How many Years Does It Take for AI Adopting Firms to Realize Productivity Effects?

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Preliminary and incomplete†

Abstract

Despite recent advances in AI technologies, we are not yet seeing a surge in economic growth. It is often attributed to the fact that a fundamental technological change, such as AI, takes time to realize its productivity effects. This paper investigates the lagged effects of AI adoption among South Korean firms by implementing an event-study analysis.

We find AI-adopting firms are significantly more productive than non-adopters, but the productivity differential is declining over time and becomes insignificant once firm characteristics are controlled for. The productivity effect of AI adoption is statistically insignificant not only contemporaneously but also up to five years after the initial adoption.

One possible explanation for the sluggish productivity effect is that AI adoption has not been accompanied by sustained increases in complementary investments. While AI-adopting firms exhibit significantly faster growth in new business entry and R&D expenditures immediately following adoption, this acceleration quickly dissipates and no longer statistically significant from two to three years after adoption.

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1 Introduction

Artificial Intelligence (AI) is widely regarded as one of the most promising technologies today. AI is also considered as a General Purpose Technology (GPT) like the steam engine, electricity and the internet, which can foster innovations across the entire economy (Goldfarb et al., 2023). Accordingly, it is expected that AI will improve aggregate productivity, thereby contributing to overcoming the persistent low-growth trend observed in many developed economies.

However, considering that other GPTs took considerable time lags to realize productivity gains at the macro level (Brynjolfsson and Syverson, 2019), it is likely that AI will also take time to realize productivity gains. The reasons might include the following. First, the portion of firms that adopt a new technology remains low in the early phase, and it takes a considerable amount of time for diffusion. Second, significant complementary investments, such as research and development, must be accumulated before productivity gains are realized.

This paper first provides an overview of trends in the diffusion of AI technologies across South Korean firms and then investigates whether the productivity of AI adopting firms have increased over time. Empirical literature on the effects of AI adoption on firm productivity is still relatively limited and reports mixed results. Moreover, the literature mainly focuses on contemporaneous effects, although the productivity gains may materialize with a lag. To address this issue, this paper empirically investigates the lagged effects of AI adoption on firm productivity.

This paper utilizes the Survey of Business Activities, conducted by the Ministry of Data and Statistics in Korea, which has been widely used in research on the AI adoption among Korean firms. The dataset includes questions on AI adoption status since 2017, enabling the direct identification of firms' AI adoption status. A brief overview of the data reveals that while the share of AI adopting firms remains low in Korea (6.4% in 2023), the share of workers employed by the adopting firms reached 23.3% in the same year. This implies that approximately one in four workers in Korea is employed by an AI-adopting firm, and that a 1% increase in the labor productivity among AI adopting firms could raise the aggregate labor productivity by 0.23%p.

AI-adopting firms in Korea are found to be disproportionately larger and more productive than non-adopting firms on average. However, these differences gradually diminish over time. Firms that adopted AI at earlier stages—referred to as early adopters—appear larger and more productive than firms that first adopted AI later. This pattern may reflect a decline in barriers to AI adoption, which has enabled smaller and less productive firms, previously constrained from adopting AI, to do so.

While the higher productivity observed among AI-adopting firms may reflect productivity gains attributable to AI, it is also possible that more productive firms with greater technological capabilities are simply more likely to adopt AI, raising concerns about endogeneity. To address this issue, regression analyses are conducted that control for firm characteristics likely to affect both AI adoption decisions and productivity, including firm size, age, industry, and tangible and intangible assets. The results indicate that AI adoption is not significantly associated with the current level of labor productivity.

Estimating the association between AI adoption and labor productivity by primary use case indicates that statistically significant positive coefficients are observed only among firms that employ AI for ”organizational management” or ”marketing strategy”. By contrast, no statistically significant effect is found for firms using AI in ”product development”, ”production processes”, or ”sales-related activities”. However, when the sample is restricted to firms in the top 50 percent of the labor productivity distribution, none of the estimated coefficients remain statistically significant across use cases, suggesting that the baseline results may reflect selection effects rather than causal relationships.

To further address the endogeneity and to examine whether the productivity effects of AI adoption increase over time, this paper employs an event study methodology, a variant of the Difference-in-Differences (DiD) approach. The results show no significant change since the initial adoption of AI, and the coefficients did not increase over time either. The coefficients remained statistically insignificant for up to 5 years after the initial adoption. Even in a separate long-difference regression that restricts the sample to firms for which at least six years have elapsed since AI adoption, no statistically significant productivity effects are found. In sum, while it remains uncertain how many years are required for AI adoption to materialize productivity gains, the findings suggest that at least 6 years is not enough.

Certain innovation activities increased significantly in the immediate aftermath of initial AI adoption; however, these increases were not sustained. For instance, entry into new business rose significantly in the year of first adoption, but declined sharply in the subsequent year and became statistically insignificant within two years. Similarly, other innovation-related activities, such as R&D and intangible investments, exhibited only temporary increases. This lack of sustained growth in innovation-related investment may partially account for the absence of a significant productivity effect following AI adoption.

In summary, although AI technologies diffused relatively rapidly across Korean firms, the intensity of AI use within adopting firms appears to have increased only slowly. Several explanations may account for this pattern. First, many firms may have adopted AI technologies largely on an experimental basis. Second, even if AI improves productivity in specific tasks, such tasks may represent only a small share of firms' overall production processes, implying that productivity gains may not be detectable at the firm level. Third, while AI may have generated substantial productivity gains among a limited number of frontier firms, these firms likely constitute only a small fraction of all AI adopters, thereby constraining AI's contribution to aggregate productivity growth.

The remainder of this paper is organized as follows. Section 2 reviews the existing literature. Section 3 examines the diffusion patterns of AI technologies among Korean firms. Section 4 analyzes the impact of AI adoption on firm performance and innovation related activities. Section 5 concludes.

2 Literature Review

2.0.1 The mechanism through which AI raises productivity

AI technologies may increase productivity by improving the efficiency of producing existing goods and services via automation of tasks previously performed by labor. While automation technologies had been improving long before the advent of AI, a significant share of tasks remain non-automatable. Routine tasks—such as work on factory assembly lines—that can be specified by codified rules are relatively easy to automate, but non-routine tasks have been more difficult to automate. However, AI technologies may enable the automation of non-routine tasks, that were previously considered unautomatable (Autor 2015; Acemoglu 2024). For example, tasks involving data-driven prediction—such as medical image interpretation and legal document analysis—were previously considered to be performable only by workers with specialized skills. However, AI may raise productivity by automating these prediction tasks (Agrawal et al., 2019).

AI not only enables more efficient production of existing goods and services but can also facilitate the introduction of new goods and services. For example, AI can enhance the efficiency of research and development by automating various routine tasks involved in the R&D process (Aghion et al., 2017). In addition, through its predictive capabilities, AI can reduce the costs associated with trial and error in R&D activities, such as new drug development (Cockburn et al., 2018). While such product innovation can increase consumer welfare and firms' competitiveness, it is inherently difficult to measure in GDP statistics. Consequently, productivity gains from AI that operate through the promotion of product innovation are likely to be underestimated and are also extremely challenging to identify empirically.

