China's National Artificial Intelligence Strategy, Firm Adoption, and Short-Run Performance Effects

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Abstract. Artificial Intelligence (AI) is becoming increasingly important in firms' performances. This paper examines how China's 2017 national AI strategy affects firm-level AI adoption and its short-run performance implications. This study constructs AI adoption intensity by counting AI-related words using A-shared list firms within the time period 2001 to 2024. A two-way fixed effects model is introduced to study the relationship between degree of adopting AI and degree of how firms performed. Results are that the initiative is effective in incentivizing more AI adoption, but more adoption in AI does not mean better financial performance of firms at least in the short-run. It is found that there is a negative association between AI adoption and firm performances. Heterogeneity and moderating analyses are further conducted to explore the relationship under different firms' characteristics. The findings contribute to the literature on the area of influences of China's AI initiative on corporate AI adoption and its subsequent impact. Future researches could focus on mechanism analysis.

Keywords: Artificial Intelligence (AI), Industrial Policy, Firm Performance, AI Adoption.

1 Introduction

Artificial Intelligence (AI), a cutting-edge technology, has profoundly reshaped firms' production processes, organizational structures and competitive dynamics. In 2017, the Chinese government released "New Generation AI Development Plan", elevating AI to a national strategic priority. However, whether AI can effectively improve firms' performances still remain unanswered. Investment on AI always comes with substantial upfront costs. Against this background, this paper answers the following questions. First, does China's plan in 2017 significantly alter firms' behaviors on adoption of AI? Second, how does level of firms' adoption of AI affect their financial performances? Heterogeneity tests across different firms are further conducted.

A growing literature conceptualizes AI as a general technology that has impacts on socio-economy. Effective application of AI requires many complementary inputs, so productivity of AI may decrease in the short run [1]. The shock on labor market is mainly related to task reconstruction rather than overall employment [2]. More skilled workers are required [3]. There are also numerous empirical evidences focused on

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innovation and performances. It is found that artificial intelligence innovation, proxied by AI patents, has a significantly positive effect on long-run economic growth, with a stronger impact than overall patenting activity [4]. Moreover, AI-driven innovation is beneficial to the growth of companies but the benefits are distributed unevenly across them [5]. Some scholars argue that firms have a positive relationship between productivity and performance because of AI [6, 7]. However, adjustment costs like employer training are inevitable [8]. Industrial policy often has a huge influence on firm behaviors. Manufacturing policy can increase firms' research and development (R&D) input by releasing clear signals and implementing fiscal incentives, particularly in strategic emerging industries [9]. Further evidences show that districts with different ownership have significant heterogeneity [10].

It is hard to find evidence about the influence of China's 2017 plan on firms' AI adoption. At the same time, literatures about the relationship between AI and firm performance are most based on Western perspectives. This study discusses the impact of China's 2017 national AI strategy on firm-level AI adoption and its implications for firm performance.

2 Methodology

2.1 Data

The dataset comes from 5720 annual reports of A-share listed companies in China from the year 2001 to the year 2024. The reason why choosing this time period is that AI-related technology is becoming popular only after 2000. There are three important variables. AI adoption rate is measured by frequency of "AI" appearing in the annual report each year after taking log transformation. A time dummy variable is generated by taking 1 for years after 2017 and 0 otherwise. Return on equity (ROE) is a popular financial index representing firms' performances.

2.2 Empirical Model

The first model (equation 1) explains whether 2017 plan has impacts or not.

$$\mathrm{AI\_adoption}_{it} = \beta_0 + \beta_1 D_{2017\,it} + \gamma_i + \lambda_t + \varepsilon_{it} \tag{1}$$

$\mathrm{AI\_adoption}_{it}$ is the dependent variable measuring AI adoption rate. $D_{2017\,it}$ is the independent variable taking a value of 1 for years 2017 onwards and 0 otherwise. γ_i denotes firm fixed effects (Firm FE) and λ_t denotes year fixed effects (Year FE). β_1 measures the effects of the policy on firm's adoption of AI technology after 2017, controlling for firm's heterogeneity and time effects. This study expects β_1 is larger than zero, indicating that the policy implementation is positively correlated with AI adoptions.

The second model (equation 2) explains how AI adoption affects firms' financial performances.

$$roe_{it} = \alpha_0 + \alpha_1 AI\_adoption_{it} + \gamma' \boldsymbol{X_{it}} + \gamma_i + \lambda_t + \theta_{it} \tag{2}$$

roe_{it} is the dependent variable of firm performance (ROE). $AI\_adoption_{it}$ has the same definition. $\boldsymbol{X_{it}}$ is a series of time-varying firm-level control variables, for example, size, and leverage rate. α_1 measures how a one-unit change in AI adoption intensity could affect a firm's ROE, ceteris paribus. This study expects α_1 is larger than zero, indicating firm's AI adoption is positively correlated with return on equity. Furthermore, a series of interaction terms are added to examine how firm characteristics would impact relationship of AI adoption and firm performance.

