

AI Pilot Zones and Labor Market Demand: Evidence from China

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Abstract. Whether artificial intelligence policy can expand labor demand, and how the additional demand is distributed across different types of jobs, is an important question in evaluating the economic consequences of technological development. This paper matches city-level annual online job posting data and city statistical yearbook data with policy information on the National New-Generation Artificial Intelligence Pilot Zones, and employs a difference-in-differences model to examine the labor market effects of pilot zone construction. The results show that the policy significantly increases overall local hiring demand. The growth in recruitment covers workers at different levels of education, skills, and experience, and is reflected in high-skill, low-technology, technology- and knowledge-intensive, and labor-intensive positions. At the same time, the posted wage gap between high-skill and low-skill positions widens. These findings indicate that the construction of AI pilot zones may bring about both a multi-tiered expansion of job demand and a divergence in skill-based wages, providing empirical evidence for coordinating technological development, worker skill upgrading, and employment policy.

Keywords: Artificial intelligence pilot zones, labor demand, online recruitment, job stratification, skill wage gap

1. Introduction

How artificial intelligence affects labor demand is a central question for understanding the relationship between technological progress and economic development. Artificial intelligence can perform some tasks previously carried out by workers, but task automation alone does not determine the final change in the number of jobs. Technological progress may also increase labor input by raising productivity, creating new tasks, and expanding product demand. The labor market consequences of artificial intelligence therefore depend on how substitution and creation forces interact, and cannot be determined solely by the expansion of technological capabilities [1]. This issue becomes more complex when artificial intelligence development is driven by regional policies. Unlike firms' voluntary adoption of a given technology, pilot zone policies may simultaneously shape firms' technology choices, business activities, and industrial composition. Their effects on labor demand therefore concern not only whether existing jobs can be substituted, but also whether new business activities emerge locally and which types of jobs absorb the additional demand.

Existing studies have documented several channels through which artificial intelligence affects labor markets. Using online recruitment data from the United States, find that firms adopting artificial intelligence reduce recruitment for some non-artificial-intelligence jobs and adjust the skill requirements of remaining jobs [2]. Other studies find that artificial intelligence investment is associated with product innovation and business growth [3]. These findings are not necessarily contradictory. They indicate that how firms adopt artificial intelligence, and the economic environment in which they operate, shape the net effect of technological change. Further evidence shows that artificial intelligence assistance can raise the productivity of less experienced workers, suggesting that gains from technology need not accrue only to workers conventionally regarded as highly skilled [4]. Related studies have also begun to examine the link between artificial intelligence pilot zones in China and demand for labor skills [5]. Building on this work, an open question is whether regional artificial intelligence policies expand overall recruitment demand while changing the distribution of demand across jobs by education, experience, technical content, and task type, and whether they affect relative pay across jobs of different skill levels. Answering this question requires observing both quantities and prices. An increase in high-skill jobs does not by itself imply that low-skill jobs are crowded out. Simultaneous growth in recruitment demand for different groups also does not imply that wage gains are distributed equally. Examining only total employment or demand for a single skill group therefore cannot fully capture the labor market consequences of the policy.

To answer these questions, this paper matches annual online recruitment data at the prefecture city level with data on artificial intelligence pilot zone policies, and combines city characteristics from the China City Statistical Yearbook to construct a city-year panel. We estimate a difference-in-differences model controlling for city and year fixed effects, as well as economic development, population, industrial structure, fiscal expenditure, and financial development. The model examines overall recruitment demand, demand by job category, and the recruitment wage gap between high-skill and low-skill jobs. The baseline analysis covers 1,987 city-year observations. We further assess the policy effects through an event study, placebo tests, and analysis by city groups.

This paper contributes to the literature in three ways. First, it extends the perspective from firm-level technology adoption to regional artificial intelligence policies, providing empirical evidence on the relationship between policy-driven technological development and urban recruitment demand. Second, within a unified framework, it combines total employment, demand for different types of jobs, and the skill wage gap, thereby distinguishing the expansion of recruitment opportunities from changes in relative pay. Third, by examining the dynamic policy effects and results across city groups, it provides further evidence on the implementation of artificial intelligence policies and the role of local conditions. The focus of this paper is not to show that artificial intelligence necessarily creates or displaces labor, but to reveal how recruitment demand growth coexists with differential gains across job groups under a specific policy environment.

