**Impact of Artificial Intelligence on Productivity Change**

**— Evidence from a DEA-Malmquist Analysis**

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**ABSTRACT:** This study examines whether the use of artificial intelligence (AI) and enabling technologies leads to improvements in firm productivity. Using DEA-Malmquist model, we estimate firm productivity change and its two components, technical progress and relative efficiency. We measure AI usage intensity using a textual measure of AI keywords disclosed in annual reports. Results show that AI usage intensity is positively associated with productivity growth, primarily through gains in relative efficiency (catching-up effect) rather than technical progress (innovation effect). Furthermore, large and high-tech firms gain productivity growth through technical progress, while small and medium enterprises and non-high-tech firms benefit from improvements in relative efficiency. The impact of AI on both components is stronger in regions with higher marketization and intellectual property protection. Additional analyses show that capital efficiency mediates the effect of AI on productivity change, technical progress, and relative efficiency change, whereas R&D efficiency mediates its effect on technical progress.

**JEL Classifications:** O33, C67, D24

**Keywords:** artificial intelligence; productivity change; technical progress; relative efficiency change

## I. INTRODUCTION

Over the past decade, artificial intelligence (AI) has become a strategic priority for businesses across various sectors. AI refers to systems that display intelligent behavior by analyzing their environment and taking actions with some degree of autonomy to achieve specific goals (Sheikh, Prins, and Schrijvers 2023). AI systems are rapidly evolving through integration with advanced enabling technologies - such as cloud computing, data analytics, and blockchain - into business operations, which holds the potential to drive substantial improvements in productivity and innovation. Leading companies, including Amazon, Netflix, and JPMorgan Chase, have leveraged AI technologies to improve operational efficiency, enhance customer experiences, and foster innovation.

Despite the increasing adoption of AI and enabling technologies in businesses, the existing literature presents mixed evidence regarding the relation between the application of AI and firm efficiency. While some studies posit that AI and enabling technologies improve efficiency (Acemoglu and Autor 2011; Acemoglu and Restrepo 2018; Babina, Fedyk, He, and Hodson 2024), others suggest a more complex, non-linear relation (Hajli, Sims, and Ibragimov 2015; Liu, Yan, Zhang, and Lin 2021). Furthermore, prior studies mainly focus on static efficiency measures, emphasizing short-term gains rather than long-term impacts of AI on the dynamics of productivity and technological adaptation. Given the importance of sustainable productivity growth in maintaining competitive advantages, it is vital to understand how the adoption and integration of AI and enabling technologies may affect productivity change over time. To this end, we employ the DEA-Malmquist model to calculate firm productivity growth and decompose it into two components, i.e., technical progress and relative efficiency change. These measures capture changes in firms' efficiency in the current year relative to the previous year (Banker, Chang, and Natarajan 2005), allowing us to explore dynamic effects beyond static comparisons.

By focusing on longitudinal changes rather than static efficiency metrics, our study offers critical insights into whether AI and its enabling technologies foster sustainable improvements or pose adaptation challenges as firms integrate them into their operations. We begin by examining whether the adoption and integration of AI are associated with long-term improvements in productivity. AI can improve productivity through several pathways. First, AI and enabling technologies facilitate more efficient capital allocation and reduce financing costs (Rajgopal, Srivastava, and Zhao 2023). Second, these technologies can improve labor efficiency by enhancing training, task allocation, and communication (Wu, Jin, and Hitt 2018; Dixon, Hong, and Wu 2021; He and Goh 2022; Forman and McElheran 2025). Third, AI applications reduce production costs and accelerate technological innovation (Nwankpa and Roumani 2016). Therefore, we expect a positive relationship between AI usage intensity - defined as the extent to which firms adopt and integrate AI and enabling technologies - and productivity change. To further explore this relationship, we identify three key mechanisms: capital, labor, and technology.

Next, we analyze the extent to which productivity change can be explained by two key factors: technical progress, reflecting a shift in industry production technology (i.e., innovation effect), and relative efficiency change, representing a change in firm's efficiency relative to its peers (i.e., catching-up effect). First, the application of AI can enhance production technology by enhancing the conversion rate of R&D and streamlining the integration of technology into production processes. Second, the application of AI can help firms bridge efficiency gaps with peers by minimizing resource waste due to overcapacity and reducing opportunity costs associated with undercapacity. Therefore, we posit that AI usage intensity is positively associated with both technical progress and relative efficiency change.

Finally, we investigate whether the relation between firm-level AI usage intensity and efficiency changes varies across different business dynamics. Firm characteristics and institutional contexts are crucial in shaping a firm's competitive advantages and strategic behaviors (DiMaggio 1998; Park and Luo 2001). These factors may exert differential effects on productivity growth and the operation of its components (i.e., technical progress and relative efficiency change). Specifically, we examine how these effects differ across firm-level attributes, such as firm size and innovativeness, as well as market-level factors, including the degree of marketization and the level of intellectual property protection.

To empirically test our hypotheses, we employ a textual analysis approach to capture the firm-level AI usage intensity by counting the frequency of AI-related words in firms' annual reports. Next, we use the DEA-Malmquist model to estimate productivity growth, technical progress, and relative efficiency change over time (Banker et al. 2005). Our sample includes 25,153 firm-year observations from China's A-share listed firms covering the period from 2011 to 2020.

Consistent with our expectation, we document a significantly positive association between firm-level AI usage intensity and productivity growth. We also find a significantly positive association between AI usage intensity and relative efficiency change, whereas no significant relation emerges with technical progress, suggesting that productivity growth is primarily driven by improvements in relative efficiency rather than technical progress.

Next, we explore how firm- and market-level factors influence the positive relation between AI usage intensity and firm efficiency changes. At the firm level, non-high-tech firms and small and medium enterprises (SMEs) achieve productivity growth predominantly through improvements in relative efficiency, while high-tech firms and large enterprises benefit primarily from technical progress. At the industry level, the positive effects of AI usage intensity on efficiency changes are more pronounced for firms located in regions with higher levels of marketization and stronger intellectual property protection.

Finally, we investigate three potential mediating mechanisms - capital, labor, and technology - through which AI and enabling technologies influence firm efficiency changes. Specifically, we measure capital efficiency as the asset turnover ratio, labor efficiency as revenue per employee, and technological efficiency as the ratio of R&D expenditure to total assets. We find that capital efficiency mediates the effect of AI usage intensity on productivity change, technical progress, and relative efficiency change. Furthermore, the positive association between AI usage intensity and technical progress is attributable to an increase in R&D efficiency.

Our study makes three contributions. First, our research advances the understanding of how firm-level AI usage intensity impacts productivity. Prior studies provide mixed evidence on the relationship between AI adoption and firm productivity (Acemoglu and Restrepo 2018; Babina et al. 2024; Hajli et al. 2015; Liu et al. 2021). Furthermore, these studies largely rely on static productivity measures, which may not adequately capture the dynamic and evolving nature of AI technologies in increasingly complex business environments. By adopting a dynamic measure of productivity change over time, our study provides evidence that firms with higher AI intensity experience sustained productivity growth. From a sustainability perspective, our findings contribute to the ongoing debate on whether AI and enabling technologies yield long-term productivity gains for firms.

Second, our study identifies the key drivers of productivity growth by decomposing it into two components: technical progress and relative efficiency change. While AI and enabling technologies have reshaped firms and industries, there is limited empirical evidence on whether these changes have fundamentally shifted the production function through innovation (i.e., technical progress) or have instead enabled firms to converge toward the production frontier by catching up with their peers (i.e., relative efficiency change). Our findings suggest that the positive effect of AI usage intensity on productivity change is primarily driven by improvements in relative efficiency, rather than technical progress. Furthermore, we provide insights into how these two components contribute to productivity growth under heterogeneous firm- and market-level conditions.

Third, our study contributes to the literature by revealing the mediating mechanisms through which AI usage intensity influences changes in firm efficiency. While prior research has primarily focused on the outcomes of AI integration within firms, our study shifts the focus to the mechanisms through which these technologies drive productivity change. Specifically, we identify three key channels: capital efficiency, labor efficiency, and technology efficiency. Our empirical analysis reveals that capital efficiency mediates the effect of AI usage intensity on overall firm efficiency changes, whereas technology efficiency only serves as a mediator between AI usage intensity and technical progress. By highlighting the distinct roles of capital and technology efficiency, our study deepens the understanding of how AI delivers value to firms and clarifies the pathways through which it enhances firm efficiency.

The remainder of the paper is organized as follows. We review the prior literature and develop hypotheses in Section 2. The methodology and research design are described in Section 3. Section 4 reports our main empirical findings. Sections 5 and Section 6 present the results of cross-sectional analyses and mediating effects. Finally, Section 7 concludes.

## II. LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

AI usage intensity, as used in this study, refers to the extent to which firms integrate artificial intelligence and enabling technologies - such as cloud computing, data analytics, and blockchain - into their operations. In practice, AI and these supporting technologies are closely connected and often implemented together. For example, cloud infrastructure supports the deployment of large-scale generative models like ChatGPT; data science enables AI systems to analyze user behavior for applications such as product recommendations; and blockchain facilitates decentralized AI models and secure data sharing.

Unlike traditional technologies that impact only specific areas of a company, AI fundamentally transforms business operations by integrating AI and enabling technologies across production processes, business models, and value chains, allowing for greater agility, data-driven decision-making, and opportunities for innovation (Bharadwaj, Sawy, Pavlou, and Venkatraman 2013; Vial 2021). Despite the worldwide growing trend of AI adoption, the existing literature presents mixed evidence regarding the relation between AI and productivity. Few studies have explored how firm-level AI usage intensity influences dynamic productivity growth over time. While some studies suggest that adopting AI and enabling technologies can enhance operational performance and productivity (Nwankpa and Roumani 2016; Lin and Xie 2023; Nucci, Puccioni, and Ricchi 2023), others highlight the implementation challenges associated with AI. Unlike traditional IT investments, deploying AI often involves substantial upfront costs, ongoing experimentation, and uncertain returns, which may lead to performance declines or growing pains (Kim 2017; Liu et al. 2021). In many cases, firms may experience initial productivity gains that are difficult to sustain. This complexity arises from the need to embed AI into existing workflows, requiring firms to reconfigure capital structures, management systems, and organizational processes (Singh and Hess 2020; Nambisan, Lyytinen, Majchrzak, and Song 2017; Brynjolfsson, Rock, and Syverson 2021).

In this paper, we examine the relation between firm-level AI usage intensity and dynamic efficiency changes, including productivity growth, technical progress, and shifts in relative efficiency. From a production economics perspective, productivity reflects a firm's ability to generate a given output with minimal inputs at a specific point in time, indicating allocative efficiency (Farrell 1957). However, in the context of rapid AI diffusion, firms increasingly face shifting production frontiers driven by continuous algorithmic improvements, automation, and real-time data utilization. To capture these dynamics, we employ the DEA-Malmquist model, which captures changes in productivity over time. In addition to mitigating the issue of non-comparability of productivity levels across different periods due to variations in inputs and outputs, this model offers a framework for analyzing how firms navigate through technological disruption and cope with competitive uncertainty in the AI era.

To begin with, we examine the impact of firm-level AI usage intensity on productivity changes. AI can enhance productivity by improving the allocation and coordination of key production factors, including capital, labor, and technology (Nelson and Winter 1985; Nucci et al. 2023).

First, AI facilitates more efficient capital allocation and reduces financing costs. *Internally,* AI and enabling technologies, such as machine learning (ML) and natural language processing (NLP), can provide real-time information to support managerial investment and financing decisions (Rajgopal et al. 2023; Wang, Huang, and Wang 2024), enhancing the effective deployment of capital. *Externally,* AI-enabled systems, such as Intelligent Process Automation (IPA) and Enterprise Resource Planning (ERP), enhance the transparency, timeliness, and accessibility of corporate disclosures (Bollaert, Lopez-de-Silanes, and Schwienbacher 2021; Wu, Hu, Lin, and Ren 2021; Hu, Su, and Yu 2024). Higher disclosure quality may lead to a lower risk premium demanded by investors, leading to a lower cost of capital Beyer, Cohen, Lys, and Walther 2010). Therefore, productivity growth is facilitated by more efficient capital allocation and a decline in financing costs.

