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Artificial Intelligence and Corporate Investment Efficiency—Based on a Natural Experiment of National New Generation Artificial Intelligence Innovation and Development Pilot Zones

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Abstract: The efficiency of enterprise investment is a key indicator of optimised resource allocation. Artificial intelligence can enhance the efficiency of capital allocation through data-driven methods and other approaches. Using data from Shanghai and Shenzhen A-shares between 2014 and 2023 collected from the National Artificial Intelligence pilot zone, this paper employs the Richardson model to measure investment efficiency and empirically examines the impact of artificial intelligence policies. The research found that the policies of the experimental zone had significantly increased enterprise investment efficiency and alleviated excessive investment. The mechanism of action involves curbing short-term thinking in management, optimising the digital development environment, and improving the inclusive finance index. Heterogeneity has a more significant impact on small-scale, non-high-tech and non-state-owned enterprises. The moderating effect indicates that a positive management tone can enhance the effectiveness of policies. This paper broadens the research perspective, addresses the shortcomings in model application, highlights the importance of tone, uncovers the 'local average processing effect' of digital inclusive finance, deepens our understanding of policy transmission heterogeneity, and offers the government guidance on how to improve the efficiency of enterprise resource allocation and regional economic development with the help of artificial intelligence.

1. Introduction

Artificial intelligence is the core driving force behind the new wave of technological revolution and has become a strategic high ground in global technological competition. Since 2015, China has elevated AI to the level of a national strategy, launching the construction of the 'National Pilot Zones for the Innovation and Development of Next-Generation AI' in 17 cities, including Beijing and Shanghai, in 2019[1]. These pilot zones pool technology, capital and talent to provide enterprises with technical application scenarios and support for digital transformation, significantly enhancing the efficiency with which corporate capital is allocated. Enterprise investment efficiency is a key indicator of resource allocation optimisation[2]. At the micro level, it determines a firm's ability to create value; at the macro level, it is fundamental to a nation's technological competitiveness. Although existing research has analysed the effects of these pilot zones from perspectives such as environmental, social and governance (ESG) performance, digital innovation and green productivity, there remains a research gap regarding the impact of artificial intelligence on firms' core financial decisions, particularly with regard to investment efficiency.

Based on information asymmetry theory and resource allocation theory, this paper proposes three hypotheses. H1 posits that establishing AI pilot zones improves corporate investment efficiency by alleviating information asymmetry and financing constraints. H2 suggests that pilot zones enhance investment efficiency by suppressing managerial myopia and strengthening long-term investment confidence. H3 argues that pilot zones improve investment efficiency by enhancing the regional digital development environment and reallocating financial resources towards the AI sector.

The paper's contributions can be summarised as follows: First, it expands the relevant literature on the impact of AI pilot zones and verifies the important role of location-oriented policies in optimising corporate investment decisions. Second, it is the first study to apply the Richardson model to AI pilot zone policy research, thereby filling a gap in the model' s policy application.

2. Data Selection and Research Design

2.1. Data Selection

Artificial Intelligence Pilot Zones. In order to construct the core explanatory variable, data regarding the establishment dates and regional names of the National New-Generation Artificial Intelligence Innovation and Development Pilot Zones, which were approved in batches from 2019 to 2021, was collected and organised from the Chinese government website. The researchers/authors then matched this data to the firm level using city and enterprise codes. Regarding enterprise data, this study initially selected,this study initially selected companies listed on the Shanghai and Shenzhen stock exchanges between 2014 and 2023, and then performed the following processing steps: First, financial companies were excluded. Second, companies listed on the ST were excluded, as were delisted companies. Third, samples with missing values were excluded. Fourth, to avoid the impact of outliers on the regression results, the top and bottom 1% of continuous variables were truncated[3]. The raw data were sourced from the Guotai-An Database, the China Urban Statistical Yearbook, the Chinese government website, the official website of the Chinese Ministry of Education, the National Coastal Port Layout Plan, and the annual reports of companies listed on the Shanghai and Shenzhen stock exchanges.

2.2. Research Design

1) Measurement of the Dependent Variable: This paper adopts the method described in Huo and Wangand uses the residual model proposed in Richardson to calculate investment efficiency 2(AbInv). The specific model is as follows:

$$\mathrm{Inv}_{i,t} = \beta_0 + \beta_1 \mathrm{Growth}_{i,t-1} + \beta_2 \mathrm{Cash}_{i,t-1} + \beta_3 \mathrm{Lev}_{i,t-1} + \beta_4 \mathrm{Size}_{i,t-1} + \beta_5 \mathrm{Ret}_{i,t-1} + \beta_6 \mathrm{Age}_{i,t-1} + \sum \mathrm{Year} + \sum \mathrm{Industry} + \varepsilon_{i,t} \tag{1}$$