2. Literature review

Research on the labor market effects of artificial intelligence has moved beyond the traditional question of job displacement to encompass firm recruitment, job composition, and skill demand. Using online recruitment data from the United States, scholars find that after firms adopt artificial intelligence, recruitment for artificial intelligence related jobs grows rapidly, while hiring for some non-artificial-intelligence jobs declines and the skill requirements of remaining jobs change. However, the effects on industry-level aggregate employment and wages remain limited within the study period [1]. In contrast, other scholars construct firm-level measures of artificial intelligence

investment from employee resumes and find that firms with greater artificial intelligence investment experience faster growth in employment, sales, and market value, with product innovation as an important accompanying feature. Such growth is concentrated among large firms [3]. These studies show that artificial intelligence may both substitute for existing labor and coincide with new firm activities and labor demand. Its aggregate employment effect does not have a simple and uniform direction.

Further research has begun to examine how artificial intelligence reshapes job composition and hiring standards. Based on the staged rollout of generative artificial intelligence in customer service jobs, scholars find that artificial intelligence significantly raises labor productivity, with gains concentrated among less experienced and lower-skilled workers, indicating marked differences in effects across human capital groups [4]. Research on the recruitment market finds that growth in artificial intelligence jobs is accompanied by shifts in skill demand. Using about 11 million online job postings from the United Kingdom, scholars document a significant increase in demand for artificial intelligence jobs, a decline in college degree requirements, and a clear wage premium for specific artificial intelligence skills, suggesting that formal education and specific skills do not move in lockstep [6]. Recent recruitment data from China also show that demand for artificial intelligence talent is becoming more specialized and engineering oriented, with greater emphasis on technical ability, communication and coordination, advanced degrees, and some work experience. Therefore, examining aggregate employment alone cannot fully capture the labor market effects of artificial intelligence, and changes in jobs by education, experience, skill, and task type must also be examined.

Compared with firms' voluntary adoption of artificial intelligence, place-based technology policies, represented by the national new-generation artificial intelligence innovation development pilot zones, provide a new setting for identifying the policy effects of artificial intelligence development. Using large-scale online recruitment data from China between 2014 and 2024, Chinese scholars find that pilot zone construction raises demand for artificial intelligence related skills and shifts labor demand toward non-routine analytical skills [5]. In addition, studies based on listed firms find that pilot zone policies improve the efficiency of labor investment and capital investment, while their effects on total employment are mixed [7, 8].

Overall, existing studies have revealed the labor market effects of artificial intelligence from the perspectives of firm-level artificial intelligence adoption, skill demand, and labor allocation efficiency, but two gaps remain. First, research on artificial intelligence pilot zones focuses more on skill demand or labor allocation in listed firms, and pays less attention to aggregate recruitment demand at the city level. Second, the number of jobs, labor demand across human capital levels, and skill wage differences are usually studied separately. A unified framework for assessing how regional artificial intelligence policies change both recruitment scale and job distribution is still lacking. This paper therefore uses city-level online recruitment data to systematically examine the labor market effects of artificial intelligence pilot zones, covering aggregate job demand, education and experience levels, technology and task types, and the skill wage gap.

3. Theoretical analysis and research hypotheses

3.1. AI pilot zone and overall recruitment requirements

The task displacement effect of artificial intelligence does not necessarily lead to recruitment contraction. The task model emphasizes that automation saves labor, while the creation of new tasks and production expansion can restore labor demand. The net effect depends on the relative strength

of these forces [1]. Pilot zones provide conditions for firm technology adoption and business expansion through technology demonstration, application scenarios, and the agglomeration of innovation resources. Artificial intelligence investment may also expand firm scale through product innovation rather than merely compress existing labor input [3]. Pilot zone policies therefore change not only the labor required per unit of output, but also firm entry, product development, and market expansion. New business activities further generate demand for production and service support. When scale expansion and new task creation outweigh the labor-saving effect of automation, aggregate local recruitment demand will increase.

Hypothesis H1: Artificial intelligence pilot zone construction promotes the growth of aggregate job recruitment demand.

