)	(0.033)	(0.033)	
Year FE	Yes	Yes	Yes	Yes	
Observations	38,197	38,197	38,197	38,197	38,197
Number of firms	5,312	5,312	5,312	5,312	5,312

Table 10. Mediation Analysis: Decomposition of AI investment

This table presents the results of the mediation analysis examining whether AI engagement affects firm value (Tobin's Q) through two mediating channels: software investment intensity (Soft_inv) and hardware investment intensity (Hard_inv). Columns (1) and (3) estimate the effect of AI_eng on the mediators Soft_inv and Hard_inv, respectively. Columns (2) and (4) include both AI_eng and the corresponding mediator to assess whether the mediation effect is statistically significant. The first-step regression, which estimates the total effect of AI_eng on Tobin's Q, is not reported here but has been presented earlier. All regressions include firm and year fixed effects, with standard errors clustered at the firm level. To facilitate interpretation, all coefficients have been multiplied by 100. Asterisks indicate significance levels: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

	(1) Soft_inv	(2) TobinQ	(3) Hard_inv	(4) TobinQ
AI_eng	0.042***	0.199**	0.004	0.189**
	(0.000)	(0.001)	(0.000)	(0.001)
AI_inv				
Soft_inv		-19.664*		
		(0.117)		
Hard_inv				24.983***
				(0.094)
Size	0.008	26.125***	-0.035**	26.134***
	(0.000)	(0.003)	(0.000)	(0.003)
B/M	-0.056**	-167.922***	-0.052*	-167.892***
	(0.000)	(0.006)	(0.000)	(0.006)
Asset	-0.003	1.351***	-0.035***	1.361***
	(0.000)	(0.002)	(0.000)	(0.002)
ROE	-0.005***	-0.051*	0.001	-0.049*
	(0.000)	(0.000)	(0.000)	(0.000)
Cash	-0.126***	-7.050***	-0.0354	-7.017***
	(0.000)	(0.005)	(0.000)	(0.005)
Intercept	0.258*	96.658***	1.170***	96.303***
	(0.001)	(0.033)	(0.002)	(0.033)
N	41142	38197	41142	38197
Fixed Effects	Yes	Yes	Yes	Yes

Table 11. Mechanism Analysis: The Role of TFP

This table reports the results of the mediation regressions testing whether AI engagement enhances firm value (Tobin's Q) through improvements in total factor productivity (TFP). Column (1) examines the effect of AI engagement on TFP, while Column (2) tests whether TFP mediates the impact of AI engagement on Tobin's Q. All regressions include firm and year fixed effects, with standard errors clustered at the firm level. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	(1)	(2)
	TFP	TobinQ
AI_eng	0.010***	0.001
	(0.003)	(0.003)
TFP		-0.002
		(0.005)
Size	-0.007	0.088***
	(0.010)	(0.009)
B/M	-0.388***	-0.737***
	(0.019)	(0.018)
Asset	0.863***	-0.108***
	(0.005)	(0.006)
ROE	0.003***	-0.002***
	(0.001)	(0.001)
Cash	-0.098***	-0.084***
	(0.020)	(0.016)
Intercept	-7.577***	3.141***
	(0.108)	(0.099)
N	36,122	28,079
R-squared	0.671	0.420
Number of firms	4,879	4,374
Fixed Effects	Yes	Yes

Table 12. Mediation Analysis: Smart transformation

This table reports the regression results on how firm-level AI engagement (AI_eng) influences firm value (Tobin's Q) through smart transformation mechanisms. Models (1) and (2) use technological application depth (Tech_depth) as the mediator, while Models (3) and (4) employ the composite Smart_Index. The first-step regression estimating the total effect of AI_eng on Tobin's Q has been presented earlier and is not repeated here. All regressions include firm and year fixed effects, with standard errors clustered at the firm level. For ease of interpretation, all coefficients are multiplied by 100. Asterisks indicate significance levels: * p < 0.1, ** p < 0.05, *** p < 0.01.

Variable	(1) Tech_depth	(2) TobinQ	(3) Smart_index	(4) TobinQ
AI_eng	239.150***	0.108	0.325***	0.168*
	(0.059)	(0.001)	(0.000)	(0.001)
Tech_depth		0.033***		
		(0.000)		
Smart_index				6.305*
				(0.035)
Size	4.086	26.110***	-0.016	26.120***
	(0.186)	(0.003)	(0.000)	(0.003)
B/M	1.635	-167.945***	-0.177**	-167.910***
	(0.346)	(0.006)	(0.001)	(0.006)
Asset	56.116***	1.330***	-0.028	1.353***
	(0.093)	(0.002)	(0.000)	(0.002)
ROE	-0.2837	-0.050*	-0.012***	-0.0430*
	(0.019)	(0.000)	(0.000)	(0.000)
Cash	-62.1345*	-7.0030***	-0.359***	-7.003***
	(0.347)	(0.005)	(0.001)	(0.005)
Intercept	-120.823***	97.128***	1.845***	96.5235***
	(2.082)	(0.033)	(0.005)	(0.033)
N	41142	38197	41142	38197
Fixed Effects	Yes	Yes	Yes	Yes

Appendix A. AI Keywords Dictionary (Yao et al., 2024)

Artificial Intelligence	AI product	AI chip	Machine translation	Machine learning
Computer vision	Human-computer interaction	Deep learning	Neural network	Biometrics
Image recognition	Data mining	Feature recognition	Speech synthesis	Speech recognition
Knowledge graph	Smart banking	Smart insurance	Human-computer collaboration	Intelligent supervision
Intelligent education	Intelligent customer service	Smart retail	Smart agriculture	Intelligent investment advisor
Augmented reality	Virtual reality	Intelligent healthcare	Smart speaker	Intelligent voice
Smart governance	Autonomous driving	Intelligent transportation	Convolutional neural network	Voiceprint recognition
Feature extraction	Driverless	Smart home	Question answering system	Face recognition
Business intelligence	Smart finance	Recurrent neural network	Reinforcement learning	Intelligent agent
Intelligent elderly care	Big data marketing	Big data risk control	Big data analysis	Big data processing
Support vector machine (SVM)	Long short-term memory (LSTM)	Robotic process automation	Natural language processing	Distributed computing
Knowledge representation	Intelligent chip	Wearable devices	Big data management	Intelligent sensors
Pattern recognition	Edge computing	Big data platform	Intelligent computing	Intelligent search
Internet of Things (IoT)	Cloud computing	Enhanced intelligence	Speech interaction	Intelligent environmental protection
Human-computer dialogue	Deep neural network	Big data operations		

Appendix B. Keyword List for AI Application Depth (Tech_depth)

Keyword	**Keyword**
Industry 4.0	Intelligent production
Intelligent transformation	Intelligent system
Business intelligence	Intelligent manufacturing
Intelligent innovation	Intelligent terminal
Intelligent design	Intelligent equipment
Intelligent R&D	Intelligent processing
Smart city	Intelligent operation & maintenance (O&M)
Intelligent product	Intelligent service
Intelligent marketing	Smart management
Intelligent factory	Intelligent customer service
Intelligent office	