3 Results and Discussion

3.1 Descriptive Statistics

According to the Table 1, the mean of AI adoption is 0.381 and that of ROE is 5.5%. The minimum and maximum for AI adoption rate are 0 and 6.133 respectively, and that for ROE are -127% and 46.9% respectively.

Table 1. Descriptive statistics

	Observations	Mean	Standard Deviation	Minimum	Maximum
AI Adoption	67,347	0.381	0.805	0.000	6.133
ROE	61,775	0.055	0.147	-1.27	0.469

3.2 Regression Results

Policy effectiveness is verified by estimating the coefficient on model 1 (equation 1) and the value obtained is 1.05 which is both statistically significant and economically intuitive. This could be explained as firms adopt 105% more AI technology on average after the policy is announced.

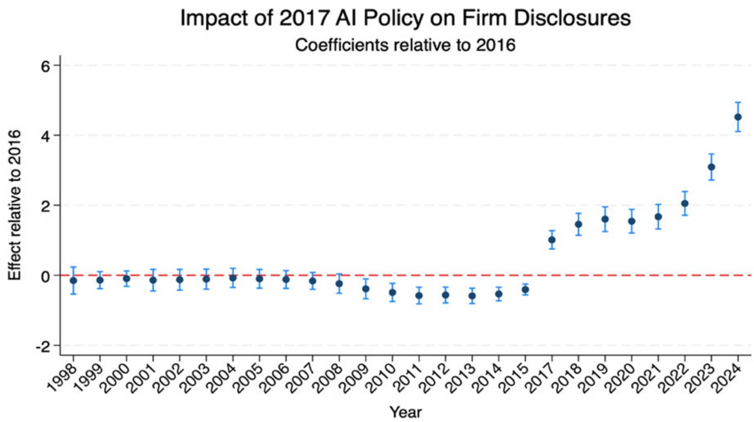

Fig. 1. Event study

Through the event study (Figure 1) with base year 2016, the policy is further believed to be very effective. This could be seen from the figure that before the year 2016, the coefficients relative to 2016 is very close to 0, while there is a sharp increase in the year 2017 and a further increase appears after 2022 probably because of recovery from pandemic.

Table 2 demonstrates the baseline specification results and the coefficient in column (1) is not statistically significant, indicating there is an endogeneity problem. Therefore, controls are needed and the coefficient on column (2) is -0.005, indicating an increase in 1% adoption of AI could decrease firm's financial performance by 0.00005 unit. For robustness check, this study uses other alternative independent variables such as AI adoption last year (lagged AI adoption), digital AI adoption which is defined by words related digitalization, and AI application adoption which is defined by words in specific AI application areas like machine learning and deep learning. Coefficients across column (3) to (5) are consistently negative and statistically significant, indicating the result is very robust. Generally, AI is regarded as a tool that could facilitate firms' growth but the result is the opposite. This could be interpreted as AI needs large investment cost but cannot transform into real productivity in the short term. Besides, high technical requirements for employees should also be considered. The reason why most papers get a positive result is that they consider long-term effect of AI through economic perspective.

Table 2. Baseline results with robustness checks

	(1) ROE	(2) ROE	(3) ROE	(4) ROE	(5) ROE
AI Adoption	0.001 (0.002)	-0.005^{***} (0.002)			
Lagged AI Adoption			-0.010^{***} (0.002)		
Digital AI Adoption				-0.003^{**} (0.001)	
AI Application Adoption					-0.002^{*} (0.001)
Controls	No	Yes	Yes	Yes	Yes
Firm FE	No	Yes	Yes	Yes	Yes
Year FE	No	Yes	Yes	Yes	Yes
Observations	14,481	13,226	10,505	33,493	27,039

Standard errors in parentheses * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. The rest of the tables follow the same style.

A heterogeneity analysis is conducted to explore the differences of the effect of AI adoption with a series of subsamples. Tech-intensity is chosen because this study wants to figure out whether adjustment cost will make a difference. Manufacturing is chosen to study AI impact on productivity. Firms in Growth Enterprise Market (GEM) are often more eager to try new things, and it is interesting to figure out whether this feature has an influence or not. Eastern regions are always more developed than non-Eastern regions, and it is anticipated the logic is also applicable when it comes to AI adoption and firm performances. The results could be found in Table 3. All models are estimated using full sample and the same controls and fixed effects as in the baseline regression.