3.2. AI pilot zone and tiered job requirements

The application of artificial intelligence requires professional knowledge, technical judgment, and system integration capacity, and may directly raise demand for jobs held by highly educated and highly skilled workers. However, the expansion of technology activities also requires production execution, operation and maintenance, and service delivery, and therefore need not come at the cost of contraction in medium- and low-skill jobs. Research on local employment multipliers shows that new economic activities can generate employment in other sectors through local demand [9]. Pilot zones may therefore develop a pattern in which technology research and development expands together with supporting business activities, so that workers at all human capital levels receive new recruitment demand, rather than all jobs raising hiring thresholds simultaneously.

Hypothesis H2a: Artificial intelligence pilot zone construction increases recruitment demand for jobs at high and low education levels and at high, medium, and low skill levels.

Work experience and formal education represent different forms of human capital. Technology deployment, process coordination, and exception handling require industry experience, while business expansion may increase executive and operational jobs. At the same time, intelligent assistance can reduce the cost of knowledge acquisition and learning. Other scholars find that its productivity gains are more pronounced for less experienced workers [4]. Under business expansion, firms may increase hiring of both experienced personnel and less experienced personnel, forming a complementary division of labor rather than unidirectionally raising experience requirements.

Hypothesis H2b: Artificial intelligence pilot zone construction increases recruitment demand for jobs requiring more than three years of experience and for jobs requiring less than three years of experience.

This complementary relationship may also extend across the technical attributes and task types of jobs. Algorithm development and business adaptation expand demand for high-technology and technology-knowledge-intensive jobs, while project implementation and service expansion support low-technology and labor-intensive jobs. Partial task automation can therefore coincide with growth in different types of jobs. The key issue is whether total business volume expands enough to offset the decline in labor input per unit of business, rather than whether any type of job remains entirely unaffected by technology.

Hypothesis H2c: Artificial intelligence pilot zone construction increases recruitment demand for high-technology and low-technology jobs, and for technology-knowledge-intensive and labor-intensive task jobs.

3.3. Artificial intelligence pilot zones and the skill wage gap

Common growth in recruitment does not imply that pay rises proportionally across jobs. Artificial intelligence may raise the value of professional analysis and technical integration capacity. If the supply of related human capital adjusts slowly, competition among firms will bid up their relative recruitment wages. The recruitment wage premium for artificial intelligence skills provides empirical evidence of the market value of professional capability [10], but it does not directly equate to a wage advantage for all high-skill jobs.

Therefore, when the relative demand for high-skill labor grows faster than its supply adjustment, while the supply of low-skill labor is more elastic, the wage gap between high-skill and low-skill jobs may widen. This is not inconsistent with simultaneous growth in the number of both types of jobs, nor does it imply that low-skill wages must decline.

Hypothesis H3: Artificial intelligence pilot zone construction widens the recruitment wage gap between high-skill and low-skill jobs.

4. Research design

4.1. Data sources

This study uses three types of data. The first is online recruitment data from Chinese internet platforms, including job posting time, work city, firm name, job title, job description, wage, education requirement, work experience, and skill keywords. After job deduplication, city identification, and annual aggregation, these data form a city-year panel of recruitment demand. The raw data cover 2016 to 2025, but 2019 and 2020 have severe missing values, and recruitment data for 2025 cover only five months. We therefore retain seven valid years of data, from 2016 to 2018 and from 2021 to 2024. Restricting the sample to cities observed in all years yields a balanced panel of 284 cities and 1,988 city-year observations, including all 18 pilot zone cities and 266 non-approved cities. Because some data do not cover all 12 months, the main measure of the number of jobs is the monthly average number of jobs standardized by the months actually available.

The second type of data concerns artificial intelligence pilot zone policies. Compiled from approval documents issued by the Ministry of Science and Technology and local governments, these data record whether each city was approved, the exact approval date, and the year the policy took effect.

The third type of data consists of socioeconomic control variables at the prefecture city level, drawn mainly from the China City Statistical Yearbook, including population size, economic development, industrial structure, fiscal expenditure, and financial development. Some missing values are supplemented with provincial statistical yearbooks, city statistical yearbooks, and statistical communiqués on national economic and social development. The three types of data are matched by the six-digit administrative division code of each city and by year.

4.2. Variable definition

The core explanatory variable indicates whether a city has entered the implementation period of the artificial intelligence pilot zone policy in a given year. Denote city by c and year by t . The policy variable is defined as $AIPZ = 1$ if city c has entered the pilot zone policy implementation period in year t , and $AIPZ = 0$ otherwise. For cities that were never approved, this variable equals zero in all

years. For approved cities, it equals zero before the policy takes effect and one from the year of approval onward.