Second, AI enhances labor productivity through improved training, task allocation, and communication. By integrating AI and enabling technologies, firms can identify skill gaps, deliver personalized training, and optimize workforce deployment, thereby enhancing human capital utilization, reducing overall labor costs, and increasing employee output per capita (Scheiding 2023). Additionally, AI-powered collaboration platforms facilitate real-time communication and workflow integration across departments and locations, mitigating inefficiencies arising from organizational or geographic fragmentation (Brynjolfsson and

McAfee 2014; Leonardi 2014). As a result, more effective labor management enabled by AI contributes to productivity growth over time.

Finally, AI reduces operational costs and facilitates technological innovation. The application of AI in business operations - such as predictive analytics for demand forecasting, and intelligent supply chain optimization systems - enhances process efficiency through automation, real-time decision-making, and resource optimization, leading to higher technical efficiency and reduced operational costs (Tang, Huang, and Wang 2018; Lin and Xie 2023). In addition, AI accelerates innovation by leveraging data-driven insights to guide research and development (R&D) and technological advancements (Kohli and Melville 2019). By extracting insights from vast and unstructured datasets, AI facilitates faster idea generation, prototype testing, and market adaptation. For example, generative AI models can support design automation, simulate product performance, and personalize innovation based on real-time consumer feedback.

Based on the above discussion, we present the following hypothesis H1:

*H1: Firm-level AI usage intensity is positively associated with productivity change.*

The adoption and integration of AI technologies offer numerous benefits but also present significant risks. First, from a capital perspective, AI systems require substantial capital investment, such as investments in information systems and infrastructure, which may not generate immediate returns (Liu et al. 2021; Rajgopal et al. 2023). This increases financial pressure and may weaken investor confidence due to delayed improvements in financial performance. Additionally, the rapid deployment of AI technologies leads to high depreciation costs, which may further reduce capital efficiency (Vial 2021). Second, from a labor perspective, adopting AI systems demands highly skilled workers (Dremel, Wulf, Herterich, Waizmann, and Brenner 2017), necessitating ongoing employee training or the recruitment of technical talent. The adoption of new technologies may also disrupt existing workflows, causing adaptation challenges and temporary declines in efficiency. Furthermore, automation may exacerbate job insecurity (Dixon et al. 2021). Third, from a technological perspective, challenges such as system failures, data migration issues, and compatibility problems (Wessel, Baiyere, Ologeanu-Taddei, Cha, and Blegind-Jense 2020) can hinder resource utilization efficiency and increase maintenance and upgrade costs. Therefore, the extent to which AI and enabling technologies enhance productivity remains an empirical question.

We then investigate how productivity change can be explained by its two components: technical progress and relative efficiency change. Technical progress reflects industry-wide advancements in production technology, representing an innovation effect, while relative efficiency change reflects a firm's ability to improve its performance relative to its industry peers, representing a catching-up effect.

First, the innovation effect is a significant way in which AI usage intensity may impact productivity changes. In addition to task automation, AI enhances innovation methods by acting as a catalyst for research and development (Crafts 2023). AI technologies enable firms to analyze large-scale transactional datasets, identifying innovation trajectories with greater accuracy and improving R&D conversion rates (Wu, Hitt, and Lou 2020). This AI-driven insight reduces uncertainty and trial-and-error costs in R&D activities, leading to higher innovation efficiency. Furthermore, AI-driven platforms foster active user engagement in product development through real-time feedback loops and co-creation mechanisms. This participatory innovation approach aligns product features more closely with market needs while minimizing production inputs, thus lowering development costs and time-to-market (Zittrain 2006). Collectively, these capabilities accelerate technological innovation in firm production processes (Babina et al. 2024; Cockburn, Henderson, and Stern 2019). Based on the above analysis, we propose the following hypothesis:

*H2: Firm-level AI usage intensity is positively associated with technical progress.*

Next, the catching-up effect serves as another critical mechanism linking AI to productivity change. On one hand, AI and enabling technologies facilitate the accumulation and diffusion of knowledge across firms, integrating high-quality knowledge into production and operational processes, which enhances firm-level productivity (Venturini 2022; Benassi, Grinza, Rentocchini, and Rondi 2022). Based on the theory of innovation diffusion (Rogers 1985), firms engaged in catching up benefit from reduced uncertainty, lower IT training costs, and an improved understanding of customer demands, all of which provide firms with a competitive edge. On the other hand, the integration of AI technologies optimizes management processes and fosters cross-departmental collaboration, leading to better resource allocation (Cockburn et al. 2019; Yang, Li, Nie, Yue, and Wang 2024). For example, in practice, generative AI models such as ChatGPT have been adopted by firms to support customer service automation and internal knowledge management, improving response efficiency and reducing labor costs; meanwhile, AI-based demand forecasting tools such as Amazon Forecast or Azure Machine Learning are widely used in warehouse operations to optimize inventory levels and reduce holding costs. These advancements enable firms to narrow the efficiency gap with industry production frontiers, thereby improving their relative efficiency. Accordingly, we propose the following hypothesis:

*H3: Firm-level AI usage intensity is positively associated with relative efficiency change.*

## III. DATA, VARIABLE DEFINITIONS, AND DESCRIPTIVE STATISTICS

### 3.1 Data

We obtain stock price, financial information, and corporate governance variables from the China Security Market and Accounting Research (CSMAR) database. To measure firm-level AI usage intensity, we obtain the text data from the WinGo platform (wingodata.com).

Our initial sample consists of all China A-share listed firms over the period 2011–2020. We exclude special treatment (ST)[1] firms and financial firms. In addition, we delete observations from firms' IPO year. Finally, we remove firm-years without the necessary data for constructing the variables used in our analysis. Our final sample includes 25,153 firm-year observations. Appendix D presents the sample selection process.

### 3.2 Variable Definitions

#### *3.2.1 Firm-level Measure of AI Usage Intensity*

To measure firm-level AI usage intensity (*AI*), we count the frequency of AI-related keywords in the firm's annual reports. These reports contain comprehensive information about a firm's history, organizational structure, financial status, and strategic initiatives. Firms that adopt and integrate AI and related enabling technologies are likely to disclose these keywords in their reports to signal a commitment to investors and stakeholders. Textual analysis of annual reports thus provides a systematic approach to capture the extent to which firms adopt and integrate AI and enabling technologies (Hanley and Hoberg 2010; Loughran and McDonald 2011). Furthermore, recent studies validate the reliability of such measure for empirical analysis (Balakrishnan, Qiu, and Srinivasan 2010; Wu et al. 2021; Chen and Srinivasan 2024).

Specifically, the methodology involves three steps. First, we develop a comprehensive dictionary of keywords related to AI and its enabling technologies, including cloud computing, data analytics, and blockchain. These terms are derived from numerous articles, research papers, and government reports. The full list of keywords is provided in Appendix B. Second, we extract and count the frequencies of these keywords within firms' annual reports. Third, to address the right-skewed and noisy nature of textual data, we define the firm-level AI usage intensity (*AI*) as the natural logarithm of one plus the frequency of keywords related to AI and

[1] Special Treatment (ST) firms refer to publicly listed companies identified by stock exchanges as financial or operational distress. The Shanghai and Shenzhen Stock Exchanges designate firms as ST when they meet specific criteria for financial instability, such as consecutive years of losses or severe financial irregularities.

its enabling technologies.

### *3.2.2 Productivity Change, Technical Progress, and Relative Efficiency Change*

Traditional production efficiency metrics, such as the Levinsohn and Petrin (LP) and the Olley and Pakes (OP) approaches, impose the restrictive assumption of constant returns to scale, thereby limiting their applicability across diverse operational contexts, particularly in the digital era. We adopt the modified Malmquist (1953) index proposed by Banker et al. (2005) to calculate productivity change (*PRODCH*) at the firm level, which measures the changes in productivity between two time periods. This measure also decomposes productivity change into two components: technical progress (*TECH*), representing shifts in production technology (innovation effect), and relative efficiency change (*RECH*), which reflects changes in a firm's efficiency relative to its peers (catching-up effect).

According to the resource-based theory and the dynamic capabilities theory, an enterprise's competitive advantage originates from the scarcity of its proprietary resources and its ability to dynamically enhance efficiency in resource utilization (Barney 1991; Teece, Pisano, and Shuen 1997). The dynamic framework of the data envelopment analysis (DEA) model is particularly well-suited for examining the evolving implications of AI technologies on firms' technical, technological, and productive efficiency.

The construction of firm efficiency change indexes involves the following steps.

**1. Model construction.** The Malmquist productivity index to compare the base period *0* with the subsequent period $t$ for the decision-making unit (DMU) $i$ is:

$$M_i(0,t) \equiv \frac{\theta_{i,t}^{0}}{\theta_{i,0}^{0}} \tag{1}$$

In equation (1), $\theta$ is the input-output distance function given by $[\theta_i(X,Y)]^{-1}=[max\{\theta:(X/\theta,Y)\in T\}]^{-1}$. The variables $X$ and $Y$ represent the input and output variable metrics, respectively; $T$ represents the production possibility set; $i$ denotes each decision-making unit (DMU, in this context, individual firm). A Malmquist index value greater than 1 indicates an increase in productivity relative to the base period.

Next, the Malmquist index for a firm *i* can be decomposed into two components:

$$M_i(0,t) \equiv \frac{\theta_{i,t}^0}{\theta_{i,0}^0} = \frac{\theta_{i,t}^t}{\theta_{i,t}^0} \times \frac{\theta_{i,t}^0/\theta_{i,t}^0}{\theta_{i,0}^0/\theta_{i,t}^0} = \frac{\theta_{i,t}^t}{\theta_{i,t}^0} \times \frac{\theta_{i,0}^0}{\theta_{i,t}^t} \tag{2}$$

Following Banker et al. (2005), productivity change is measured using a logarithmic transformation of the index in (2). This transformed measure naturally represents the percentage change in productivity, technical progress, and relative efficiency. A value greater than zero signifies an improvement in efficiency relative to the base period.

$$\begin{aligned} PRODCH &= \ln\big(M_i(0,t)\big) = \ln\big(\theta_{i,t}\big) - \ln\big(\theta_{i,0}\big) \\ &= \ln\left(\frac{\theta_{i,t}^t}{\theta_{i,t}^0}\right) + \ln\left(\frac{\theta_{i,0}^0}{\theta_{i,t}^t}\right) \\ &= TECH + RECH \end{aligned} \tag{3}$$

The relationship in (3) is illustrated in Figure 1. To intuitively demonstrate the relationship between the components of efficiency changes, we assume that the input remains constant between two periods. *F* denotes the production function. The production level of firm *i* is *A*, while its maximal output level is *S*. In this case, productivity change (*PRODCH*) is expressed as $PRODCH = \ln\,(A_t/A_0)$, representing the percentage change in productivity of firm *i* relative to the baseline period. Technical progress (*TECH*), which reflects shifts in production technology and represents the innovation effect, is denoted as $TECH = \ln\,(S_t/S_0)$. Meanwhile, relative efficiency change (*RECH*), which captures changes in the firm's distance from the optimal production frontier and represents the catching-up effect, is denoted as $RECH = \ln\,[(A_t/S_t)/(A_0/S_0)]$.

Combining these components, we derive the following relationship:

$$A_t/A_0 = S_t/S_0 \times [(A_t/S_t)/(A_0/S_0)], \tag{4}$$

which is consistent with equation (3), that is, *PRODCH* = *TECH* + *RECH*.

**2. Parameter setting**. Previous research has shown that firm production efficiency is influenced by three key factors: capital, labor, and technology (Nelson and Winter 1985; Nucci et al. 2023). Consistent with this framework, we use *net fixed assets, the number of employees,* and *research and development expenditure* as the input factors, and *operating revenue* as the output factor (Banker et al. 2005; Liu et al. 2021; Demerjian, Lev, and McVay, 2012).

#### *3.2.3 Control Variables*

We employ a series of control variables, including firm size (*Size*), leverage ratio (*Lev*), cash holdings (*Cash*), post-listing age and its square term (*Age*, $Age^2$), audit opinion (*AuditOpinion)*, CEO-Chairman duality (*Dual*), book-to-market ratio (*BM*), and return on total assets (*ROA*). Appendix A provides detailed descriptions of these variables.