2.0.2 Empirical Studies on the productivity effects of AI

To assess the potential macroeconomic effects of AI, it is necessary to understand to what extent AI has already affected productivity. However, empirical studies on the productivity effects of AI remains limited, largely due to the limitation of data that identify firms' adoption status of AI technologies.

A strand of studies has inferred AI adoption using indirect measures, such as AI-related hiring data and patent applications. In Babina et al. (2024) , an increase in the share of AI-related employment within firms is found to be significantly and positively correlated with firms' employment growth and sales growth, while having no statistically significant effect on labor productivity (measured as sales per worker) or TFP growth. Alderucci et al. (2020) find, using data on the U.S. manufacturing firms, that firms holding AI-related patents have significantly higher levels of employment, labor productivity, and total factor productivity. Using patent data on approximately 5,257 firms worldwide, Damioli et al. (2021) show that the number of AI-related patent applications is positively and significantly associated with firms' labor productivity levels.

The recent availability of large-scale survey data in which firms directly report their AI adoption status has led to a growing body of research worldwide.

Acemoglu et al. (2024) analyze U.S. firms over the period 2016–2018 using data from the 2019 Annual Business Survey conducted by the U.S. Census Bureau. They find that AI adoption is positively and significantly correlated with labor productivity, but this association becomes statistically insignificant once other types of new technologies, such as cloud computing, are included as control variables. Using firm-level data from nine OECD countries, including South Korea, Calvino and Fontanelli (2023) report a positive and significant correlation between AI adoption and labor productivity. Nevertheless, this positive association declines substantially once varialbes related to firms' innovative activities—such as ICT capabilities, digital infrastructure, and the adoption of other digital technologies—are controlled for. Czarnitzki et al. (2023), using survey data on 5,851 German firms, find a statistically significant positive association between AI adoption and productivity.

In South Korea, Song et al. (2021) utilize firm-level data from the Survey of Business Activities and find that AI adoption has no statistically significant effect on labor productivity among manufacturing firms. Chang (2025) also analyze the same survey data—the Survey of Business Activities—and find that AI adoption has no statistically significant effect on labor productivity, although it has a statistically significant positive effect on profitability.

3 Trends of AI diffusion among Korean firms

This paper analyzes firm-level data from the Survey of Business Activities (SBA) conducted by the Ministry of Data and Statistics of Korea. A key strength of the dataset is that it enables the direct identification of firms that have adopted AI technologies, while providing comprehensive coverage of the population of domestic firms above a certain size threshold. Accordingly, the survey has been widely used in empirical studies examining the effects of AI adoption in Korea.

The SBA provides a panel dataset that includes firms with at least 50 full-time employees and capital of at least 300 million KRW. For the wholesale, retail, and other service industries, firms with fewer than 50 employees are also included if their capital exceeds 1 billion KRW. As of the most recent survey year, 2023, the dataset includes responses from 14,546 firms, covering not only manufacturing but also a wide range of service industries. Since 2017, the survey has included questions related to the development and utilization of new technologies associated with the Fourth Industrial Revolution, including AI. (The others are big data analytics, cloud computing, IoT, robotics, mobile technologies, blockchain, and 3D printing.) In this paper, AI adoption is defined to include both firms that have developed AI technologies themselves and those that utilize AI technologies developed elsewhere.

3.1 Trends in AI adoption in Korea

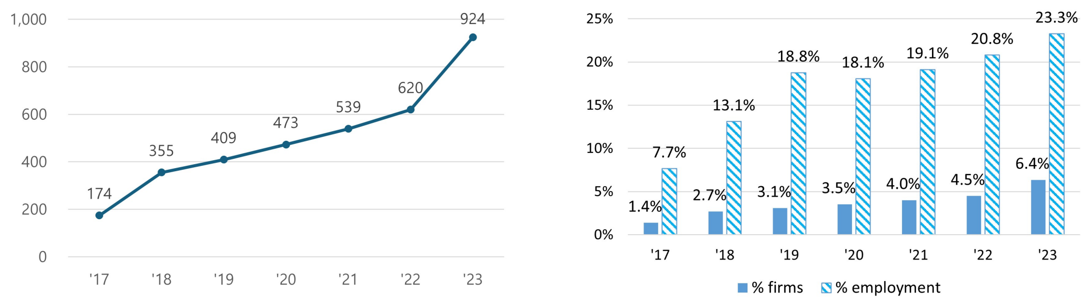
The trends in AI adoption among Korean firms are reported in Figure 1. The number of firms adopting AI technologies has increased steadily over time; however, the overall share of adopting firms remains relatively low. Specifically, the number of AI-adopting firms rose from 174 in 2017 to 924 in 2023. Correspondingly, the share of AI adopters increased from

1.4 percent to 6.4 percent over the same period.

Figure 1: The Diffusion of AI Technologies among Korean Firms

(a) Number of AI-adopting firms

(b) AI adoption rate



Since AI adoption tends to be concentrated among larger firms, the employment-weighted share of AI-adopting firms is substantially higher than the unweighted share. The proportion of regular workers employed by AI-adopting firms increased from 7.7 percent in 2017 to 23.3 percent in 2023. This indicates that nearly one quarter of workers are already employed by firms that have adopted AI technologies.

Figure 2: AI adoption rates by industry (2023)

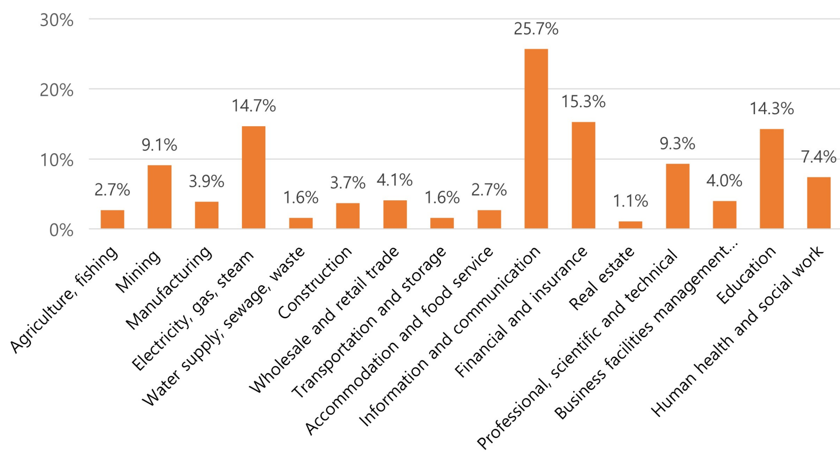


Figure 2 reports the average adoption rates of AI technologies across industries. AI-adopting firms are found not only in high-tech sectors but also in traditional sectors, which is consistent with the hypothesis that AI technology is a GPT (General Purpose Technology), as argued by Goldfarb et al. (2023). However, adoption rates differ considerably across sectors. As of 2023, the industry with the highest adoption rate (in terms of the number of firms) was Information Services (25.7%), followed by finance and insurance (15.3%), electricity, gas, and steam (14.7%), and education (14.3%).

