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Research Article

How Local Government Spending on S&T Influences AI Development

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Abstract

This paper examines whether local fiscal expenditure on science and technology (S&T) promotes regional artificial intelligence (AI) development in China. A main empirical challenge is the lack of consistent city-level measures of AI activity. To address this issue, the paper constructs a city-level AI indicator by identifying AI-related firms from business scope descriptions using TF–IDF text mining and aggregating firm counts for prefecture-level cities from 2011 to 2023. Using panel data for Chinese prefecture-level cities, the analysis first estimates the relationship between the local S&T spending share and AI development within a two-way fixed effects framework. To mitigate endogeneity concerns, the paper further employs an instrumental-variable strategy. The results show that a higher local S&T spending share is significantly associated with stronger AI development. In economic terms, a one-percentage-point increase in the S&T spending share is associated with an approximately 1.09% increase in the AI indicator. The main finding remains robust across alternative specifications and IV estimation. The paper also explores heterogeneity across cities with different initial AI endowments. The positive effect of local S&T spending is stronger in cities with higher baseline AI levels and weaker in lower-endowment cities. These results suggest that the effectiveness of fiscal S&T support depends on local initial conditions. Overall, the paper provides a replicable city-level measure of AI development and new evidence on the role of local public S&T expenditure in shaping regional AI development.

Keywords

Fiscal Expenditure, Artificial Intelligence, Technological Innovation, Two-way Fixed Effects

1. Introduction

In China, as the economy shifts from high-speed to high-quality growth, enhancing scientific and technological innovation capabilities and nurturing new productive forces are essential. Recent studies further suggest that artificial intelligence and digital technologies affect labor productivity, labor income, production organization, and high-quality development [6, 7, 13-16, 18, 20]. Local fiscal science and technology expenditure (S&T) serves as a vital policy tool for governments to promote innovation. However, the specific impact of local STE on regional AI development levels and its underlying mechanisms necessitates thorough empirical investigation, which is the primary focus of this study.

A growing literature documents that fiscal spending on science and technology can foster innovation and productivity [1, 2]. Related studies on emerging technologies suggest that fiscal instruments—such as direct appropriations, tax incentives, and government procurement—may support AI-related R&D

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and industrial development [3, 4]. Related work also emphasizes the roles of fiscal support, infrastructure investment, and innovation element concentration in technology-oriented development [1, 9, 11]. However, rigorous evidence on how local S&T fiscal spending affects regional AI development remains limited, particularly at the prefectural-city level where local fiscal capacity, industrial structure, and innovation bases vary substantially. This study addresses this gap by using a panel of prefectural cities to estimate the impact of the S&T spending share on AI development.

This study seeks to fill existing gaps by examining how local STE influences AI development levels, using panel data from 289 prefectural-level cities in China spanning 2011 to 2023. Our contributions are threefold: (1) Data Granularity and Timeliness: We leverage recent, disaggregated city-level panel data, providing a more detailed analysis than provincial-level studies and more accurately capturing local dynamics. (2) Comprehensive Empirical Strategy: We apply a two-way fixed effects model to account for time-invariant city characteristics and time trends, and we use instrumental variable (IV) methods to address potential endogeneity, thereby enhancing causal inference. (3) Foundational Analysis: This study establishes a solid baseline relationship at the city level, serving as a foundation for future research to explore specific mechanisms and heterogeneous effects in greater depth.

The rest of this paper is organized as follows: Section 2 reviews the relevant literature and formulates the research hypothesis. Section 3 outlines the data sources, defines the variables, and explains the empirical model. Section 4 presents the baseline regression results, along with robustness, endogeneity tests and Heterogeneity analysis. Section 5 concludes by discussing policy implications and offering suggestions for future research.