### 3.3 Descriptive Statistics

Table 1 presents the descriptive statistics for the variables. All continuous variables are winsorized at the 1% and 99% levels, respectively. The mean value of productivity change (*PRODCH*) is 0.028, indicating a trend of continuous productivity growth throughout the sample period. The mean and median values of firm-level AI usage intensity (*AI*) are 1.293 and 1.099, respectively, showing a notable right skewness, which aligns with the nature of textual indicators.

## IV. EMPIRICAL RESULTS

### 4.1 Distribution of Firms Using AI Technologies

We first examine the yearly distribution of firms using AI technologies. Figure 2 Panel A and Panel B illustrate the number and proportion of firm-year observations disclosing AI terms in annual reports during the period 2011-2020, respectively. We find a steady increase in the adoption of AI technologies. This trend highlights the growing importance of AI.

Next, Appendix C presents the industry distribution of firms using AI technologies. We find that the proportion of AI observations is the highest in the information transmission, software, and information technology services industry (92.38%). In contrast, this proportion is the lowest in the mining (32.00%) and the production and supply of electricity, heat, gas, and water (40.96%) industries. This evidence suggests that firms in technology-intensive industries are more inclined to engage in AI activities, whereas those with high fixed costs are less likely to do so.

**4.2 Association between AI Usage Intensity and Firm Efficiency Changes**

Table 2 presents the pairwise Pearson correlation coefficients of the main variables. We find that AI usage intensity (*AI*) and productivity change (*PRODCH*) are positively correlated, consistent with hypothesis H1. Similarly, positive correlations are observed between AI usage intensity (*AI*) and both technical progress (*TECH*) and relative efficiency change (*RECH*), which align with hypotheses H2 and H3.

To further investigate the association between AI usage intensity and firm efficiency changes, we estimate the following equation.

$$\begin{aligned} Efficiency\ Change_{i,t} = {} & \beta_0+\beta_1 AI_{i,t}+\beta_2 Size_{i,t}+\beta_3 Lev_{i,t}+\beta_4 Cash_{i,t}+\beta_5 Age_{i,t}+\beta_6 Age^2_{i,t} \\ & +\beta_7 AuditOpinion_{i,t}+\beta_8 Dual_{i,t}+\beta_9 BM_{i,t}+\beta_{10} ROA_{i,t} \\ & + YearFE + IndustryFE+\epsilon_{i,t} \end{aligned} \quad (5)$$

In Equation (5), *Efficiency Change* represents productivity change (*PRODCH*), technical progress (*TECH*), and relative efficiency change (*RECH*). We include industry (72 industries) and year fixed effects[2]. The regressions are estimated using ordinary least squares (OLS) with heteroscedasticity-robust standard errors clustered at the firm level.

Table 3 reports the results of estimating the association between AI usage intensity and firm efficiency changes. Columns (1) and (2) present the results using *PRODCH* as the

[2] We assess the optimal fixed effects to include in the model following Breuer and Dehaan (2024). The untabulated results indicate that industry and year fixed effects yield smaller model errors compared to firm and year fixed effects. For robustness checks, we also use firm and year fixed effects in the regressions, and the results are robust.

dependent variable. First, we estimate Equation (5) by including just year and industry fixed effects. In Column (1), the coefficient on *AI* is 0.010 and statistically different from zero (t-statistic = 4.097), suggesting that firm-level AI usage intensity is positively associated with productivity change. In Column (2), such an effect is robust to adding a series of controls. The coefficient on *AI* remains positive and significant (coefficient = 0.007, t-statistic = 3.753). In addition, a one-standard-deviation increase in AI usage intensity (*AI*) results in a 0.959% (0.007*1.370 = 0.959%) increase in productivity change over time. Therefore, greater use of AI and enabling technologies leads to a continuous increase in firm productivity change, supporting Hypothesis 1.

Next, we decompose productivity change into two components: technical progress (*TECH*) and relative efficiency change (*RECH*), and examine the impact of *AI* on each. Columns (3) and (4) present the results using *TECH* and *RECH* as the dependent variables, respectively. The coefficient on *AI* for technical progress is not significant (Column (3), whereas the coefficient on *AI* for relative efficiency change is significantly positive (Column (4): coefficient = 0.006, t-statistic = 2.789). These results suggest that the adoption and integration of AI technologies increase relative efficiency change (catching-up effect), but have a limited impact on technical progress (innovation effect).

Overall, the evidence presented in Table 3 supports H1 and H3, suggesting that firms with higher levels of AI usage intensity exhibit greater productivity growth, primarily driven by an improvement in relative efficiency change rather than technical progress. This indicates that the adoption and integration of AI technologies enhance a firm's efficiency relative to its peers, but do not drive innovation-led technological advancement. We further investigate these effects across different firm and institutional contexts in subsequent analyses to better understand how AI and enabling technologies affect firm-level outcomes.

### 4.3 Endogeneity Test

While we include two sets of fixed effects for identification, there can be other unobservable factors that simultaneously drive both AI usage intensity and firm productivity change. In addition, firms experiencing higher efficiency changes may pursue high levels of AI to maintain their competitiveness, raising concerns about reverse causality. To mitigate these concerns, we leverage the adoption of AI and enabling technologies as a quasi-natural experiment. Following Wu et al. (2021), we implement a difference-in-differences (DID) model, as specified in Equation (6).

$$Efficiency\ Change_{i,t}=\theta_0+\theta_1 AIAdopt_{i,t}+\sum_j \varphi_j X_{i,j,t}+YearFE+IndustryFE+\epsilon_{i,t} \qquad (6)$$

In Equation (6), we construct an indicator variable, *AIAdopt*, to capture firm-level AI adoption during the sample period. For example, if a firm begins to report AI-related keywords in its annual reports in 2013, we assign the value of *AIAdopt* as 0 for all years prior to 2013 and 1 for the period from 2013 to 2020. Additionally, we exclude firms that report AI-related keywords in only one year, as well as those that consistently disclose such keywords throughout the entire sample period. *Efficiency Change* represents productivity change (*PRODCH*), technical progress (*TECH*), and relative efficiency change (*RECH*). $\sum_j \varphi_j X_j$ represent the list of control variables.

We further isolate the effect of AI usage intensity in the difference-in-differences analysis by incorporating the interaction term between *AIAdopt* and *AI* using the following model:

$$Efficiency\ Change_{i,t}=\theta'_0+\theta'_1 AIAdopt_{i,t}\times AI_{i,t}+\sum_j \varphi_j' X_{i,j,t}+YearFE+IndustryFE+\epsilon_{i,t} \qquad (7)$$

In models (6) and (7), the coefficient $\theta_1$ ($\theta'_1$) on the variable of interest, *AIAdopt* (*AIAdopt*×*AI*), is expected to be positive. Table 4 presents the results. Columns (1) and (2) present the results using *PRODCH* as the dependent variable, Columns (3) and (4) present the results using *TECH* as the dependent variable, and Columns (5) and (6) present the results using *RECH* as the dependent variable. We find that the coefficients on *AIAdopt* and *AIAdopt* $\times$*AI* are positive and significant in Columns (1), (2), (5), and (6), suggesting that AI usage intensity is positively associated with productivity change and relative efficiency change. These results provide further support for our main findings that the greater use of AI and enabling technologies leads to a continuous increase in productivity change and relative efficiency improvement.

**4.4 Robustness Tests**

***4.4.1 Excluding Firms with Poor Disclosure Quality***

For firms with poor disclosure quality, texts in annual reports may not reliably capture their levels of AI usage intensity. To mitigate this concern, we exclude firms with low disclosure quality from our sample. Specifically, we use disclosure evaluation ratings from the Shenzhen Stock Exchange (SZSE) and the Shanghai Stock Exchange (SSE) and exclude firms rated as “unqualified” or “D” during the sample period. Table 5, Panel A, Column (1) presents the result when the dependent variable is *PRODCH*. We find that the coefficient on *AI* is significantly positive, consistent with the main finding.

***4.4.2 Including Firm and Year Fixed Effects***

In the main regressions, we include industry and year fixed effects and report t-values based on standard errors clustered at the firm level. Following Breuer and Dehaan (2024), we assess the optimal fixed effects specification. The untabulated results show that industry and year fixed effects yield smaller model errors compared to firm and year fixed effects. As a robustness check, we also estimate a model with firm and year fixed effects. Table 5, Panel A, Column (2) presents the result using *PRODCH* as the dependent variable. The coefficient on *AI* is significantly positive, supporting the main finding.

#### *4.4.3 Alternative Measures of AI*

In the previous analyses, we define AI usage intensity (*AI*) by counting the frequency of AI-related keywords in annual reports. To ensure robustness, we employ three alternative measures of AI usage intensity.

First, to account for the potential delayed effect of AI on productivity change, we use a one-year lag of *AI*, as shown in Table 5, Panel A, Column (3). Second, to address the concern that raw keyword counts may be noisy, we follow Chen and Srinivasan (2024) and categorize firms into terciles based on word frequency: 0 if no AI-related keyword is disclosed, and 1, 2, or 3 if the frequency falls in the bottom, middle, or top tercile of AI-related keywords in the year, respectively, with the result presented in Column (4). Third, to mitigate the concern that firms may only disclose AI terms without actually adopting AI, we use *AI Intangible Assets* as a proxy, defined as the proportion of AI technology-related components in year-end intangible assets (Zhang, Li, and Xing 2021). We present the result in Column (5).

Columns (3), (4) and (5) present the results using *PRODCH* as the dependent variable. Across all specifications, we find that the coefficients on $AI_{t-1}$, *AI Code*, and *AI Intangible Assets* are positive and statistically significant, consistent with *H1*.

#### *4.4.4 Alternative Measures of Firm Efficiency*

In the previous section, firm efficiency is measured using the DEA-Malmquist model (Banker et al. 2005). To mitigate measurement errors, we also employ alternative production efficiency metrics, calculated using Ordinary Least Squares (OLS), Fixed Effects (FE), LP (Levinsohn and Petrin) semiparametric, OP (Olley and Pakes) semiparametric, and systematic GMM (Generalized Method of Moments) approaches. All columns of Table 5, Panel B show that the coefficients on *AI* remain positive and significant, supporting our main findings.

## V. HETEROGENEOUS ANALYSIS

The impact of AI usage intensity on efficiency changes likely varies with firm-specific attributes and institutional environments, both of which are critical in shaping competitive dynamics and strategic behavior (DiMaggio 1998; Park and Luo 2001). To capture this heterogeneity, we explore how the effects differ across firm-level characteristics, such as firm size and high-tech status, and market-level factors, including marketization intensity and the strength of intellectual property protection. Tables 6 and 7 report the results. Columns (1) and (2) of each panel present the results when dependent variable is *PRODCH*, Columns (3) and (4) of each panel present the results when dependent variable is *TECH*, and Columns (5) and (6) of each panel present the results when dependent variable is *RECH*.

### 5.1 Firm-level Heterogeneity

#### *5.1.1 Large Enterprises and small and medium enterprises (SMEs)*

First, we examine the heterogeneity in the scale effects of AI and its enabling technologies. We expect that large enterprises benefit more from AI, as they are better positioned to integrate AI technologies into management and production processes, thereby achieving higher efficiency gains. As a result, we expect greater productivity gains in large enterprises compared to small and medium enterprises (SMEs). Following China's official regulation *Statistical Division of Large, Medium, Small, and Micro Enterprises (2017)*, we categorize firms as either large enterprises or SMEs based on total assets, revenue, and number of employees.

The results are presented in Panel A of Table 6. In Columns (1) and (2), the coefficients on *AI* are both positive and significant (coefficient = 0.006, t-statistic = 2.258; coefficient = 0.008, t-statistic = 2.496), suggesting that firm-level AI usage intensity is positively associated with productivity change for both large enterprises and SMEs. For large enterprises, the coefficient on *AI* is positive and significant for technical progress (Column (3): coefficient =

0.002, t-statistic = 1.896), but insignificant for relative efficiency change (Column (5)). In contrast, for SMEs, the coefficient on *AI* is insignificant for technical progress (Column (4)), but positive and significant for relative efficiency change (Column (6): coefficient = 0.007, t-statistic = 2.009). These results suggest that large enterprises enhance productivity primarily through advancements in production technology, while SMEs improve efficiency through a catching-up effect relative to their peers.