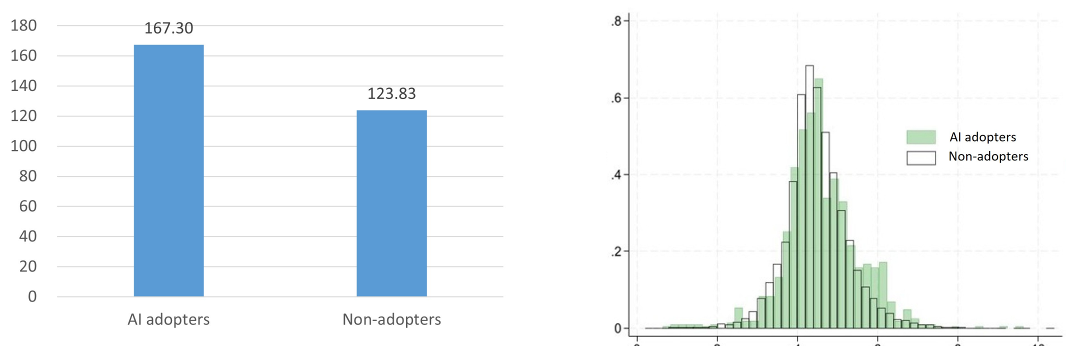
3.2 Productivity distribution of AI adopters

Figure 3 reports the difference in the productivity of AI adopters and non-adopters. On average, AI-adopting firms have a considerably higher level of labor productivity than non-adopting firms. The average level of value added per worker for AI-adopting firms was 167.3 million KRW (in 2015 prices), which is 35.1% higher than that of non-adopting firms (123.8 million KRW).

Nevertheless, not all adopters are more productive than non-adopters. The right panel of Figure 3 illustrates the distributions of log labor productivity for AI-adopting firms and non-adopting firms. The dispersion of labor productivity is very large for both adopters and non-adopters, which is consistent with the literature, including Hsieh and Klenow (2009) and Syverson (2004).

Figure 3: Labor productivity of AI-adopting and non-adopting firms

(a) avg. labor productivity (b) dist. of log labor productivity



3.2.1 The productivity deciles of AI adopters

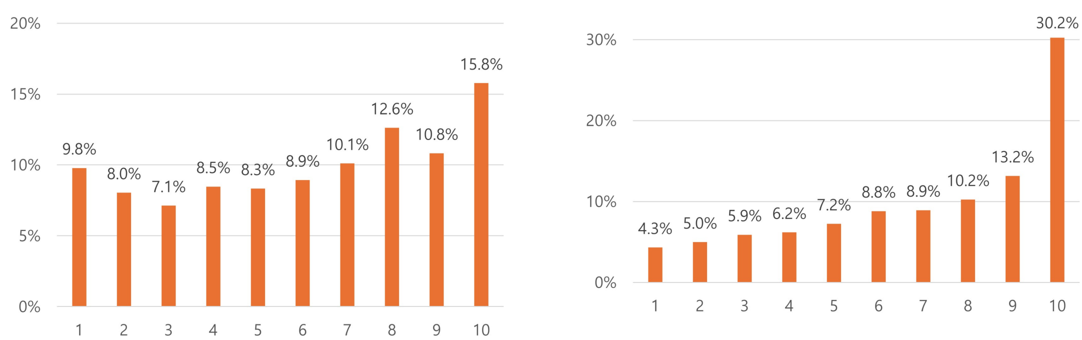
Figure 4 illustrates the differences in the productivity distribution between AI-adopting and non-adopting firms by classifying them into deciles within each two-digit industry in each year, based on their productivity ranking. The results indicate that AI adopting firms are more likely to be in the upper decile of the labor productivity distribution.

Between 2017 and 2023, approximately 15.8% of AI-adopting firms were in the top decile (the 10th decile) of the labor productivity distribution. In addition, 10.8% were in the 9th decile and 12.6% in the 8th decile, indicating that AI-adopting firms are disproportionately represented in the higher deciles of the productivity distribution.[1] The sum of the shares of AI-adopting firms in the upper half of the distribution (the 6th through 10th deciles) amounts to 58.2%, which exceeds 50%. Nevertheless, it is noteworthy that a considerable number of AI-adopting firms are also found in the lower half of the productivity distribution. Moreover, 9.8% of all AI-adopting firms fall into the bottom decile (the 1st decile) of labor productivity.

Figure 4: Decile distribution of AI-adopting firms

(a) by labor productivity

(b) by employment size



Notes: Deciles are constructed within each two-digit KSIC industry based on average labor productivity and regular employment during 2017–2023.
Source: the Survey of Business Activities

The difference between AI-adopting and non-adopting firms is more pronounced in terms of employment size (see the right panel of Figure 4). As many as 30.2% of AI-adopting firms are in the top decile of the employment size distribution, and the share of firms in the upper half of the distribution reaches 71.4%. This concentration of AI adoption among large firms is substantially stronger than the corresponding concentration among high-productivity firms, for which 15.8% are in the top decile of productivity distribution. In contrast, only 4.3% of AI-adopting firms are found in the bottom decile of the employment size distribution.

3.2.2 Changes in the Productivity Distribution

Figure 5 illustrates the evolution of the productivity distribution of AI-adopting firms between 2017 and 2023. The share of AI-adopting firms whose labor productivity (or em-

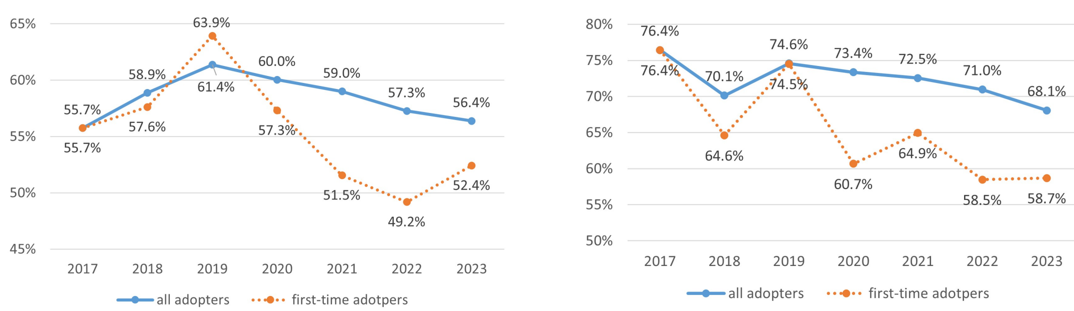
[1]If the productivity distribution of AI-adopting firms were identical to that of non-adopting firms, the share of AI-adopting firms in each decile would be uniformly 10%.

ployment size) is above the industry median temporarily increased from 55.7% in 2017 to 61.4% in 2019, before steadily declining to 56.4% in 2023.

This pattern may reflect a decline in the productivity of existing AI adopters (i.e., firms that have already adopted AI) relative to non-adopters over time, but it could also be driven by the fact that firms adopting AI more recently (late adopters) tend to have lower productivity. To assess which explanation is more relevant, the productivity distribution of firms that adopted AI for the first time in each year is examined separately. Figure 5 shows that the productivity of first-time AI adopters declined more sharply. The share of firms with above-median labor productivity increased from 55.7% in 2017 to a peak of 63.9%, but then fell steadily to 52.4% in 2023. This implies that nearly half of first-time AI adopters have productivity levels below the industry median, suggesting that the perception that AI is adopted only by exceptionally advanced firms is not consistent with the data.

