Industrial Robot Application and Employment Reallocation

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Abstract: *In recent years, a new generation of robots integrated with artificial intelligence has rapidly proliferated across China. Drawing on firm-level tax survey data (2010-2016), city-level data (1999-2019), and micro-data from the China Labor-force Dynamics Survey (2012-2018), this paper constructs an instrumental variable based on city-level robot penetration to investigate the regional employment effects of robot adoption from multiple perspectives. The main findings are as follows: (1) Widespread robot adoption significantly strengthens the market position of incumbent firms, supports overall employment growth within these firms, and facilitates labor reallocation across sectors, with labor tending to shift toward industries characterized by larger average firm size. (2) Evidence at both the aggregated level and the individual level shows that while robot adoption markedly improves firm productivity, it slows the pace of job creation while simultaneously reducing job displacement. As a result, labor mobility at the regional level shows a declining trend. (3) Robot adoption generates significant market spillover effects. It fosters employment growth among incumbent firms but tends to slow the pace of entry of new firms, an important mechanism behind the observed deceleration in regional employment growth. (4) Heterogeneity analysis reveals that robots have a greater impact on job transitions for highly educated and middle-aged workers, increasing their preference for stable employment. No significant differences are found across occupational types or between genders in terms of job mobility impacts.*

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1. Introduction

Since the turn of the 21st century, rapid advancements in artificial intelligence (AI) and information technology have profoundly reshaped both production processes and everyday life. As a representative technology of "new quality productive forces," the new generation of industrial robots—integrated with AI—is seeing rapid adoption across China. At present, industrial robots are deployed across 60 major industry categories and 168 sub-sectors of the Chinese economy. China has been the world's largest industrial robot market for ten consecutive years. In 2022 alone, it produced over 440,000 units, accounting for more than 50% of global installations. Actively developing these new productive forces is crucial for boosting China's industrial competitiveness and cultivating new engines of economic growth.

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This will also accelerate the transition to high-quality development. At the same time, however, the rapid and widespread application of industrial robots has sparked considerable debate and concern over their disruptive impact on employment.

The growing concern over the employment impact of AI-based, next-generation automation primarily stems from a fundamental shift in the theoretical frameworks used to understand technological progress and job growth. New analytical perspectives argue that advancements in AI and robotics exhibit systematic differences from earlier, more traditional forms of technological progress. The conventional skill-biased technological change (SBTC) framework (Autor et al., 2003) posited that while technological progress might displace certain traditional jobs, such technological transformations typically lead to capital deepening and significant increases in productivity. The resulting expansion in output and reduction in prices would, in turn, stimulate increased demand, generating compensating and job-creating effects. This dynamic was expected to largely offset initial job displacement, meaning overall employment levels would not significantly decline due to technological advancement. Technological emphasized that fundamental technological changes, often referred to as factor-augmenting technological innovation, would enhance efficiency across all stages of the work process.

In contrast to the SBTC framework, the more recently proposed task-based framework (Acemoglu & Restrepo, 2019) offers a different perspective. It posits that technological progress, exemplified by industrial robots and AI, is primarily characterized by automation task innovation. This means it specifically improves the efficiency of a particular task and does not necessarily lead to a broad increase in productivity across all production processes. If automation only boosts the efficiency of specific tasks without driving an overall enhancement in factor productivity or creating a significant number of new tasks, this type of advancement is considered a specific technological improvement within a task-based model. Such task-based technological progress, the framework suggests, may lead primarily to substantial job displacement effects with minimal employment complementarity. Empirical evidence further supports this view: since 2000, alongside the rapid advancement of automation technology, there has been a marked decline in the growth of new job tasks (Autor & Salomons, 2018; Acemoglu & Restrepo, 2019). Moreover, recent empirical research has more finely distinguished between factor-augmenting technological progress and automation technological progress in terms of their labor market impacts. These studies consistently find that while factor-augmenting technological progress has indeed had very little impact on employment growth, while task automated technological progress has generated significant avderse effects on employment and wage growth across virtually all skill and occupational groups (Autor et al., 2022; Kogan et al., 2023).

While many discussions emphasize differences in the nature of technology type—especially the shift from factor-augmenting to task- automated innovations—an alternative framework focuses on demand-side dynamics. It argues that today's automation is not fundamentally different from earlier technological advances in its ability to boost productivity. Modern technologies like AI and robotics still deliver significant efficiency gains, comparable to those of past industrial revolutions. The key difference lies in the declining elasticity of demand. As societies modernize and basic needs are met, demand for many goods becomes far less responsive to changes in price, income, or productivity. For instance, from 1850 to 1950, global price elasticity of demand for products like textiles, steel, and automobiles fell by a factor of eight (Bessen, 2019). As a result, even with prices falling and productivity rising substantially, demand expands only marginally—limiting the potential for job growth.

Thus, it is not that new technologies are more disruptive by nature, but that they now operate in a demand environment with less room for expansion. This structural shift weakens the job-creating effects that once offset labor displacement, making automation's job impact more evident today.

Automation technologies often have heterogeneous effects on employment and income across skill levels and occupations. Early studies characterized industrial robots as routine-task-biased innovations. Using earlier data, researchers found that robots mainly replaced routine, middle-skilled jobs, while non-routine tasks, whether high-skilled or low-skilled—were harder to automate and thus grew in demand. This led to a pattern of job polarization, with employment increasing at both the high and low ends of the skill spectrum (Goos et al., 2014; De Vries et al., 2020; Reijnders et al., 2018; Graetz & Michaels, 2018). More recent research, however, finds that automation may now exert stronger negative effects on high-skilled employment and wages (Feng & Graetz, 2020; Faber et al., 2022; Kogan et al., 2023). One explanation is that firms using robots are typically more productive and thus more likely to replace expensive, high-skilled labor. Replacing workers who require intensive education and training with automation can substantially boost firm profits.

Some studies emphasize that AI- and machine learning-based automation technologies are more likely than traditional industrial robots to substitute high-skilled labor, potentially narrowing the income gap between high- and low-skilled workers (Webb, 2020; Brynjolfsson, 2018). At the same time, as AI and machine learning continue to advance, automation is no longer confined to routine tasks. Increasingly, non-routine tasks are also being automated. According to estimates, around 47% of U.S. occupations are at high risk of automation (Frey & Osborne, 2017). With these advances, AI-enabled robots are expanding rapidly beyond manufacturing and into service sectors such as healthcare, education, finance, media, warehousing, and transportation. This has driven a sharp rise in service sector automation. Since services employ a much larger share of the workforce than manufacturing in most countries, the large-scale deployment of intelligent technologies in services is expected to have far-reaching impacts on global labor markets (Baldwin, 2022).

It is important to distinguish between firm-level and regional-level analyses of the impact of industrial robots on employment, as they represent fundamentally different analytical frameworks. Firm-level studies consistently find that robot-adopting companies are more productive than non-adopters. Robots use significantly boosts firm productivity and, in many cases, even increases employment rather than displacing it (Acemoglu et al., 2022; Bessen et al., 2019; Domini et al., 2020; Feng & Graetz, 2020; Koch et al., 2021). This is largely because such studies focus on the internal effects within the adopting firm and typically ignore broader market spillovers. However, some research has shown that while a firm's own robot adoption may raise its employment, the adoption of robots by competitors can negatively affect its job growth. Once these spillover effects are taken into account, higher regional robot penetration is found to have a significant negative impact on overall employment growth (Acemoglu et al., 2020). Therefore, regional-level analyses offer a more complete picture of the labor market effects of automation by capturing both direct impacts on incumbent firms and indirect effects such as job reallocation resulting from firm entry and exit triggered by widespread robot adoption.

In recent years, Chinese scholars have conducted extensive research on the impact of industrial robots on China's labor market. Most studies find that widespread robot adoption in manufacturing has had significant displacement effects on employment (Wang & Dong, 2020; Kong et al., 2020; Song & Zuo, 2022; Dong et al., 2022; Wang et al., 2022; Yan et al., 2020). However, some studies offer different perspectives. Li et al. (2021) report that robot adoption significantly boosts employment at the firm level. Others find that robots reduce inflows of migrant labor but do not significantly affect overall regional employment (Li et al., 2021; Chen et al., 2022). Several studies focus on the differentiated impact of robots on routine and non-routine jobs. Findings suggest that robot adoption tends to reduce employment and wages in routine tasks while promoting job growth and income in non-routine roles (Yu et al., 2021; Wei, Zhang & Du, 2020; He & Liu , 2023).

Other research explores the role of AI in reshaping occupational structures, showing that AI can induce shifts from traditional to emerging occupations (Wang et al., 2023). Meanwhile, some studies point to a deterioration in labor welfare associated with robot adoption, driven by wage cuts and reduced implicit benefits (Zhang et al., 2023).

This paper expands the analysis along several dimensions. First, drawing on firm-level tax survey data (2010-2016), city-level data (1999-2019), and micro-level labor force survey data (2012-2018), we examine how changes in regional industrial robot penetration affect employment reallocation, with particular attention to labor mobility at the regional level. Unlike prior studies, our results show that robot adoption significantly displaces employment not only in manufacturing but also in non-manufacturing sectors. Overall, it leads to a marked decline in regional labor reallocation. Second, taking market spillover effects into account, we distinguish between the impact of robot adoption on employment in incumbent firms versus all firms, including entrants and exits. The results show that robots do not significantly reduce employment in incumbent firms; on the contrary, they slightly promote overall job growth of those firms. However, widespread robot adoption significantly deters new firm from market entry, which ultimately suppresses net employment growth at regional level. This perspective—differentiating between incumbent and all firms to evaluate the broader employment impact—has been largely neglected in prior research on China's labor market. Third, to ensure robustness, we not only examine robot impacts ,, of employment using aggregated dataset but also investigate those impacts using a large survey dataset over the period of 2012 to 2018, the China Labor Force Dynamics Suvey This allows us to assess how regional robot penetration affects job transitions across age, occupation, education, and gender groups. We find that robot adoption significantly lowers the occurrence of job switching, particularly for highly educated and middle-aged workers. In contrast to earlier studies, we find no significant variation in transition effects across occupational types.

The remainder of the paper is organized as follows: Section 2 outlines the empirical framework and identification strategy; Section 3 presents stylized facts on China's labor market; Section 4 reports empirical results and interpretation; and Section 5 concludes with key implications.

2. Empirical Framework and Identification

This study develops a theoretical model based on the analytical frameworks of Acemoglu & Restrepo (2020) and Faber et al. (2022), which explore the impact of robotics on employment growth and labor mobility. Specifically, we examine how changes in regional robot penetration affect employment reallocation through three main channels: the direct displacement effect, the productivity-price-demand effect, and the labor supply-income effect[1].