***5.1.2 High-tech and Non-high-tech Enterprises***

Next, we examine the heterogeneity based on firms' innovative capabilities. High-tech enterprises, characterized by stronger innovation capacity and greater growth potential, are expected to leverage AI technologies more effectively to enhance production technologies and realize greater productivity gains. In contrast, non-high-tech firms, constrained by limited innovation capabilities, are more likely to rely on existing AI tools to enhance productivity. We categorize firms as either high-tech enterprises or non-high-tech enterprises based on *China's High-Tech Enterprise Certification* standards.

Table 6, Panel B presents the results. In Columns (1) and (2), we find significantly positive coefficients on *AI*, indicating that both high-tech and non-high-tech enterprises benefit from the adoption and integration of AI technologies (coefficient = 0.005, t-statistic = 2.024; coefficient = 0.009, t-statistic = 2.604). For high-tech enterprises, *AI* is positively and significantly associated with technical progress (Column (3): coefficient = 0.002, t-statistic = 2.249), but shows no significant association with relative efficiency change (Column (5)). In contrast, for non-high-tech enterprises, *AI* is not significantly associated with technical progress (Column (4)), but exhibits a positive and significant association with relative efficiency change (Column (6): coefficient = 0.009, t-statistic = 2.302). These results show that productivity growth in high-tech enterprises is primarily driven by technical progress, while in non-high-tech enterprises, relative efficiency improvements account for the main source of productivity gains.

## 5.2 Market-level Heterogeneity

### *5.2.1 High- and Low-marketization Regions*

For the market-level heterogeneity analysis, we first examine cross-sectional differences based on regional marketization levels. Firms operating in high-marketization regions benefit from lower transaction costs and a more equitable competitive environment (Joskow 2002), which facilitates the adoption and integration of AI technologies into their operations. In addition, intense market competition in these regions incentivizes firms to optimize investments in AI technologies through more efficient resource allocation. Accordingly, we expect that the impact of AI usage intensity on firm productivity is more pronounced in high-marketization regions. We measure marketization using the provincial marketization index developed by Fan, Wang, Zhang, and Zhu (2003) and classify firms based on whether they fall above or below the yearly median value.

Table 7, Panel A presents the results. In Columns (1) and (2), we find significantly positive coefficients on *AI* for both high- and low-marketization regions (coefficient = 0.009, t-statistic = 3.174; coefficient = 0.006, t-statistic = 1.994), suggesting that AI generally enhances firm productivity. For firms operating in high-marketization regions, the coefficients on *AI* are positive and significant for both technical progress and relative efficiency change (Column (3): coefficient = 0.002, t-statistic = 1.779; Column (5): coefficient = 0.006, t-statistic = 2.090), indicating that the adoption and integration of AI promote both technical progress and relative efficiency. However, for firms in low-marketization regions, the coefficient on *AI* is insignificant for technical progress (Column (4)), but positive and significant for relative efficiency change (Column (6): coefficient = 0.006, t-statistic = 1.873), indicating that AI technologies primarily contribute to relative efficiency improvements rather than technical innovation. These findings suggest that high marketization levels foster the effective adoption and integration of AI technologies, leading to both technical progress and relative efficiency improvements.

### *5.2.2 Intellectual Property Protection Level*

Next, we examine the heterogeneity based on the strength of intellectual property protection in the provinces where firms are located. Strong intellectual property protection enables firms to leverage AI technologies for business model innovation and enhanced management services, sustaining their competitive advantages. In contrast, weak intellectual property protection increases the risk of imitation (Helpman 1992; Anton and Yao 2004), potentially deterring innovation and limiting productivity growth. Therefore, we predict that the impact of AI usage intensity on firm productivity, particularly on technical progress, is more pronounced in regions with stronger intellectual property protection. To test this, we classify firms into high and low intellectual property protection groups based on the yearly median value of the Intellectual Property Protection (IPP) index, developed by the China National Intellectual Property Administration, which measures both patent protection strength and enforcement at the provincial level.

Table 7, Panel B presents the results. In Columns (1) and (2), we find significantly positive coefficients on *AI*, indicating that AI technologies enhance productivity growth in both high and low intellectual property protection regions (coefficient = 0.006, t-statistic = 2.253; coefficient = 0.010, t-statistic = 3.075). For firms operating in high IPP regions, the coefficient on *AI* is positive and significant for technical progress (Column (3): coefficient = 0.003, *t*-statistic = 2.190), but insignificant for relative efficiency change (Column (5)). In contrast, for firms in low IPP regions, the coefficient on *AI* is insignificant for technical progress (Column (4)), but positive and significant for relative efficiency change (Column (6): coefficient = 0.010, *t*-statistic = 2.912). These patterns suggest that in provinces with strong intellectual property protection, productivity growth is primarily driven by technical progress, whereas in regions with weaker protection, it is largely attributable to relative efficiency improvements.

## VI. MEDIATING EFFECT

In Section 2, we argue that the adoption and integration of AI lead to better utilization of capital, labor, and technology (Nelson and Winter 1985; Nucci et al. 2023), which, in turn, improves firm efficiency. In this section, we explicitly examine these proposed channels by employing the following three-step mediation analysis suggested by Baron and Kenny (1986).

First, we estimate the proposed model without the mediating variables, with the results reported in Table 3. As noted, the coefficients on *AI* for productivity change and relative efficiency change are positive and significant, while the coefficient on *AI* for technical progress is not significant. This suggests that a higher level of AI usage intensity leads to greater productivity growth, primarily driven by relative efficiency improvements rather than technical progress. This is the effect to be mediated.

Second, we show that the integration of AI and enabling technologies leads to expected changes in the mediating variables (*MediatingVar*), that is, capital efficiency (*CapEfficiency*), labor efficiency (*LaborEfficiency*), and technology efficiency (*RDEfficiency*). *CapEfficiency* is defined as total asset turnover, calculated as operating income divided by total assets. *LaborEfficiency* is measured as the natural logarithm of one plus the ratio of operating income to the number of employees. *RDEfficiency* is calculated as the natural logarithm of one plus research and development expenses to total assets. $\sum_j \varphi_j X_j$ represent the list of control variables. We estimate the following model (8):

$$MediatingVar_{i,t}=\gamma_0+\gamma_1 AI_{i,t}+\sum_j \varphi_j X_{i,j,t}+YearFE+IndustryFE+\epsilon_{i,t} \tag{8}$$

In Equation (8), we expect the coefficient of *AI* ($\gamma_1$) to be positive and significant, indicating that the adoption and integration of AI technologies enhance capital, labor, and technology efficiencies. Table 8, Panel A presents the results. Columns (1), (2), and (3) present the results using *CapEfficiency*, *LaborEfficiency*, *RDEfficiency* as the dependent variables, respectively. In Columns (1) and (3), we find significantly positive coefficients on *AI* (Column (1): coefficient = 0.032, t-statistic =3.846; Column (3): coefficient = 0.002, t-statistic = 7.526), suggesting that AI usage intensity is positively associated with capital and technology efficiency. However, the coefficient on *AI* is insignificant in Column (2), indicating that AI does not relate to labor efficiency.

Third, we estimate the full model, including two mediating variables, *CapEfficiency* and *RDEfficiency*, the independent variable *AI,* and the list of control variables $\sum_j \varphi_j X_{,j}$ as follows:

$$Efficiency\ change_{i,t}=\delta_0+\delta_1 Dig_{i,t}+\delta_2 MediatingVar_{i,t}+\sum_j \varphi_j X_{i,j,t}+YearFE+IndustryFE+\epsilon_{i,t} \quad (9)$$

In Equation (9), we expect significantly positive coefficients on *CapEfficiency* and *RDEfficiency* ($\delta_2$), confirming their roles as mediators linking *AI* to efficiency changes. Table 8, Panel B presents the mediated effect of AI usage intensity on firm efficiency changes. Columns (1), (2), and (3) present the results using *CapEfficiency* as the mediating variable, whereas Columns (4), (5), and (6) present the results using *RDEfficiency* as the mediating variable. In the first three columns, we find that for productivity change, technical progress, and relative efficiency change, the coefficients on *CapEfficiency* are positive and significant (coefficient = 0.072, t-statistic = 6.957; coefficient = 0.007, t-statistic = 3.610; coefficient = 0.066, t-statistic = 6.387). These results indicate that capital efficiency mediates the impact of AI usage intensity on productivity change. Consistent with our expectations, AI technologies enhance capital allocation efficiency and reduce financing costs, thereby improving productivity, technical progress, and relative efficiency over time. In the last three columns, we find that only when the dependent variable is *TECH*, the coefficient on *RDEfficiency* is positive and significant (Column (5): coefficient = 0.112, t-statistic = 2.100). However, the coefficient on *RDEfficiency* is insignificant when the dependent variables are *PRODCH* and *RECH* (Columns (4) and (6)). These findings suggest that R&D efficiency mediates the impact of AI usage intensity on technical progress, but not on productivity or relative efficiency change. Consequently, the adoption and integration of AI technologies accelerate advancements in production technology, achieving the innovation effect (Cui and Mak 2002).

In conclusion, our findings indicate that the positive association between AI usage intensity and firm efficiency changes is primarily attributable to an increase in capital efficiency, while R&D efficiency serves as a mediating factor in the effect of AI usage intensity on technical progress.

## VII. CONCLUSION AND IMPLICATION

This paper examines the impact of AI usage intensity on firm efficiency changes over time, specifically productivity change, technical progress, and relative efficiency change. Using a sample of 25,153 firm-year observations from China A-share listed firms over the period from 2011 to 2020, we examine the relation between AI usage intensity and firm efficiency changes and further explore how this relation varies based on firm attributes and market contexts.

Our findings show that firms with higher levels of AI usage intensity experience greater productivity growth, primarily driven by improvements in relative efficiency change (catching-up effect) rather than technical progress (innovation effect). Heterogeneity tests show that large and high-tech enterprises enhance productivity primarily through advancements in production technology, while SMEs and non-high-tech enterprises improve efficiency through the catching-up effect. Furthermore, the impact of AI usage intensity on both technical progress and relative efficiency change is more pronounced in regions with higher marketization and strong intellectual property protection. Finally, mediation analysis suggests that the positive association between AI usage intensity and firm efficiency changes is driven by increased capital efficiency, while R&D efficiency mediates the effect of AI usage intensity on technical progress.

Our study offers important implications for managerial practice and policymaking. First, our findings provide empirical evidence that the adoption and integration of AI and enabling technologies contribute to long-term productivity improvements, addressing managerial skepticism regarding the practical benefits of AI. Second, the results underscore the importance of aligning AI deployment strategies with firm- and market-specific characteristics. For example, SMEs and non-high-tech enterprises can improve relative efficiency and gain productivity growth by adopting existing AI solutions, such as intelligent customer service systems, AI-driven decision-support tools, and automated data analytics platforms. Finally, our study suggests that government policies promoting market liberalization and protecting intellectual properties can amplify the productivity-enhancing effects of AI technologies. Future research could further explore whether the adoption and integration of AI by industry leaders generate spillover effects on the efficiency dynamics of related firms through mechanisms such as knowledge diffusion, supply chain integration, or shared AI infrastructure.