Figure 5: Share of Top-50% firms among AI adopters

(a) by labor productivity (b) by employment size

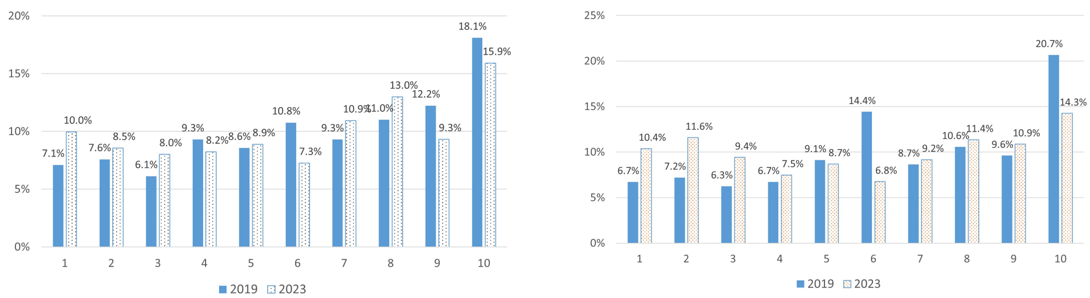


The proportion of AI-adopting firms in the upper 50% of the industry by employment size has also declined steadily since 2019 (see the right panel of Figure 5). After falling from 76.4% in 2017 to 70.1% in 2018, the proportion rebounded to 74.6% in 2019, but then declined steadily to 68.1% in 2023. A similar pattern is observed for first-time AI adopters: the proportion declined from 74.5% in 2019 to 58.7% in 2023. This implies that approximately 40% of first-time AI adopters had firm sizes below the industry median.

The changes in the distribution of AI-adopting firms across all labor productivity deciles between 2019-when the downward trend began—and 2023 are presented in Figure 6. In 2019, 18.1% of AI-adopting firms were in the top decile (top 10%) of labor productivity within their respective industries, but this share declined to 15.9% by 2023 (see the left panel of Figure 6). In contrast, the proportion of firms in the bottom decile (bottom 10%) increased from 7.1% to 10.0% over the same period (see the right panel of Figure 6).

Figure 6: Distribution of AI-Adopting Firms across Productivity Deciles, 2019 vs. 2023

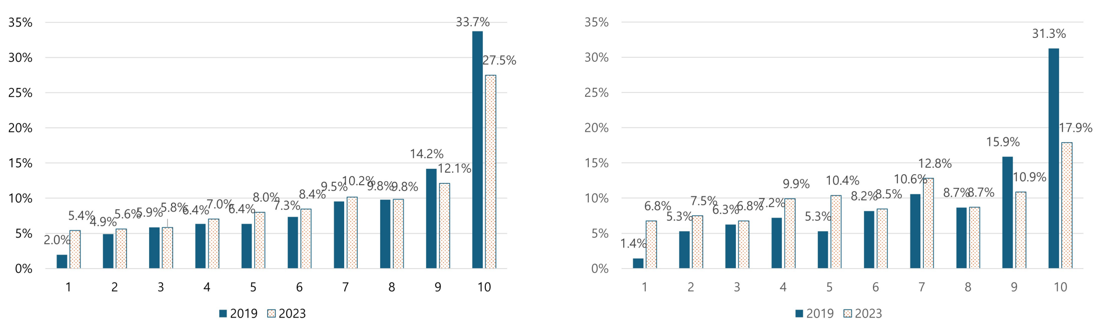
(a) All adopting firms (b) First-time adopters



The distribution of AI-adopting firms by employment size also shifted, with a declining share in the upper deciles and an increasing share in the lower deciles. Among AI-adopting firms, the proportion belonging to the top 10% of their industry in terms of firm size declined modestly from 33.7% in 2019 to 27.5% in 2022, while the share in the bottom 10% increased from 2.0% to 5.4% (see the left panel of Figure 7). This pattern was even more pronounced when focusing only on firms that adopted AI for the first time in a given year (see the right panel of Figure 7): the share in the top 10% declined from 31.3% to 17.9% over the same period, whereas the share in the bottom 10% increased from 1.4% to 6.8%.

Figure 7: Distribution of AI Adopters across Firm Size Deciles, 2019 vs. 2023

(a) All adopting firms (b) First-time adopters



4 The impact of AI adoption on firm productivity

For the diffusion of AI technologies to contribute significantly to aggregate productivity or GDP growth, two conditions must be satisfied. First, the share of AI-adopting firms must be sufficiently large; second, the productivity of adopters must increase substantially. As shown in the previous section, the employment share of AI-adopting firms reached as high as 23.3%, implying that a one percent increase in the average labor productivity of adopting firms would raise aggregate labor productivity by 0.23 percentage points. Therefore, the latter condition appears to be the binding constraint and is examined in this chapter.

As shown in the previous section, AI-adopting firms are more likely to exhibit higher levels of labor productivity than non-adopting firms. However, this correlation may be driven by reverse causality, as firms' decisions to adopt AI are not exogenous to productivity: more productive firms are more likely to adopt AI. The sources of endogeneity in AI adoption are as follows. First, more productive firms typically earn higher profits, which increases their capacity to invest in new technologies such as AI. Second, larger firms tend to be more productive and are also more likely to adopt new technologies (Haller and Siedschlag, 2011). Third, more productive firms possess greater innovative capabilities, such as higher R&D expenditures and intangible investments (Alekseeva et al. 2021; Czarnitzki et al., 2023; Calvino and Fontanelli 2023).

To address these endogeneity concerns, this paper employs two approaches. First, control variables that are correlated with both AI adoption and productivity are included in the regression analysis. Second, an event-study analysis is implemented to account for the possibility that AI adopters and non-adopters followed different trends even prior to the initial adoption of AI.

4.1 The contemporaneous effect of AI adoption on firm productivity

4.1.1 Cross-section analysis (Pooled OLS)

The effects of AI adoption on firm outcomes, such as labor productivity, value added or output, are estimated using a pooled OLS regression, as specified in equation (1). Labor productivity is measured as value-added[2] per regular worker.

As labor productivity is defined as the ratio of firm value added to employment, the effects on value added and employment are analyzed separately.

$$\ln y_{i,t} = \alpha + \beta_1 \cdot D^{AI}_{i,t} + \beta_2 \cdot X_{i,t} + \mu_t + \mu_j + \varepsilon_{i,t} \tag{1}$$

Here, $y_{i,t}$ is the outcome variable of firm i at time t, which may correspond to labor

[2] Deflated using GDP deflators

productivity, value added or employment. $D_{i,t}^{AI}$ is a dummy variable indicating whether the firm adopted AI at t, and its coefficient β_1 is of interest here. Year (μ_t) and industry fixed effects (2-digit, μ_j) are included to control for factors specific to a given year or industry. Since firm age may influence both AI adoption and the outcome variables, including firm size and productivity, a categorical dummy variable, $age_{i,t}$, indicating the decile of firm i's age within its industry at time t is also included.