The dependent variables fall into four groups. (1) Aggregate job recruitment demand: $TotalDemand = \ln(1 + \text{Total number of positions (monthly average)})$. (2) Demand for artificial intelligence jobs, measured by both absolute level and relative share. The absolute measure is defined as $AIJobDemand = \ln[1 + (\text{credible artificial intelligence jobs} / \text{number of available months})]$. (3) The artificial intelligence exposure structure of recruited jobs: $AIExposure = (3 \times \text{high-exposure jobs} + 2 \times \text{medium-exposure jobs} + 1 \times \text{low-exposure jobs}) / \text{number of classifiable jobs}$. A higher index indicates that recruitment in that city and year is more concentrated in occupations with high artificial intelligence exposure. (4) Wage, education, experience, and skill requirements, including the logarithm of the median monthly recruitment wage, the share of jobs requiring a bachelor's degree or above, with classifiable jobs as the denominator, and the share of jobs requiring more than three years of experience, with jobs carrying identifiable experience information as the denominator.

The control variables include per capita GDP, population size, the share of the secondary industry, fiscal expenditure intensity, and financial development.

4.3. Model specification

The baseline model uses two-way fixed effects at the city and year levels:

$$Y_{ct} = \alpha + \beta AIPZ_{ct} + \gamma X_{ct} + \mu_c + \lambda_t + \varepsilon_{ct}$$

where Y_{ct} denotes, in turn, aggregate job demand, demand for artificial intelligence jobs, the artificial intelligence exposure structure of recruited jobs, recruitment wages, education requirements, experience requirements, and job task structure. $AIPZ_{ct}$ is the artificial intelligence pilot zone policy variable. X_{ct} denotes lagged city control variables. μ_c is the city fixed effect, λ_t is the year fixed effect, and ε_{ct} is the idiosyncratic error term. Standard errors are clustered at the city level. When the dependent variable is in logarithms, β approximates a percentage change; when the dependent variable is a share or an index, β represents a change in level.

City fixed effects control time-invariant city characteristics, such as geographic location, long-term industrial base, urban culture, historical institutional environment, and long-term talent attractiveness. Year fixed effects control shocks common to all cities, such as the national business cycle, the pandemic, employment policies, the overall expansion of recruitment platforms, and national digitalization trends.

Robustness checks further add province-year fixed effects or region-year fixed effects to control for concurrent economic policies and industrial changes.

5. Results

5.1. Descriptive statistics

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
aggregate job demand	1987	6047.242	14237.922	1	231994

Table 1. (continued)

DID	1987	0.044	0.205	0	1
Logarithm of per-capita GDP	1987	11.048	0.507	9.384	12.561
Logarithm of population	1987	5.876	0.759	3.045	8.136
Proportion of the secondary industry in GDP	1987	40.367	10.346	8.85	73.03
Fiscal expenditure intensity	1987	0.215	0.127	0.059	1.414
Level of financial development	1987	1.337	0.726	0.327	12.817

Descriptive statistics show that the sample contains 1,987 observations. The dependent variable, aggregate job demand, has a mean of about 6,047.24 and a standard deviation of 14,237.92, with a maximum of 231,994 and a minimum of only 1. The distribution is clearly right-skewed with heavy tails, indicating substantial variation in job scale across cities. The core explanatory variable, DID, has a mean of 0.044, showing that about 4.4 percent of observations in the sample are in a policy processing state, with a low proportion of the treatment group.

5.2. Baseline regression

Table 2. Baseline regression

	(1)	(2)	(3)
	Total number of jobs (raw data)	Total number of jobs (raw data)	Total number of jobs (raw data)
DID	35254.332*** (1346.064)	5839.507*** (1517.576)	5881.539*** (1543.039)
Logarithm of per-capita GDP			-13407.016*** (2240.986)
Logarithm of population			-8734.775*** (1458.516)
Proportion of the secondary industry in GDP			179.812*** (54.900)
Fiscal expenditure intensity			-2323.778 (7253.840)
Level of financial development			1352.305** (608.760)
cons	4503.645*** (281.661)	5791.561*** (188.682)	196666.463*** (28707.153)
Year FE	No	Yes	Yes
City FE	No	Yes	Yes
Adjusted R ²	0.256	0.694	0.707
N	1987	1987	1987

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2 reports the main regression results. The first column includes fixed effects and control variables, the second column adds year and city fixed effects, and the third column includes all fixed effects and control variables. The DID coefficients in all three columns are significant at the 1 percent level, indicating that the stimulating effect of artificial intelligence pilot zones on labor market demand is stable. The DID coefficient in the third column is 5,881.539, suggesting that cities implementing the artificial intelligence pilot zone policy created 5,881.539 more jobs than cities

without the policy. In other words, the artificial intelligence pilot zone policy stimulates the growth of local labor demand, which supports Hypothesis 1.