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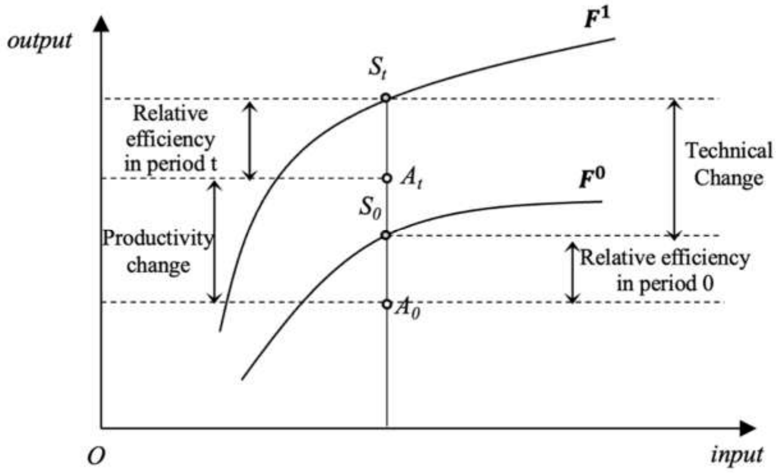
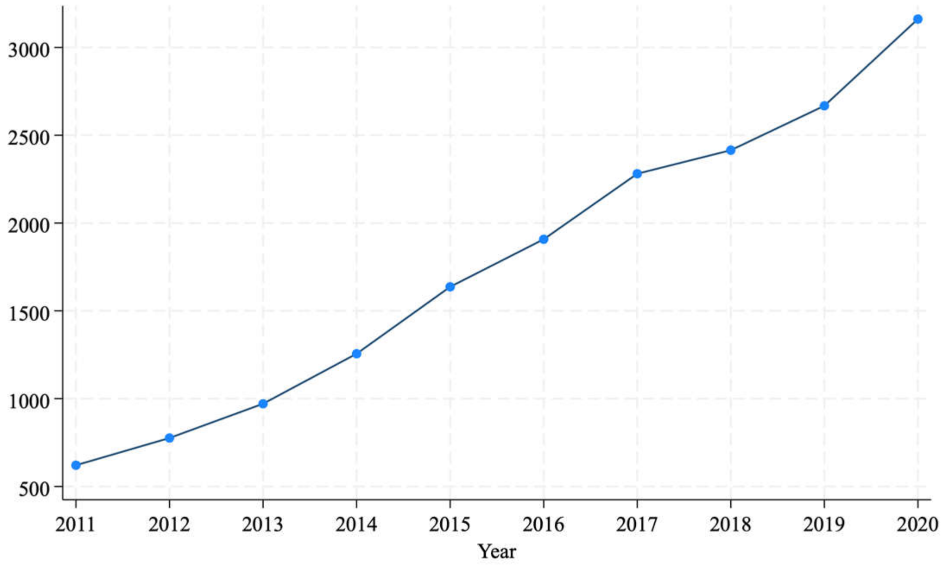
**Figure 1. Productivity Change, Technical Progress, and Relative Efficiency Change**

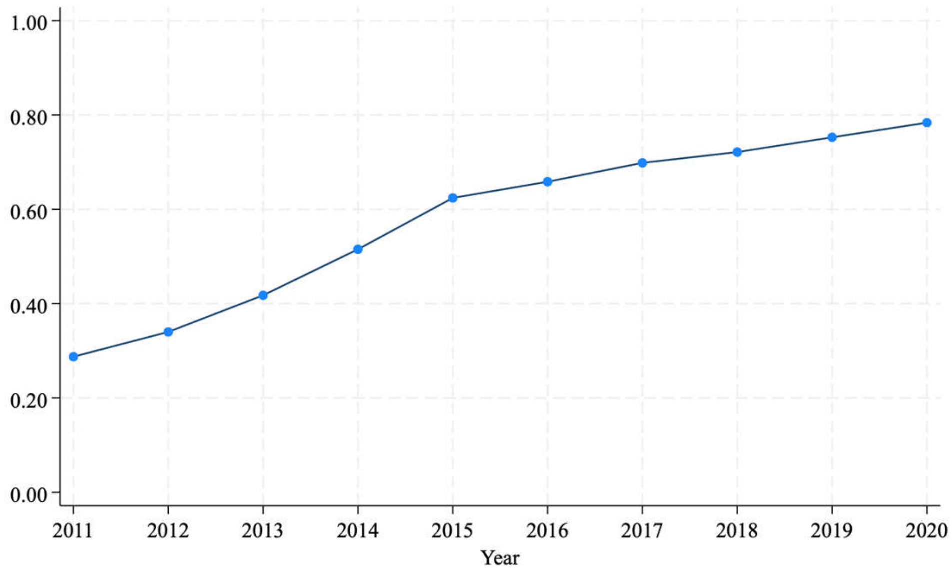



**Notes:** This figure illustrates the decomposition of productivity change into technical progress and relative efficiency change. *F* represents the production function, *A* denotes the production level of firm *i*, and *S* signifies the maximum output level of firm *i*. Productivity change (*PRODCH*) can be expressed as $PRODCH=ln(A_t/A_0)$ . This equation represents the percentage change in productivity of firm *i* relative to the baseline period. Technical progress (*TECH*) is denoted as $TECH=ln(S_t/S_0)$, which reflects shifts in production technology and represents the innovation effect. Relative efficiency change (*RECH*) is expressed as $RECH=ln[(A_t/S_t)/(A_0/S_0)]$, which captures changes in the firm's distance from the optimal production frontier, representing the catching-up effect. Combining these components, the decomposition of productivity change can be expressed as $A_t/A_0=S_t/S_0\times[(A_t/S_t)/(A_0/S_0)]$, which leads to the fundamental relationship *PRODCH = TECH + RECH.* This equation demonstrates that productivity change can be decomposed into technical progress and relative efficiency change. Variable definitions are presented in Appendix A.

**Figure 2. Time Trend of Firms Using AI Technologies**




Panel A. Number of Firms Using AI Over Time




Panel B. Proportion of Firms Using AI Over Time

**Notes:** Figure 2 Panel A illustrate the number of firm-year observations disclosing AI terms in the annual reports over the period 2011-2020. Figure 2 Panel B illustrates the proportion of firm-year observations disclosing AI terms in the annual report out of all firm-year observations over the period 2011-2020.

**Table 1. Descriptive Statistics**

| | N | Mean | Std. Dev. | 25% | Median | 75% |
|---|---|---|---|---|---|---|
| *PRODCH* | 25,153 | 0.028 | 0.327 | -0.093 | 0.045 | 0.167 |
| *TECH* | 25,153 | 0.092 | 0.236 | -0.102 | 0.089 | 0.301 |
| *RECH* | 25,153 | -0.063 | 0.414 | -0.275 | -0.050 | 0.170 |
| *AI* | 25,153 | 1.293 | 1.370 | 0.000 | 1.099 | 2.197 |
| *Size* | 25,153 | 22.210 | 1.282 | 21.295 | 22.033 | 22.932 |
| *Lev* | 25,153 | 0.428 | 0.207 | 0.263 | 0.419 | 0.582 |
| *Cash* | 25,153 | 0.178 | 0.124 | 0.090 | 0.144 | 0.231 |
| *Age* | 25,153 | 10.333 | 7.194 | 4.000 | 9.000 | 16.000 |
| *AuditOpinion* | 25,153 | 158.532 | 176.850 | 16.000 | 81.000 | 256.000 |
| *Dual* | 25,153 | 0.034 | 0.180 | 0.000 | 0.000 | 0.000 |
| *BM* | 25,153 | 1.726 | 0.446 | 1.000 | 2.000 | 2.000 |
| *ROA* | 25,153 | 0.598 | 0.240 | 0.413 | 0.593 | 0.779 |

**Notes:** This table provides descriptive statistics of the main variables used in analyses. The sample includes 25,153 firm-year observations between 2011 and 2020. The decreased sample size in the table is due to missing values of the variable, as documented in Appendix D. Variables are defined as in Appendix A. All continuous variables are winsorized at the 1% and 99% levels, respectively.

**Table 2. Pearson Correlation Matrix**

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| (1) *PRODCH* | 1.000 | | | | | | | | | | | | |
| (2) *TECH* | 0.022*** | 1.000 | | | | | | | | | | | |
| (3) *RECH* | 0.795*** | -0.569*** | 1.000 | | | | | | | | | | |
| (4) *AI* | 0.035*** | 0.013** | 0.017*** | 1.000 | | | | | | | | | |
| (5) *Size* | 0.041*** | -0.006 | 0.034*** | 0.036*** | 1.000 | | | | | | | | |
| (6) *Lev* | 0.020*** | 0.005 | 0.011* | -0.069*** | 0.498*** | 1.000 | | | | | | | |
| (7) *Cash* | -0.030*** | -0.024*** | -0.007 | 0.131*** | -0.214*** | -0.351*** | 1.000 | | | | | | |
| (8) *Age* | 0.007 | 0.004 | 0.002 | -0.058*** | 0.367*** | 0.337*** | -0.168*** | 1.000 | | | | | |
| (9) $Age^2$ | -0.005 | -0.002 | -0.004 | -0.047*** | 0.319*** | 0.286*** | -0.114*** | 0.966*** | 1.000 | | | | |
| (10) *AuditOpinion* | -0.054*** | 0.007 | -0.044*** | -0.004 | -0.057*** | 0.152*** | -0.065*** | 0.079*** | 0.068*** | 1.000 | | | |
| (11) *Dual* | 0.007 | 0.004 | 0.003 | -0.104*** | 0.175*** | 0.128*** | -0.074*** | 0.228*** | 0.200*** | 0.002 | 1.000 | | |
| (12) *BM* | -0.035*** | -0.072*** | 0.014** | -0.133*** | 0.547*** | 0.367*** | -0.178*** | 0.147*** | 0.158*** | -0.027*** | 0.106*** | 1.000 | |
| (13) *ROA* | 0.043*** | -0.002 | 0.035*** | -0.020*** | 0.039*** | -0.303*** | 0.174*** | -0.131*** | -0.107*** | -0.139*** | -0.040*** | -0.164*** | 1.000 |

**Notes:** This table presents the Pearson correlation of the main variables. Variables are defined in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Table 3. Association between AI Usage Intensity and Firm Efficiency Changes**

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Dependent variable | *PRODCH* | *PRODCH* | *TECH* | *RECH* |
| *AI* | 0.010*** | 0.007*** | 0.001 | 0.006*** |
| | (4.097) | (3.753) | (1.138) | (2.789) |
| *Size* | | 0.006** | 0.002*** | 0.004 |
| | | (2.530) | (2.608) | (1.538) |
| *Lev* | | 0.061*** | 0.008 | 0.042*** |
| | | (4.143) | (1.447) | (2.658) |
| *Cash* | | -0.036* | -0.012 | -0.020 |
| | | (-1.830) | (-1.429) | (-0.900) |
| *Age* | | 0.007*** | -0.001*** | 0.008*** |
| | | (5.970) | (-3.152) | (6.458) |
| *Age2* | | -0.000*** | 0.000** | -0.000*** |
| | | (-6.364) | (2.414) | (-6.635) |
| *AuditOpinion* | | -0.108*** | 0.002 | -0.101*** |
| | | (-6.063) | (0.368) | (-5.131) |
| *Dual* | | 0.005 | 0.001 | 0.004 |
| | | (1.260) | (0.765) | (0.867) |
| *BM* | | -0.057*** | -0.032*** | -0.019 |
| | | (-4.248) | (-6.042) | (-1.284) |
| *ROA* | | 0.827*** | -0.127 | 0.861*** |
| | | (3.997) | (-1.430) | (3.710) |
| *Intercept* | 1.070*** | -0.141*** | 0.061*** | -0.207*** |
| | (284.630) | (-3.069) | (3.591) | (-4.116) |
| *Observations* | 25152 | 25,152 | 25,152 | 25,152 |
| *R-squared* | 0.028 | 0.038 | 0.428 | 0.147 |
| *Adj $R^2$* | 0.025 | 0.034 | 0.426 | 0.144 |
| *YearFE* | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes |

**Notes:** This table presents results of estimating the association between AI usage intensity and firm efficiency changes. The dependent variables are productivity change (*PRODCH*) in Columns (1) and (2), technical efficiency change (*TECH*) in Column (3), and relative efficiency change (*RECH*) in Column (4). The decreased sample size in the table is due to singleton observations. All Columns control for year and industry fixed effects. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined as in Appendix A. All continuous variables are winsorized at 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Table 4. Endogeneity Test**

| Dependent variable | (1)<br>*PRODCH* | (2)<br>*PRODCH* | (3)<br>*TECH* | (4)<br>*TECH* | (5)<br>*RECH* | (6)<br>*RECH* |
|---|---|---|---|---|---|---|
| *AIAdopt* | 0.012* | | -0.005* | | 0.017** | |
| | (1.726) | | (-1.711) | | (2.155) | |
| *AIAdopt×AI* | | 0.011*** | | -0.000 | | 0.010*** |
| | | (3.691) | | (-0.011) | | (2.986) |
| *Size* | 0.011*** | 0.010*** | 0.002* | 0.002 | 0.010*** | 0.009** |
| | (3.247) | (2.834) | (1.769) | (1.622) | (2.601) | (2.331) |
| *Lev* | 0.037* | 0.039* | 0.013 | 0.013* | 0.011 | 0.012 |
| | (1.753) | (1.822) | (1.625) | (1.662) | (0.467) | (0.506) |
| *Cash* | -0.009 | -0.011 | -0.012 | -0.012 | 0.006 | 0.004 |
| | (-0.309) | (-0.389) | (-1.038) | (-1.046) | (0.191) | (0.130) |
| *Age* | 0.005*** | 0.005*** | -0.000 | -0.000 | 0.005*** | 0.005*** |
| | (3.189) | (3.115) | (-0.672) | (-0.694) | (3.005) | (2.950) |
| *Age2* | -0.000*** | -0.000*** | 0.000 | 0.000 | -0.000*** | -0.000*** |
| | (-4.024) | (-3.946) | (0.663) | (0.682) | (-3.862) | (-3.801) |
| *AuditOpinion* | -0.132*** | -0.134*** | 0.007 | 0.007 | -0.128*** | -0.129*** |
| | (-6.185) | (-6.248) | (1.000) | (1.003) | (-5.055) | (-5.096) |
| *Dual* | 0.006 | 0.007 | -0.002 | -0.002 | 0.007 | 0.008 |
| | (0.960) | (1.092) | (-0.732) | (-0.676) | (1.094) | (1.175) |
| *BM* | -0.075*** | -0.072*** | -0.027*** | -0.027*** | -0.049** | -0.046** |
| | (-3.802) | (-3.615) | (-3.618) | (-3.576) | (-2.225) | (-2.105) |
| *ROA* | 0.301 | 0.311 | 0.035 | 0.034 | 0.137 | 0.147 |
| | (1.000) | (1.032) | (0.279) | (0.273) | (0.402) | (0.428) |
| *Intercept* | -0.223*** | -0.201*** | 0.063** | 0.063*** | -0.295*** | -0.277*** |
| | (-3.348) | (-2.996) | (2.557) | (2.596) | (-4.075) | (-3.797) |
| *Observations* | 12,715 | 12,715 | 12,715 | 12,715 | 12,715 | 12,715 |
| *R-squared* | 0.044 | 0.044 | 0.498 | 0.498 | 0.170 | 0.170 |
| *Adj $R^2$* | 0.037 | 0.038 | 0.495 | 0.494 | 0.164 | 0.164 |
| *YearFE* | yes | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes | yes |

**Notes:** This table presents the results of the endogeneity test assessing the impact of AI technology adoption on firm efficiency changes. The dependent variables are productivity change (*PRODCH*) in Columns (1) and (2), technical progress (*TECH*) in Columns (3) and (4), and relative efficiency change (*RECH*) in Columns (5) and (6). *AIAdopt* is a binary variable that equals one from the year a firm first begins disclosing keywords related to AI and enabling technologies in annual reports, and zero prior. Columns (1), (3), and (5) present the results of the multi-period difference-in-differences (DID) model using the adoption of AI and enabling technologies as a quasi-natural experiment. Columns (2), (4), and (6) report the results incorporating the moderating effects of *AI*. All Columns include year and industry fixed effects. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined as in Appendix A. All continuous variables are winsorized at 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Table 5. Robustness Tests**

*Panel A. Alternative Sample, Model Specification, and Measures of Independent Variable*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent variable | *PRODCH* | *PRODCH* | *PRODCH* | *PRODCH* | *PRODCH* |
| *AI* | 0.008*** | 0.010*** | | | |
| | (3.766) | (2.727) | | | |
| $AI_{t-1}$ | | | 0.006*** | | |
| | | | (2.744) | | |
| *AI Code* | | | | 0.006*** | |
| | | | | (3.191) | |
| *AI Intangible Assets* | | | | | 0.021** |
| | | | | | (2.440) |
| *Size* | 0.006** | 0.036*** | 0.007*** | 0.007*** | 0.008*** |
| | (2.286) | (4.397) | (2.723) | (2.741) | (3.430) |
| *Lev* | 0.066*** | 0.091*** | 0.060*** | 0.061*** | 0.060*** |
| | (4.453) | (2.824) | (4.132) | (4.151) | (4.174) |
| *Cash* | -0.038* | 0.049 | -0.035* | -0.035* | -0.040** |
| | (-1.891) | (1.544) | (-1.772) | (-1.776) | (-2.000) |
| *Age* | 0.007*** | 0.014 | 0.007*** | 0.007*** | 0.006*** |
| | (5.887) | (0.688) | (5.890) | (6.009) | (5.805) |
| *Age2* | -0.000*** | -0.000*** | -0.000*** | -0.000*** | -0.000*** |
| | (-6.313) | (-5.035) | (-6.308) | (-6.432) | (-6.363) |
| *AuditOpinion* | -0.085*** | -0.124*** | -0.108*** | -0.108*** | -0.094*** |
| | (-4.257) | (-5.516) | (-6.084) | (-6.051) | (-5.107) |
| *Dual* | 0.007* | 0.017** | 0.005 | 0.005 | 0.006 |
| | (1.741) | (1.994) | (1.197) | (1.190) | (1.488) |
| *BM* | -0.050*** | -0.061*** | -0.058*** | -0.059*** | -0.059*** |
| | (-3.697) | (-2.854) | (-4.349) | (-4.407) | (-4.451) |
| *ROA* | 0.823*** | 1.137*** | 0.825*** | 0.817*** | 0.833*** |
| | (4.022) | (3.333) | (3.982) | (3.955) | (4.028) |
| *Intercept* | -0.137*** | -0.921*** | -0.148*** | -0.149*** | -0.174*** |
| | (-2.990) | (-3.308) | (-3.199) | (-3.245) | (-3.898) |
| *Observations* | 24,709 | 24,955 | 25,152 | 25,152 | 24,373 |
| *R-squared* | 0.038 | 0.122 | 0.038 | 0.038 | 0.039 |
| *Adj* $R^2$ | 0.035 | -0.014 | 0.034 | 0.034 | 0.035 |
| *YearFE* | yes | yes | yes | yes | yes |
| *IndFE* | yes | no | yes | yes | yes |
| *FirmFE* | no | yes | no | no | no |

**Notes:** This panel reports the results using alternative samples, model specifications, and proxies for AI. Column (1) excludes firms with poor disclosure quality. Column (2) estimates the model with firm and year fixed effects. Column (3) introduces a one-year lag of the independent variable $AI_{t-1}$. Column (4) replaces the independent variable *AI* with *AI Code*, which equals 0 if no AI-related keyword is disclosed, and 1, 2, or 3 if the frequency falls in the bottom, middle, or top tercile (Chen and Srinivasan 2024). Column (5) replaces the independent variable *AI* with *AI Intangible Assets*, defined as the proportion of AI technology-related components in year-end intangible assets (Zhang et al. 2021). t-values (reported in parentheses) are based on standard errors that are robust to heteroscedasticity and clustered by firm. Variables are defined in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

*Panel B. Alternative Measures of Dependent Variable*

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| Dependent variable | *TFP_OLS* | *TFP_FE* | *TFP_LP* | *TFP_OP* | *TFP_GMM* |
| *AI* | 0.045*** | 0.043*** | 0.063*** | 0.027*** | 0.080*** |
| | (6.058) | (5.764) | (8.100) | (3.768) | (8.092) |
| *Size* | 0.838*** | 0.885*** | 0.659*** | 0.535*** | 0.140*** |
| | (92.773) | (95.829) | (72.008) | (64.432) | (12.602) |
| *Lev* | 0.849*** | 0.854*** | 0.876*** | 0.711*** | 0.820*** |
| | (15.126) | (14.917) | (15.617) | (13.356) | (12.075) |
| *Cash* | 0.321*** | 0.279*** | 0.575*** | 0.366*** | 1.032*** |
| | (5.220) | (4.461) | (9.151) | (5.999) | (12.867) |
| *Age* | 0.004 | 0.004 | -0.001 | 0.004 | -0.007 |
| | (0.966) | (1.110) | (-0.157) | (1.213) | (-1.504) |
| *Age2* | -0.000 | -0.000 | 0.000 | -0.000 | 0.000** |
| | (-0.708) | (-0.910) | (0.571) | (-0.464) | (2.286) |
| *AuditOpinion* | -0.303*** | -0.313*** | -0.275*** | -0.219*** | -0.166*** |
| | (-7.107) | (-7.256) | (-6.369) | (-5.120) | (-3.202) |
| *Dual* | 0.054*** | 0.057*** | 0.043*** | 0.039*** | 0.012 |
| | (3.873) | (4.005) | (2.937) | (2.909) | (0.673) |
| *BM* | 0.005 | 0.009 | -0.042 | 0.063 | -0.079 |
| | (0.123) | (0.208) | (-1.010) | (1.607) | (-1.594) |
| *ROA* | 10.506*** | 10.508*** | 10.839*** | 9.647*** | 10.776*** |
| | (19.683) | (19.315) | (20.218) | (18.921) | (16.686) |
| *Intercept* | -8.211*** | -8.750*** | -6.277*** | -4.395*** | -0.297 |
| | (-46.004) | (-48.011) | (-34.630) | (-26.619) | (-1.340) |
| *Observations* | 24,564 | 24,564 | 24,564 | 24,564 | 24,564 |
| *R-squared* | 0.841 | 0.850 | 0.772 | 0.742 | 0.437 |
| *Adj* $R^2$ | 0.841 | 0.849 | 0.771 | 0.741 | 0.435 |
| *YearFE* | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes |

**Notes:** This panel reports the results using alternative production efficiency metrics. The dependent variable is proxied using the Ordinary Least Squares (OLS) model in Column (1), the Fixed Effects (FE) model in Column (2), the LP (Levinsohn and Petrin) semiparametric model in Column (3), the OP (Olley and Pakes) semiparametric model in Column (4), and the systematic GMM (Generalized Method of Moments) model in Column (5). All Columns include year and industry fixed effects. t-values (reported in parentheses) are based on standard errors that are robust to heteroscedasticity and clustered by firm. Variables are defined in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Table 6. Firm-level Heterogeneous Analysis**

*Panel A. Large Enterprises vs Small and Medium Enterprises (SMEs)*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | *PRODCH* | *PRODCH* | *TECH* | *TECH* | *RECH* | *RECH* |
| | Large enterprises | Small and medium enterprises | Large enterprises | Small and medium enterprises | Large enterprises | Small and medium enterprises |
| *AI* | 0.006** | 0.008** | 0.002* | 0.000 | 0.004 | 0.007** |
| | (2.258) | (2.496) | (1.896) | (0.107) | (1.281) | (2.009) |
| *Size* | 0.002 | 0.020** | 0.001 | 0.008** | 0.001 | 0.011 |
| | (0.530) | (2.478) | (1.167) | (2.507) | (0.223) | (1.293) |
| *Lev* | 0.077*** | 0.046** | 0.018** | -0.006 | 0.053** | 0.039 |
| | (3.748) | (2.061) | (2.532) | (-0.736) | (2.372) | (1.577) |
| *Cash* | -0.006 | -0.046 | -0.020* | -0.009 | 0.015 | -0.031 |
| | (-0.200) | (-1.548) | (-1.736) | (-0.713) | (0.471) | (-0.946) |
| *Age* | 0.001 | 0.011*** | 0.000 | -0.003*** | 0.000 | 0.014*** |
| | (0.822) | (5.736) | (0.103) | (-3.872) | (0.308) | (6.803) |
| *Age2* | -0.000 | -0.000*** | -0.000 | 0.000*** | -0.000 | -0.001*** |
| | (-1.306) | (-6.001) | (-0.102) | (3.170) | (-0.783) | (-6.860) |
| *AuditOpinion* | -0.142*** | -0.078*** | 0.002 | 0.006 | -0.137*** | -0.074** |
| | (-5.816) | (-2.973) | (0.343) | (0.740) | (-5.170) | (-2.561) |
| *Dual* | -0.003 | 0.013** | -0.001 | 0.004 | -0.004 | 0.011 |
| | (-0.444) | (2.054) | (-0.334) | (1.422) | (-0.581) | (1.613) |
| *BM* | -0.052*** | -0.075*** | -0.039*** | -0.029*** | -0.012 | -0.036 |
| | (-2.822) | (-3.182) | (-5.298) | (-2.996) | (-0.561) | (-1.400) |
| *ROA* | 0.620** | 1.003*** | -0.124 | -0.182 | 0.665** | 1.089*** |
| | (2.113) | (3.309) | (-1.013) | (-1.390) | (1.975) | (3.210) |
| *Intercept* | -0.009 | -0.448*** | 0.079*** | -0.043 | -0.088 | -0.389** |
| | (-0.143) | (-2.839) | (3.375) | (-0.723) | (-1.227) | (-2.237) |
| *Observations* | 13,460 | 11,690 | 13,460 | 11,690 | 13,460 | 11,690 |
| *R-squared* | 0.048 | 0.036 | 0.501 | 0.367 | 0.191 | 0.118 |
| *Adj $R^2$* | 0.042 | 0.028 | 0.497 | 0.362 | 0.185 | 0.111 |
| *YearFE* | yes | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes | yes |
| *$Chi^2$* | 0.82 | | 0.23 | | 0.37 | |
| *SUR p-value* | 0.365 | | 0.631 | | 0.545 | |