$X_{i,t}$ is a vector of firm characteristics that can influence both the outcome variables and AI adoption, including categorical dummies for firm-size deciles, tangible and intangible assets per employee, a dummy for export status, and a dummy for large business conglomerates. Here, data on intangible assets are drawn from the Survey of Business Activities and refer to year-end balances of items such as intellectual property rights.[3]

Table 1 presents the estimation results of equation (1). Columns (1) to (4) correspond to specifications with log labor productivity as the dependent variable. Column (1) reports the results from the baseline specification, which includes only firm age–decile dummies, industry dummies, and year dummies as covariates. In this specification, the effect of AI adoption on log labor productivity is positive and highly significant at the 1 percent level. Column (2) presents the estimation results from the specification with interaction terms between AI adoption and year dummies. The coefficients on AI adoption begin to increase from 2017 onward, but decline continuously after 2019. This pattern is consistent with the finding in the previous section that the difference in the productivity distributions of AI-adopting and non-adopting firms began to narrow after 2019.

Nevertheless, once additional covariates—including firm size and other firm characteristics—are included in the regression, as shown in columns (3) and (4), the productivity effect of AI adoption is no longer statistically significant. This result supports the view that the positive correlation between AI adoption and productivity reflects selection effects: AI-adopting firms are more productive not because AI adoption raises productivity per se, but because the decision to adopt AI is correlated with other firm characteristics that are themselves associated with higher productivity.

Column (4) reports the year-specific effects of AI adoption, none of which are statistically significant after controlling for firm characteristics. The implication is that the decline in the productivity difference between AI-adopting and non-adopting firms does not reflect a declining causal effect of AI on productivity, but rather a decline in selection effects over

[3]including patents, trademarks, industrial designs, software, and other rights such as licenses for franchises, mining, and fishing.

time.

Table 1: The effects of AI adoption on firm outcomes

Dep. var.:	(1) labor prod.	(2) labor prod.	(3) labor prod.	(4) labor prod.	(5) emp.	(6) value add.
AI adoption(0/1)	0.135***	-	-0.004	-	0.914***	1.048***
	(0.023)		(0.021)		(0.047)	(0.058)
AI×2017	-	0.027	-	-0.102	-	-
		(0.070)		(0.065)		
AI×2018	-	0.104**	-	-0.003	-	-
		(0.044)		(0.040)		
AI×2019	-	0.208***	-	0.05	-	-
		(0.038)		(0.034)		
AI×2020	-	0.195***	-	0.04	-	-
		(0.040)		(0.036)		
AI×2021	-	0.146***	-	0.001	-	-
		(0.042)		(0.039)		
AI×2022	-	0.123***	-	-0.024	-	-
		(0.036)		(0.033)		
AI×2023	-	0.106***	-	-0.02	-	-
		(0.029)		(0.027)	-	-
$K_{tangible}/L$	-	-	0.116***	0.116***	-	-
			(0.003)	(0.003)		
$K_{intangible}/L$	-	-	0.070***	0.070***	-	-
			(0.004)	(0.004)		
Export(0/1)	-	-	0.132***	0.132***	-	-
			(0.010)	(0.010)		
Conglomerates (0/1)	-	-	0.258***	0.258***	-	-
			(0.021)	(0.021)		
Emp.(deciles)	N	N	Y	Y	N	N
Observations	90,879	90,879	90,667	90,667	90,891	90,879
R-squared	0.241	0.241	0.328	0.328	0.214	0.188

Notes: (1) Standard errors are reported in parentheses and are clustered at the firm level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively. (2) Labor productivity, value added, employment, and tangible and intangible assets are expressed in logarithms and measured at 2015 constant prices. (3) All estimation models include controls for firm age and industry fixed effects.

The effects of AI adoption on firm size, measured by employment or value added (both in logs), are presented in columns (5) and (6) of Table 1. The effects on firm size are positive and statistically significant when firm size is measured by employment or value added, controlling for industry, year, and firm age. One notable feature is that the effect of AI adoption on value added is larger than the effect on employment, which is consistent with the finding that labor productivity is positively related to AI adoption. This also implies that AI-adopting firms have a higher level of labor productivity not because they employ fewer workers, but because they produce more output.

4.1.2 Heterogeneous productivity effects of AI

The effects of complementary investments

The adoption of new technology may require complementary investments to realize productivity effects (Brynjolfsson et al. 2019; Brynjolfsson et al. 2021). Therefore, firms with higher levels of tangible or intangible capital may capture greater productivity gains from AI adoption. To address this issue, a set of interaction terms is included in the regression, and the results are reported in columns (1) and (2) of Table 2. The coefficient on the interaction term between AI adoption and tangible capital is positive and statistically significant, whereas the interaction term between AI adoption and intangible capital is not statistically different from zero. This result is somewhat puzzling, given that intangible capital is generally considered more likely to complement the adoption of new technologies such as AI. One possible explanation is that the positive relationship reflects selection effects: firms with stronger financial capacity are more likely both to invest in tangible capital and to adopt AI.

The productivity effects of AI adoption may differ by its primary field of use. The survey classifies the use of AI into five categories: "product development," "production process," "sales," "marketing strategy," and "organizational management." Columns (3)–(5) report the estimation results by field of use. In column (3), without controlling for firm characteristics, all categories exhibit statistically significant positive coefficients, with the largest effects observed for "organizational management" and "marketing strategy," and the smallest for "product development." However, the specification controlling for firm characteristics, reported in column (4), shows that statistically significant positive effects remain only for "organizational management" and "marketing strategy," while the effects of all other categories become statistically insignificant.

The finding that the estimated (contemporaneous) productivity effect is lowest when AI is adopted in the production process is somewhat puzzling, given that production is typically viewed as the firm activity most directly related to productivity. In contrast, the largest productivity effect is observed for "organizational management," which is generally considered to be only indirectly related to productivity.

When the analysis is restricted to firms in the upper 50% of the labor productivity distribution to address selection concerns, the coefficients on AI adoption are insignificant across all categories of AI use, including "organizational management." One possible explanation is that that firms in the lower half of the productivity distribution may face greater difficulty investing in areas—including organizational management—that do not immediately translate into higher revenue. If this interpretation holds, the relatively larger coefficients for the "organizational management" category compared with those for the "production process" category may reflect stronger selection effects rather than stronger productivity effects.

Table 2: Productivity effects by primary field of use and interaction with capital stock

	(1)	(2)	(3)	(4)	(5)
AI adoption(0/1)	-0.152***	-0.025	-	-	-
	(0.049)	(0.033)			
AI×$K_{tangible}/L$	0.039***	-	-	-	-
	(0.011)				
AI×$K_{intangible}/L$	-	0.011	-	-	-
		(0.013)			
Main Field:					
product development	-	-	0.074**	-0.055**	0.003
			(0.030)	(0.027)	(0.024)
production process	-	-	0.270***	0.081*	0.031
			(0.049)	(0.042)	(0.037)
sales	-	-	0.136***	0.012	-0.006
			(0.050)	(0.043)	(0.035)
marketing strategy	-	-	0.303***	0.141***	0.03
			(0.050)	(0.042)	(0.042)
org. management	-	-	0.292***	0.144***	0.03
			(0.059)	(0.055)	(0.051)
$K_{tangible}/L$	0.115***	0.116***	-	0.116***	0.058***
	(0.003)	(0.003)		(0.003)	(0.003)
$K_{intangible}/L$	0.070***	0.069***	-	0.070***	0.060***
	(0.004)	(0.004)		(0.004)	(0.004)
Export(0/1)	0.132***	0.132***	-	0.132***	0.074***
	(0.010)	(0.010)		(0.010)	(0.010)
Conglomerates(0/1)	0.256***	0.257***	-	0.257***	0.153***
	(0.021)	(0.021)		(0.021)	(0.019)
Emp.(deciles)	Y	Y	N	Y	Y
Top 50% by labor prod.	N	N	N	N	Y
Observations	90,667	90,667	90,879	90,667	45,472
R-squared	0.328	0.328	0.241	0.328	0.557

4.2 Lagged effects of AI adoption - Event Study

In this paper, we implement an event-study analysis for two reasons: first, to fully address endogeneity concerns arising from the possibility that AI-adopting firms may have already been on a different growth trajectory even before the adoption of AI; and second, to examine whether the effect of AI adoption is strengthened over time, as suggested by Brynjolfsson et al. (2019).