Table 3. Education requirements

	(1)	(2)
	High-education jobs	Low-education jobs
DID	3785.682*** (538.579)	2454.983*** (752.462)
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
Adjusted R-squared	0.680	0.700
N	1987	1987

Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3 reports the regression results for education requirements. Columns (1) and (2) report the effects of DID on the number of high-education jobs and low-education jobs, respectively. The DID coefficients in both columns are significant at the 1 percent level, indicating that the effect of artificial intelligence pilot zones on changes in education requirements in the labor market is stable. The coefficient in column (1) is 3,785.682, meaning that the artificial intelligence pilot zone policy increases the number of high-education jobs in the labor market by 3,785.682. The coefficient in column (2) is 2,454.983, indicating an increase of 2,454.983 low-education jobs. The coefficient in column (1) is notably larger than that in column (2), showing that the artificial intelligence pilot zone policy has a stronger effect on high-education jobs, which supports Hypothesis H2a.

Table 4. Experience requirements

	(1)	(2)
	Number of jobs requiring more than three years of experience	Number of jobs requiring less than three years of experience
DID	3584.837*** (473.514)	2250.991** (1091.706)
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
Adjusted R-squared	0.681	0.711
N	1987	1987

Robust standard errors in parentheses. $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4 reports the regression results for experience requirements. Columns (1) and (2) report the effects of DID on the number of jobs requiring more than three years of experience and less than three years of experience, respectively. The coefficient in column (1) is 3,584.837 and is significant at the 1 percent level, meaning that the artificial intelligence pilot zone policy increases the number of jobs requiring more than three years of experience by 3,584.837. The coefficient in column (2) is 2,250.991 and is significant at the 5 percent level, indicating that the policy increases the number of jobs requiring less than three years of experience by 2,250.991. The coefficient in column (1) is notably larger than that in column (2), showing that the policy has a stronger effect on jobs requiring rich work experience, which supports Hypothesis H2c.

Table 5. Technical requirements

	(1)	(2)	(3)	(4)	(5)
	high-technology jobs	low-technology jobs	general professional and managerial jobs	technology-knowledge-intensive task jobs	labor-intensive task jobs
DID	2175.666*** (338.694)	3738.297*** (360.645)	-195.986 (866.523)	4406.925*** (890.846)	953.280** (401.222)
Control variables	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Adjusted R-squared	0.689	0.709	0.700	0.700	0.708
N	1987	1987	1987	1987	1987

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

Table 5 reports the regression results for technical requirements. Columns (1) to (5) report the results for high-technology jobs, low-technology jobs, general professional and managerial jobs, technology-knowledge-intensive task jobs, and labor-intensive task jobs, respectively. The coefficient in column (1) is 2,175.666 and is significant at the 1 percent level, indicating that the artificial intelligence pilot zone policy increases high-technology jobs by 2,175.666. The coefficient in column (2) is 3,738.297 and is significant at the 1 percent level, indicating an increase of 3,738.297 low-technology jobs. The coefficient in column (3) is -195.986 and is not significant, meaning that the policy does not yet affect the number of general professional and managerial jobs. The coefficient in column (4) is 4,406.925 and is significant at the 1 percent level, indicating that the policy increases technology-knowledge-intensive task jobs by 4,406.925. The coefficient in column (5) is 953.28 and is significant at the 5 percent level, indicating an increase of 953.28 labor-intensive task jobs. The coefficient in column (4) is notably larger than those in the other columns, showing that the policy has the strongest effect on technology-knowledge-intensive task jobs, which supports Hypothesis H2c.

