

Artificial Intelligence Policy and Wage Gaps: Evidence from China

Jinghai Li¹, Jingshan Huang^{1*}, Huanhuan Yang²

1. School of Economics, Guangdong University of Finance and Economics, Guangzhou, Guangdong, 510320, China

2. Guangzhou Market Supervision and Management Development Research Center, Guangzhou, Guangdong, 510410, China

*Corresponding author: Jingshan Huang, Stayrealhuang@163.com

Copyright: 2026 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY-NC 4.0), permitting distribution and reproduction in any medium, provided the original author and source are credited, and explicitly prohibiting its use for commercial purposes.

Abstract: A new round of technological revolution centered on artificial intelligence (AI) is reshaping the global labor market. Using panel data for 280 Chinese cities from 2011 to 2023, this study treats the establishment of National New-Generation Artificial Intelligence Innovation and Development Pilot Zones (AIIDPZs) as a quasi-natural experiment and employs a staggered difference-in-differences model to examine the impact of AI policy on wage gaps. The results show that the AIIDPZs significantly widen wage gaps within cities. Mechanism tests point to three channels: innovation technology benefit bias, industrial restructuring, and technology diffusion. The effects are stronger in cities in the eastern region, cities with well-developed digital infrastructure, and cities with lower human capital. These findings support incorporating the effects of income distribution into policy evaluation, strengthening skills training and mechanisms for sharing innovation gains, tailoring support to local conditions, and coordinating AI policy with employment policy.

Keywords: Artificial Intelligence Policy; Wage Gap; Innovation Technology Benefit Bias; Industrial Structure; Technology Diffusion

Published: Oct 14, 2026

DOI: <https://doi.org/10.62177/apemr.v3i5.1737>

1. Introduction

The Fourth Industrial Revolution, characterized by digitalization and intelligentization, is transforming production and people's lifestyles. As a general technology, artificial intelligence (AI) can improve the productivity of enterprises through automation, intelligent decision-making and human-computer collaboration^[1,2]. At the same time, these changes affect workers' wages by replacing or supplementing work tasks, changing the demand of enterprises for workers with different skills, and affecting the ability of workers to obtain skill-related returns^[3-5]. The difference between different workers in terms of productivity improvement and wage return may change the wage gaps within the city. Therefore, thinking about the efficiency improvement brought by AI and its distribution effect has become an important policy consideration.

Existing research has not reached a consensus on whether AI should widen or narrow the wage gaps. There is a view that AI will exacerbate the wage gaps between workers. On the one hand, technological change is often skill-biased^[3,6], and AI has improved the relative productivity and return of technical workers, thereby expanding their wage premium^[7,8]. On the other hand, robotics technology and automation technology can also replace routine tasks, thereby pushing up the skill premium and widening the wage gaps^[9,10]. Another point is that AI helps to narrow the wage gaps between workers. Within the

enterprise, AI policies can narrow the pay gaps by enhancing the bargaining power of ordinary employees and reducing the risk compensation of management^[11]. At the level of workers, AI can bring greater productivity improvement to workers with less experience and skills, thereby improving their wages^[12]. Relevant studies also found that as the supply of skilled labor increases, the skill premium decreases after developing to a certain stage^[13], thereby narrowing the wage gaps.

The direction, extent and conditions of AI's impact on the wage gaps are still unclear, and further research is urgently needed. China's National New-Generation Artificial Intelligence Innovation and Development Pilot Zones (AIIDPZs) provide a relatively clear policy framework for exploring this issue. In 2017, the State Council issued the New Generation Artificial Intelligence Development Plan, which proposed to organize innovation pilots in areas with solid AI foundation and development potential. Since 2019, AIIDPZs have been established one after another. Relying on local governments, these institutions carry out AI technology demonstrations, policy pilots and social experiments, playing a pioneering role in promoting the development of AI, and playing a leading role. AIIDPZs take a specific region as a policy carrier to promote the spread of AI in the region through institutional innovation, expansion of application scenarios and gathering of innovative resources. Therefore, this policy may affect the production activities, industrial development and employment of workers of urban enterprises, thus causing differentiated policy shocks in different cities and different years.

There have been studies on the impact of AIIDPZs, focusing on the total factor productivity, innovation performance and labor income shares of enterprises^[14-16]. These studies clarify how AI policy affects corporate behavior, but the average effect at the firm level does not reveal the changes in the wage gaps within cities. Urban wage structures depend not only on the internal wage adjustment of enterprises, but also on cross-enterprise technology diffusion, and cross-industry mobility of workers. Therefore, this study aims to explore whether the establishment of AIIDPZs changes wage gaps within cities, and if so, what is the mechanism?