2. Hypothesis

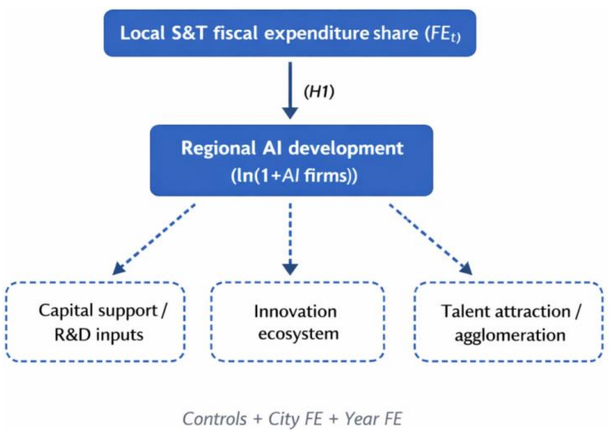

Figure 1. *How Does S&T Affect the Development of AI.*

As shown in Figure 1, Local government S&T expenditure can shape regional AI development by easing R&D financing constraints and improving local innovation conditions. Greater public support helps research institutions, universities, and firms acquire research equipment, build R&D capacity, and attract skilled talent, while a stronger local innovation ecosystem can facilitate knowledge spillovers and the formation of AI-related firms. This mechanism is consistent with evidence on talent agglomeration, university expansion, technology spillovers, and regional innovation capacity [8, 12, 17, 19]. Therefore, a higher share of S&T expenditure is expected to be associated with higher regional AI development.

Based on the above content, we propose H1: A higher share of local government S&T expenditure promotes regional AI development.

3. Data Sources, Variable Descriptions, and Model Specifications

3.1. Data Sources

This study analyzes panel data from 289 prefecture-level cities in mainland China, covering the years 2011 to 2023. Data on robot installation density are sourced from the International Federation of Robotics (IFR), while information on AI firms comes from Tianyancha. Additional socioeconomic and control variables are mainly sourced from authoritative databases such as the "China Statistical Yearbook" and local statistical yearbooks. Linear interpolation is used to fill minor data gaps, ensuring a balanced panel.

3.2. Variable Descriptions

Dependent Variable: Artificial Intelligence Development Level (AI). Adopting the methodology of Wang Linhui [5] from China Industrial Economics, we have identified and compiled data on artificial intelligence enterprises. Specifically, we identify AI enterprises using a TF–IDF text-mining approach applied to firms' business scope descriptions. Firms are classified as AI-related if their business scopes contain high-salience AI keywords extracted by TF–IDF. Companies with business scopes that include AI-related keywords—such as chips, image recognition, computer vision, speech recognition, and sensors—are categorized as AI enterprises. We then aggregate this data annually and regionally, creating a panel dataset of AI enterprises across prefecture-level cities from 2011 to 2023. The AI development level is quantified by the logarithm of the number of AI enterprises in a city for a given year. Existing studies have also attempted to construct composite indices of AI development, although such measures are less directly applicable to prefecture-level cities [10]. Firm counts provide a transparent and comparable proxy for the scale and vibrancy of local AI activities, capturing entry, clustering, and commercial deployment when more direct measures of AI output are unavailable at the city level.

Core Independent Variable: Local Fiscal Expenditure on

Science and Technology (FE_t) is derived from government fiscal reports. It is quantified as the annual ratio of a city's fiscal appropriation for science and technology to its overall public budget expenditure.

The control variables include economic development level (Pgdp), higher education level (EDU), labor force quality (Labo), industrial structure (Cind), population density (Cp), and the stock of artificial intelligence enterprises (S_AI), in order to control for other potential influencing factors.

3.3. Model Specification

The regression model constructed in this paper is as follows:

$$AI_{it} = \alpha + \beta FE\_t_{it} + \delta Controls + year + city + \epsilon_{it} \quad (1)$$

In this study, $\mathrm{AI}_{\mathrm{it}}$ denotes the artificial intelligence level of city i in year t, while $\mathrm{FE\_t}_{\mathrm{it}}$ represents the local fiscal expenditure on science and technology for city i in the same year. The term Controls signifies a series of control variables, and ϵ_{it} is the random error term. Additionally, year and city represent the time fixed effect and province fixed effect, respectively. The coefficient of interest is β; a positive β supports H. Unless stated otherwise, standard errors are clustered at the city level.