4.2.1 Estimation Model

The evolution of firm outcome variables - including labor productivity, employment, value added, innovation activities - around the year of initial AI adoption is analyzed using an event-study framework. To this end, the following estimating equation is specified:

$$y_{i,t} = \sum_{\ell} \beta_{\ell} \cdot D^{AI}_{i,t-\ell} + \delta_i + \mu_s + \mu_t + \varepsilon_{i,t} \tag{2}$$

Here, an index variable, $I_{i,s}$, is equal to one if the year of firm i's initial AI adoption is s, and equal to zero otherwise. ℓ represents the time distance from the year of initial adoption, taking negative values before and positive values after adoption. For example, if a firm first adopted AI in 2018, $\ell = -1$ in 2017 and $\ell = 2$ in 2020. Fixed effect terms for firm (δ_i), industry(μ_s) and year(μ_t) are also included in the specification.

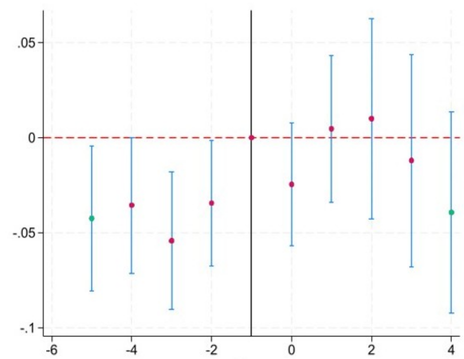
Here, the meaning of β_l is interpreted as follows. Those firms that had adopted AI l years earlier constitute the treatment group, while the other firms belong to the control group. β_l represents the difference in the outcome variable y between the treatment and the control group, normalized to zero in the year immediately before the initial adoption, so $\beta_{-1} = 0$.

One critical assumption is that the firms in the control group followed the parallel trend with the treatment group before the event - the adoption of AI. If the estimated coefficients were already increasing — exhibiting significantly negative values for $l < -1$ — prior to the initial adoption, the significantly positive values observed after adoption ($l \geq 0$) cannot be interpreted as evidence of a causal effect.

4.2.2 Estimation Results

In the 2017 survey—the first year that AI-related questions were introduced—, it is difficult to determine whether firms that reported developing or using AI in that year had newly adopted the technology or had already done so prior to 2017; therefore, they are excluded from this analysis, and a separate analysis is implemented later in this paper. (Observations corresponding to four or more years after the initial adoption ($l >= 4$) and those corresponding to five or more years prior to the initial adoption ($l <= -5$) are each aggregated into a single category, such that they are represented by a single estimated coefficient.) The estimated coefficients are reported in Table 3 and illustrated in Figure 8.

Figure 8: Lagged effect of AI adoption on labor prod.



Note: 1) Horizontal axis: ℓ (=0 in the year of first adoption)
Vertical line: 95% confidence interval
2) green obs. : $\ell \geq 4$ (lag) or $\ell \leq -5$ (lead)

It appears that AI-adopting firms did not exhibit faster growth in labor productivity relative to the non-adopting firms. The estimated coefficients (β_l) are not significantly different from zero not only in the year of initial adoption, but also $1 \sim 5$ years after initial adoption. No clear upward or downward trend is observed in the pre-adoption period; however, significantly negative coefficients at specific leads suggest that the estimated post-adoption effects may be upward-biased rather than downward-biased.

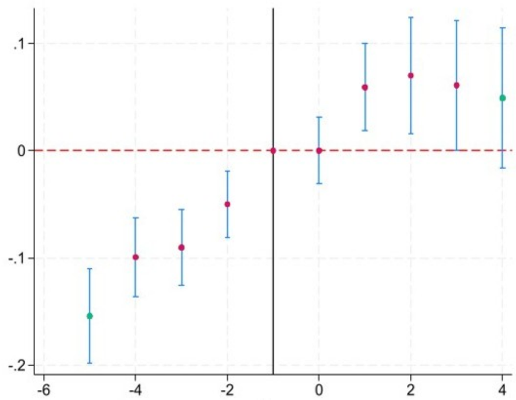
However, not all digital technologies—particularly more mature technologies—require a long period for their productivity effects to materialize. For example, the study by Brynjolfsson and Hitt (2003), which examines the effects of growth in computer capital on firms' total factor productivity in the United States over the period 1987–1994, finds broadly significant positive effects over horizons of five years or longer. Moreover, even over shorter horizons of four years or less, the estimated coefficients increase monotonically as the time horizon increases.

The estimated lead-lag coefficients of AI adoption with respect to firm size, measured by value added and employment, are reported in Table 3 and also illustrated in Figure 9. For employment, the estimated coefficient is significantly positive in the first year of

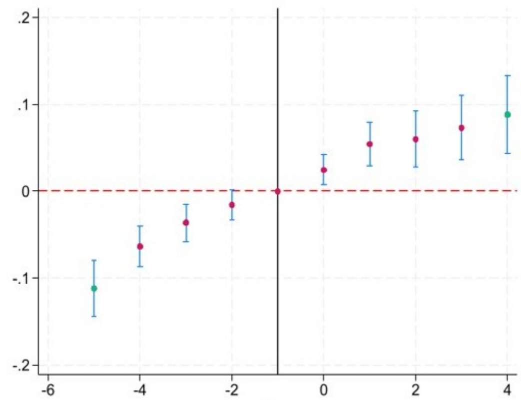
AI adoption ($l = 0$) and continues to increase over all subsequent lags. For value added, the coefficient is not statistically significant in the year of initial adoption but becomes significantly positive in the subsequent years.