To answer the above questions, this study uses panel data of 280 Chinese cities from 2011 to 2023 and regards the establishment of AIIDPZs as a quasi-natural experiment. A staggered difference-in-differences (DID) model is used to estimate its impact on wage gaps within cities, and at the same time, mechanism tests examine innovation technology benefit bias, industrial restructuring, and technology diffusion. The contributions of this study are as follows: First, by evaluating a place based policy, it expands the scope of research on AI and income distribution, and provides direct evidence for the impact of AI policy on regional income distribution. Second, it identifies three transmission channels of AIIDPZs affecting wage gaps. Third, it reveals how the effect varies with regional conditions and factor endowments, thus providing a basis for seeking policies to balance efficiency and distribution fairness in different local environments.

2. Theoretical Analysis and Research Hypothesis

2.1 AI and Wage Gap

The AIIDPZs policy improves conditions for AI research and application by expanding access to application settings, building innovation platforms, and attracting talent. It may therefore change urban labor demand. Existing evidence shows that AI adoption changes firms' hiring needs and job skill requirements^[5]. When skill supply cannot adjust fully in the short run, workers with greater technological absorptive capacity are more likely to obtain new jobs and capture technological gains, while less adaptable workers may face employment and wage pressures. By accelerating technology adoption, AIIDPZs may magnify these differences and widen wage gaps. We therefore propose:

Hypothesis 1: The AIIDPZs widen wage gaps within cities.

2.2 Mechanisms Linking AI Policy to Wage Gap

(1) Innovation technology benefit bias. AI innovation requires specialized knowledge and technical skills. By supporting innovation platforms and collaboration among firms, universities, and research institutions, AIIDPZs may increase demand for specialists in algorithms, software development, and data processing. Research documents growing demand for AI skills and wage premiums in related jobs^[17]. More recent evidence from job postings also points to shortages of AI talent and high returns to specialized skills^[18]. When talent supply cannot keep pace, workers with relevant skills are better placed to participate in innovation and earn higher returns, while other workers cannot share these gains as quickly. AIIDPZs may therefore direct a larger share of innovation gains toward specialized workers and widen wage gaps. We propose:

Hypothesis 2: The AIIDPZs widen wage gaps by strengthening innovation technology benefit bias.

(2) Industrial restructuring. AIIDPZs attract capital, technology, and skilled labor to high-value-added industries, changing industrial structures. Expansion of digital industries and professional services increases demand for specialized workers and may raise their wages when skill supply is constrained. Traditional industries, meanwhile, require equipment upgrades, organizational adjustments, and training to realize technological gains. Routine tasks may also be displaced by automation, slowing wage growth. Evidence links automation-induced task displacement to declines in affected workers' relative wages^[19]. Resource reallocation across industries thus generates differences in labor returns and widens wage gaps. We propose:

Hypothesis 3: The AIIDPZs widen wage gaps by promoting industrial restructuring.

(3) Technology diffusion. AI innovations generate economic returns only when they reach the exchange and application stages. Information asymmetries, valuation difficulties, and contract-enforcement risks can constrain commercialization. Technology markets connect innovators with adopting firms and facilitate the commercialization of new technologies^[20]. Through technology trading and commercialization platforms, intellectual property services, and the matching of technologies to application needs, AIIDPZs may reduce search, valuation, and negotiation costs and speed diffusion into production. Yet technology assessment, transaction services, and system implementation are knowledge-intensive. Workers with specialized knowledge and greater absorptive capacity can adopt new technologies earlier and earn service income and productivity gains. Less-skilled workers benefit mainly from subsequent improvements in production efficiency, and their gains depend on equipment investment, process redesign, and training. International evidence also suggests that technology diffusion can reinforce skill bias^[21]. Wider adoption benefits more workers in the long run, but differences in the timing of gains during diffusion and adjustment may widen wage gaps. We propose:

Hypothesis 4: The AIIDPZs widen wage gaps by promoting technology diffusion.

3. Research Design

3.1 Model Design

The establishment of AIIDPZs constitutes a distinct policy shock, with pilot cities approved in successive batches. Specifically, seven locations were established in 2019, including six prefecture-level cities and Deqing County in Zhejiang Province. Another six cities were established in 2020 and five in 2021, bringing the total number of AIIDPZs to 18 by the end of 2021. Deqing County is the only county-level pilot. Because the Huzhou municipal government coordinates AIIDPZs construction and implements the relevant policies throughout its jurisdiction, we classify Huzhou as a whole as treated to maintain consistency in the city-level unit of analysis. The staggered establishment of AIIDPZs across cities and years provides a quasi-natural experimental setting for identifying the policy's effect on wage gaps. We estimate the following staggered DID model:

$$wagegap_{i,t} = \alpha + \beta DID_{i,t} + \gamma Controls_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad (1)$$

where $wagegap_{i,t}$ denotes the wage gap within cities, $DID_{i,t}$ is the AIIDPZs policy indicator, and $Controls_{i,t}$ is a vector of control variables. μ_i and τ_t denote city and year fixed effects, respectively, and $\varepsilon_{i,t}$ is the error term. The coefficient of interest β , captures the average effect of the establishment of AIIDPZs on wage gaps within cities. A significantly positive β indicates that the policy widens these gaps.