4. Empirical Test Results and Analysis

4.1. Descriptive Statistics

Table 1. *Variable definitions and descriptive Statistics.*

Variable	Obs	Mean	Std.dev	Min	Max
AI	2309	1.3975	0.5246	0	5.2257
FE_t	2309	0.0168	0.0177	0.0005	0.2068
Cind	2309	0.4316	0.1007	0.1015	0.8387
Pgdp	2309	2773.332	4088.975	61.35	44652.8
Cp	2309	431.0547	339.2303	5	2648
EDU	2309	8.6089	14.7693	0	93
Labo	2309	98380.76	173901.1	231	1057281
S_AI	2309	1129.831	4315.41	0	80257

Table 1 provides a descriptive statistical analysis of the core variables in the model. Descriptive statistics show that there are significant differences in the development level of AI (AI) and the proportion of technology expenditure (FE_t) among different cities. Initial observations suggest a positive correlation between artificial intelligence development (AI) and the proportion of municipal fiscal expenditure on science and technology (FE_t).

4.2. Benchmark Regression Results

Table 2. *Benchmark Regression Results.*

VARIABLES	(1)	(2)	(3)	(4)
	AI	AI	AI	AI
FE_t	6.111***	2.995***	1.086***	2.221***
	(0.326)	(0.248)	(0.294)	(0.253)
Cind			-0.0107	0.0073

VARIABLES	(1) AI	(2) AI	(3) AI	(4) AI
			(0.0101)	(0.0097)
Pgdp			8.84e-07***	2.96e-06***
			(2.91e-07)	(2.35e-07)
Cp			0.000108***	0.000191***
			(5.43e-05)	(3.82e-05)
EDU			-0.0574***	-0.0601***
			(0.0125)	(0.0141)
Labo			3.19e-06***	-1.42e-07
			(3.17e-07)	(1.21e-07)
S_AI			2.14e-05***	3.48e-06**
			(6.44e-06)	(1.69e-06)
Constant	1.292***	1.191***	1.314***	1.075***
	(0.00632)	(0.00861)	(0.0434)	(0.0327)
Year	No	Yes	No	Yes
City	No	Yes	No	Yes
Observations	2309	2309	2309	2309
R-squared	0. 090	0.502	0.496	0.533

*Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We choose fixed-effects estimator using the Hausman test. We further include city and year fixed effects to absorb time-invariant city heterogeneity and common year shocks, with standard errors clustered at the city level.

As shown in Column (4) of Table 2, after controlling for a series of variables and fixed effects for cities and years, the coefficient of the proportion of technology expenditure (FE_t) is significantly positive at the 1% level (coefficient = 2.221. This indicates that for every 1 percentage point increase in the proportion of technology expenditure, the number of AI enterprises will increase by approximately 2.2%.

4.3. Robustness Test

To verify the robustness of the results, we conducted tests such as shortening the sample period, replacing the dependent variable, and eliminating outliers. As shown in Table 3, the coefficient of the core explanatory variable FE_t remained significantly positive throughout, confirming the reliability of the benchmark results.

Table 3. *Robustness Test.*

VARIABLES	(1) Shortening the sample period	(2) Replacing the Dependent Variable	(3) Removal of Outliers
FE_t	1.086*	0.0189*	2.437***
	(0.294)	(0.0101)	(0.317)
Constant	1.314***	3.619***	1.069***

VARIABLES	(1) Shortening the sample period	(2) Replacing the Dependent Variable	(3) Removal of Outliers
	(0.0434)	(0.00134)	(0.0328)
Controls	Yes	Yes	Yes
Year	Yes	Yes	Yes
City	Yes	Yes	Yes
Observations	2,430	2,309	2,309
Number of city_id	270	270	270
R-squared	0.486	1.000	0.531
FE_t	1.086*	0.0189*	2.437***

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.4. Endogeneity Test

To address potential endogeneity issues, we employ an instrumental-variable (IV) approach using two-stage least squares (2SLS). Following the shift–share (Bartik) design, the instrument is constructed as the interaction between province-year S&T spending intensity and each city's baseline fiscal scale, which provides exogenous variation in the local S&T spending share (FE_t). The first-stage results indicate that the Bartik instrument is significantly correlated with FE_t (Table 4 Panel B) supporting instrument relevance. Identification and weak-IV diagnostics further reject underidentification (K-P rk LM p =0.0055) and suggest acceptable first-stage strength (K-P rk Wald F = 9.61); weak-IV robust inference also remains significant (Anderson–Rubin p = 0.0010).