2.1 Evidence from Firmand City-Level Data

Drawing on influential studies that examine the labor market impacts of artificial intelligence and industrial robots (Acemoglu & Restrepo, 2020; Doms et al., 2020; Autor et al., 2021), this paper employs a long-difference empirical specification for causal identification. This methodological choice is motivated by three main considerations: First, the robot Bartik instrumental variable (IV) approach essentially operates as a different version of the difference-in-differences (DiD) method. Constructing the Bartik IV allows us to capture the technological shock of robot adoption over a defined period, which facilitates a more accurate identification of its true effects. Accordingly, the long-difference specification is particularly appropriate for modeling the continuous treatment effect (Goldsmith-Pinkham et al., 2020; Borusyak et al., 2022). Second, compared to using panel data with two-way fixed effects (TWFE), the long-difference model controls for baseline levels in the pre-treatment period. This helps mitigate the problem of negative weighting caused by heterogeneous treatment effects across multiple time points (De Chaisemartin & D'Haultfeuille, 2020). It also avoids the endogeneity risk that can arise from including post-treatment control variables, which may themselves be affected by the key explanatory variable. Such interactions can complicate causal inference (Caetano & Callaway, 2022). Third, the long-difference approach facilitates placebo tests to assess pre-trend equivalence prior to the robot shock,

[1] For details, please contact us for the supplementary theoretical model.

thereby enhancing the transparency and credibility of the empirical analysis.

Based on this framework, we estimate the following empirical equation using data aggregated at the prefecture level:

$$\Delta Y_{i,c,(t_0,t_1)} = \alpha + \beta RBK_{c,(t_0,t_1)} + \lambda_j \Delta X_{i,c,(t_0-T,t_0)} + \delta_j Base_c + \eta_i + \varepsilon_{i,c} \quad (1)$$

In empirical equation (1), the dependent variable $\Delta Y_{i,c(t_0,t_1)}$ measures the change in employment indicators for a given industry i within a prefecture-level c from time t_0 to t_1. To capture the overall dynamics of labor mobility and reallocation at the regional level, i define the dependent variable by drawing on the representative studies of labor reallocation and job flows (Davis & Haltiwanger, 1992). Following established methodologies, we decompose employment dynamics into the following components: job creation, job destruction , job net growth, job reallocation effect, and net job reallocation effect, as expressed in the following equation:

$$\Delta Y = [\Delta ANET, \Delta JC, \Delta JD, \Delta NET, \Delta REA, \Delta NEA]$$

Using aggregated data at the prefecture-level, we can only obtain the aggregate employment indicator for each industry within that city, without access to more detailed employment components. To address this limitation, we use firm-level tax survey data to calculate the following indicators for each prefecture-level :

Job Creation change: $\Delta JC_{i,c,(t_0,t_1)} = Ln(\sum_{\substack{s\in,i,c,t_1 \\ \Delta semp_{t_1}>0}} \Delta semp_{t_1}) - Ln(\sum_{\substack{s\in,i,c,t_0 \\ \Delta semp_{t_0}>0}} \Delta semp_{t_0})$ where $\Delta semp_{t_1}$ represents the number of employees at firm s at the end of the year t_1 minus the number at the beginning of the year. $\Delta semp_{t_0}$ denotes the number of employees at firm s at the end of the year t_0 minus the number at the beginning of the year.

Similarly, we define the Job Destruction change as:

$$\Delta JD_{i,c,(t_0,t_1)} = Ln(\sum_{\substack{s\in,i,c,t_1 \\ \Delta semp_{t_1}<0}} \left|\Delta semp_{t_1}\right|) - Ln(\sum_{\substack{s\in,i,c,t_0 \\ \Delta semp_{t_0}<0}} \left|\Delta semp_{t_0}\right|)$$

Job Net Growth Rate:

$$\Delta NET_{i,c,(t_0,t_1)} = Ln(\sum_{s\in,i,c,t_1} \Delta semp_{t_1}) - Ln(\sum_{s\in,i,c,t_0} \Delta semp_{t_0}) = \Delta JC_{i,c,(t_0,t_1)} - \Delta JD_{i,c,(t_0,t_1)}$$

Job Reallocation change: $\Delta REA_{i,c,(t_0,t_1)} = \Delta JC_{i,c,(t_0,t_1)} + \Delta JD_{i,c,(t_0,t_1)}$

Net Job Reallocation change: $\Delta NEA_{i,c,(t_0,t_1)} = \Delta REA_{i,c,(t_0,t_1)} - \left|\Delta NET_{i,c,(t_0,t_1)}\right|$

It is important to note that, because the firm-level tax survey sample does not form a panel dataset over time, the above indicators are calculated using the number of employees at the end of each year minus the number at the beginning of the same year for each firm. As such, they only reflect employment changes among incumbent firms within the given year. These above indicators do not capture reallocation effects resulting from changes in the survey sample or from firm entry and exit. To reflect the total employment change that includes these factors, the calculation would be:

$$\Delta ANET_{i,c,(t_0,t_1)} = Ln(\sum_{s\in t_1} semp_{t_1}) - Ln(\sum_{s\in t_0} semp_{t_0})$$

where $semp_{t_1}$ and $semp_{t_1}$ denote the average number of employees across all firms in the survey year, including those affected by survey sample adjustments as well as firms that entered or exited during that year. To better understand the relationship between $\Delta ANET_{i,c,(t_0,t_1)}$ and $\Delta NET_{i,c,(t_0,t_1)}$, and to clarify the mechanisms through which robots affect employment growth, we decompose overall employment growth into three components: (1) employment changes resulting from firm entry and exit, (2) employment changes caused by incumbent firms at each year, and (3) cross-period employment adjustments caused by continuously operating firms. Specifically:

$$\begin{aligned}\Delta ANET_{i,c,(t_0,t_1)} = & \underbrace{Ln(\sum_{\substack{s\in t_1,\ s\notin t_0\\ \Delta semp_{t_1}=0}} semp_{t_1}) - Ln(\sum_{\substack{s\notin t_1, s\in t_0\\ \Delta semp_{t_0}=0}} semp_{t_0})}_{\text{Employment changes resulting from firm sample adjustment (entry and exit)}(\Delta Net\_ADJ)} \\ & + \underbrace{Ln(\sum_{\substack{s\in t_1,\ s\in t_0\\ \Delta semp_{t_1}=0}} semp_{t_1}) - Ln(\sum_{\substack{s\in t_1, s\in t_0\\ \Delta semp_{t_0}=0}} semp_{t_0})}_{\text{Cross-period employment adjustments caused by continuously operating firms }(\Delta NET\_INC)} \\ & + \underbrace{Ln(\sum_{\substack{s\in t_1,\ s\notin t_0\\ \Delta semp_{t_1}\neq 0}} \Delta semp_{t_1}) - Ln(\sum_{\substack{s\notin t_1, s\in t_0\\ \Delta semp_{t_0}\neq 0}} \Delta semp_{t_0})}_{\text{Employment changes caused by incumbent firms }(\Delta NET)}\end{aligned}$$

The first and second terms in the decomposition represent employment changes among firms whose employment levels did not change within the year (i.e., $\Delta semp_{t_1}$=0 and $\Delta semp_{t_0}$=0**)**, but did change across periods. The first term captures the difference in total employment between firms newly entering the survey sample at the end of the period t_1 and firms exiting the sample by that time (ΔNET_ADJ). The second term reflects the net employment change from continuously operating firms that had no within-year employment change, but experienced overall adjustments between periods (ΔNET_INC). The third term represents the overall employment change (ΔNET) caused by within-year adjustments among incumbent firms ($\Delta semp_{t_1}\neq 0$ and $\Delta semp_{t_0}\neq 0$).

The overall employment reallocation effect in the labor market $\Delta AREA_{i,c,(t_0,t_1)}$ includes not only job creation and destruction by incumbent firms, but also employment changes resulting from firm entry (job creation, $\Delta JC^{Entry}_{i,c,(t_0,t_1)}$) and firm exit (job destruction, $\Delta JD^{Exit}_{i,c,(t_0,t_1)}$). This overall reallocation effect can be expressed as:

$$\begin{aligned}\Delta AREA_{i,c,(t_0,t_1)} &= \Delta JC_{i,c,(t_0,t_1)} + \Delta JD_{i,c,(t_0,t_1)} + \Delta JC^{Entry}_{i,c,(t_0,t_1)} + \Delta JD^{Exit}_{i,c,(t_0,t_1)} \\ &= \Delta REA_{i,c,(t_0,t_1)} + \Delta REA^{EnEx}_{i,c,(t_0,t_1)}\end{aligned}$$

The overall employment reallocation effect includes both the reallocation resulting from employment changes within incumbent firms $\Delta RET_{i,c,(t_0,t_1)}$ and the reallocation caused by firm entry and exit $\Delta REA^{EnEx}_{i,c,(t_0,t_1)}$. To comprehensively assess the impact of robots on labor market reallocation, we examine both the reallocation effects within incumbent firms and the influence of robots on firm entry and exit.

It is important to note that in the tax survey data from 2010 to 2016, a total of over 1.35 million firms were surveyed across the two years. Among them, fewer than 11,200 firms appeared in both 2010 and 2016 and showed no employment change in the respective years. These firms account for only 0.6% of the full sample in terms of firm count and employment share, and thus have a negligible impact on overall employment changes. Therefore, this study primarily focuses on the first and third components of employment change: those resulting from firm sample adjustments (which include actual firm entry and exit as well as changes due to survey sampling) and from incumbent firms.

$RBK_{c,(t_0,t_1)}$ is the core explanatory variable in this study, representing the industrial robot penetration rate at the prefecture level. We construct a prefecture-level Bartik variable by combining industry-level robot installation density with the region's baseline employment share across industries. Specifically:

$$RBK_{c,(t_0,t_1)}=[chnbk_{c,(t_0,t_1)},\ eurobk6_{c,(t_0,t_1)},\ eurobk5_{c,(t_0,t_1)}]$$

where $chnbk_{c,(t_0,t_1)}$ denotes the robot Bartik variable, constructed using China's industry-level robot installation density and the regional industry employment share:

$$chnbk_{c,(t_0,t_1)} = \sum_{i \in I} l_{ci,1995} \times APR^{chn}_{i,(t_0,t_1)}$$

where $l_{ci,1995}$ represents the employment share of a prefecture-level c in industry i in 1995, based on industry classification. $APR^{chn}_{i,(t_0,t_1)}$ indicates the average rate of change in robot installation density (per thousand workers) in industry i in China from time t_0 to t_1. Specifically:

$$APR^{chn}_{i,(t_0,t_1)} = \frac{R^{chn}_{i,t_1} - R^{chn}_{i,t_0}}{L^{chn}_{i,1995}} - g^{chn}_{i,(t_0,t_1)} \times \frac{R^{chn}_{i,t_0}}{L^{chn}_{i,1995}}$$

R^{chn}_{i,t_1} and R^{chn}_{i,t_0} represent the stock of installed robots in China's industry i at times t_1 and t_0, respectively. $L^{chn}_{i,1995}$ denotes the number of employees in China's industry i in 1995. To account for asymmetries in output growth across industries, we apply a correction by multiplying each industry's output growth rate over the sample period $g^{chn}_{i,(t_0,t_1)}$ by its initial robot density.

An endogeneity issue exists between the Bartik variable for robot penetration in Chinese prefecture-level regions and local employment changes. To address this, we construct an instrumental variable (IV) based on robot adoption trends in other countries. The IV must meet not only the relevance condition but, more importantly, the exclusion restriction (uniqueness) assumption. To satisfy these requirements, selected countries must meet several criteria: First, they should have adopted robots earlier than China, representing the technological frontier and providing a demonstration effect that could influence China's adoption behavior. Second, their robot adoption speed and density changes during the same period should exhibit a trend similar to that of China, enabling the IV to effectively predict China's robot penetration. Third, these countries must not have strong industrial competition or complementarity with China. If such relationships exist, robot adoption in these countries could indirectly affect China's labor market—for example, through intensified outsourcing or reshoring (Krenz et al., 2021; Faber, 2020)—thus violating the exclusion restriction.