3.2 Variable Definition

3.2.1 Dependent Variable: Wage Gap

AI development raises productivity and skill returns in digitally intensive sectors while affecting labor demand and wage structures in manufacturing. We measure the wage gap ($wagegap$) as the difference between average employee wages in information transmission, software, and information technology services and those in manufacturing, expressed in units of RMB 10,000.

We select the information transmission, software, and information technology services sector as the higher-wage sector because it concentrates AI, digital technologies, and data applications. Its wages can reflect returns to skilled labor associated with digital development^[22]. Manufacturing provides the reference sector because it is a major setting for AI adoption, automation, and task reorganization, which can alter labor demand, skill composition, and wage determination^[4]. The difference

between these sectors' wages captures relative changes in labor compensation following AIIDPZs establishment. A larger value indicates a wider wage gap.

3.2.2 Explanatory Variable: AIIDPZs Policy

We construct a staggered DID indicator using each city's AIIDPZ approval date: $DID = Treat \times Post$. Treat equals one for designated cities and zero otherwise; Post indicates the post-policy period. Policy announcements, supporting measures, and policy effects take time to materialize, so effects may not emerge immediately in the approval year. Following the treatment of policy timing in the literature ^[23], approvals after September are assigned to the following year. For other approvals, Post equals one from the approval year onward and zero beforehand.

3.2.3 Mechanism Variable

(1) AI innovation (AIInnov). Following the measurement approach of Dong et al. ^[24], we divide the number of AI invention patent applications in a city by its permanent resident population in units of 10,000, measuring innovation output per capita. (2) Industrial restructuring (ISU). Following Gan et al. ^[25], we use the ratio of tertiary-sector to secondary-sector value added. (3) Technology market activity (TechMarket). Drawing on Zhang et al. ^[26], we use the natural logarithm of the actual transaction value of technology contracts.

3.2.4 Control Variable

To reduce omitted-variable bias, we include city-level controls following Zhao et al. ^[27] and Ning et al. ^[28]:

(1) Economic development (lngdp): the logarithm of GDP per capita. (2) Investment (lninv): the logarithm of fixed asset investment. (3) Government intervention (lngov): the logarithm of fiscal expenditure. (4) Urbanization (urban): the share of urban residents in the permanent resident population. (5) Human capital (edu): college and university enrollment relative to the permanent resident population. (6) R&D intensity (RD): intramural R&D expenditure relative to fiscal expenditure. (7) Foreign direct investment (lnfdi): the logarithm of realized annual FDI. (8) Digital infrastructure (digfra): an entropy-weighted index covering infrastructure provision and use. Its six indicators are optical fiber cable density, broadband access ports per capita, employment in information transmission, software, and information technology services, telecommunications revenue, mobile phone penetration, and Internet penetration.

3.3 Data Source and Descriptive Statistics

The sample comprises 280 Chinese cities over 2011–2023. Information on the establishment of AIIDPZs is obtained from the official websites of Ministry of Science and Technology of the People's Republic of China and Ministry of Industry and Information Technology of the People's Republic of China. Other variables come from the China City Statistical Yearbook, China Statistical Yearbook, China Population and Employment Statistical Yearbook, and local statistical yearbooks and communiqués. A small number of missing values are filled using linear interpolation and trend extrapolation to improve sample completeness. Table 1 reports descriptive statistics.

Table 1. Descriptive Statistics

Type	Variable	Symbol	Obs.	Mean	Std. dev.	Min.	Max.
Dependent variable	Wage gap	wagegap	3,639	2.773	2.314	-1.404	10.754
Interpreted variable	AIIDPZs	DID	3,639	0.018	0.133	0.000	1.000
	AI innovation	AIInnov	3,639	0.112	0.240	0.000	2.404
	Industrial restructuring	ISU	3,639	1.115	0.631	0.114	6.387
Mechanism variable	Technology market activity	TechMarket	3,639	12.730	2.020	5.371	18.263
	Economic development	lngdp	3,639	10.805	0.569	9.446	12.101
	Investment	lninv	3,639	16.574	1.104	13.531	18.964
Control variable	Government intervention	lngov	3,639	15.009	0.734	13.493	17.548
	Urbanization	urban	3,639	0.570	0.145	0.276	0.952
	Human capital	edu	3,639	1.853	1.867	0.115	8.908
	R&D intensity	RD	3,639	9.215	9.648	0.014	46.683
	Foreign direct investment	lnfdi	3,639	9.905	2.047	4.263	14.082
	Digital infrastructure	digfra	3,639	0.190	0.136	0.000	1.381

4. Empirical Result and Analysis

4.1 Baseline Result

Table 2 reports the baseline estimates. Columns (1) and (3) exclude fixed effects, while columns (2) and (4) include city and year fixed effects. Columns (3) and (4) also include the control variables. The DID coefficient is positive and significant at the 1% level in every specification, indicating that AIIDPZs widen wage gaps within cities and supporting Hypothesis 1.