Table 6. Skill requirements

	(1)	(2)	(3)	(4)
	high-skill jobs	medium-skill jobs	low-skill jobs,	log wage gap between high-skill and low-skill jobs
DID	3785.682*** (538.579)	1275.322** (607.015)	1179.661*** (163.881)	0.116** (0.054)
Control variables	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.680	0.703	0.653	0.187
N	1987	1987	1987	1715

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

Table 6 reports the regression results for skill requirements. Columns (1) to (4) report the results for high-skill jobs, medium-skill jobs, low-skill jobs, and the log wage gap between high-skill and low-skill jobs, respectively. The coefficient in column (1) is 3,785.682 and is significant at the 1 percent level, indicating that the artificial intelligence pilot zone policy increases high-skill jobs by 3,785.682. The coefficient in column (2) is 1,275.322 and is significant at the 5 percent level,

indicating an increase of 1,275.322 medium-skill jobs. The coefficient in column (3) is 1,179.661 and is significant at the 1 percent level, indicating an increase of 1,179.661 low-skill jobs. The coefficient in column (4) is 0.116 and is significant at the 5 percent level, meaning that the policy increases the log wage gap between high-skill and low-skill jobs by 11.6 percent. The coefficient in column (1) is notably larger than those in the other columns, showing that the policy has the strongest effect on demand for high-skill jobs, which supports Hypothesis H2a.

5.3. Heterogeneity analysis

Table 7. Heterogeneity of GDP analysis

	Low-GDP group	High-GDP group
	Total number of jobs (raw data)	Total number of jobs (raw data)
DID	6567.412*** (2476.158)	2923.659 (2011.777)
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
Adjusted R-squared	0.701	0.754
N	995	992

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

Table 7 reports the grouped regression results by GDP. Column (1) reports the low-GDP group, where the DID coefficient is 6,567.412 and is significant at the 1 percent level. Column (2) reports the high-GDP group, where the DID coefficient is not significant. The coefficient for the high-GDP group is smaller than that for the low-GDP group, indicating that the artificial intelligence pilot zone policy generates larger marginal effects in regions with less abundant economic resources.

Table 8. Heterogeneity of the population

	low-population group	high-population group
	Total number of jobs (raw data)	Total number of jobs (raw data)
DID	4165.956* (2431.322)	4884.636** (2008.787)
Control variables	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
Adjusted R-squared	0.902	0.733
N	996	991

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

Table 8 reports the heterogeneity results by population size. Column (1) reports the low-population group, where the DID coefficient is 4,165.965 and is significant at the 10 percent level. Column (2) reports the high-population group, where the DID coefficient is 4,884.636 and is significant at the 5 percent level. The coefficient for the high-population group is larger than that for

the low-population group, indicating that the artificial intelligence pilot zone policy generates larger marginal effects in more populous regions.

5.4. Parallel trends test

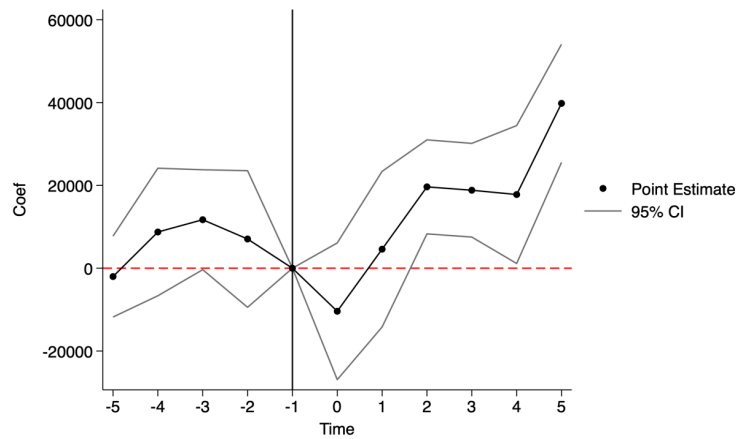


Figure 1. Parallel trends test

Figure 1 reports the results of the parallel trends test. The coefficients for all pre-policy periods are insignificant and their confidence intervals cross zero, indicating that pre-trends are broadly comparable and that the parallel trends assumption holds. Relative to the year before the policy, the coefficient in the policy year is negative but insignificant, and the coefficient in the first post-policy year turns positive but remains insignificant. This pattern shows that the policy effect is released with a lag and does not appear immediately upon implementation. From the second year after the policy onward, the coefficients become significantly positive and continue to grow, indicating that the artificial intelligence pilot zone policy requires time to accumulate and brings about a large and significant expansion of urban labor market demand around the second year of implementation.

