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Robots and post-retirement labor supply: Evidence from China

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ABSTRACT

Population aging and rapid automation are jointly reshaping labor markets in major economies, yet their interaction at older ages remains poorly understood. This paper examines how robot adoption shapes post-retirement reemployment among older individuals in China. Leveraging data from the China Health and Retirement Longitudinal Study (CHARLS) matched with industrial robot adoption from the International Federation of Robotics (IFR), we find that automation has no significant effect on aggregate post-retirement reemployment but substantially reshapes its sectoral composition. The share of retirees engaged in agricultural work rises while the share in non-agricultural work declines, with an expansion of agricultural self-employment alongside contractions in both self-employed and wage-based non-agricultural employment. This pattern is not driven by a contraction in aggregate non-agricultural hiring. Instead, it reflects adjustment frictions facing older workers with limited digital access and lower skills, and it is amplified among retirees under greater economic pressure from intergenerational transfers and constrained household resources. Non-agricultural reemployment continues to command a wage premium while agricultural returns decline as automation intensifies, widening sectoral earnings gaps among working retirees.

1. Introduction

Population aging and the diffusion of labor-saving technologies are two defining forces reshaping labor markets worldwide. A growing literature documents how industrial robots affect employment, wages, and task allocation, primarily through changes in labor demand and production technologies (Acemoglu & Restrepo, 2020; Dauth et al., 2021; Giuntella et al., 2025). Yet this evidence has focused mainly on prime-age workers and firm-level outcomes. Much less is known about how exposure to robots shapes labor supply decisions later in the life cycle, particularly in contexts where older individuals increasingly rely on post-retirement reemployment as a source of income. Understanding how robot adoption influences the reemployment patterns and labor market outcomes of older workers is therefore central to assessing the broader distributional consequences of technological change.

China offers a salient setting in which demographic aging has expanded the scope for post-retirement labor supply while production technologies are undergoing rapid change. Gains in life expectancy have lengthened the post-retirement period, and younger cohorts

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of older adults largely retain the physical capacity to engage in market work.[1] Consequently, individuals aged 60 and above have become an increasingly important component of the labor force. Post-retirement reemployment has also emerged as an important adjustment margin, typically involving transitions into sectors and occupations that differ from pre-retirement jobs, as illustrated in Fig. 1. Despite this potential, reemployment among older individuals remains limited. In 2020, the reemployment rate of individuals aged 60-69 in China was 34.6 percent, markedly lower than the employment rates in advanced economies,[2] even though survey evidence indicates strong willingness to return to work, particularly among the younger elderly.[3] Against this backdrop, China has begun to gradually raise statutory retirement ages to make fuller use of older human capital. Whether this reform succeeds depends on how effectively older workers are reallocated across jobs as production technologies change.

Rapid population aging has coincided with one of the fastest expansions of industrial robot adoption worldwide. Over the past decade, China has become the world's largest market for industrial robots, accounting for more than half of global installations. By 2023, the operational stock had reached nearly 1.8 million units, far surpassing that of any other major economy, as shown in Fig. 2. This expansion has been concentrated in manufacturing and other non-agricultural activities, where robots increasingly substitute for routine and codifiable tasks and reshape the structure of available jobs. Because older workers returning to the labor market rely disproportionately on these non-agricultural opportunities, the scale and sectoral concentration of automation may shape their reemployment patterns and labor market returns at older ages.

Using individual-level data from CHARLS matched with prefecture-level measures of industrial robot adoption from IFR, this paper studies how robot adoption shapes post-retirement labor supply among older individuals. We find no statistically significant effect on overall reemployment. At the sectoral level, however, robot exposure reshapes the composition of post-retirement work. A one-unit increase in robot density raises the probability of agricultural reemployment by 0.89 percentage points, corresponding to roughly 2.5 percent relative to the baseline mean, while reducing non-agricultural reemployment by 0.51 percentage points, or about 3.9 percent relative to its mean. These patterns indicate that automation operates through sectoral recomposition rather than changes in aggregate reemployment among retirees.