Table 2. Baseline Regression Results

Variable	(1)	(2)	(3)	(4)
	wagegap	wagegap	wagegap	wagegap
DID	1.429*** (0.141)	1.658*** (0.558)	2.608*** (0.454)	1.742*** (0.497)
lngdp			0.897*** (0.113)	1.050*** (0.367)
lninv			-0.159*** (0.054)	-0.070 (0.110)
lngov			0.845*** (0.091)	1.182** (0.557)
urban			-0.150 (0.438)	-1.316 (1.408)
edu			-0.359*** (0.026)	-0.309** (0.155)
RD			0.004* (0.002)	-0.004*** (0.001)
lnfdi			-0.100*** (0.023)	0.018 (0.051)
digfra			5.238** (2.143)	-7.234 (9.861)
City FE	No	YES	No	YES
Year FE	No	YES	No	YES
Observations	3,639	3,639	3,639	3,639
R ²	0.020	0.727	0.322	0.739
Adjusted R ²	0.020	0.703	0.320	0.716

Notes: Robust standard errors clustered at the city level are in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. The same conventions apply to subsequent tables.

4.2 Parallel Trends Test

A key identifying assumption of DID is that treated and control units satisfy parallel trends ^[29]. In view of the staggered establishment of AIIDPZs, we use an event-study model to estimate dynamic effects before and after the implementation of the policy, and examine differential pre-policy trends. The event-time indices are constructed relative to the year of policy implementation in each city. The event window runs from -4 to 3, with the year before implementation ($s = -1$) as the reference period:

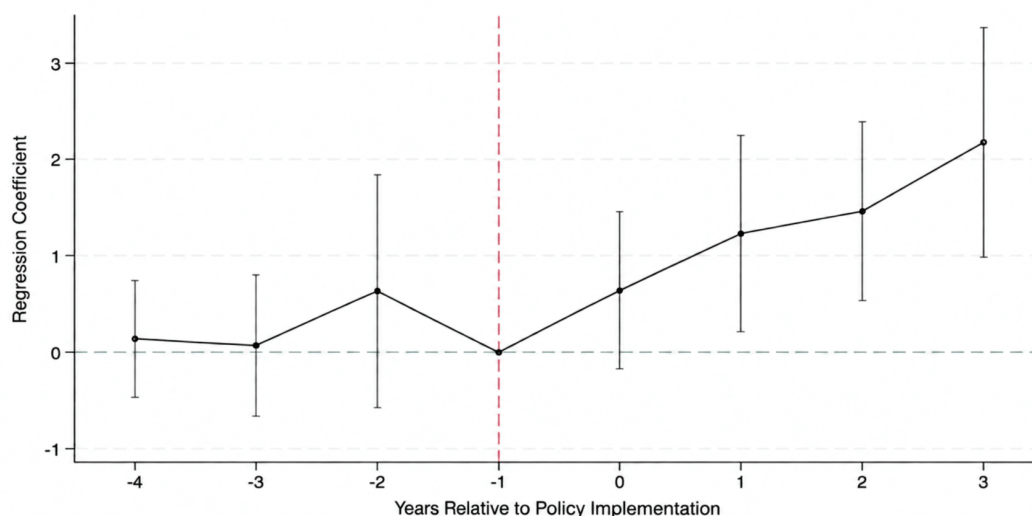
$$wagegap_{i,t} = \alpha + \sum_{s=-4, s \neq -1}^3 \beta_s D_{i,t}^s + \gamma Controls_{i,t} + \mu_i + \tau_t + \varepsilon_{i,t} \quad (2)$$

$D_{i,t}^s$ equals one if city i in year t is in event period s , and zero otherwise. The coefficient β_s captures the dynamic effect on wage gaps relative to the year before implementation. Controls and fixed effects are the same as in Equation (1).

Figure 1 shows that the pre-policy coefficients ($s < 0$) fluctuate around zero and are statistically insignificant, indicating no systematic differential trends in wage gaps between treated and control cities before implementation and supporting the

parallel trends assumption. Post-policy coefficients ($s \geq 0$) are generally positive and increase over time, suggesting that the policy widens wage gaps persistently. Innovation, industrial restructuring and the commercialization and promotion of technology all take time, which may explain why the impact on urban wage structures is gradually emerging.