Figure 9: The lagged effects of AI adoption on firm size

(a) Value added (log)



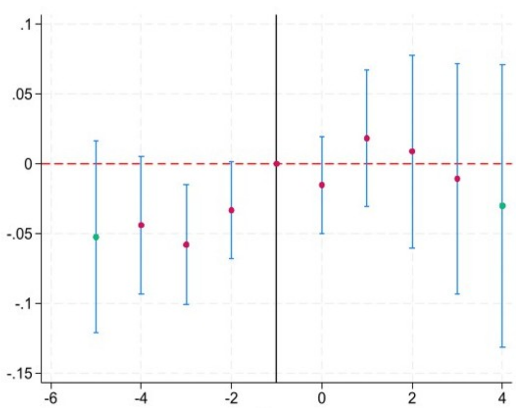
(b) Employees (log)



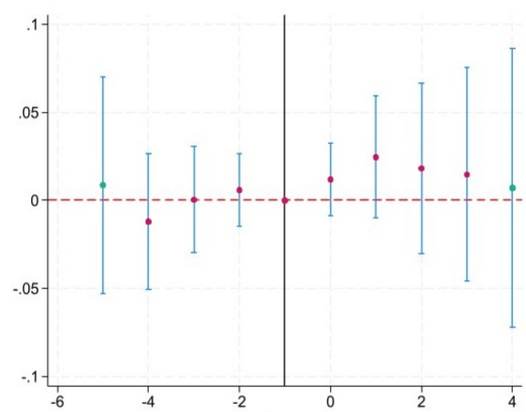
However, it is shown that AI-adopting firms were already growing faster than non-adopters in terms of both value added and employment even before the initial adoption, suggesting a pre-trend and selection effect.

Figure 10: The lagged effects of AI adoption within adopters

(a) Value added (log)



(b) Employees (log)



Since AI-adopting firms were already following a different growth trajectory from non-adopters even before the adoption, a separate analysis was conducted focusing only on firms that had ever adopted AI, in order to mitigate potential bias arising from such pre-existing differences. The estimated coefficients are illustrated in Figure 10, and appear to be not significantly differ from zero before initial adoption, satisfying the assumption of parallel pre-trend. However, none of the lagged coefficients after initial adoption is significantly different from zero. In sum, although AI-adopting firms are larger and exhibit faster growth in firm size than non-adopting firms, these differences are unlikely to reflect the causal effect of AI adoption, which is consistent with Acemoglu et al. (2023).

Table 3: The lead-lag effects of AI adoption

	(1)	(2)	(3)	(4)	(5)
Sample:	all firms			only adopters	
Dep. var:	lab. Prd.	emp.	value add.	emp.	value add.
t-5∼	-0.043**	-0.112***	-0.154***	0.009	-0.052
	(0.020)	(0.016)	(0.023)	(0.031)	(0.035)
t-4	-0.036*	-0.063***	-0.099***	-0.012	-0.044*
	(0.018)	(0.012)	(0.019)	(0.020)	(0.025)
t-3	-0.054***	-0.036***	-0.090***	0	-0.058***
	(0.019)	(0.011)	(0.018)	(0.015)	(0.022)
t-2	-0.034**	-0.016*	-0.050***	0.006	-0.033*
	(0.017)	(0.009)	(0.016)	(0.011)	(0.018)
t: initial adoption	-0.025	0.025***	0.000	0.012	-0.015
	(0.016)	(0.009)	(0.016)	(0.011)	(0.018)
t+1	0.005	0.054***	0.059***	0.025	0.018
	(0.020)	(0.013)	(0.021)	(0.018)	(0.025)
t+2	0.01	0.060***	0.070**	0.018	0.009
	(0.027)	(0.017)	(0.028)	(0.025)	(0.035)
t+3	-0.012	0.073***	0.061**	0.015	-0.011
	(0.028)	(0.019)	(0.031)	(0.031)	(0.042)
t+4∼	-0.039	0.088***	0.049	0.007	-0.03
	(0.027)	(0.023)	(0.033)	(0.040)	(0.052)
Observations	162,346	162,368	162,346	14,115	14,111
R-squared	0.011	0.022	0.017	0.072	0.075

4.3 Firms that first adopted AI in 2017 or earlier

For those firms that reported having adopted AI in 2017 - the first year in which the survey included questions on AI - at least 6 years had passed since the first adoption by 2023, the last year of the survey. Therefore, a separate long-difference analysis is implemented as specified in equation (3):

$$\Delta \ln y_{i,t} = \alpha + \beta_1 \cdot D^{AI}_{t-1} + \beta_2 \cdot \Delta X^c_{i,t} + \beta_3 \cdot X^i_{i,t-1} + \mu_j + \varepsilon_{i,t} \tag{3}$$

The estimated coefficients indicate whether firms that adopted AI in 2017 experienced faster growth in labor productivity and related outcomes between 2017 and 2023 compared with firms in the control group. Firms that first adopted AI after 2018 are excluded from the analysis, and the control group consists only of firms that never adopted AI. The results are reported in Table 4.

Equation (3) is a long-difference regression of changes in firm outcomes from 2017 to 2023 on the AI adoption status in 2017, controlling for firm characteristics, industry, and year dummies. $X^i_{i,t-1}$ is a vector of binary status variables of a firm in 2017, including whether the firm belongs to a large business conglomerate or whether the firm exports. $\Delta X^c_{i,t}$ is the change in the continuous variables from 2017 to 2023, representing firm characteristics that include (the logs of) tangible and intangible capital stocks. The firms that first adopted AI in 2017 or earlier constitute the treatment group, while those firms that never adopted AI constitute the control group. Those firms that first adopted AI in 2018 or later are excluded in this analysis. Figure 5 presents the estimation results.

Table 4: The effects of AI adoption in 2017 on the growth of labor productivity and firm size between 2017-2023

	(1) ΔLab. Prd.	(2) Δlab.Prd.	(3) Δemp.	(4) Δvalue add.
AI adoption(0/1)	0.056	0.017	0.076*	0.131**
	(0.061)	(0.061)	(0.043)	(0.059)
$\Delta K_{tangible}/L$	-	0.070***	-	-
		(0.009)		
$\Delta K_{intangible}/L$	-	0.021**	-	-
		(0.009)		
Conglomerates(0/1)	-	0.003	-	-
		(0.037)		
Export(0/1)	-	-0.026	-	-
		(0.017)		
Employment(deciles)	N	Y	N	N
Observations	8,904	8,875	8,904	8,908
R-squared	0.031	0.056	0.039	0.046

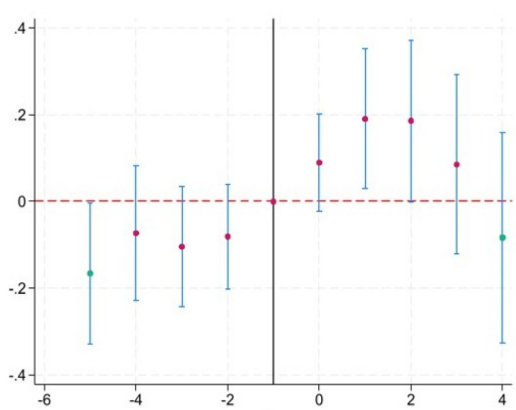
The effect of AI adoption in 2017 on the subsequent growth of labor productivity between 2017 and 2023 is reported in columns (1) and (2) of Table 4 and appears statistically insignificant, regardless of whether control variables are included. As discussed above, the productivity effect of AI adoption is not statistically significant within a five-year horizon. This pattern remains unchanged when the horizon is extended to six years. The effects on firm size growth, measured by employment (number of employees) and value added, are reported in columns (3) and (4) and appear to be significantly positive; however, when firm size is measured by employment, the effect is statistically significant only at the 10 percent level.