The second-stage estimates (Table 4, Panel A) show that after instrumenting FE_t, the effect of local S&T spending on AI development remains positive and statistically significant. Overall, the IV results corroborate the baseline findings and strengthen the evidence that higher local fiscal support for S&T contributes to stronger regional AI development.

Table 4*. Endogeneity Test.*

VARIABLES	(1) OLS (FE)	(2) 2SLS (IV)
FE_t	2.58*** (0.36)	14.57*** (4.04)
Controls	Yes	Yes
City	Yes	Yes
Year	Yes	No
Prov ×Year	No	Yes
Observations	2,160	2,160
Panel B: First stage (dependent variable: FE_t)		
z_bartik	0.489*** (0.158)	
Panel C: Identification and weak-IV diagnostics		
K-P rk LM p-value 0.0055		
K-P rk Wald F 9.61		

VARIABLES	(1) OLS (FE)	(2) 2SLS (IV)
Anderson–Rubin p-value 0.0010		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

4.5. Heterogeneity Analysis

To examine whether the effect of local fiscal S&T expenditure on AI development varies across cities with different initial AI foundations, we divide the sample into two groups based on the baseline AI indicator (Q1–Q2). The estimation results suggest clear heterogeneity. The positive effect of FE_t is substantially stronger in the high-endowment group (Q2), whereas the effect is weak or statistically insignificant in the low-endowment group (Q1). This pattern indicates that local S&T fiscal support is more likely to translate into measurable AI development in cities with more advanced initial AI ecosystems and stronger absorptive capacity. In practice, cities in the Q2 group are primarily located in the eastern and southeastern regions (e.g., Beijing, Shanghai, and Guangzhou), where industrial bases, innovation resources, and market demand for AI applications are relatively concentrated. Overall, the heterogeneity evidence reinforces the baseline conclusion while highlighting that the effectiveness of S&T fiscal spending depends on local initial conditions.

***Table 5**. Heterogeneity analysis by baseline AI quantile groups.*

	(1) Low group (Q1)	(2) High group (Q2)
FE_t	-0.686	7.413***
	(1.427)	(1.567)
Controls	Yes	Yes
City	Yes	Yes
Year	Yes	No
Observations	806	481
Difference test (p-value) 0.0010		

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

5. Conclusions

Amid the ongoing scientific and technological revolution and industrial transformation, artificial intelligence (AI) has become a strategic technology shaping production and economic upgrading. This paper constructs a city-level AI development indicator by identifying AI-related firms via TF–IDF text mining and aggregating firm counts for prefecture-level cities in China. Using a two-way fixed effects framework and an instrumental-variable strategy to address endogeneity, we find that a higher local fiscal S&T spending share is associated with significantly stronger regional AI development, with economically meaningful magnitudes.

The effect is not uniform across cities. Our heterogeneity analysis based on baseline AI endowments shows that the positive impact of S&T fiscal spending is concentrated in the high-endowment group (Q2), while it is weak or insignificant in the low-endowment group (Q1). This pattern is consistent with the role of local absorptive capacity—such as existing industrial bases, talent pools, and innovation infrastructure—in shaping the marginal returns to public S&T inputs. This interpretation is also consistent with evidence that the effects of artificial intelligence depend on local factor endowments and development conditions [16]. Several limitations remain. Due to space constraints, this study does not formally test mechanisms or examine non-linearities. Future research could leverage micro-level firm data, richer policy information, and alternative subgroup definitions to better identify channels and boundary conditions.

Abbreviations

S&T	Science and Technology
AI	Artificial Intelligence
R&D	Research and Development
FE_t	Fiscal Expenditure on Science and Technology
Pgdp	GDP per Capita
EDU	Higher Education Level
Labo	Labor Force Quality
Cind	Industrial Structure
Cp	Population Density
S_AI	Stock of Artificial Intelligence Enterprises

Author Contributions

Jihan Liu: Conceptualization, Funding acquisition, Resources

Doudou Zhu: Data curation, Formal Analysis, Methodology

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Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript.

Conflicts of Interest

The authors declare no conflicts of interest.

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