Accordingly, countries such as the United States, South Korea, Japan, and Germany, which have had significant prior investment in China, or emerging economies like India, Vietnam, and Mexico, which compete directly with China in global manufacturing and have increasingly adopted robots, may influence China's labor market through capital relocation. As a result, robot adoption data from these countries should not be used to construct the IV for China's robot penetration rate.

Following the principles outlined above, this paper first constructs a Bartik instrumental variable *eurobk*6 using data from six European countries with advanced industrial foundations: Denmark, Sweden, Finland, the Netherlands, France, and Italy. These countries were among the earliest to adopt automation technologies and were not only far ahead of China in the early stages of automation adoption, but also ahead of other developed nations such as the United States, Japan, Germany, and the United Kingdom (Acemoglu & Restrepo, 2020). Additionally, due to their relatively small economic size, these countries exhibit weaker direct industrial competition and complementarity with China. One limitation, however, is that their pace of robot adoption has lagged behind China in recent years.

To address this, we further construct an alternative Bartik instrument *eurobk*5 using data from five other European countries with solid industrial bases: Austria, the Czech Republic, Hungary, Slovakia, and Slovenia. These countries adopted robotics earlier than China and have demonstrated more recent trends in robot adoption that are closer to China's trajectory. Moreover, they maintain relatively low levels of industrial competition and complementarity with China, making them better suited to satisfy the exogeneity assumption required for instrumental variables. All eleven countries are EU members, which ensures consistency in data sources and enhances the comparability and reliability of the constructed Bartik instruments.

$$eurobk6_{c,(t_0,t_1)} = \sum_{i \in I} l_{ci,1995} \times \overline{APR}_{i,(t_0,t_1)}^{euro6}$$

$$\overline{APR}_{i,(t_0,t_1)}^{euro6} = \frac{1}{6} \sum_{j \in euro6} \left[\frac{R_{i,t_1}^{j} - R_{i,t_0}^{j}}{L_{i,1995}^{j}} - g_{i,(t_0,t_1)}^{j} \frac{R_{i,t_0}^{j}}{L_{i,1995}^{j}} \right]$$

$$eurobk5_{c,(t_0,t_1)} = \sum_{i \in I} l_{ci,1995} \times \overline{APR}_{i,(t_0,t_1)}^{euro5}$$

$$\overline{APR}_{i,(t_0,t_1)}^{euro5} = \frac{1}{5} \sum_{j \in euro5} \left[\frac{R_{i,t_1}^{j} - R_{i,t_0}^{j}}{L_{i,1995}^{j}} - g_{i,(t_0,t_1)}^{j} \times \frac{R_{i,t_0}^{j}}{L_{i,1995}^{j}} \right]$$

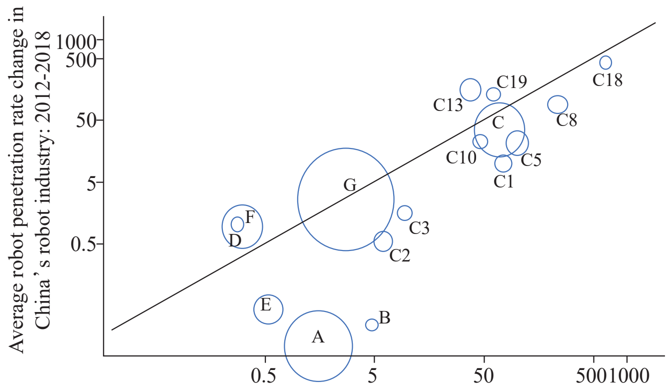

Figure 1: Average Robot Penetration Rate Changes in China and Six European Countries

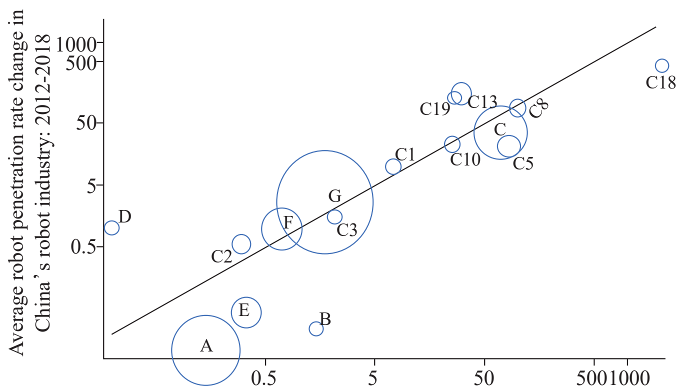

Figure 2: Average Robot Penetration Rate Changes in China and Five European Countries

Notes: Industry Classifications: A: Agriculture, Forestry, Animal Husbandry, and Fishery B: Mining and Quarrying C: Manufacturing C1: Food and Beverage Manufacturing C2: Textile and Apparel Manufacturing C3: Wood, Furniture, and Paper Manufacturing C5: Plastics, Rubber, and Non-metallic Minerals C8: Basic Metals and Metal Products C10: Machinery and Equipment Manufacturing C13: Household Appliances and Electronic Equipment C18: Transport Equipment and Components C19: Other Manufacturing D: Electricity, Gas, and Water Supply E: Construction F: Education, Scientific Research, and Healthcare G: Other Non-manufacturing Industries.

Figures 1 and 2 compare the average changes in robot penetration across major industries in six and five European countries, respectively ($\overline{APR}$), with the corresponding changes in Chinese industries over a similar time period. The size of each circle represents the average level of employment in 1995—the base year—in both China and the European countries. The 45-degree diagonal line indicates a one-to-one relationship between changes in the two regions. With the exception of sectors where robot adoption remains relatively low—such as agriculture, construction, mining, and gas supply—most manufacturing and service sectors are clustered around the 45-degree line. This indicates that the industry-level changes in robot penetration observed in these European countries are strong predictors of corresponding changes in China. This pattern lends strong support to the validity of using robot adoption trends in European countries as an instrumental variable. The primary channel through which European robot adoption affects China's labor market is via its influence on China's own adoption of robotics. Other indirect or confounding channels appear limited, which is essential for satisfying the exclusion restriction required for valid instrumental variable identification.

$\Delta X_{i,c,(t_0,-T,t_0)}$ represents the pre-trend change variable , T periods prior to time t_0. It is used to control for the influence of pre-existing trends on the potential outcome variable, with a lead period of T=10. Specifically, it includes changes in total employment, population size, fixed asset investment, and per capita wages in each prefecture-level region, T periods prior to the treatment.

$Base_c$ denotes time-invariant control variables at the prefecture- level, with 2003 used as the base year[2]. These controls include the share of tertiary industry, average wage level, total passenger and freight transport volume, R&D investment ratio, the employment share of foreign direct investment (FDI) enterprises, wastewater discharge density, and the employment shares of major industry categories in each prefecture-level region. Including employment shares by industry category is particularly important. According to theoretical and empirical findings (Ado et al., 2019), when constructing Bartik instrumental variables, regional industrial structures that are very similar may lead to correlated error terms across regions. If not properly accounted for, this can result in underestimated standard errors and wrong statistical inference. Moreover, theory indicates that if the sum of baseline industry employment shares does not equal one, overall industrial employment shares must be controlled for to ensure validity (Borusyak et al., 2022). To address these concerns, we directly control for each region's employment shares across major industries in the base year. η_i represents industry fixed effects, and $\varepsilon_{i,c}$ denotes the error term.

2.2 Identification Using Micro-level Survey Data

This study also utilizes individual and household-level data from the China Labor-force Dynamics Survey (CLDS) to examine the impact of industrial robots on job outcomes and occupational transitions (or job transition) . In addition, we explore heterogeneity in these effects across different groups. The empirical model is specified as follows:

$$jbstatus_{k,c,(t_0,t_1)} = \theta + \gamma RBK_{c,(t_0,t_1)} + \vartheta_j RBK_{c,(t_0,t_1)} \times X_{k,c} + \eta_j X_{k,c} + \rho_j Base_c + \delta_h + \sigma_{k,c} \qquad (2)$$

where $jbstatus_{k,c,(t_0,t_1)}$ is a binary variable indicating whether an individual k experienced an employment change or occupational transition between time t_0 and t_1. We define this outcome as follows:

$$jbstatus_{k,c,(t_0,t_1)} = [jobst_{k,c,(t_0,t_1)}, jobed_{k,c,(t_0,t_1)}, jobrea_{k,c,(t_0,t_1)}]$$

Corresponding to the aggregated indicator of job creation effect, $jobst_{k,c,(t_0,t_1)}$ is coded as 1 if an individual started a new job or occupation between time t_0 and t_1, and 0 otherwise. For the aggregated

[2] Other pre-trend years could be used as the base without affecting the empirical results; 2003 was chosen because it has the most complete set of indicators at the prefecture level.

indicator of job destruction, $jobed_{k,c,(t_0,t_1)}$ is coded as 1 if an individual ended their existing job or occupation between t_0 and t_1, and 0 otherwise. For the job reallocation indicator, $jobrea_{k,c,(t_0,t_1)}$ is set to 1 if an individual experienced any job or occupational status change between t_0 and t_1, and 0 otherwise. $X_{k,c}$ denotes a set of individual-level control variables, $X_{k,c}$ =[$Age_{k,c}$,$Gender_{k,c}$,$Edu_{k,c}$,$Occ_{k,c}$]. These include age $Age_{k,c}$, gender $Gender_{k,c}$, education level $Edu_{k,c}$, and occupational category $Occ_{k,c}$=[$gov_{k,c}$, $pro_{k,c}$, $clerk_{k,c}$, $busi_{k,c}$, $agr_{k,c}$, $maf_{k,c}$]. Occupations are grouped into six broad types:

(1) leaders and managers in government agencies ($gov_{k,c}$),
(2) professional and technical personnel ($pro_{k,c}$),
(3) clerical staff ($clerk_{k,c}$),
(4) social service workers ($busi_{k,c}$),
(5) agricultural, forestry, animal husbandry, and fishery workers ($agr_{k,c}$),
(6) manufacturing and production workers ($maf_{k,c}$).

Equation (2) includes interaction terms between the Bartik-type robot penetration variable and individual characteristics $RBK_{c,(t_0,t_1)}\times X_{k,c}$ to examine heterogeneity in the effect of robot adoption on job and occupational transition probabilities. The core explanatory variables and all other controls are defined in the same way as in Equation (1). δ_h represents household fixed effects, and $\sigma_{k,c}$ denotes the error term.