Where i and t represent Shanghai and Shenzhen A-share companies and the year, respectively; Inv represents a company's new investment; Growth is the revenue growth rate, representing investment opportunities; Cash refers to cash flow; Lev is the debt-to-asset ratio; Size is firm size; Ret is the annual stock return; Age is the firm's years since listing. Equation (1) measures investment efficiency by quantifying the deviation between actual and expected investment. We use the least squares method to estimate Equation (1), and the absolute value of the regression residuals represents investment efficiency (AbInv). The smaller the value of AbInv, the fewer inefficient investments the firm has, and thus the higher its investment efficiency. Furthermore, if $\varepsilon_{i,t} > 0$, it indicates that the firm is overinvesting; conversely, if $\varepsilon_{i,t} < 0$, it indicates that the firm is underinvesting.

2) Since the policy shocks discussed in this paper—the national "New Generation Artificial Intelligence Innovation and Development" initiative—differ significantly from traditional policy shocks (as pilot policies were rolled out in phases across different regions or industries), we adopt the method described in Beck, Levin et al and use an incremental DID model. The specific model specification is as follows:

$$\mathrm{AbInv}_{i,t}\& = \alpha + \beta \mathrm{AI}_i \times \mathrm{Post}_t + X_{i,t} + Z_{i,t} + \rho_i + \tau_t + \varepsilon_{it} \quad (2)$$

where i and t represent the firm and the year, respectively; $\mathrm{AbInv}_{i,t}$ denotes the investment efficiency indicator that varies across firms and over time; AI_i is a dummy variable indicating whether firm i is located in an AI pilot zone, with a value of 1 indicating yes and 0 indicating no; Post_t is a dummy variable indicating the implementation of AI pilot zone policies, taking a value of 1 when the AI policy is implemented during the construction period and thereafter, and 0 otherwise;$X_{i,t}$ represents a series of control variables that vary by firm and year, including return on net assets, firm size, firm revenue, debt-to-equity ratio, book-to-market ratio, capital intensity, cash and cash equivalents ratio, the largest shareholder's ownership stake, and whether the chairman and general manager hold dual roles; $Z_{i,t}$ represents a series of control variables that vary by city and year, including per capita GDP, total city population, actual utilized foreign direct investment, and the share of secondary industry GDP (%). ρ_i and τ_t represent individual fixed effects and time fixed effects, respectively; ε_{it} represents the random disturbance term.

3. Analysis of Empirical Results

3.1. Descriptive Statistics

Table 1 presents the descriptive statistics for the main variables. The mean investment efficiency value is 0.0327, which is higher than the median. This indicates that the current investment status of most enterprises deviates from the norm and that there is inefficient investment behaviour[4]. The mean value for the implementation of AI pilot zone policies is 0.3427, suggesting that 34.27% of enterprises have been impacted by AI pilot zones. The statistical results for the remaining control variables are also presented in Table 1.

Table 1 Descriptive Statistics

Variable	Mean	Median	Standard Deviation	Minimum	Maximum
Variable 1	0.0327	0.0246	0.0382	9.71×10^{-7}	1.1864
Variable 2	0.3427	0	0.4745	0	1
Variable 3	0.01	0.06	1.942	-186.56	64.06
Variable 4	21.6829	21.55	1.515	15.51	28.72
Variable 5	22.407	22.22	1.3478	15.98	28.7
Variable 6	0.3123	0	0.4634	0	1
Variable 7	2.7282	1.96	3.786	0.07	181.88
Variable 8	32.6414	30.18	14.6967	0.29	89.99

Variable 9	0.0094	0.01	0.0832	-1.03	0.94
Variable 10	0.487	0.3818	0.4158	-5.3477	7.5237
Variable 11	0.4299	0.42	0.2091	0.01	3.65
Variable 12	11.6901	11.8253	0.444	9.5768	12.237
Variable 13	15.7733	15.8023	0.6361	13.267	17.3467
Variable 14	22.3107	22.562	1.8809	11.9829	25.0139
Variable 15	3.5396	3.63	0.3666	2.55	4.27

3.2. Main Regression Results

We examine the impact of the artificial intelligence pilot zone policy on firm investment efficiency using a two-way fixed-effects model. After sequentially incorporating firm- and city-level control variables, the coefficients of the pilot zone policy variable were all found to be significantly negative at the 1% level. This indicates that the policy significantly reduces deviation in investment efficiency, i.e. it improves efficiency[5]. The results of the full model estimation confirm Hypothesis H1, showing that the establishment of pilot zones reduces the deviation in firm investment efficiency by 0.0035915. Regarding control variables, micro-level characteristics have a significant impact on investment efficiency[6]. These characteristics include firm size, debt-to-asset ratio and cash flow. Meanwhile, macro-level environmental variables also play an important role. These include the level of urban economic development and the degree of financial development. The model's adjusted R^2 is 0.2756, indicating a good fit.