5.5. Placebo test

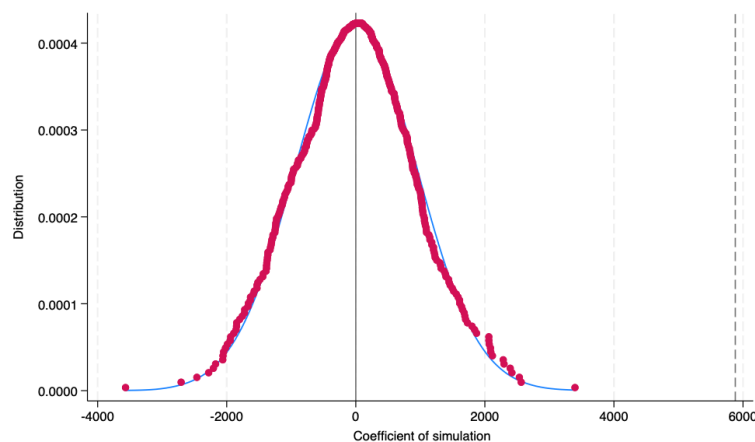


Figure 2. Placebo test

Figure 2 reports the results of the placebo test. The estimated coefficients from random simulation cluster around zero and approximately follow a symmetric distribution centered at zero, while the true estimated coefficient lies clearly outside the simulated distribution and far from the main range of the confidence interval. This indicates that the policy effect observed in the baseline regression is not driven by sample randomness or accidental factors, and that the effect of artificial intelligence pilot zones on urban labor market demand is statistically genuine and robust.

6. Discussion and conclusions

This study matches city-level online recruitment data with urban economic and social characteristics and information on China's national next-generation artificial intelligence pilot zones. Using a difference-in-differences model, we examine how the establishment of pilot zones affects labor demand. The results show that the establishment of pilot zones leads to a relative increase in the number of annual online job postings in local cities, indicating an expansion of labor demand in the recruitment market. This finding passes the parallel trends test and the placebo test. Dynamic analysis shows that the policy effect does not appear immediately; a significant positive recruitment effect emerges in the second year after implementation and thereafter. Heterogeneity analysis by job category shows that recruitment growth is not confined to a single level of human capital. Job postings increased for both high-education and low-education positions, for high-, medium-, and low-skill positions, and for positions requiring more than three years of experience as well as those requiring less than three years. When classified by technological attributes and task type, high-tech, low-tech, knowledge-intensive, and labor-intensive positions all exhibited positive changes. Overall, the establishment of pilot zones corresponds to an expansion of demand across multiple types of positions. The expansion in the number of job postings is accompanied by changes in the wage structure. Recruitment wages across skill levels did not change proportionally. Further results grouped by city characteristics show that the effect is more pronounced in cities within pilot zones with lower GDP and in cities with larger populations.

Based on these findings, this study offers the following policy recommendations. The evaluation of AI-related policies should consider both the scale of job creation and the distribution of earnings. The construction of pilot zones should not be judged solely by the number of projects, technological investment, or the recruitment of high-end talent. Sustained monitoring of job postings, actual hiring, employment stability, and wage changes across skill groups is equally necessary. In view of the simultaneous expansion of jobs at multiple skill levels, talent policies can better connect professional and technical training with vocational programs, providing workers with lower skills or less experience with training oriented toward actual work processes and with job-matching services. Moreover, the widening skill wage premium indicates that increased hiring opportunities brought about by technological development cannot substitute for continuous support for skill upgrading and career development among workers.

This study has several limitations. First, online job postings reflect firms' labor demand rather than actual hiring or net employment growth, and both platform coverage and duplicate postings may affect the measurement of job counts. Second, city-level aggregate data cannot distinguish between firm entry, expansion of incumbent firms, and adjustments in hiring standards within the same occupation. In addition, pilot zones represent a comprehensive regional policy, so our estimates capture the overall effect of policy implementation rather than the pure technological effect of any single AI tool. Future research could combine data on firm technology adoption, investment, and worker flows to identify the specific channels, and could further address issues of concurrent policies, cross-city spillovers, and staggered implementation in estimation. Part of the

hiring growth in pilot zone cities may also stem from the spatial reallocation of economic activity, so it should not be directly extrapolated to net job creation or welfare gains at the national level. This is consistent with the requirement in place-based policy evaluation to distinguish regional gains from aggregate gains.

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