Robot adoption affects both the allocation and returns of post-retirement employment. It increases agricultural self-employment while reducing both self-employed and wage-based non-agricultural reemployment. We find no evidence that robot exposure reduces overall non-agricultural hiring, suggesting that the decline in non-agricultural reemployment does not arise from a contraction in total vacancies. Rather, this shift reflects changes in job matching and the composition of labor demand. The shift toward agriculture is concentrated among retirees facing greater digital and skill constraints, indicating that barriers to adapting to technology-intensive jobs limit continued participation in non-agricultural work. Economic pressures further shape these adjustments. Individuals with heavier financial obligations, limited intergenerational support, and lower household assets show a higher likelihood of agricultural reemployment when non-agricultural opportunities weaken, consistent with necessity-driven labor supply responses. Wage outcomes also diverge across sectors. Non-agricultural reemployment retains a wage premium, whereas agricultural earnings show no comparable improvement and decline relative to non-agricultural income as robot exposure intensifies. These patterns imply that automation widens sectoral earnings gaps primarily through sectoral recomposition.

This paper speaks to three strands of literature. First, it builds on a growing literature on the labor market effects of robot adoption. Existing work has examined these effects of robot adoption from multiple dimensions, including overall employment (Autor et al., 2015; Zhang et al., 2023), labor demand (Akerman et al., 2015), workers' skill requirements and task content (Autor & Dorn, 2013; Frey & Osborne, 2017), the labor income share (Acemoglu & Restrepo, 2019; Acemoglu et al., 2023) and within-firm workforce composition (Dixon et al., 2019). Collectively, this literature shows that robot adoption generates both displacement and job-creating effects (Acemoglu and Restrepo, 2018a, 2020; Graetz & Michaels, 2018; Autor et al., 2024). However, prior studies have focused predominantly on firm-level workforce dynamics and on incumbent workers' employment outcomes, leaving the post-retirement reemployment margin largely unexamined. Little is known about how robot adoption affects retirees who reenter the labor market, an increasingly important margin of labor supply adjustment at older ages. By shifting attention to post-retirement reemployment, our paper studies an overlooked adjustment channel and shows that robot adoption systematically reshapes both the likelihood and sectoral patterns of reemployment among older individuals.

Second, this paper contributes to the literature on late-life labor supply and labor force participation. A large body of research has shown that labor market participation is shaped by pension incentives and social security arrangements (Bratberg et al., 2004; French, 2005; Inderbitzin et al., 2016; Engels et al., 2017; Khanna et al., 2025), family background and intergenerational transfers (Blau & Goodstein, 2016), and individual constraints such as health status and functional limitations (Capatina, 2015; Fadlon & Nielsen, 2021; Kolsrud et al., 2024). Participation also depends on marital status (Chen & Zhao, 2022), job characteristics, and working conditions (Somanathan et al., 2021; Hampton & Totty, 2023; Chen et al., 2025). But the role of technological change in shaping employment opportunities at older ages remains underexplored, especially when population aging and large-scale robot adoption unfold simultaneously. Our paper extends this literature by documenting how robot adoption interacts systematically with

[1] According to the Seventh National Population Census and related studies, more than 90 percent of younger elderly individuals in China are classified as being in good or basic health, and only 7.1 percent require long-term medical care.

[2] In 2023, the employment rate of individuals aged 60-69 was 50.9 percent across the 27 EU member states. Among OECD countries, employment rates were 57 percent for those aged 60-64 and 29.8 percent for those aged 65–69. By comparison, the reemployment rate of individuals aged 60-69 in China was 34.6 percent in 2020.

[3] Survey evidence from 51job (2022) further indicates that 68 percent of older individuals in China express a strong willingness to return to work after retirement, with younger elderly accounting for the majority.