Table 1: Definitions of Key Variables

	Key variables	Variable explanation and definition
Based on aggregate firm and city-level data	$\Delta ANET$	Total employment growth rate (all firms)
	$\Delta AREA$	Total employment reallocation change (all firms)
	ΔNET_ADJ	Employment growth due to sample adjustment (including firm entry and exit)
	ΔNET_INC	Cross-period employment change (continuous firms)
	ΔNET	Net job growth rate (incumbent firms)
	ΔJC	Job creation change (incumbent firms)
	ΔJD	Job destruction change (incumbent firms)
	ΔREA	Job reallocation change (incumbent firms)
	ΔNEA	Net job reallocation change (incumbent firms)
	$\Delta Entry$	Firm entry rate change
	$\Delta Exit$	Firm exit rate change
	$\Delta EnEx$	Firm entry and exit rate changes
Based on china labor-force dynamics survey (clds) data	*jobst*	Individual starts new job: defined as 1 if the individual starts a new job, 0 otherwise.
	jobed	Individual ends existing job: defined as 1 if the individual ends an existing job, 0 otherwise.
	jobre	Individual's job transition: defined as 1 if the individual starts or ends a job, 0 otherwise.
Core explanatory variable definitions	*chnbk*	Prefecture-level Bartik variable (based on China's industry robots)
	*eurobk*6	Prefecture-level Bartik instrumental variable (based on 6 European countries' industry robots)
	*eurobk*5	Prefecture-level Bartik instrumental variable (based on 5 European countries' industry robots)

3. Stylized Facts on China's Employment Status: Overview and Descriptive Analysis

3.1 Overview

The indicators used to measure employment reallocation at the prefecture-level regions are derived from the National Tax Survey Database (2010-2016), jointly administered by the State Taxation Administration and the Ministry of Finance. This annual survey covers more than 650,000 enterprises, including both key surveyed enterprises (80%) and randomly sampled firms (20%). The dataset spans large and medium-sized industrial firms, a wide range of small-scale service enterprises, and some individual businesses. Compared to datasets limited to above-scale industrial enterprises, it offers a more representative view of overall employment dynamics in China. The significant turnover of sampled firms across years prevents the database from forming a strict panel, making it impossible to track longitudinal employment changes within the same enterprise. However, it does report the number of employees at both the beginning and end of each year for each firm, providing a solid empirical basis for analyzing firm-level employment fluctuations.

Table 2 reports descriptive statistics from the 2010-2016 National Tax Survey of Enterprises. Based on more than 4.81 million firm-level observations, the data reveals substantial heterogeneity in both employment size and employment dynamics across firms. Notably, average employment per firm is significantly higher than the median, highlighting the skewed distribution of firm size. Across all industries, the average number of employees per firm per year is approximately 148, whereas the median is only 23. This indicates that while a small number of large firms employ many workers, the majority of firms are small or medium-sized with considerably fewer employees. Regarding employment dynamics, around 1.325 million firm-year observations (27.5% of the total) show an increase in end-of-year employment relative to the beginning of the year—indicating job creation. In contrast, about 1.088 million observations (22.5%) experienced employment declines—indicative of job destruction. Together, these figures suggest that approximately half of all firm observations experienced employment adjustments in a given year, while the remaining half remained stable. On average, firms that expanded employment added about 40 workers per year, while those that downsized lost about 36 workers annually. The median values for both job creation and destruction are much lower than the respective averages, underscoring that employment fluctuations are more significant among large firms compared to smaller ones.

By industry, other sectors (including agriculture, mining, construction, and gas/water/heat supply) exhibit significantly larger employment scales than manufacturing and services. The average annual employment per firm in these "other" industries exceeds 273 individuals, compared to 198 in manufacturing and 96 in services. The proportion of firms experiencing employment changes varies significantly across industries. In manufacturing, job creation and destruction observations account for over 64.7% of all samples, compared to 41.4% in services and 48.7% in other industries, indicating a higher rate of employment adjustments in manufacturing. For the average annual number of jobs created and lost per firm, manufacturing shows similar figures: approximately 45 new jobs and 43 lost jobs. In contrast, services and other industries exhibit greater job creation than loss. In services, average job creation is about 31 individuals, with destruction at 23 individuals. In other industries, average new jobs reach 69 individuals, with losses around 60 individuals. This suggests non-manufacturing firms drive employment growth more significantly than manufacturing firms.

Table 3 presents data on approximately 94,000 instances of individual-level employment and occupational transitions, aggregated at the prefecture-level , and derived from the China Labor-force Dynamics Survey (CLDS) conducted by Sun Yat-sen University. The data span the survey years 2012, 2014, 2016, and 2018, and capture information on the start and end dates of individual job spells. Prior to 2008, the number of individuals starting a new job exceeded those ending a existing job , although this gap showed a declining trend over time. However, since 2008, the number of individuals losing jobs began to outpace those finding new jobs , and the disparity between the two has widened steadily .

Table 2: Statistics on Enterprise Employment from Tax Survey Database (2010-2016)

Sector classification	Indicator	Observations	Mean	Median	Min.	Max.	Standard deviation
All sectors	Start-of-year employment	4815882	146.1	23	0	2103378	2654.1
	End-of-year employment	4817327	149.3	23	0	2121354	2699.8
	Average employment	4815255	147.7	23.5	0	2112366	2670.2
	Job creation	1325560	40.5	6	1	144800	597.9
	Job loss	1088665	35.6	5	1	93047	483.5
Manufacturing	Start-of-year employment	1660267	196.9	58	0	492530	1028.2
	End-of-year employment	1660825	199.3	58	0	533860	1070.8
	Average employment	1660224	198.1	59	0	513195	1028.2
	Job creation	570936	45.0	8	1	99576	580.9
	Job loss	503334	42.8	8	1	77905	453.8
Services	Start-of-year employment	2703212	94.2	12	0	2103378	3357.3
	End-of-year employment	2703937	97.2	12	0	2121354	3409.5
	Average employment	2702686	95.7	12.5	0	2112366	3379.7
	Job creation	631148	30.8	5	1	144800	568.0
	Job loss	488357	23.4	4	1	71998	445.1
Others	Start-of-year employment	452403	270.6	35	0	331664	1927.5
	End-of-year employment	452565	276.7	35	0	331664	1971.6
	Average employment	452345	273.6	35.5	0	331664	1930.9
	Job creation	123476	68.9	7	1	97077	791.8
	Job loss	96974	59.8	6	1	93047	745.5

Source: National Bureau of Statistics (NBS) Firm-Level Tax Survey Database. "Other industries" include agriculture, forestry, fishing, animal husbandry, mining, construction, and the supply of gas, heat, electricity, and water. To ensure data reliability, firms reporting implausibly high employment figures—those with more than 3 million employees at either the beginning or end of the year—were excluded as clear outliers. Furthermore, for firms with annual employment changes exceeding 100,000 people, we conducted detailed cross-checks using publicly available online information regarding employment and business activity. Most of these were found to be statistical errors and were accordingly removed from the dataset.

Table 3: China Labor-force Dynamics Survey (CLDS), 2012-2018

Sample	Job transition	2014-2018	2009-2013	2004-2008	2000-2004	Before 2000
Total	Start	7157	12160	9684	8039	35869
	End	9701	14898	8023	6256	9262
by gender						
Male	Start	3543	6164	4952	4231	18899
	End	4254	6686	3405	2657	4926
Female	Start	3535	5960	4695	3766	16823
	End	5355	8177	4591	3578	4303
by level of education						
Junior middle school and below	Start	4174	6715	5718	5158	26765
	End	6388	9348	5174	4173	6524
Technical secondary school / High school / Vocational college	Start	2247	4093	2993	2205	7802
	End	2767	4582	2447	1802	2468
Bachelor's degree and above	Start	729	1316	943	650	1201
	End	527	906	382	254	234

Table 3 Continued

Sample	Job transition	2014-2018	2009-2013	2004-2008	2000-2004	Before 2000
by job type						
Leaders and managers in government agencies and enterprises	Start	110	109	80	66	222
	End	108	72	54	38	64
Professionals and technical personnel	Start	626	1022	631	463	1650
	End	647	858	454	312	385
Clerical and related workers	Start	304	612	380	270	712
	End	302	424	227	162	134
Social and production service workers	Start	3129	3752	2362	1813	3700
	End	3207	2779	1495	1108	1056
Agricultural, forestry, animal husbandry, Fishery production and support personnel	Start	918	1031	917	1040	14222
	End	2043	2418	1037	765	1200
Production and manufacturing and related workers	Start	1867	3078	2449	2012	6580
	End	2933	3366	2266	1844	3000

Source: Sun Yat-sen University , China Labor-force Dynamics Survey (CLDS).

Distribution by individual characteristics: Both men and women exhibit the aforementioned trends, though men show a clear and consistent employment advantage. Between 2000 and 2008, the number of men starting new jobs significantly exceeded those losing jobs. In contrast, for women, the number of job starts and job losses remained relatively close. After 2008, the disparity widened: women were notably more likely to lose jobs than to find new ones, and their employment outcomes lagged further behind those of men.

Distribution by educational attainment: Higher education confers a distinct employment advantage over lower education levels. From 2000 to 2008, individuals with a junior high school education or below typically started slightly more new jobs than they lost, though the figures were close. After 2008, this group experienced a sharp increase in job losses, clearly surpassing job gains. Among individuals with a mid-level education, job losses also exceeded new job starts after 2008, but the difference remained modest. In contrast, individuals with higher education consistently started more new jobs than they lost, both before and after 2008, with the employment advantage being especially significant in the pre-2008 period.

Distribution by occupational category: The most evident shifts in the balance between new jobs gained and jobs lost occurred among agricultural, forestry, animal husbandry, fishery and sideline production workers, as well as manufacturing personnel. For other occupational categories, new job starts generally exceeded job losses before 2014, with a small gap between job starts and losses from 2014 to 2018. However, for agriculture, forestry, animal husbandry, and fishery workers, job losses began to outpace job starts as early as 2004, with the gap widening thereafter. Between 2014 and 2018, job losses in this sector were more than double job starts. Similarly, for production and manufacturing personnel, job losses exceeded job starts after 2008, with a small initial gap that grew significantly after 2014, when job losses far surpassed job gains.

3.2 Other Data Sources and Explanations

Robot installation data for constructing the industrial robot Bartik variable and its instrumental variables are sourced from the International Federation of Robotics. Employment statistics for Chinese prefecture-level by industry are obtained from the *China City Statistical Yearbook*. Industry-level employment data for the 11 EU countries are sourced from the EU KLEMS database. All other city-level data are drawn from the *China City Statistical Yearbook*, covering 1985-2021.