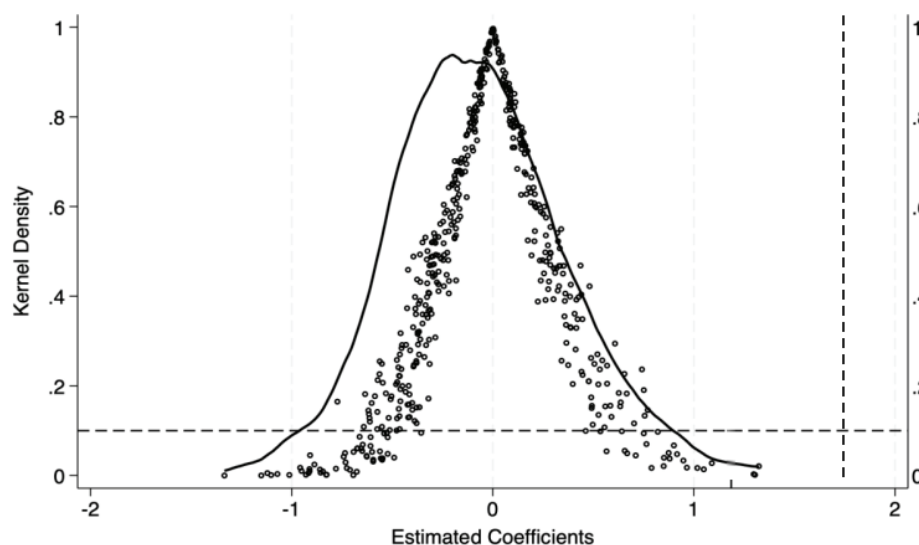
Figure 1. Parallel Trends Test



4.3 Placebo Test

We conduct a placebo test that preserves the actual policy cohort structure. A number of cities that have never been treated were randomly selected as placebo test cities, and the number was matched with the actual number of pilot cities, and a corresponding placebo implementation year was assigned. The regression is repeated 500 times. Figure 2 shows that placebo coefficients are concentrated around zero, whereas the baseline estimate lies well away from this concentration, supporting the robustness of the baseline finding.

Figure 2. Placebo Test



Note: The vertical dashed line denotes the baseline coefficient (1.742).

4.4 Endogeneity Test

AIIDPZs selection may correlate with unobserved factors, including a city's innovation capacity and economic conditions. We therefore estimate a two-stage least squares (2SLS) model, instrumenting DID with the interaction between the number of fixed telephone lines per 100 people in 1984 and a time variable. Column (1) of Table 3 reports a positive and significant first-stage coefficient. The F-statistic exceeds the conventional threshold of 10, so weak identification is unlikely under

this criterion. The second-stage DID coefficient in column (2) is significantly positive, supporting the baseline finding that AIIDPZs widen wage gaps within cities.

Table 3. Instrumental Variable Estimates

Variable	(1)	(2)
	DID (first stage)	wagegap (second stage)
IV	0.918*** (0.148)	
DID		2.242*** (0.591)
Controls	YES	YES
City FE	YES	YES
Year FE	YES	YES
F-statistic	38.691	
LM statistic		6.513**
Wald F-statistic		38.702 [16.380]
Observations	3,639	3,639

4.5 Robustness Check

This paper conducts robustness tests from the following five perspectives: First, we lag DID by one period to allow for delayed policy effects. Second, to address potential selection bias, we use the controls for propensity score matching (PSM), construct cross-sectional and period-by-period matched samples, and re-estimate the DID model. Third, we exclude 2020–2022 to remove potential labor market disruptions caused by COVID-19. Fourth, we separately control for the contemporaneous Broadband China and Smart City pilot policies. Fifth, we change the sample composition. Because Deqing is a county-level pilot but the baseline specification treats its parent city, Huzhou, as treated, we exclude Huzhou and re-estimate the model. We also exclude Beijing, Tianjin, Shanghai, and Chongqing, whose administrative status, economic size, policy resources, and labor markets differ from those of other cities. Across columns (1)–(8) of Table 4, the policy coefficients remain significantly positive. The robustness checks therefore continue to support the conclusion that AIIDPZs widen wage gaps within cities.

Table 4. Robustness Checks

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	One-period lag	Cross-sectional PSM-DID	Period-by-period PSM-DID	Excluding 2020–2022	Broadband China control	Smart City control	Excluding Huzhou	Excluding municipalities
DID		1.928*** (0.630)	1.564** (0.704)	2.010*** (0.497)	1.753*** (0.495)	1.736*** (0.497)	1.719*** (0.527)	1.753*** (0.637)
L.DID	1.864*** (0.496)							
Controls	YES	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Observations	3,359	3,470	3,561	2,739	3,639	3,639	3,626	3,587
Adjusted R ²	0.728	0.677	0.694	0.697	0.716	0.716	0.713	0.697

Note: L.DID denotes DID lagged by one period.