Table 3. Heterogeneity analysis

	(1)	(2)	(3)	(4)
	Tech-Intensive	Non-Tech-Intensive	Manufacturing	Non-Manufacturing
AI Adoption	-0.006***	0.000	-0.005**	-0.005*
	(0.002)	(0.004)	(0.002)	(0.003)
Observations	8,873	4,247	8,185	4,981
	(5)	(6)	(7)	(8)
	GEM	Non-GEM	East	Non-East
AI Adoption	-0.010***	-0.003	-0.004**	-0.009***
	(0.003)	(0.002)	(0.002)	(0.003)
Observations	3,483	9,743	9,641	2,556

From column (1) and (2), the strong negative effect in tech-intensive firms reflect huge adjustment cost arising from integrating AI into previous complex technological system. From column (3) and (4), coefficients are similar, indicating there is no huge difference between manufacturing and non-manufacturing firms. This is because mature AI currently is a general-purpose technology like ChatGPT, which is very hard to affect production activities directly. From column (5) and (6), firms categorized into GEM have a coefficient with smaller absolute value. This is because this type of firms is often more growth-oriented, and they are more willing to accept and apply new technology like AI, which means companies could amplify the power of AI more compared to companies refusing to accept AI. That is why AI adoption and firm performances are less negatively correlated in these companies. From column (7) and (8), the negative impact for Eastern firms is much smaller than firms in non-Eastern regions, since less-developed regions often has large constraints in resources and managerial capabilities, amplifying the adjustment cost.

From all columns in Table 4 and Table 5, this study finds that whether a firm is state-owned, where a firm is publicly listed, whether a firm is in Science and Technology Innovation Board (known as the Star market) and whether a firm is asset intensive, have no clear moderating effects. The corresponding coefficients in Table 4 and Table 5 are non-significant at 1% level. There are three columns showing significant moderating effects. The firms in labor intensive market have 0.00006-unit higher return than those in non-labor-intensive market, because the former has a larger improvement space in marginal benefit maybe due to low efficiency in management and production.

Table 4. Moderating effects analysis 1

	(1) State Owned	(2) Asset Intensive	(3) Labor Intensive	(4) Tech-Intensive
AI Adoption	-0.007***	-0.006***	-0.007***	0.000
	(0.002)	(0.002)	(0.002)	(0.003)
AI ×	0.004			
State-owned	(0.004)			
AI ×		0.009		
Asset-Intensive		(0.006)		
AI ×			0.006*	
Labor-Intensive			(0.003)	
AI ×				-0.008**
Tech-Intensive				(0.003)
Observations	12216	13226	13226	13226

Table 5. Moderating effects analysis 2

	(1) Star Market	(2) GEM	(3) Beijing Stock Exchange (BSE)	(4) Shanghai and Shenzhen Stock Exchanges (SHSZ)
AI Adoption	-0.006***	-0.002	-0.006***	0.001
	(0.002)	(0.002)	(0.002)	(0.012)
AI ×	0.003			
Star Market	(0.004)			
AI × GEM		-0.012***		
		(0.003)		
AI × BSE			0.006	
			(0.012)	
AI × SHSZ				-0.006
				(0.012)
Observations	12216	13226	13226	13226

Column (4) in Table 4 and column (2) in Table 5 are tech-intensive and GEM respectively. This study finds that firms in tech-intensive market have 0.00008-unit lower return than those in non-tech-intensive market. This could be explained by the fact that tech-intensive firms have already applied much AI-related technology into production than non-tech-intensive firms, which means the latter still have large space to introduce these state-of-the-art technologies to improve management and production. Also, this study discovers that firms in GEM have 0.012-unit lower return than those in non-GEM market, which is contradicted to the results found in heterogeneity analysis. Therefore, there is no significant evidence on the differences between GEM and non-GEM firms.

4 Conclusion

This paper investigates how 2017 AI initiative influences AI adoption and how it relates to firms' financial performance. Using a huge panel of A-share listed firms, a clear increase in AI adoption appears after the announcement of the initiative is found. In terms of AI adoption and firm performances, the baseline results and robustness analysis further suggest AI adoption is negatively related to firms' financial performances measured by return of equity. The negative association is different in various environments. Through heterogeneity and moderating analysis, tech-intensive firms and non-Eastern firms have a more negative relationship, while there is little evidence on differences between firms in growth emerging market and not in, state-owned and non-state-owned firms, specific places to publicly list, and manufacturing and non-manufacturing firms. This research systematically studying heterogeneity and the findings contribute to the emerging literature on AI and firms under the China context. From policy perspective, stimulating AI adoption alone might not be insufficient to improve firms' productivity owing to huge adjustment cost. Therefore, supporting policies addressing this should be considered. Future study could focus on endogeneity problems, long-run effects in this study's setting and quantifying mechanism between firm performances and AI adoption.

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