**Notes:** This panel reports results of estimating the association between AI usage intensity and firm efficiency changes, conditional on firm size. Firms are classified as large enterprises or small and medium enterprises (SMEs) based on China's official regulation *Statistical Division of Large, Medium, Small, and Micro Enterprises (2017)*, which defines firm size using assets, revenue, and number of employees. The dependent variables are productivity change (*PRODCH*) in Columns (1) and (2), technical progress (*TECH*) in Columns (3) and (4), and relative efficiency change (*RECH*) in Columns (5) and (6). Seemingly unrelated regression (SUR) is used to test for differences between the groups. All Columns include year and industry fixed effects. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

*Panel B. High-tech Enterprises vs. Non-high-tech Enterprises*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | *PRODCH* | *PRODCH* | *TECH* | *TECH* | *RECH* | *RECH* |
| | High-tech enterprises | Non-high-tech enterprises | High-tech enterprises | Non-high-tech enterprises | High-tech enterprises | Non-high-tech enterprises |
| *AI* | 0.005** | 0.009*** | 0.002** | -0.001 | 0.003 | 0.009** |
| | (2.024) | (2.604) | (2.249) | (-0.552) | (1.053) | (2.302) |
| *Size* | -0.000 | 0.013*** | 0.004*** | 0.001 | -0.003 | 0.012*** |
| | (-0.059) | (3.770) | (3.117) | (0.915) | (-0.702) | (3.016) |
| *Lev* | 0.061*** | 0.065*** | -0.003 | 0.017** | 0.054** | 0.037 |
| | (3.125) | (2.911) | (-0.417) | (1.973) | (2.534) | (1.506) |
| *Cash* | -0.039 | -0.014 | -0.001 | -0.029** | -0.037 | 0.023 |
| | (-1.572) | (-0.474) | (-0.086) | (-2.068) | (-1.333) | (0.653) |
| *Age* | 0.001 | 0.009*** | -0.001* | -0.001 | 0.003 | 0.010*** |
| | (0.727) | (5.397) | (-1.941) | (-1.577) | (1.421) | (5.156) |
| *Age2* | -0.000 | -0.000*** | 0.000 | 0.000 | -0.000* | -0.000*** |
| | (-1.156) | (-5.164) | (1.362) | (0.770) | (-1.660) | (-4.745) |
| *AuditOpinion* | -0.092*** | -0.118*** | -0.002 | 0.003 | -0.097*** | -0.101*** |
| | (-3.764) | (-4.672) | (-0.309) | (0.355) | (-3.691) | (-3.544) |
| *Dual* | 0.007 | 0.005 | 0.001 | 0.002 | 0.006 | 0.004 |
| | (1.477) | (0.594) | (0.273) | (0.466) | (1.125) | (0.464) |
| *BM* | -0.021 | -0.085*** | -0.033*** | -0.036*** | 0.014 | -0.039* |
| | (-1.232) | (-4.044) | (-5.190) | (-4.303) | (0.724) | (-1.663) |
| *ROA* | 0.561** | 1.113*** | -0.232** | -0.028 | 0.657** | 1.084*** |
| | (1.975) | (3.597) | (-2.097) | (-0.196) | (2.060) | (3.081) |
| *Intercept* | 0.014 | -0.315*** | 0.030 | 0.084*** | -0.046 | -0.395*** |
| | (0.212) | (-4.808) | (1.205) | (3.205) | (-0.605) | (-5.419) |
| *Observations* | 12,768 | 12,382 | 12,768 | 12,382 | 12,768 | 12,382 |
| *R-squared* | 0.041 | 0.044 | 0.463 | 0.421 | 0.171 | 0.144 |
| *Adj $R^2$* | 0.035 | 0.037 | 0.460 | 0.417 | 0.165 | 0.137 |
| *YearFE* | yes | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes | yes |
| *Chi2* | 0.04 | | 0.08 | | 0.00 | |
| *SUR p-value* | 0.846 | | 0.782 | | 0.960 | |

**Notes:** This panel reports results of estimating the association between AI usage intensity and firm efficiency changes, conditional on whether a firm is classified as a high-tech enterprise. High-tech enterprises are identified according to *China's High-Tech Enterprise Certification*. The dependent variables are productivity change (*PRODCH*) in Columns (1) and (2), technical progress (*TECH*) in Columns (3) and (4), and relative efficiency change (*RECH*) in Columns (5) and (6). Seemingly unrelated regression (SUR) is used to test for differences between the groups. All Columns include year and industry fixed effects. t-values (reported in parentheses) are based on standard errors that are robust to heteroscedasticity and clustered by firm. Variables are defined in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Table 7. Market-level Heterogeneous Analysis**

*Panel A. High-marketization Level vs. Low-marketization Level*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | *PRODCH* | *PRODCH* | *TECH* | *TECH* | *RECH* | *RECH* |
| | High Marketization | Low Marketization | High Marketization | Low Marketization | High Marketization | Low Marketization |
| *AI* | 0.009*** | 0.006** | 0.002* | -0.001 | 0.006** | 0.006* |
| | (3.174) | (1.994) | (1.779) | (-0.718) | (2.090) | (1.873) |
| *Size* | 0.000 | 0.010*** | 0.003** | 0.002 | -0.002 | 0.009** |
| | (0.017) | (2.962) | (1.991) | (1.300) | (-0.458) | (2.337) |
| *Lev* | 0.053** | 0.074*** | -0.004 | 0.020*** | 0.042* | 0.047** |
| | (2.447) | (3.582) | (-0.456) | (2.730) | (1.738) | (2.161) |
| *Cash* | -0.050* | -0.022 | -0.025** | 0.006 | -0.023 | -0.020 |
| | (-1.804) | (-0.807) | (-2.078) | (0.464) | (-0.711) | (-0.691) |
| *Age* | 0.008*** | 0.005*** | -0.001* | -0.002** | 0.008*** | 0.008*** |
| | (4.858) | (3.388) | (-1.929) | (-2.501) | (4.611) | (4.365) |
| *Age2* | -0.000*** | -0.000*** | 0.000 | 0.000* | -0.000*** | -0.000*** |
| | (-5.144) | (-3.759) | (1.599) | (1.842) | (-4.888) | (-4.460) |
| *AuditOpinion* | -0.078*** | -0.133*** | -0.001 | 0.003 | -0.066** | -0.129*** |
| | (-2.923) | (-5.772) | (-0.143) | (0.455) | (-2.179) | (-5.198) |
| *Dual* | 0.002 | 0.009 | 0.004* | -0.002 | -0.004 | 0.013* |
| | (0.287) | (1.427) | (1.834) | (-0.904) | (-0.697) | (1.885) |
| *BM* | -0.045** | -0.067*** | -0.031*** | -0.026*** | -0.012 | -0.033 |
| | (-2.382) | (-3.450) | (-3.881) | (-3.578) | (-0.540) | (-1.556) |
| *ROA* | 0.483 | 1.116*** | -0.335** | 0.125 | 0.624* | 0.975*** |
| | (1.526) | (3.891) | (-2.283) | (1.088) | (1.710) | (3.127) |
| *Intercept* | -0.007 | -0.237*** | 0.059** | 0.068*** | -0.073 | -0.316*** |
| | (-0.106) | (-3.543) | (2.275) | (2.895) | (-0.982) | (-4.353) |
| *Observations* | 12312 | 12839 | 12312 | 12839 | 12312 | 12839 |
| *R-squared* | 0.033 | 0.050 | 0.388 | 0.480 | 0.132 | 0.170 |
| *Adj $R^2$* | 0.026 | 0.043 | 0.383 | 0.476 | 0.126 | 0.164 |
| *YearFE* | yes | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes | yes |
| *Chi2* | 0.54 | | 13.40*** | | 5.27** | |
| *SUR p-value* | 0.463 | | 0.000 | | 0.022 | |

**Notes:** This panel reports results of estimating the association between AI usage intensity and firm efficiency changes, conditional on the provincial marketization level in which the firm operates. The marketization index is derived from Fan et al. (2003). Firms with a marketization level larger than the yearly median value are classified into the high marketization level group, while firms with a marketization level smaller than the yearly median value are classified into the low marketization level group. The dependent variables are productivity change (*PRODCH*) in columns (1) and (2), technical efficiency change (*TECH*) in columns (3) and (4), and relative efficiency change (*RECH*) in columns (5) and (6). Seemingly unrelated regression (SUR) is used to test for differences between the groups. All columns control for year and industry fixed effects. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined as in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

*Panel B. High Intellectual Property Protection Level vs. Low Intellectual Property Protection Level*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | *PRODCH* | *PRODCH* | *TECH* | *TECH* | *RECH* | *RECH* |
| | High Intellectual Property Protection | Low Intellectual Property Protection | High Intellectual Property Protection | Low Intellectual Property Protection | High Intellectual Property Protection | Low Intellectual Property Protection |
| *AI* | 0.006** | 0.010*** | 0.003** | -0.001 | 0.003 | 0.010*** |
| | (2.253) | (3.075) | (2.190) | (-0.798) | (1.036) | (2.912) |
| *Size* | 0.002 | 0.010*** | 0.002 | 0.003** | 0.001 | 0.007* |
| | (0.625) | (2.812) | (1.096) | (2.422) | (0.184) | (1.820) |
| *Lev* | 0.077*** | 0.043** | -0.001 | 0.016* | 0.072*** | 0.011 |
| | (3.834) | (2.029) | (-0.133) | (1.892) | (3.284) | (0.472) |
| *Cash* | -0.046* | -0.023 | -0.038*** | 0.016 | 0.003 | -0.041 |
| | (-1.650) | (-0.788) | (-3.002) | (1.248) | (0.083) | (-1.283) |
| *Age* | 0.006*** | 0.007*** | -0.002** | -0.001** | 0.007*** | 0.009*** |
| | (3.830) | (4.290) | (-2.260) | (-2.127) | (3.966) | (4.854) |
| *Age2* | -0.000*** | -0.000*** | 0.000 | 0.000** | -0.000*** | -0.000*** |
| | (-4.049) | (-4.541) | (1.456) | (1.986) | (-3.901) | (-5.109) |
| *AuditOpinion* | -0.089*** | -0.127*** | 0.001 | 0.001 | -0.085*** | -0.116*** |
| | (-3.742) | (-4.806) | (0.119) | (0.088) | (-3.422) | (-3.737) |
| *Dual* | 0.009* | 0.001 | 0.005** | -0.004 | 0.004 | 0.006 |
| | (1.695) | (0.207) | (1.968) | (-1.337) | (0.594) | (0.839) |
| *BM* | -0.038** | -0.075*** | -0.020** | -0.040*** | -0.012 | -0.030 |
| | (-2.023) | (-3.656) | (-2.477) | (-5.285) | (-0.541) | (-1.318) |
| *ROA* | 0.845*** | 0.784*** | -0.184 | -0.053 | 0.955*** | 0.724** |
| | (2.768) | (2.740) | (-1.328) | (-0.435) | (2.732) | (2.249) |
| *Intercept* | -0.069 | -0.214*** | 0.072** | 0.048* | -0.144* | -0.269*** |
| | (-1.049) | (-3.100) | (2.516) | (1.901) | (-1.954) | (-3.503) |
| *Observations* | 12,927 | 12,222 | 12,927 | 12,222 | 12,927 | 12,222 |
| *R-squared* | 0.042 | 0.041 | 0.414 | 0.451 | 0.151 | 0.149 |
| *Adj $R^2$* | 0.036 | 0.034 | 0.410 | 0.446 | 0.145 | 0.143 |
| *YearFE* | yes | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes | yes |
| *Chi2* | 0.06 | | 12.38*** | | 3.19* | |
| *SUR p-value* | 0.810 | | 0.000 | | 0.074 | |