5. Further Analysis

5.1 Mechanism Test

Building on the theoretical analysis presented earlier, and to further uncover the underlying mechanisms through which the AIIDPZs policy affects wage gaps, we construct the following model to test these mechanisms:

$$M_{it} = \alpha + \beta DID_{it} + \gamma Controls_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (3)$$

$$wagegap_{it} = \alpha + \delta DID_{it} + \rho M_{it} + \gamma Controls_{it} + \mu_i + \tau_t + \varepsilon_{it} \quad (4)$$

M_{it} denotes the mechanism variables: AI innovation, industrial restructuring, and technology market activity. Other variables are defined as in the baseline model. Equation (3) estimates the policy's effect on each mechanism variable; Equation (4) examines the relationship between that variable and wage gaps.

(1) Innovation technology benefit bias. Column (2) of Table 5 shows that the policy significantly increases urban AI innovation. In column (3), AIInnov has a significantly positive coefficient, and the DID coefficient declines after its inclusion. AI research requires specialized knowledge and technical skills. Workers possessing these skills can more readily capture innovation gains, while others cannot benefit as quickly, resulting in wage gaps. These findings support Hypothesis 2.

(2) Industrial restructuring. Column (4) of Table 5 shows that the policy significantly promotes industrial restructuring. In column (5), the coefficient on ISU is significantly positive, while the DID coefficient declines. Expansion of high-value-added industries increases demand for specialized workers and may raise wages in these industries. Slower wage growth in traditional industries then widens wage gaps. These findings support Hypothesis 3.

(3) Technology diffusion. Column (6) of Table 5 shows that the policy significantly promotes technology market development. In column (7), TechMarket has a significantly positive coefficient, while the DID coefficient declines. Technology market expansion accelerates commercialization, but agents with greater absorptive capacity obtain returns sooner. Delayed gains for other workers may reinforce wage gaps^[21]. These findings support Hypothesis 4.

Table 5. Mechanism Tests

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	wagegap	AIInnov	wagegap	ISU	wagegap	TechMarket	wagegap
DID	1.742*** (0.497)	0.470*** (0.046)	1.006** (0.508)	0.127** (0.059)	1.597*** (0.488)	0.068*** (0.023)	1.708*** (0.497)
AIInnov			1.566*** (0.595)				
ISU					1.143** (0.538)		
TechMarket							0.488*** (0.188)
Controls	YES	YES	YES	YES	YES	YES	YES
City FE	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES
Observations	3,639	3,639	3,639	3,639	3,639	3,639	3,639
Adjusted R ²	0.716	0.822	0.735	0.918	0.722	0.990	0.717

5.2 Heterogeneity Analysis

5.2.1 Heterogeneity by Region

Industrial foundations, innovation resources, and technological absorptive capacity differ between eastern and central–western China. We define Area as one for eastern cities and zero for central and western cities, and include its interaction with DID. Column (1) of Table 6 shows a positive interaction coefficient significant at the 10% level, indicating that the policy widens wage gaps more strongly in eastern cities. This may reflect their greater concentration of innovation resources and specialized workers and faster AI adoption.

5.2.2 Heterogeneity by Digital Infrastructure

Better digital infrastructure can reduce AI adoption costs and accelerate diffusion, although workers may differ in their access to technological gains. We interact digital infrastructure (digfra) with DID. Column (2) of Table 6 reports a positive interaction coefficient significant at the 1% level, indicating that better digital infrastructure strengthens the policy's widening effect on wage gaps. One possible explanation is that infrastructure accelerates technology adoption while skilled workers obtain the associated returns earlier.

5.2.3 Heterogeneity by Human Capital

The ability of workers to adapt to new technologies depends on the local level of human capital. We conduct an interaction analysis of human capital (edu) and DID to explore how the policy effect differs with changes in this condition. The interaction coefficient in column (3) of Table 6 is negative and significant at the 1% level, indicating that a higher level of human capital will weaken the policy's widening effect on the wage gaps. Better human capital helps workers master new skills and realize career mobility, so that more workers can share the benefits of technological progress.

Table 6. Heterogeneity Analysis

Variable	(1)	(2)	(3)
	wagegap	wagegap	wagegap
DID	0.783* (0.409)	-0.089 (0.659)	3.604*** (0.683)
DID × Area	1.886* (0.975)		
DID × digfra		24.764*** (7.770)	
DID × edu			-0.368*** (0.118)
Controls	YES	YES	YES
City FE	YES	YES	YES
Year FE	YES	YES	YES
Observations	3,639	3,639	3,639
Adjusted R ²	0.717	0.721	0.718

6. Conclusion and Policy Implication

6.1 Conclusion

Using panel data for 280 Chinese cities from 2011 to 2023, this study treats AIIDPZs establishment as a quasi-natural experiment. A staggered DID model estimates the effect of the policy on wage gaps within cities and examines the underlying mechanisms.