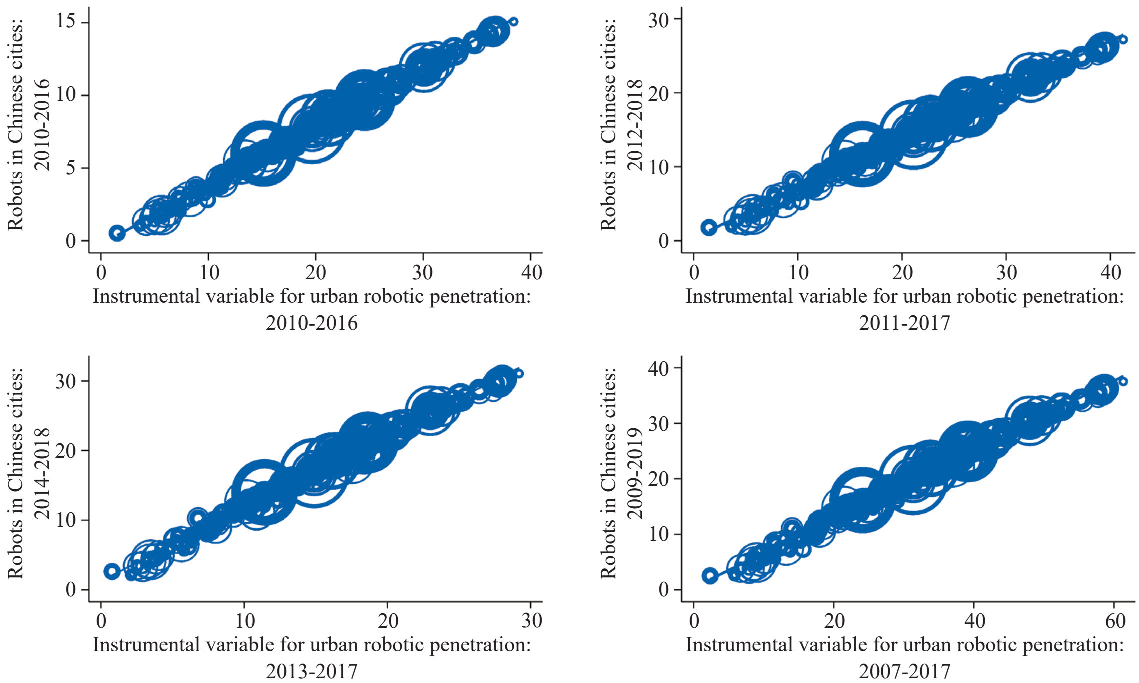

Figure 3: Changes in Robot Penetration in Chinese Cities vs. Six European Countries

Figure 3 illustrates the relationship between the robot Bartik variable for 296 Chinese prefecture-level cities and the Bartik instrumental variable constructed using robot adoption data from six industrialized European countries. The scatter plots show the endogenous variable plotted against the instrumental variable, weighted by each city's baseline employment size across different time periods. The plots reveal a strong correlation between robot penetration at the prefectural level cities in China and the Bartik instrumental variable. This indicates that the instrument—based on robot adoption trends in the six European economies—effectively predicts changes in robot penetration across Chinese prefecture-level cities over time. A similar pattern is observed when using Bartik instruments constructed from five of the European countries, with trends and characteristics closely aligned with those shown in Figure 3.

4. Empirical Results and Explanation

4.1 Empirical Results from Aggregated Firm-Level Data

This section begins by using China's firm-level tax survey data to calculate employment change rates from 2010 to 2016 at the prefecture level cities for all surveyed firms across three broad sectors: manufacturing, services, and other industries. It also computes, at the same level, the change of job creation, job destruction, net employment , gross job reallocation, and net job reallocation based on incumbent firms. To examine the impact of industrial robot adoption on job market reallocation in China, we employ Bartik instrumental variables constructed from robot adoption patterns in eleven EU countries. Table 4 presents the results from two-stage least squares regressions using instrumental variables.

Column (1) uses the overall employment growth rate of all firms as the dependent variable. Both the two-stage and reduced-form regression coefficients are significantly negative at the 1% level, indicating that greater robot penetration significantly suppresses overall employment growth at the regional level.

According to the IV regression, a 1% increase in robot penetration is associated with approximately a 1% decline in employment growth—suggesting that industrial robots have a strong displacement effect on aggregate employment.

Columns (2) through (6) focus on incumbent firms to explore the reallocation effects of robot adoption. The regression results from both the two-stage estimations (Panel 1) and the reduced-form regressions (Panel 3) are consistent in both direction and statistical significance. In Column (2), coefficients are significantly negative at the 5% level, indicating that higher robot penetration significantly reduces job creation among incumbent firms. The estimates suggest that a 1 percentage point increase in robot penetration leads to a 0.8% decline in job creation.

Column (3) also yields coefficients that are significantly negative at the 1% level, showing that rising robot penetration substantially decreases job destruction among incumbent firms. Specifically, a 1% increase in robot penetration corresponds to roughly a 2%decline in the job destruction rate. Clearly, the reduction in job destruction exceeds the decline in job creation, indicating that robot adoption improve net employment growth for overall incumbent firms.Column (4) presents coefficients that are significantly positive at least at the 10% level, confirming that increased robot penetration promotes net employment growth among incumbent firms. The two-stage regression suggests that a 1% increase in robot penetration raises the net employment growth rate by approximately 0.88%.

Table 4: Automation on Job Reallocation (2SLS)

Panel 1	All firms	Incumbent firms				
	(1)	(2)	(3)	(4)	(5)	(6)
Explained variable	$\Delta ANET$	ΔJC	ΔJD	ΔNET	ΔREA	ΔNEA
chnbk	-1.024*** (0.373)	-0.796** (0.352)	-1.981*** (0.579)	0.877** (0.443)	-1.135** (0.456)	-1.874*** (0.408)
Base period control variables	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	741	739	741	739	741	739
Number of cities	247	247	247	247	247	247
Panel 2	First-stage estimated results (First_Stage)					
First-stage coefficient	0.437					
Kp.F value	29905.3	29817.9	29905.3	29817.9	29905.3	29817.9
Hansen J Ovid. (probability value)	1.147 (0.284)	1.679 (0.195)	0.050 (0.823)	0.150 (0.699)	0.028 (0.866)	1.921 (0.166)
Panel 3	Reduced-form estimated results (OLS-ITT)					
Explained variable	$\Delta ANET$	ΔJC	ΔJD	ΔNET	ΔREA	ΔNEA
*eurobk*6	-0.431*** (0.154)	-0.341** (0.151)	-0.822*** (0.241)	0.359* (0.189)	-0.471** (0.190)	-0.790*** (0.174)
Calibrated R^2	0.254	0.254	0.254	0.254	0.254	0.254
*eurobk*5	-0.443*** (0.162)	-0.346** (0.155)	-0.853*** (0.252)	0.376* (0.194)	-0.489** (0.198)	-0.812*** (0.179)
Calibrated R^2	0.233	0.149	0.162	0.068	0.133	0.255
Base period control variables	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	741	739	741	739	741	739
Number of cities	247	247	247	247	247	247

Note: Robust standard errors, clustered at the city level, are reported in parentheses. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively. The two-stage estimation simultaneously uses Bartik instrumental variables constructed from six European countries (eurobk6) and five European countries (eurobk5). The first-stage coefficient reflects the sum of the estimated coefficients for the two instruments.

Columns (2) and (3) of Table 4 report significantly negative coefficients, indicating that higher regional robot penetration not only reduces potential job creation but also significantly lowers job destruction among incumbent firms. Moreover, the reduction in job destruction is larger in magnitude than the reduction in job creation. This suggests that while robot adoption may displace some potential employment opportunities, it also likely improves productivity within incumbent firms. At the aggregate regional level, this productivity enhancement may effectively offset the substitution effect on existing jobs.

Columns (1) and (4) of Table 4 estimate the impact of regional robot penetration on employment growth for all firms and for incumbent firms, respectively. The results show a significant negative effect on employment growth among all firms, but a significant positive effect for incumbent firms. This contrast is primarily explained by the employment growth decomposition discussed in Section 2. Specifically, overall employment growth for all firms reflects two components: changes in employment among incumbent firms and the effects of robot penetration on firm entry and exit. The findings suggest that the job displacement effect caused by changes in firm entry and exit due to rising robot penetration is larger than the net employment gains within incumbent firms.

Incumbent firms that adopt robots tend to be more productive. Widespread adoption of robotics likely enhances their productivity further, creating barriers to entry for new firms and pushing out less competitive rivals. This dynamic enables incumbent firms to expand their market share and employment. Such a mechanism is consistent with evidence from firm-level studies in other countries (Acemoglu et al., 2022; Koch et al., 2021).

Robot adoption leads to declines in both job creation and job destruction among incumbent firms, indicating reduced overall labor mobility at the regional level—fewer new employment opportunities and lower job exit rates. As a result, both gross and net labor reallocation growth rates for incumbent firms decline. This conclusion is supported by the results in Columns (5) and (6) of Table 4, where the estimated coefficients are significantly negative at the 5% level or lower. Column (5) reflects the gross reallocation effect, while Column (6) captures the net reallocation effect. The coefficients indicate that a 1% increase in industrial robot penetration reduces the gross labor reallocation growth rate for incumbent firms by approximately 1.1% and the net reallocation growth rate by around 1.9% .

Furthermore, the first-stage results in Panel 2 of Table 4 demonstrate the strength and validity of the instrumental variables. Both the Hansen J overidentification test and the Kp.F statistic confirm that the two Bartik instruments used in this study are robust and well-specified.

Table 5 shows the impact of regional robot penetration on employment reallocation across different industries. The two-stage least squares (2SLS) estimates in Panel 1 examine the impact of robot penetration on employment dynamics within the manufacturing sector. The results show that increased industrial robot adoption significantly reduces overall employment growth in manufacturing. Moreover, robot penetration has statistically significant negative effects on both job creation and job destruction among incumbent firms, with a larger and more statistically significant effect on job destruction.

Specifically, a 1% increase in robot penetration leads to a decline of approximately 0.75% in the job creation growth rate, while reducing the job destruction growth rate by about 1.6 %. Since the decline in job destruction exceeds the decline in job creation, robot adoption tends to generate a net employment gain among incumbent manufacturing firms. Column (4) provides further evidence, showing that increased robot penetration is associated with a positive—albeit statistically insignificant—effect on net employment growth for incumbent firms in manufacturing.

However, despite reducing job destruction among incumbent firms, robot adoption still has a significant negative impact on overall employment growth across all manufacturing firms. This suggests that the displacement effect—mainly driven by firm entry and exit—is more substantial than the productivity-induced gains among incumbents. Additionally, Columns (5) and (6) present coefficients that are significantly negative at the 5% level or lower, indicating that robot adoption also reduces labor mobility within the manufacturing sector at the regional level. This reflects a decline in both gross and net job reallocation.

Table 5: Automation and Labor Market Reallocation by Industries (2010-2016)

Panel 1: Manufacturing						
	Total firms	Incumbent firms				
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\Delta ANET$	ΔJC	ΔJD	ΔNET	ΔREA	ΔNEA
chnbk	-1.119** (0.419)	-0.753** (0.372)	-1.624** (0.660)	0.434 (0.596)	-1.103** (0.499)	-1.427** (0.476)
First-stage coefficient	0.437					
Kp.F value	28315.8	28049.8	28315.8	28049.8	28315.8	28049.8
Hansen J Ovid. (Probability value)	0.203 (0.652)	0.200 (0.655)	0.348 (0.555)	0.000 (0.991)	1.031 (0.310)	0.032 (0.858)
Calibrated R^2	0.040	0.031	0.088	0.085	0.023	0.108
Panel 2: Service sector						
Dependent variable	$\Delta ANET$	ΔJC	ΔJD	ΔNET	ΔREA	ΔNEA
chnbk	-0.882** (0.343)	-1.853*** (0.478)	-1.675** (0.710)	-0.179 (0.681)	-1.528** (0.516)	-2.146*** (0.600)
First-stage coefficient	0.437					
Kp.F value	28315.8	28049.8	28315.8	28049.8	28315.8	28049.8
Hansen J Ovid. (Probability value)	0.104 (0.748)	0.007 (0.933)	0.267 (0.605)	0.231 (0.630)	0.004 (0.950)	0.810 (0.368)
Calibrated R^2	0.107	0.065	0.016	0.045	0.010	0.072
Panel 3: Other sectors						
Dependent variable	$\Delta ANET$	ΔJC	ΔJD	ΔNET	ΔREA	ΔNEA
chnbk	-1.070** (0.526)	0.267 (0.791)	-2.644** (0.911)	2.373** (0.859)	-0.773 (0.849)	-2.038** (0.671)
First-stage coefficient	0.437					
Kp.F value	28315.8	28049.8	28315.8	28049.8	28315.8	28049.8
Hansen J Ovid. (Probability value)	1.887 (0.169)	3.373 (0.066)	0.258 (0.612)	0.844 (0.358)	0.878 (0.349)	4.289 (0.038)
Calibrated R^2	0.084	0.016	0.122	0.060	0.038	0.134
Base period control variables	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes
Observations	247	246	247	246	247	246
Number of cities	247	246	247	246	247	246

Note: Same as Table 4.