**Notes:** This panel reports results of estimating the association between AI usage intensity and firm efficiency changes, conditional on the provincial intellectual property protection level in which the firm operates. The IPP index, issued by the China National Intellectual Property Administration, is used to classify firms into two groups: those with an IPP index above the yearly median are categorized as high IPP firms, while those below the median are classified as low IPP firms. The dependent variables are productivity change (*PRODCH*) in Columns (1) and (2), technical efficiency change (*TECH*) in Columns (3) and (4), relative efficiency change (*RECH*) in Columns (5) and (6). Seemingly unrelated regression (SUR) is used to test for differences between the groups. All Columns include year and industry fixed effects. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined as in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Table 8. Mediating Effects**

*Panel A. Effect of AI on Capital, Labor and Technology Efficiency*

| | (1) | (2) | (3) |
|---|---|---|---|
| Dependent variable | *CapEfficiency* | *LaborEfficiency* | *RDEfficiency* |
| *AI* | 0.032*** | -0.003 | 0.002*** |
| | (3.846) | (-0.327) | (7.526) |
| *Size* | -0.028*** | 0.176*** | 0.000 |
| | (-3.577) | (14.364) | (0.677) |
| *Lev* | 0.578*** | 0.517*** | -0.001 |
| | (10.422) | (7.289) | (-0.669) |
| *Cash* | 0.211*** | 0.365*** | 0.008*** |
| | (3.205) | (4.241) | (3.166) |
| *Age* | 0.004 | 0.006 | -0.000*** |
| | (1.062) | (1.195) | (-2.580) |
| *Age2* | -0.000 | -0.000 | 0.000 |
| | (-0.213) | (-0.210) | (1.073) |
| *AuditOpinion* | -0.095* | -0.149*** | -0.001 |
| | (-1.953) | (-2.658) | (-0.619) |
| *Dual* | 0.037*** | 0.021 | -0.000 |
| | (2.748) | (1.100) | (-0.464) |
| *BM* | 0.009 | 0.179*** | -0.015*** |
| | (0.230) | (3.252) | (-10.388) |
| *ROA* | 5.929*** | 9.043*** | 0.033 |
| | (13.557) | (12.687) | (1.357) |
| *Intercept* | 0.757*** | 9.359*** | 0.025*** |
| | (5.092) | (38.755) | (3.499) |
| *Observations* | 25152 | 25152 | 20633 |
| *R-squared* | 0.258 | 0.394 | 0.314 |
| *Adj $R^2$* | 0.256 | 0.392 | 0.311 |
| *YearFE* | yes | yes | yes |
| *IndFE* | yes | yes | yes |

**Notes:** This panel examines the effect of AI usage intensity on capital, labor, and technology efficiency. Capital efficiency (*CapEfficiency*) is defined as the total asset turnover rate, calculated as operating income divided by total assets. Labor efficiency (*LaborEfficiency*) is defined as the natural logarithm of one plus operating income to the number of employees. Technology efficiency (*RDEfficiency*) is defined as the natural logarithm of one plus research and development (R&D) expenses to total assets. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined as in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

*Panel B. Mediated Effect of AI Usage Intensity on Firm Efficiency Changes*

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Dependent variable | *PRODCH* | *TECH* | *RECH* | *PRODCH* | *TECH* | *RECH* |
| *AI* | 0.005** | 0.001 | 0.004* | 0.006*** | 0.001 | 0.005** |
| | (2.507) | (0.865) | (1.769) | (3.218) | (1.513) | (2.120) |
| *CapEfficiency* | 0.072*** | 0.007*** | 0.066*** | | | |
| | (6.957) | (3.610) | (6.387) | | | |
| *RDEfficiency* | | | | 0.093 | 0.112** | 0.012 |
| | | | | (0.878) | (2.100) | (0.103) |
| *Size* | 0.008*** | 0.003*** | 0.006** | 0.003 | 0.002* | 0.002 |
| | (3.274) | (2.789) | (2.177) | (1.319) | (1.689) | (0.728) |
| *Lev* | 0.019 | 0.004 | 0.004 | 0.059*** | 0.011* | 0.042*** |
| | (1.197) | (0.716) | (0.242) | (3.958) | (1.889) | (2.592) |
| *Cash* | -0.052*** | -0.013 | -0.034 | -0.041** | -0.006 | -0.022 |
| | (-2.591) | (-1.601) | (-1.528) | (-2.059) | (-0.719) | (-0.976) |
| *Age* | 0.006*** | -0.001*** | 0.008*** | 0.005*** | -0.001*** | 0.006*** |
| | (5.636) | (-3.204) | (6.181) | (4.276) | (-3.115) | (5.160) |
| *Age2* | -0.000*** | 0.000** | -0.000*** | -0.000*** | 0.000** | -0.000*** |
| | (-6.187) | (2.428) | (-6.483) | (-4.312) | (2.517) | (-4.975) |
| *AuditOpinion* | -0.101*** | 0.003 | -0.095*** | -0.119*** | 0.006 | -0.121*** |
| | (-5.623) | (0.489) | (-4.743) | (-6.452) | (1.117) | (-6.076) |
| *Dual* | 0.003 | 0.001 | 0.002 | 0.007* | 0.002 | 0.006 |
| | (0.602) | (0.621) | (0.323) | (1.660) | (0.874) | (1.265) |
| *BM* | -0.058*** | -0.032*** | -0.020 | -0.040*** | -0.033*** | -0.001 |
| | (-4.227) | (-6.058) | (-1.308) | (-2.828) | (-5.903) | (-0.076) |
| *ROA* | 0.397* | -0.166* | 0.468* | 0.743*** | -0.188** | 0.866*** |
| | (1.838) | (-1.842) | (1.950) | (3.429) | (-2.062) | (3.616) |
| *Intercept* | -0.196*** | 0.056*** | -0.257*** | -0.084* | 0.073*** | -0.168*** |
| | (-4.135) | (3.270) | (-4.990) | (-1.726) | (4.089) | (-3.102) |
| *Observations* | 25,152 | 25,152 | 25,152 | 20,633 | 20,633 | 20,633 |
| *R-squared* | 0.048 | 0.429 | 0.153 | 0.042 | 0.455 | 0.169 |
| *Adj* $R^2$ | 0.045 | 0.426 | 0.149 | 0.038 | 0.452 | 0.165 |
| *YearFE* | yes | yes | yes | yes | yes | yes |
| *IndFE* | yes | yes | yes | yes | yes | yes |

**Notes:** This panel reports the mediated effect of AI usage intensity on firm efficiency changes. Columns (1), (2), and (3) present the capital channel, and Columns (4), (5), and (6) show the technology channel. All columns include year and industry fixed effects. t-values (reported in parentheses) are calculated based on robust standard errors clustered at firm level. Variables are defined as in Appendix A. All continuous variables are winsorized at the 1% and 99% levels. *, ** and *** represent significance at or below the 10%, 5%, and 1% levels, respectively.

**Appendix A. Variable Definitions**

| *Variables* | *Definition* |
|---|---|
| *PRODCH* | The natural logarithm of productivity change (Banker et al. 2005). |
| *TECH* | The natural logarithm of technical efficiency change (Banker et al. 2005). |
| *RECH* | The natural logarithm of relative efficiency change (Banker et al. 2005). |
| *AI* | The natural logarithm of one plus the frequency of the keywords related to AI and enabling technologies in the annual report. |
| *Size* | The natural logarithm of one plus total assets. |
| *Lev* | Total liabilities divided by total assets. |
| *Cash* | The level of cash holdings, measured as the ratio of the firm's cash and cash equivalents to total assets. |
| *Age* | The number of years since the company was first listed. |
| $Age^2$ | The square term of *Age.* |
| *AuditOpinion* | A dummy variable that equals 0 if an unqualified opinion is issued, and 1 otherwise. |
| *Dual* | A dummy variable that equals 1 if the same individual holds both the chairman and CEO positions and 0 otherwise. |
| *BM* | Total equity divided by market value. |
| *ROA* | Net profit divide by total assets. |
| *CapEfficiency* | Total asset turnover rate, calculated as operating income divided by total assets. |
| *LaborEfficicency* | The natural logarithm of one plus the ratio of operating income to the number of employees. |
| *RDEfficiency* | The natural logarithm of one plus the ratio of R&D expenditure to total assets. |

**Appendix B. AI Terms Keyword List**

| AI Term | Keywords |
|---|---|
| *Artificial Intelligence* | Artificial Intelligence, Business Intelligence, Image Understanding, Investment Decision Support System, Intelligent Data Analytics, Intelligent Robots, Machine Learning, Deep Learning, Semantic Search, Biometric Technology, Facial Recognition, Speech Recognition, Identity Verification, Autonomous Driving, Natural Language Processing, Mobile Internet, Industrial Internet, Mobile Connectivity, Internet Healthcare, E-Commerce, Mobile Payment, Third-Party Payment, NFC Payment, Smart Energy, B2B, B2C, C2B, C2C, O2O, Network Connectivity, Smart Wearables, Smart Agriculture, Smart Transportation, Smart Healthcare, Smart Customer Service, Smart Home, Robo-Advisory, Smart Tourism, Smart Environmental Protection, Smart Grid, Smart Marketing, AI Marketing, Unmanned Retail, Internet Finance, AI Finance, Fintech, Quantitative Finance, Open Banking |
| *Enabling Technologies of AI* | *Blockchain*: Blockchain, Digital Currency, Distributed Computing, Differential Privacy Technology, Smart Financial Contracts<br>*Cloud Computing:* Cloud Computing, Stream Computing, Graph Computing, In-Memory Computing, Secure Multi-Party Computation, Brain-Like Computing, Green Computing, Cognitive Computing, Converged Architecture, Millions of Concurrent Users, Exabyte-Level Storage, Internet of Things, Cyber-Physical Systems<br>*Data Analytics:* Big Data, Data Mining, Text Mining, Data Visualization, Heterogeneous Data, Credit Reporting, Augmented Reality, Mixed Reality, Virtual Reality |

**Notes:** This table presents a list of keywords related to AI and its enabling technologies. The original AI-term dictionary is in Chinese.

**Appendix C. Industry Distribution of Firms Using AI Technologies**

| CSRC Industry Codes | Industry | No. of Firm-year Observations | Proportion of Firm-year Observations Using AI |
|---|---|---|---|
| A | Agriculture, Forestry, Animal Husbandry, and Fishery | 342 | 58.48% |
| B | Mining | 675 | 32.00% |
| C | Manufacturing | 18,390 | 58.24% |
| D | Production and Supply of Electricity, Heat, Gas, and Water | 1,001 | 40.96% |
| E | Construction | 730 | 51.23% |
| F | Wholesale and Retail Trade | 1,394 | 75.82% |
| G | Transportation, Warehousing, and Postal Services | 897 | 66.33% |
| H | Accommodation and Catering Services | 77 | 75.32% |
| I | Information Transmission, Software, and Information Technology Services | 2,296 | 92.38% |
| K | Real Estate Industry | 1,000 | 48.50% |
| L | Leasing and Business Services | 485 | 83.51% |
| M | Scientific Research and Technical Services | 314 | 75.48% |
| N | Water Conservancy, Environment, and Public Facility Management | 478 | 48.54% |
| P | Education | 4 | 100.00% |
| Q | Healthcare and Social Work | 95 | 64.21% |
| R | Culture, Sports, and Entertainment | 114 | 56.14% |
| S | General Services | 433 | 83.14% |
| Total | | 28,854 | 61.24% |

**Notes:** This table reports the industry distribution of the proportion of firm-year observations using AI technology out of all firm-year observations from 2011 to 2020. The sample includes 28,854 firm-year observations based on the original data without missing industry information. Industry classification is based on China Securities Regulatory Commission (CSRC) industry classification.

**Appendix D. Sample Selection**

| | No. of Firm-years |
|---|---|
| Original sample | 29,474 |
| Less: Observations with a “Special Treatment” tag | (810) |
| Observations from firms’ IPO year | (2,462) |
| Observations without data on *PRODCH, TECH* and *RECH* | (668) |
| Observations without data on control variables | (381) |
| Final sample | 25,153 |