3.3. Further Examination of Underinvestment and Overinvestment

To further explore the effects of the policy, this paper distinguishes between underinvestment and overinvestment for the purposes of analysis. As shown in Table 2, the AI Pilot Zone policy has a significantly different impact on these two types of inefficient investment. Column (1) shows that the policy's coefficient in the underinvestment sample is 0.0008829, which is significantly positive at the 10% level (p-value = 0.095)[7]. This indicates that the policy may slightly exacerbate underinvestment, but the impact is limited. Column (2) shows that the coefficient of the policy in the underinvestment sample is -0.0044744. This is a significant negative value at the 5% level, indicating that the policy effectively mitigated overinvestment. In summary, the main way in which the AI pilot zone improves corporate investment efficiency is by preventing overinvestment.

Table 2 Further Examination of Underinvestment and Overinvestment

	(1) Underinvestment	(2) Overinvestment
AI × post	0.0008829*	-0.0044744**
	-0.0005	-0.00128
Firm-level Controls	Yes	Yes
City-level Controls	Yes	Yes
Firm Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
Observations	15,037	15,037
Adjusted R2	0.4668	0.3061

3.4. Endogeneity Analysis

1) Parallel Trends Test. In order to verify the reliability of the estimation results, it is necessary

to verify the parallel trends assumption, meaning that the trends in the experimental and control groups must have been consistent prior to the implementation of the policy. As the construction of the artificial intelligence pilot zone in this study spanned multiple time periods, the model was set up as follows, in accordance with the method described in:

$$\mathrm{AbInv_{it}} = \alpha + \sum_{l=-4}^{4} \beta_l \, D_{it}^{l} + \gamma' X_{it} + \varphi_i + \delta_t + \varepsilon_{it} \tag{3}$$

In equation (3), l represents relative time in the event study and D_{it}^{l} denotes the dummy variable for relative time l. These symbols have the same meaning as those in equation (1). The key coefficient is β, reflecting the dynamic changes before and after the establishment of the pilot zone. The test results are shown in Figure 1. The coefficients for each period prior to policy implementation have been found to be insignificant, thus satisfying the parallel trends assumption. After policy implementation, a significantly lower investment efficiency has been observed in the experimental group compared to the control group. This indicates that the deviation in corporate investment efficiency in cities where AI pilot zones were established has been significantly diminished, thus showing that the parallel trends test has been passed[8].

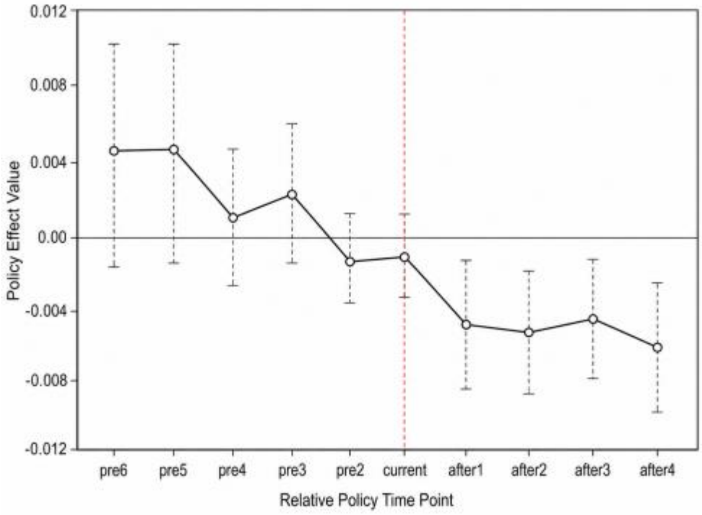

Figure 1: Parallel Trends Test

2) Instrumental Variables Method. Of the 17 cities in which AI pilot zones have been established to date, 10 are located in the eastern or southern coastal regions. Furthermore, terms such as 'smart logistics', as referenced in documents including the 'Notice of the State Council on Issuing the Development Plan for the New Generation of Artificial Intelligence', highlight the fundamental role of logistics in the establishment of national pilot zones for the innovative development of the new generation of artificial intelligence[9]. Furthermore, a city's distance from major ports is a core geographical indicator and key influencing factor of regional logistics capacity, directly determining its logistics accessibility and costs. This paper employs the product of each city's distance from the nearest port and a variable representing the year of policy implementation as the instrumental variable in Model (1).The results of the instrumental variable regression in Table 3 demonstrate the following: In the first-stage regression in Column (1), the instrumental variable coefficient is significantly positive at the 1% level, thus satisfying the correlation assumption. In the second-stage regression in Column (2), the coefficient remains significantly negative, thereby confirming the robustness of the conclusion. Column (3) incorporates both the policy variable and the instrumental variable, both of which remain significant at the 1% and 10% levels respectively. This further validates the effectiveness of the instrumental variable[10].