Panel 2 of Table 5 presents the impact of changes in robot penetration on employment reallocation within the service sector. Column (1) reports a negative coefficient significant at the 5% level, indicating that increased robot penetration exerts a significant displacement effect on service sector employment—similar to the effect observed in manufacturing. Based on the regression coefficient, a 1% increase in robot penetration is associated with a decline of approximately 0.9% in the overall employment growth rate of the service sector, slightly lower than the 1.1 percentage point decrease observed in manufacturing. Columns (2) and (3) further show that rising robot penetration significantly reduces both job creation and job destruction growth rates among incumbent firms in the service sector. In contrast to manufacturing—where the impact on job destruction is more evident—the effects in the service sector are relatively balanced. Specifically, a 1% increase in robot penetration is associated with a 1.8% decline in job creation growth and a 1.7% decline in job destruction growth. Consequently, the net employment effect for incumbent service firms is very small.

This implies that robot adoption exerts a greater suppressive effect on job creation in the service sector than in manufacturing, resulting in a more substantial negative impact on employment reallocation. Columns (5) and (6) support this, showing that a 1% increase in robot penetration reduces the gross employment reallocation growth rate by about 1.5 percentage points and the net reallocation growth rate by approximately 2.1 percentage points. The underlying reasons are twofold: first, the employment substitution shock caused by large-scale robot adoption in manufacturing tends to spill over into the service sector and other industries, amplifying the initial labor market impact of automation. Second, the service sector employs a much larger and more densely concentrated workforce than manufacturing, making it more elastic and therefore more vulnerable to technological shocks from robotics (Faber et al., 2022).

Panel 3 of Table 5 presents the impact of changes in robot penetration on employment dynamics in other industries, including agriculture, mining, construction, and utilities (gas, heat, electricity, and water supply). The estimation results indicate that increased robot penetration significantly reduces overall employment growth in these sectors—consistent with the effects observed in both manufacturing and services, and of comparable magnitude. However, unlike in those sectors, robot penetration does not have a statistically significant impact on job creation among incumbent firms in these industries; in fact, the estimated coefficient is positive. In contrast, it significantly reduces job destruction. The coefficient in Column (3) is negative and statistically significant at the 1% level, indicating a strong dampening effect on job destruction. Specifically, a 1% increase in robot penetration leads to a 2.6 percentage point reduction in the job destruction growth rates substantially larger than the corresponding effects in manufacturing and services.

As a result, rising robot penetration significantly enhances net employment growth for incumbent firms in other industries. Column (4) shows that a 1% increase in robot penetration is associated with an approximate 2.4 percentage point increase in net employment growth. This suggests that labor displaced by automation in manufacturing and services is being reallocated into sectors with relatively low robot penetration. The significant net labor inflow into incumbent firms in these industries reflects a clear pattern of cross-sectoral labor reallocation.

In summary, our industry-specific estimates indicate that rising regional robot penetration has a significant substitution effect not only on manufacturing employment but also on overall employment in the service sector and other industries (agriculture, mining, construction, and utilities such as gas, heat, electricity, and water supply). At the level of incumbent firms, the suppressive effect of robot penetration on job creation is particularly significant in the service sector. Additionally, robot adoption more strongly hinders within-region labor mobility in services compared to other sectors. These findings suggest that, in response to the shock from robot adoption, labor in both manufacturing and services tends to reallocate toward other industries with lower levels of automation, contributing to cross-sectoral employment reallocation.

To further investigate the heterogeneous effects of robots on employment across more detailed industry segments, we introduce interaction terms between robot penetration rates and fine-grained industry dummy variables. This approach allows us to examine industry-specific variations in how robot adoption influences employment growth[3].

[3] Detailed results will be provided upon request.

4.2 Mechanism and Robustness Checks

Our empirical results reveal that increased robot penetration exerts contrasting effects on employment growth: a significant negative impact when considering all firms, but a positive effect for incumbent firms. This pattern suggests that the negative influence of robots on overall employment growth—largely driven by firm entry and exit dynamics—substantially outweighs their positive effect on employment growth within continuing firms. Nonetheless, this proposed mechanism warrants further empirical check.

Table 6 examines the effects of changes in robot penetration on firm entry and exit rates, as well as employment fluctuations arising from sample composition changes and cross-period adjustments in employment among continuously operating firms.

Thanks to the 2010 and 2016 firm-level tax survey data including exact founding dates for each firm. By aggregating these, we obtained the number of newly established (newly entering) firms in different prefecture-level cities for both years, enabling us to examine the relationship between changes in robot penetration and the growth rate of new firm entry. Since the tax survey database does not provide direct indicators for firm exit, we approximate firm exit indicator by identifying firms with zero employees at year-end and investigate the impact of robot penetration on firm exits accordingly.

Regression results in Column (1) of Table 6 show that, whether using two-stage least squares or reduced-form estimates, all coefficients are negative and statistically significant at least at the 5% level. This indicates that a 1% increase in regional robot penetration reduces the new firm entry growth rate by approximately 1.6% . Columns (2) to (5) examine the effects of increased robot penetration on firm exit, employment growth changes caused by sample adjustments, and employment changes due to cross-period adjustments in continuing firms. All estimated coefficients are negative but statistically insignificant, with elasticities much smaller than those for new firm entry growth. This further confirms that the negative impact of robot penetration on overall firm employment growth is mainly driven by the suppression of new firm entry, rather than by the exit of incumbent firms or other channels.

Table 6: Mechanism Test of Automation on Employment Growth (2SLS)

	New firm entry	Firm exit	Sample adjustment	Cross-period adjustment	Entry/exit
	(1)	(2)	(3)	(4)	(5)
Dependent variable	$\Delta Entry$	$\Delta Exit$	ΔNet_ADJ	ΔNet_Inc	$\Delta EnEx$
Panel 1: Two-Stage Least Squares Estimation (2SLS)					
chnbk	-1.651**	-0.120	-0.582	-0.509	-1.410**
	(0.599)	(0.308)	(0.388)	(0.328)	(0.468)
First-stage coefficient	0.437				
Kp F value	22841.6	29905.3	29905.3	22920.3	27044.5
Hansen J Overid	0.594	0.019	1.661	0.002	0.120
(probability value)	(0.441)	(0.890)	(0.197)	(0.967)	(0.729)
Panel 2: Reduced-Form Estimation					
*eurobk*6	-0.692**	-0.048	-0.252	-0.208	-0.586**
	(0.251)	(0.131)	(0.162)	(0.139)	(0.196)
*eurobk*5	-0.712**	-0.051	-0.254	-0.217	-0.607**
	(0.263)	(0.135)	(0.169)	(0.144)	(0.205)
Base period control variables	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Observations	532	741	741	558	598
Number of cities	229	247	247	238	243
Calibrated R^2	0.20	0.55	0.23	0.03	0.36

Note: Same as Table 4.

This implies that widespread robot adoption may significantly strengthen incumbent firms' advantages and inhibit new firm entry. Since new firms are a key driver of employment growth and labor mobility, this suggests that large-scale robot adoption substantially restricts new firm entry, thereby notably reducing labor reallocation at the regional level.

To further clarify the overall impact of robot adoption on labor reallocation, Column (6) of Table 6 presents the aggregate effects of robot penetration on firm entry and exit. The regression coefficient remains negative and statistically significant at the 5% level, indicating that greater robot penetration significantly reduces both firm entry and exit rates. Taken together with the earlier analysis, these results suggest that robot adoption not only weakens reallocation dynamics among incumbent firms but also dampens overall levels of firm turnover. Since firm entry and exit are key mechanisms driving labor market reallocation, this implies that the adoption of industrial robots significantly reduces labor mobility at the regional level in China. This conclusion is consistent with empirical findings based on Chinese population census sample data (Chen et al., 2022), and it also aligns with evidence on the impact of industrial robots on labor markets in U.S. commuting zones (Acemoglu & Restrepo, 2020; Faber et al., 2022).

To assess the robustness of the above empirical findings, this study further examines the relationship between robot penetration and employment growth using longer-term aggregate employment data (1999-2019) at the prefecture-level cities[4]. Table 7 presents the empirical results based on city-level data. Since the Bartik estimation strategy essentially operates as a difference-in-differences method with a continuous treatment variable, it can also be used to test whether changes in robot penetration affect pre-treatment employment trends—serving as a placebo test.

Columns (1) through (3) of Table 7 use employment growth rates from 2004 to 2010 at the prefecture level as the dependent variable. Both the two-stage and reduced-form regression estimates yield coefficients that are statistically insignificant and close to zero, suggesting that robot penetration changes during 2011-2017 had no effect on pre-trend employment growth. Columns (4) through (6) of Table 7 use employment growth rates from 2013 to 2019 as the dependent variable, while controlling for city-level trends in employment, population, wages, and fixed asset investment from 2000 to 2010. All estimated coefficients are negative and statistically significant at the 5% level. The two-stage estimate in Column (4) indicates that a 10% increase in robot penetration leads to an approximate 2 % reduction in regional employment growth. These results are fully consistent with the earlier findings based on aggregated firm-level data, further supporting the conclusion that robot adoption exerts a significantly negative effect on regional employment growth in China. Together, the results in Tables 6 and 7 suggest that sample selection is not a major factor driving the observed adverse impact of increased robot penetration on overall employment growth.

Although the firm tax survey data used in this study are carefully cleaned, a small number of firm-level observations still showed exceptionally large employment adjustments. For instance, between 2010 and 2016, 651 firm-year observations reported annual employment changes exceeding 10,000 employees, 197 exceeded 50,000, and 119 exceeded 100,000. To assess whether such extreme values—potentially stemming from unusually large firms or statistical reporting errors—might bias our results, we excluded observations with annual employment changes greater than approximately 10,000, 50,000, and 100,000 employees, respectively, and re-estimated the key regressions.

The revised results showed only slight changes in the estimated coefficients, and the main

[4] Relevant data from the *China City Statistical Yearbook* (2021-2023) were also consulted, revealing that comprehensive city-level employment indicators were not published for the years 2020-2022. Given the potential confounding effects and uncertainties brought about by the COVID-19 pandemic, restricting the sample period to the pre-pandemic period is more conducive to identifying the true impact of robot adoption on the labor market.