AIIDPZs have significantly widened the wage gaps within cities. This finding is still valid in the instrumental variable estimates to address endogeneity, as well as in the robustness test of adjusting the sample period and controlling other policy variables. Mechanism testing reveals the following three paths: first, AI innovation strengthens skill bias and technology bias, so that more income flows to workers with professional knowledge and technical skills; second, industrial restructuring accelerates the expansion of high value-added industries, which in turn widens the wage gaps between different industries; third, the development of the technology market has accelerated the commercialization process and the speed of technology application, while the difference in the absorption capacity of cities has led to an uneven distribution of income. The above effects are more significant in cities in the eastern region, cities with relatively complete digital infrastructure, and cities with low levels of human capital.

6.2 Policy Implication

These findings suggest the following policy priorities.

First of all, achieve a balance between efficiency and fairness by incorporating distributive results into the AIIDPZs policy evaluation system. In addition to focusing on innovation performance, policymakers should also monitor the distribution effect of technology diffusion. The existing evaluation of innovative output, industrial development and technology adoption can be supplemented by the following indicators: the accessibility of innovative achievements, the transformation of employment structure, cross-industry wage differences, and income changes of different worker groups. With the support of continuous monitoring, a comprehensive evaluation of innovation performance and distribution results is conducive to matching the innovation incentive mechanism with the allocation goals.

Secondly, improve the innovative benefit sharing mechanism and improve the ability of workers to benefit from AI. Strengthen AI and digital skills training, especially for manufacturing and traditional industry practitioners, to enhance their digital literacy and help career transformation. Promoting the establishment of a more efficient coordination mechanism between vocational education, continuing education and enterprise training will provide strong support for the above measures. Enterprises should be encouraged to combine the application of AI with skill cultivation, career development and salary growth, so that more workers can share the dividends brought by AI.

Third, promote the implementation according to local conditions. The differences in the level of economic development, digital infrastructure and human capital require the adoption of differentiated coping strategies. Eastern cities and cities with relatively complete digital infrastructure should pay special attention to the difference in wages and skills in the process of rapid development of AI, and monitor the wage structure, skill return and employment changes in the industry in a timely manner; central and western cities and cities with relatively weak human capital should continue to increase investment in digital infrastructure, skill cultivation and industrial development to enhance the ability of technology absorption and improve capacity to undertake industrial transfer. The above measures will help promote more balanced industrial proliferation, thereby narrowing the regional development gaps.

Fourth, coordinate innovation support with employment policies. While supporting key AI technologies and innovators, policymakers should also pay attention to the quality improvement of employment brought about by technological progress. Policy incentives should encourage enterprises to provide training services, help employees transform their careers, and create more employment opportunities. Enterprises that implement intelligent upgrading should establish supporting training and job matching mechanisms, so that technological progress can effectively promote the optimization of income distribution.

6.3 Limitation and Future Research

This study still has certain limitations: First, the sample ends in 2023, limiting assessment of policy effects after technologies mature and workers' skills adjust over longer periods. Second, city-level data availability restricts the dependent variable to wage differences between two representative industries. Future research could use linked microdata to examine disparities across occupations, firms, and individuals and identify effects on workers with different skills more precisely. Third, the sample primarily covers the period before and at the outset of large-scale commercial deployment of generative AI. Since 2023, large models and related technologies have spread rapidly through labor markets. Their task substitution patterns and distributional mechanisms differ from earlier decision-oriented AI, making changes in policy effects an important subject for future research.

Funding

This research is supported by the Guangdong Office of Philosophy and Social Science (Grant No. GD23CYJ20).

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

- [1] Luo, S., Lei, W., & Hou, P. (2024). Impact of artificial intelligence technology innovation on total factor productivity: An empirical study based on provincial panel data in China. *National Accounting Review*, 6(2), 172–194.