Table 3 Instrumental Variable Regression

Variables	-1	-2	-3
	AI × post	AbInv	AbInv
AI × post		-0.0050159***	-0.0090143**
		-0.00068	-0.00355
Port × post	0.2106034***		0.0012346*
	-0.00086		-0.00075
Firm-level Controls	Yes	Yes	Yes
City-level Controls	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	14,994	14,994	14,994
Adjusted R^2	0.9237	—	0.2761

3) Placebo test. The impact of AI pilot zones on corporate investment efficiency is further examined in this paper through a placebo test to determine whether this can be attributed to other random factors. Specifically, based on the establishment of AI pilot zones in 2019, an equal number of cities were randomly selected for the treatment group, with the treatment period remaining 2019. These two variables were then multiplied to create a "pseudo" AI pilot zone variable, which was substituted for the actual AI pilot zone variable in Model (1) for regression analysis. The P-value density distribution of the regression coefficients for corporate investment efficiency levels under the"pseudo" AI pilot zone is shown in Figure 2. It can be seen that the values of the coefficients for the randomly generated 'pseudo' AI pilot zone are distributed near zero and are all greater than those in the baseline regression results. Most values are far from zero, with only a few falling within the 5% significance level. This suggests that the results of this study are not coincidental, but are indeed attributable to the establishment of AI pilot zones.

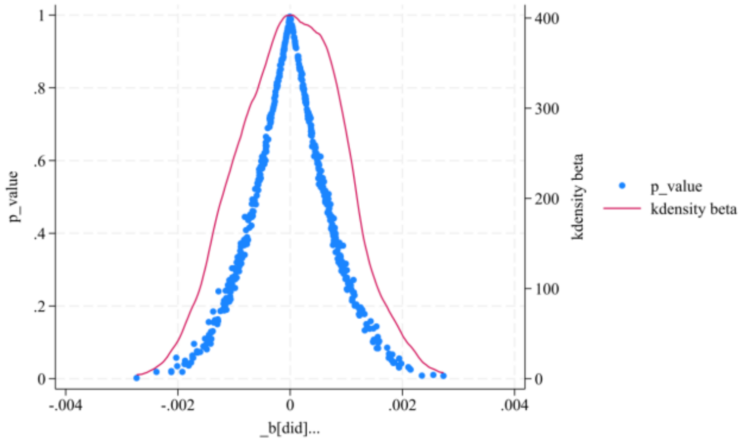

Figure 2: Placebo Test

4) Other robustness tests — replacing the dependent variable. In order to test the robustness of the study's conclusions, the model was used to create a proxy variable for investment efficiency. The results of the regression analysis are presented in Table 4. In all three sets of regressions, the interaction term coefficient for the AI pilot zone policy was significantly negative at the 1% statistical level, indicating that the implementation of the policy significantly improved corporate investment efficiency. This finding is highly consistent with the main regression conclusions. The significance and consistency of the model estimates reinforce the paper's main conclusion: the national New Generation Artificial Intelligence Innovation and Development Pilot Zone policy

robustly and positively affects corporate investment efficiency. Despite the differences in theoretical framework between the two models, both measurement methods validate this positive effect.

Table 4: Benchmark Regression Results under the Model

Biddle_invest			
	(1)	(2)	(3)
AI × post	-0.0052323***	-0.0052964***	-0.0046247***
	-0.0017	-0.0016	-0.0016
Firm-level Controls	No	Yes	Yes
City-level Controls	No	No	Yes
Firm Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	14,185	14,185	14,185
Adjusted R^2	0.4535	0.4629	0.4633

4. Conclusions and Policy Recommendations

This paper empirically examines how AI pilot zone policies affect corporate investment efficiency, based on data from listed companies in Shanghai and Shenzhen (2014-2023). The findings show that these policies significantly enhance investment efficiency by curbing managerial myopia and improving digital infrastructure. The effects are stronger for non-state-owned, large and non-high-tech enterprises. Managerial positivity amplifies the effects of the policies. Notably, the policies exhibit a 'localised average treatment effect' through digital finance channels, proving effective only for firms with moderate investment shortfalls. The following five policy recommendations are proposed: Policymakers should expand digital infrastructure to under-developed regions. The government should enhance technological empowerment for non-state-owned and traditional enterprises. Authorities should establish diversified evaluation mechanisms with differentiated regional targets. Regulators should integrate textual information quality into intelligent regulation. Policymakers should shift from broad-based to targeted resource allocation, prioritising moderately constrained firms while providing comprehensive support for severely undercapitalised ones.

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