Table 7: Automation and Employment Growth: Empirical results from City-Level Data

	(1)	(2)	(3)	(4)	(5)	(6)
Estimate method	2SLS	OLS	OLS	2SLS	OLS	OLS
Dependent variable	$\Delta ANET_{c,2004\text{-}2010}$			$\Delta ANET_{c,2013\text{-}2019}$		
$chnbk_{c,2011\text{-}2017}$	-0.014 (0.062)			-0.201** (0.069)		
$eurobk6_{c,2011\text{-}2017}$		-0.009 (0.044)			-0.134** (0.048)	
$eurobk5_{c,2012\text{-}2018}$			-0.009 (0.042)			-0.129** (0.047)
$\Delta ANET_{c,2000\text{-}2010}$				0.037 (0.031)	0.029 (0.030)	0.031 (0.030)
$\Delta Pop_{c,2000\text{-}2010}$				0.212** (0.087)	0.212** (0.090)	0.213** (0.090)
$\Delta Wage_{c,2000\text{-}2010}$				0.106 (0.080)	0.101 (0.083)	0.101 (0.083)
$\Delta FC_{c,2000\text{-}2010}$				-0.018 (0.023)	-0.020 (0.024)	-0.021 (0.024)
First-stage estimated coefficient	0.437			0.437		
Kp.F value	3339.0			4099.0		
Hansen J Ovid. (Probability value)	0.001 (0.998)			2.049 (0.152)		
Base period control variables	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	244	244	244	242	242	242
Observations	244	244	244	242	242	242
Number of cities	0.300	0.301	0.301	0.109	0.108	0.107

Note: Same as Table 4.

conclusions remained robust. Importantly, the statistical significance of the coefficient on net employment growth among incumbent firms improved, rising from the 10% to the 5% level. Therefore, we conservatively report the results using the more stringent significance threshold.

4.3 Further Evidence from Micro-Level Data

The previous empirical findings primarily focused on investigating the macro-level effects and mechanisms of regional robot penetration on labor reallocation. However, direct evidence on how robot adoption influences micro-level employment outcomes—such as individual employment status or occupational transitions—remains limited. Moreover, the heterogeneous effects on different types of individuals and transitions are not yet well understood.

Using data from the China Labor-force Dynamics Survey (CLDS), this study further investigates the impact of regional robot penetration on micro-level individual work transitions by tracking individuals' job-switching frequencies across different time intervals. Table 8 presents the baseline results derived from this micro-level analysis. As the 2012 CLDS lacked detailed occupational transition data, though it did include job change indicators —we focus on the period 2014-2018 to ensure consistency in the transition indicators. Panel 1 reports the baseline 2SLS estimation results using a Bartik-style instrumental variable constructed from robot adoption patterns in European countries. Column (1)

Table 8: Automation and Occupational Transitions: Evidence from CLDS Data (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	*jobst*	*jobed*	*jobre*	*jobst*	*jobst*	*jobed*	*jobed*
Timeframe	2014-2018	2014-2018	2014-2018	2000-2012	Before 2000	2000-2012	Before 2000
Panel 1: Industrial robots and occupational transitions: 2sls estimates							
$chnbk_{2013(2011)\text{-}2017}$	-0.034**	-0.039**	-0.061**	0.015	0.005	0.008	0.012
	(0.012)	(0.019)	(0.024)	(0.030)	(0.048)	(0.029)	(0.020)
First-stage estimated coefficient	1.038			0.647			
Kp. F value	2059.6			1132.1			
Hansen J Overid	0.166	1.527	0.357	3.058	0.167	0.312	0.043
(Probability value)	(0.683)	(0.216)	(0.550)	(0.080)	(0.683)	(0.576)	(0.837)
Panel 2: Industrial robots and occupational transitions: reduced-form estimates							
$eurobk6_{2013\text{-}2017}$	-0.034**	-0.044**	-0.066**	0.009	0.004	0.005	0.008
	(0.013)	(0.019)	(0.025)	(0.020)	(0.032)	(0.019)	(0.013)
$eurobk5_{2013\text{-}2017}$	-0.034**	-0.045**	-0.066**	0.010	-0.003	0.005	0.007
	(0.013)	(0.019)	(0.025)	(0.020)	(0.031)	(0.019)	(0.013)
Individual-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	51,991	51,991	51,991	51,991	51,991	51,991	51,991
Number of cities	141	141	141	141	141	141	141
Calibrated R^2	0.108	0.108	0.108	0.108	0.108	0.108	0.108

Note: Consistent with Table 4, Columns (1)-(3) employ instrumental variables constructed using 2013-2017 data, while Columns (4)-(7) use instruments based on data from 2011-2017.

examines the effect of robot penetration on the probability of an individual starting a new job. The estimated coefficient is negative and statistically significant at the 5% level, indicating that increased robot penetration significantly reduces the likelihood of job entry. Specifically, a 1% increase in regional robot penetration is associated with a 3.4 % decline in the probability of starting a new job.

Column (2) analyzes the impact on the probability of job loss. The coefficient is likewise negative and significant at the 5% level, suggesting that higher robot penetration reduces the likelihood of individuals losing their jobs. A 1% increase in robot penetration leads to an approximate 4 percentage point decline in the probability of job separation. Column (3) investigates the effect on occupational transitions. The result is again a negative and significant coefficient at the 5% level, showing that a 1% increase in robot penetration is linked to a roughly 6 % decrease in the probability of switching occupations. These micro-level findings are highly consistent with our earlier macro-level evidence. Robot penetration appears to reduce labor mobility through both direct and indirect channels: it directly lowers job creation via displacement effects, while also reducing job destruction through productivity-driven complementarity effects. As a result, overall labor mobility and job turnover rate decline significantly.

To further assess the robustness of the empirical findings, we conducted a placebo test by examining the effect of robot penetration on pre-treatment individual work transitions. Specifically, Columns (4) and (5) of Table 8 analyze the impact of changes in robot penetration from 2012 to 2018 on the probability that individuals started a new occupation during the periods 2000-2012 and before 2000, respectively. Columns (6) and (7) evaluate the corresponding effect on the probability of losing an existing occupation during these same time intervals. Across all four regressions, the estimated coefficients are statistically insignificant and close to zero, consistent with the placebo test results from Table 7 using pre-treatment city-level employment growth rates as dependents.

Panel 2 of Table 8 reports reduced-form regressions using two alternative sets of Bartik instrumental variables—constructed from industrial robot adoption in European countries, respectively. The estimated coefficients and their statistical significance remain consistent with those reported in Panel 1, confirming the reliability of the results. Whether at the macro (city) level or the micro (individual) level, the evidence consistently shows that increased robot penetration does not enhance regional labor reallocation. On the contrary, it significantly reduces overall labor mobility and job turnover rates.

4.4 Heterogeneity

As emphasized in the introduction, the impact of robot penetration on individual job transitions may vary systematically by individual characteristics such as skills, occupation, age, and gender. To explore these potential sources of heterogeneity, we examine how changes in robot penetration affect job transition probabilities across different demographic and occupational groups. For clarity and conciseness, all heterogeneity analyses are conducted using reduced-form OLS estimations with instrumental variables.

Table 9: Automation and Job Reallocation: Age Heterogeneity

	(1)	(2)	(3)	(4)	(5)	(6)
Timeframe	2014-2018	2014-2018	2012-2018	2014-2018	2012-2018	2014-2018
Panel 1: Industrial robot adoption and new job creation (*jobst*)						
*eurobk*6	-0.038*** (0.013)	-0.027* (0.014)	-0.030** (0.018)	-0.039** (0.015)	-0.038** (0.015)	-0.040*** (0.014)
$Age_{15\text{-}25}$	0.145*** (0.038)					
$eurobk6 \times Age_{15\text{-}25}$	0.034* (0.020)					
$Age_{26\text{-}50}$		0.057*** (0.013)	0.079*** (0.016)			
$eurobk6 \times Age_{26\text{-}50}$		-0.026*** (0.008)	-0.022*** (0.008)			
$Age_{51\text{-}70}$				-0.076*** (0.015)	-0.107*** (0.021)	
$eurobk6 \times Age_{51\text{-}70}$				-0.000 (0.010)	-0.001 (0.010)	
Age_{70+}						-0.055** (0.026)
$eurobk6 \times Age_{70+}$						0.006 (0.017)
Calibrated R^2	0.087	0.059	0.075	0.072	0.094	0.059
Panel 2: Industrial robot adoption and job loss (*jobst*)						
Timeframe	2014-2018	2014-2018	2012-2018	2014-2018	2012-2018	2014-2018
*eurobk*6	-0.044** (0.020)	-0.032 (0.021)	-0.015 (0.022)	-0.062** (0.026)	-0.030 (0.023)	-0.047** (0.021)
$Age_{15\text{-}25}$	0.164*** (0.037)					
$eurobk6 \times Age_{15\text{-}25}$	-0.015 (0.022)					
$Age_{26\text{-}50}$		0.000 (0.013)	-0.009 (0.016)			

Table 9 Continued

$eurobk6 \times Age_{26\text{-}50}$		-0.031*** (0.007)	-0.018** (0.007)			
$Age_{51\text{-}70}$				-0.036** (0.018)	-0.029 (0.019)	
$eurobk6 \times Age_{51\text{-}70}$				0.032*** (0.011)	0.015* (0.008)	
Age_{70+}						0.001 (0.036)
$eurobk6 \times Age_{70+}$						-0.031 (0.024)
Calibrated R^2	0.041	0.035	0.028	0.031	0.025	0.030
Individual-level control variables	Yes	Yes	Yes	Yes	Yes	Yes
City-level control variables in base period	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,063	52,063	52,063	52,063	52,063	52,063
Number of cities	141	141	141	141	141	141

Note: Same as Table 4.

Table 9 first examines the relationship between age and the impact of industrial robots on micro-individual job transitions. Panel 1 investigates how industrial robots affect an individual's probability of starting a new job across different age cohorts. This paper categorizes individuals into four age groups: Youth (15-25 years), young to middle-aged adults (26-50), older working-age adults (51-70), and seniors (over 70), each represented by a dummy variable. By using interaction terms between robot penetration and these age group dummy variables, we examine the influence of robot adoption on the likelihood of individuals in different age stages starting new jobs.

The estimation results from Columns (1) through (6) show that after controlling for interaction terms and age, the estimated coefficients for robot penetration remain significantly negative at least at the 5% level. The estimated age parameters are significantly positive for the youth and young to middle-aged adult groups but significantly negative for older working-age adults and seniors. This indicates that youth and young to middle-aged adults have a significantly higher probability of starting new jobs compared to older working-aged adults and seniors, which aligns with intuition and real-world observations.

The interaction terms are of particular interest here. The estimation results show that only the interaction terms in Columns (2) and (3) are significantly negative, while those for other age groups are not statistically significant, especially for the older working-age adults and seniors, where coefficients are essentially zero. This means that increased robot penetration significantly reduces the probability of individuals in the middle age range starting new jobs compared to other age groups.