4.3.1 The effect of AI adoption on firms' innovation activities

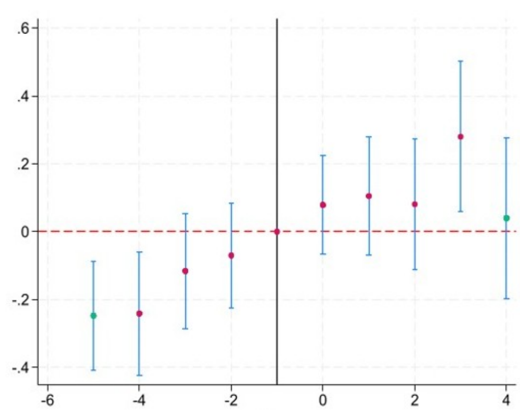
The adoption of AI technologies can be interpreted as a process of accumulation of intangible capital (Czarnitzki et al. 2023; Damioli et al. 2021; Mihet and Philippon 2019). The adoption of AI involves R&D investment and acquisition of intellectual rights, and such cumulative innovation efforts constitute intangible capital, gradually increasing productivity (Brynjolfsson et al., 2019). The implication is that the productivity effect is not realized simply as time goes on but depends on complementary investments. Figure 11 presents the lagged effect of AI adoption on innovation activities. After the initial adoption of AI, R&D spending increases, but only temporarily. The coefficient is statistically significant and positive 1 and 2 years after the initial adoption, but diminishes from 3 years after, and does not appear significant any more. The annual increase in intangible capital had already shown an increasing trend before AI adoption, but the increasing trend decelerated after AI adoption, with coefficients not statistically different from zero afterward.

Figure 11: Lagged effects on innovation activities

(a) Total R&D spending



(b) $\Delta K_{intangible}$

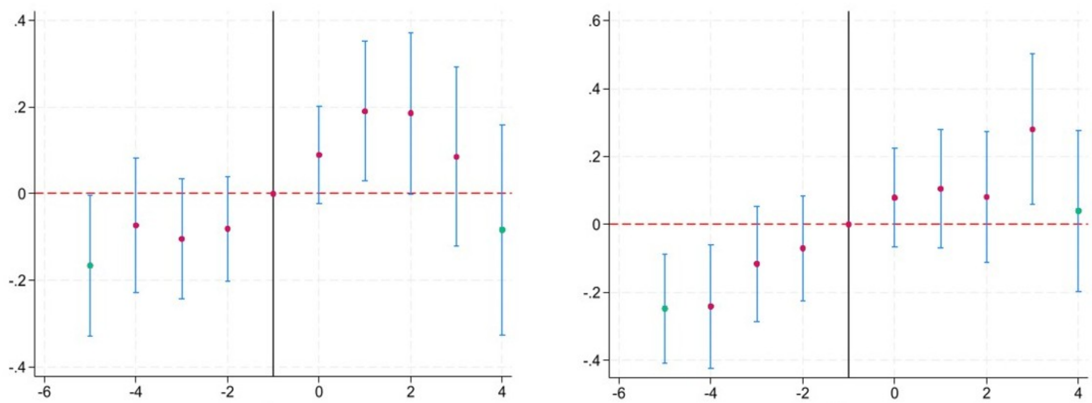


This result implies that AI has not significantly accelerated investments in innovative activities, which may partly explain why labor productivity has not increased significantly even several years after the initial adoption of AI.

Figure 12 shows that the entry into a new business, measured as a binary indicator, increases significantly in the year of initial adoption immediately. This effect persists one year after initial adoption but disappears from the second year onward. A similar pattern is found for the total sales generated from the new business, which show significantly positive coefficients only in the initial adoption year and the following year.

Figure 12: Lagged effects on new business entry

(a) Total R&D spending (b) $\Delta K_{intangible}$



The increase in new business entry following AI adoption can be attributed to two potential mechanisms. First, AI adoption may have reduced the costs of developing new products or services (Babina et al. 2024; Cockburn et al. 2018), thereby facilitating new business entry. Second, the adoption of AI itself may have constituted a new business. However, if the former mechanism were dominant, the cost-reducing effects of AI would be expected to persist over time. This is inconsistent with the empirical finding that the increase in new business entry almost completely dissipates within two years after initial adoption.

Taken together, one possible interpretation is that a substantial share of AI adoption among Korean firms may have been experimental in nature. In such cases, firms initiate a new business and increased R&D expenditures primarily at the time of initial adoption, but may not have sustained subsequent investments thereafter.

It is noteworthy that the measure of R&D expenditures in this paper refers to firm-wide spending and is not limited to AI-related activities. Therefore, it is possible that AI-related R&D continued to increase after adoption, while R&D investment in other technologies was substantially reduced, resulting in a crowding-out effect that prevented total R&D expenditures from rising. Nevertheless, even in this scenario, the lack of an increase in overall R&D investment would still be unfavorable for long-term productivity growth at the firm level.

Table 5: Lagged effects of AI adoption on innovation activities

	(1)	(2)	(3)	(4)
	Investments		New Business	
	R&D	$\Delta K_{intangible}$	entry(0/1)	revenue
t-5∼	-0.166**	-0.248***	-0.014*	-0.060*
	(0.083)	(0.081)	(0.008)	(0.035)
t-4	-0.073	-0.241***	-0.014	-0.045
	(0.079)	(0.093)	(0.009)	(0.041)
t-3	-0.104	-0.116	-0.007	-0.029
	(0.071)	(0.086)	(0.009)	(0.044)
t-2	-0.081	-0.07	0.005	0.006
	(0.062)	(0.079)	(0.009)	(0.046)
t: initial adoption	0.09	0.079	0.069***	0.251***
	(0.057)	(0.073)	(0.011)	(0.056)
t+1	0.191**	0.105	0.031***	0.149**
	(0.082)	(0.089)	(0.011)	(0.061)
t+2	0.186*	0.081	0.018	0.005
	(0.095)	(0.098)	(0.011)	(0.052)
t+3	0.085	0.280**	0.001	-0.012
	(0.105)	(0.113)	(0.012)	(0.057)
t+4∼	-0.083	0.04	0.006	0.047
	(0.124)	(0.121)	(0.013)	(0.061)
Observations	162,367	162,361	162,368	162,368
R-squared	0.013	0.003	0.005	0.005

5 Conclusion

AI adoption has been increasing rapidly in South Korea, and approximately one quarter of the workers surveyed are employed by AI adopting firms. Although adoption was previously concentrated among large and high-productivity firms, it has increasingly spread to smaller and lower productivity firms. This pattern suggests that the hurdle of AI-adoption has been reduced, thereby accelerating the diffusion of AI technologies.

Although AI-adopting firms tend to be more productive than non-adopters, AI adoption has no significant contemporaneous effect on labor productivity once firm characteristics are controlled for. We tested whether the productivity effect strengthens over time after initial AI adoption, but it remained statistically insignificant for up to five years thereafter. Even in a separate analysis restricted to firms for which more than six years have elapsed since the initial adoption of AI, no statistically significant productivity effects are found. It remains unclear how long it takes for the productivity effects of AI adoption to materialize. However, this study suggests that a period of five to six years is not sufficient.

Moreover, AI-adoption has not induced a sustained increase in investments, including R&D and intangible capital, which may partly explain the limited productivity effects. However, certain measures of innovation, including new business entry, increased following AI-adoption. Given the recent surge of interest in AI, this finding is somewhat puzzling and calls for further investigation into its underlying causes.

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