- [2] Zhang, Y., Chang, Y., Zhang, X., et al. (2025). Artificial intelligence and enterprise technological innovation: Evidence from China. *Managerial and Decision Economics*, 46(7), 4056–4069.
- [3] Autor, D. H., Levy, F., & Murnane, R. J. (2003). The skill content of recent technological change: An empirical exploration. *The Quarterly Journal of Economics*, 118(4), 1279–1333.
- [4] Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: How technology displaces and reinstates labor. *Journal of Economic Perspectives*, 33(2), 3–30.
- [5] Acemoglu, D., Autor, D., Hazell, J., & Restrepo, P. (2022). Artificial intelligence and jobs: Evidence from online vacancies. *Journal of Labor Economics*, 40(S1), S293–S340.
- [6] Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *The Quarterly Journal of Economics*, 113(4), 1169–1213.
- [7] Liu, H. Y., Huang, X., & Zhu, Q. (2024). Artificial intelligence, skill training, and wage gap among workers. *Journal of Central University of Finance & Economics*, (11), 103–116.
- [8] Lü, Y., Qiao, X. R., & Kong, X. (2026). Research progress on the impact of artificial intelligence on the evolution of employment structure. *Economic Perspectives*, (5), 203–224.
- [9] Wei, X. H., Zeng, C. Y., Chen, J. W., et al. (2025). Robots, aging workforce, and wage gap. *Economic Research Journal*, 60(6), 38–56.
- [10] Zhu, Q., & Liu, H. Y. (2020). The income distribution effect of artificial intelligence technology: Frontier progress and literature review. *Chinese Journal of Population Science*, (2), 111–125, 128.
- [11] Zhang, X., & Lao, Z. B. (2026). How can artificial intelligence narrow the intra-firm pay gap? A quasi-natural experiment based on the National New Generation AI Innovation Pilot Zones. *Journal of Technology Economics*, 45(3), 98–112.
- [12] Brynjolfsson, E., Li, D., & Raymond, L. (2025). Generative AI at work. *The Quarterly Journal of Economics*, 140(2), 889–942.
- [13] Wang, X. H., & Xi, H. N. (2025). Digital economy, skill premium, and labor wage gap. *Economic Review*, (2), 21–37.
- [14] Li, C., Zhang, J., Zhong, C. B., et al. (2026). New-generation artificial intelligence and total factor productivity of service-sector enterprises. *Journal of Yunnan University of Finance and Economics*, 42(4), 59–71.
- [15] Yu, D. S., Yu, J. J., & Chen, M. Y. (2026). AI empowerment and new quality productivity: Evidence from enterprises' green total factor productivity. *China Soft Science*, (2), 137–148.
- [16] He, X. G., & Guo, X. B. (2026). AI technological innovation and corporate total factor productivity. *Research on Economics and Management*, 47(3), 144–160.
- [17] Alekseeva, L., Azar, J., Giné, M., Samila, S., & Taska, B. (2021). The demand for AI skills in the labor market. *Labour Economics*, 71, 102002.
- [18] Bone, M., González Ehlinger, E., & Stephany, F. (2025). Skills or degree? The rise of skill-based hiring for AI and green jobs. *Technological Forecasting and Social Change*, 214, 124042.
- [19] Acemoglu, D., & Restrepo, P. (2022). Tasks, automation, and the rise in U.S. wage inequality. *Econometrica*, 90(5), 1973–2016.
- [20] Gans, J. S., & Stern, S. (2003). The product market and the market for “ideas”: Commercialization strategies for technology entrepreneurs. *Research Policy*, 32(2), 333–350.
- [21] Schulte, P. (2021). Skill bias magnified: Identifying the role of international technology diffusion. *Journal of International Economics*, 129, 103442.
- [22] Li, T. L. (2026). Integration of the digital economy and the real economy and inter-industrial wage inequality: A theoretical analysis. *Economic Theory and Business Management*, 46(2), 121–136.
- [23] Chen, L., & Wu, H. J. (2015). Research status and potential problems of the difference-in-differences method in China. *Journal of Quantitative & Technological Economics*, 32(7), 133–148.
- [24] Dong, Z. Q., Tan, Y. S., & Zhao, H. (2022). Does artificial intelligence technology induce industry reverse-gradient

- transfer? Evidence from industries and interprovincial characteristics. *Academic Monthly*, 54(8), 55–66.
- [25] Gan, C. H., Zheng, R. G., & Yu, D. F. (2011). An empirical study of the effects of industrial structure on economic growth and fluctuations in China. *Economic Research Journal*, 46(5), 4–16, 31.
- [26] Zhang, L., Lu, D. F., & Wei, Z. Y. (2023). Can the digital economy drive the development of China's technology market? An empirical analysis based on provincial panel data. *Science & Technology Progress and Policy*, 40(22), 12–21.
- [27] Zhao, T., Zhang, Z., & Liang, S. K. (2020). Digital economy, entrepreneurship, and high-quality economic development: Empirical evidence from urban China. *Journal of Management World*, 36(10), 65–76.
- [28] Ning, L., Wang, F., & Li, J. (2016). Urban innovation, regional externalities of foreign direct investment and industrial agglomeration: Evidence from Chinese cities. *Research Policy*, 45(4), 830–843.
- [29] Callaway, B., & Sant'Anna, P. H. C. (2021). Difference-in-differences with multiple time periods. *Journal of Econometrics*, 225(2), 200–230.