From a demand-side perspective, this pattern reflects a stronger displacement effect of robots on middle-aged workers, who typically occupy positions more vulnerable to automation. From a supply-side viewpoint, this group may prioritize job stability when faced with automation risk, thereby exhibiting lower job mobility. To ensure robustness, regressions are conducted using two different sample periods—2012-2018 and 2014-2018—with consistent findings: interaction term coefficients remain negative and statistically significant at the 5% level or lower. This empirical finding aligns perfectly with the theoretical and empirical conclusions of Acemoglu & Restrepo (2022) regarding aging and robot adoption. They posit that aging significantly promotes robot adoption, with robots primarily serving to compensate for labor shortages among middle-aged workers and also demonstrating the strongest tendency to substitute middle age group.

Panel 2 in Table 9 continues to examine the relationship between age, robot penetration, and the probability of individual job loss. Similar to the estimation results in Panel 1, the coefficients for the interaction terms in Columns (2) and (3) remain significantly negative at least at the 5% level. This likewise indicates that increased robot penetration significantly reduces the probability of individuals in the middle age range losing their jobs relative to other age groups. This means that while robot penetration may displace potential job opportunities for the middle age range group, it also stabilizes the job market by expanding output through productivity gains, thereby reducing the probability of existing middle-aged individuals losing their jobs.

However, the estimated coefficient for the interaction term defining employment changes in Column (4) (using the 2014-2018 time interval) is positive and significant at the 1% level. Similarly, the estimated coefficient for the interaction term defining job changes in Column (5) (using the 2012-2018 time interval) is also positive and significant at the 10% level. Given that the robot penetration's own estimated parameter is significantly negative, the positive regression parameter of the interaction term implies that the increase in robot penetration is less effective in reducing job loss for older working-age adults. This likely has a strong correlation with the greater susceptibility of older working-age adults to skill and job demand mismatches. The interaction parameters in Columns (1) and (6) are not significant.

The regression results in Table 9 show that the impact of changes in robot penetration on individual work transitions has a significant relationship with the proportion of the middle age group. The widespread adoption of robots significantly reduces the probability of work transitions for the middle age group.

Table 10 further examines how the effect of robot penetration on job transitions varies with individuals' educational attainment. Education is divided into three categories: low (junior high school and below), medium (vocational school, high school, and junior college), and high (bachelor's degree and above), each represented by a dummy variable. Interaction terms between robot penetration and education level dummies are introduced to assess whether individuals with different educational backgrounds are differentially affected in terms of starting or losing jobs. Columns (1) and (2) test whether the effect of robot penetration on the probability of starting a new job differs for individuals with low and medium education relative to other groups. The estimated coefficients of the interaction terms are statistically insignificant, suggesting that changes in robot penetration do not significantly alter the probability of low- or medium-educated individuals starting new jobs compared to others.

Column (3), using data from the 2012-2018 period, examines whether robot penetration affects highly educated individuals' likelihood of starting a new job differently from that of other groups. The interaction term is significantly negative at the 5% level, indicating that increased robot penetration further decreases the probability of highly educated individuals starting new jobs relative to those with lower education. To test the robustness of this finding, Column (4) applies the same specification using data from 2014-2018, and the interaction term remains negative and statistically significant at the 10% level.

Moreover, when household fixed effects are excluded from the model, the interaction terms in Columns (3) and (4) remain significantly negative at the 5% level or lower, reinforcing the robustness of this result[5]. Columns (5) through (7) assess whether the probability of job loss is differentially affected by robot penetration across education levels. In all specifications, the interaction terms are statistically insignificant and their magnitudes are close to zero, indicating that changes in robot penetration have no significant differential effect on job loss probabilities by education level. The results from Table 10 suggest that robot penetration is more likely to reduce the probability of highly educated individuals starting new jobs. This finding is consistent with previous research showing that robots are increasingly

[5] These robustness results are not reported in the table but are available from the authors upon request.

capable of substituting for high-skilled labor, leading to negative employment and income effects for this group (Bessen et al., 2019; Feng & Graetz, 2020; Koch et al., 2021; Kogan et al., 2023).

This phenomenon can be understood from both the demand and supply sides of the labor market. On the demand side, firms that adopt robots tend to be highly productive and face high costs for skilled labor. Replacing highly skilled workers or positions that require intensive training with robots can significantly enhance firm profitability. Furthermore, rapid advances in robot technology have increased their capacity to perform non-routine tasks and substitute for high-skill jobs (Frey & Osborne, 2017). On the supply side, highly educated individuals may respond to technological displacement by placing a premium on job stability, thereby exhibiting a lower propensity to transition into new roles (Fossen & Sorgner, 2019).

Table 10: Industrial Robot Adoption and Job Reallocation (Education Heterogeneity)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent variable	*jobst*	*jobst*	*jobst*	*jobst*	*jobed*	*jobed*	*jobed*
Timeframe	2014-2018	2014-2018	2012-2018	2014-2018	2014-2018	2014-2018	2014-2018
$eurobk6_{2013(2011)\text{-}2017}$	-0.047** (0.020)	-0.039** (0.015)	-0.038** (0.015)	-0.039** (0.015)	-0.052** (0.025)	-0.048** (0.020)	-0.049** (0.021)
edu_{low}	-0.071*** (0.019)				-0.037* (0.021)		
$eurobk6_{2013\text{-}2017}\times edu_{low}$	0.009 (0.012)				0.004 (0.013)		
edu_{mid}		0.041** (0.020)				0.039* (0.020)	
$eurobk6_{2013\text{-}2017}\times edu_{mid}$		-0.006 (0.012)				-0.006 (0.012)	
edu_{hig}			0.262*** (0.052)	0.161*** (0.036)			0.014 (0.030)
$eurobk6_{2013(2011)\text{-}2017}\times edu_{hig}$			-0.052** (0.021)	-0.038* (0.021)			-0.003 (0.019)
Individual-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City-level control variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Urban industry share	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	52,104	52,104	52,104	52,104	52,104	52,104	52,104
Number of cities	141	141	141	141	141	141	141
R^2	0.046	0.042	0.053	0.046	0.024	0.024	0.023

Note: Same as Table 4.

To further investigate whether the application of industrial robots in China leads to systematic differences in job transitions between men and women, we adopt the same analytical framework as outlined earlier. The regression results indicate that, regardless of whether the dependent variable reflects job start or job separation, and whether the sample period is 2014-2018 or 2012-2018, all interaction terms between robot penetration and the gender dummy variable are statistically insignificant and have coefficients close to zero. This suggests that changes in robot penetration at the prefecture level do not have a significantly different impact on job transition rates for men and women.

Finally, we examine whether the effect of regional robot penetration on individual job transitions varies by occupational category. Based on micro-level data from 2014 to 2018, we classify individuals' occupations into six major categories according to China's occupational classification standards and represent each category with a dummy variable. We then include interaction terms between robot penetration and these occupational dummies to assess whether the effect of robot adoption on job transition probabilities differs by occupation. The estimated coefficients of these interaction terms are generally insignificant, indicating that the influence of robot penetration on individual job transitions does not significantly vary across different occupational types (see Appendix for details).

Robot penetration does not produce systematic differences in job transitions across gender or occupational groups. This finding is logically consistent with our earlier result that increases in robot penetration significantly displace employment not only in manufacturing but also in the service and other sectors—with an even greater potential displacement effect observed among incumbent firms in the service sector. Since women are disproportionately employed in services compared to men, and the service sector accounts for a much larger share of overall employment than manufacturing, these structural factors inevitably dilute gender or occupational differences in robot impacts at the aggregate regional level.

5. Conclusion and Policy Implications

The rapid expansion of intelligent industrial robots across various sectors in China has significantly influenced labor reallocation while driving substantial gains in firm productivity. Based on empirical analysis using firm-level and micro survey data, this study presents the following key findings:

First, the adoption of robots primarily strengthens the competitive position of incumbent firms, contributing to overall employment growth within these firms. Labor has shifted from industries with higher robot density to those with relatively lower robot density and larger average firm sizes. At the same time, robot adoption also generates market spillover effects that, to some extent, contribute to a deceleration in overall employment growth.

Second, while robot adoption tends to dampen job creation, it significantly improves firm productivity and reduces job destruction. As a result, employment stability at the regional level has improved.

Third, robot adoption notably increases the tendency of highly educated and middle-aged workers to seek job stability. This suggests that, in the long run, the application of robots may help alleviate operational pressures associated with an aging population and rising labor costs, thereby promoting the accumulation of human capital within firms.

Our empirical findings offer several important policy insights: (1) Take a comprehensive and long-term view of the benefits of intelligent robot adoption. The development of intelligent and automated technologies tends to displace existing jobs relatively quickly, whereas the creation of new job opportunities is often a slower, more gradual process. While the application of automation technologies may slow overall employment growth in the short term, the advancement of next-generation automation is closely tied to the expansion of the digital economy and continuous innovation in digital technologies. The widespread adoption of intelligent robots, in particular, will further stimulate the growth of related digital sectors—such as cloud computing, big data, firm supply chain management, and the platform economy. In the long run, this process not only accelerates digital transformation and enhances firm productivity but also helps to offset short-term employment pressures. Ultimately, it supports broader and higher-quality employment across the economy by facilitating the reallocation of labor into more dynamic and digitally driven sectors.

(2) The impact of robots on employment growth is not solely determined by productivity gains; they are also deeply influenced by market demand conditions. In markets with elastic supply, employment growth primarily hinges on demand expansion. As emphasized in the introduction, if traditional industries face market saturation and experience a sharp decline in demand elasticity, then even

substantial productivity improvements from widespread automation may not generate enough new job tasks to offset the short-term displacement effects of robot adoption.

This underscores the urgency for firms to accelerate digital transformation and to deploy next-generation automation and digital technologies within emerging industries. Automation in these sectors can significantly enhance productivity and drive down prices. Given that emerging industries typically exhibit high demand elasticity, such price reductions are likely to stimulate greater output demand. In turn, this will support the creation of more jobs and contribute to stable, long-term employment growth.

(3) The displacement effect of robot adoption on employment should be assessed on a case-by-case basis. In sectors characterized by high pollution, high risk, or high labor intensity, the use of intelligent robots to replace human labor can not only significantly improve production efficiency but also help control pollution, reduce occupational hazards, and ease the physical burden on workers. For instance, our industry-specific empirical research indicates that robot adoption tends to have a stronger displacement effect in high-pollution industries such as plastics and rubber product manufacturing. This transformation can enhance overall labor welfare, facilitate the restructuring of employment, promote high-quality job growth, and support enterprises in transitioning toward green, low-carbon development. Conversely, in traditional labor-intensive industries that are less likely to stimulate related industrial development or create substantial new employment opportunities in the short term, robot adoption should follow a gradual approach. This helps to avoid significant short-term disruptions to employment growth.

(4) The widespread adoption of robots has heightened the preference for career stability among highly educated and middle-aged workers. Given China's accelerating aging trend and the persistent shortage of middle-aged labor, the increased use of robots can effectively address future labor scarcity in this age group. Globally, the intensifying trend of population aging and rising costs of high-skilled labor have significantly driven robot adoption. This growing emphasis on job stability among highly educated and middle-aged individuals will further enhance human capital accumulation and investment among firms. Moreover, advancements in artificial intelligence extend beyond intelligent robots. The development of non-robot AI technologies generates significant complementary effects for many jobs, substantially boosting production efficiency. This is a critical area for future research. CE

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