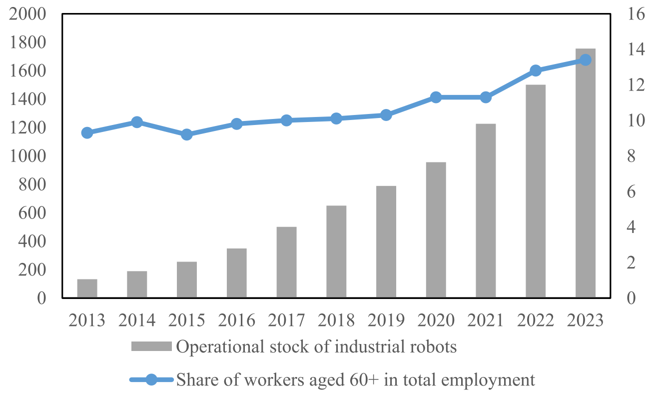

Fig. 1. Industrial robot stock and the share of older workers in employment in China.
Notes: This figure depicts the evolution of the operational stock of industrial robots and the share of workers aged 60 and above in total employment in China over the period 2013-2023. The operational stock of industrial robots is measured in thousands of units and corresponds to the left vertical axis. The share of older workers is measured as a percentage of total employment and corresponds to the right vertical axis.
Data source: IFR and *China Labor Statistical Yearbook*.

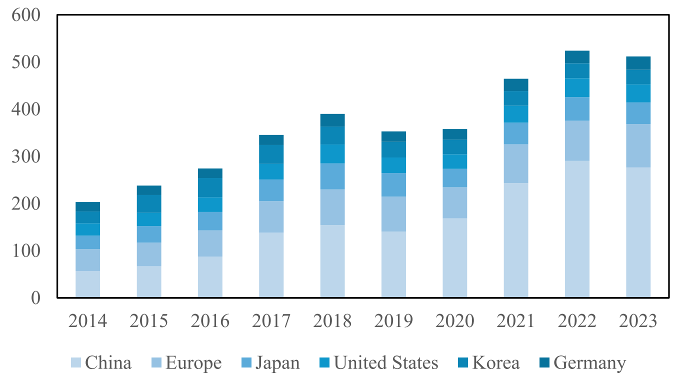

Fig. 2. Annual installations of industrial robots across major economies, 2014-2023.
Notes: This figure reports annual installations of industrial robots in China, Europe, Japan, the United States, Korea, and Germany over the period 2014-2023. Installations are measured in thousands of units.
Data source: IFR.

socioeconomic vulnerabilities among older workers, including digital constraints and financial pressures, thereby reshaping the sectoral composition of post-retirement reemployment without altering its aggregate level.

Third, this paper relates to the broader literature on technological change and inequality. A large literature documents that technological progress affects workers differently across skill levels (Autor et al., 1998; Wang et al., 2024), age groups (Abeliansky et al., 2024; Peng et al., 2017), and demographic characteristics (Mason, 2021; Wang et al., 2022). This work has also linked technological change to widening inequality through channels such as skill-biased demand and task reallocation (Autor & Dorn, 2013; Acemoglu & Restrepo, 2024; Ma et al., 2025). Less attention, however, has been paid to how these distributional forces operate later in the life cycle. Our paper shows that technological change influences inequality beyond prime working ages by raising the concentration of disadvantaged retirees in sectors with lower returns. The unequal effects of automation therefore extend beyond contemporaneous wage adjustments and also arise through post-retirement labor recomposition.

2. Data and empirical strategy

2.1. Data

Our paper combines micro-level individual data with city-level robot exposure data to examine how industrial robot adoption affects elderly reemployment in China. The individual-level data are drawn from the 2011, 2013, 2015, and 2018 waves of the CHARLS, a nationally representative panel survey of middle-aged and older adults. We rely on CHARLS for three reasons. First, it targets individuals aged 45 and above, a group that typically has clearer preferences and constraints regarding retirement and post-retirement employment than the general working-age population. Second, its longitudinal design allows us to track changes in retirement and reemployment intentions over time and provides rich demographic, socioeconomic, and household-level covariates.

Third, the survey employs a multistage probability-proportional-to-size (PPS) sampling strategy that covers a wide range of provinces and administrative units, ensuring broad geographic representativeness.

The city-level robot data are obtained from IFR, which reports annual industrial robot installations across 50 countries and regions from 1993 to 2018. To construct a city-level measure of robot exposure in China, we follow a widely used shift-share approach (Graetz & Michaels, 2018; Acemoglu & Restrepo, 2020; Goldsmith-Pinkham et al., 2020; Dauth et al., 2021). We combine the IFR industry-level installation data with employment distributions from China's Second National Economic Census to compute robot penetration intensity at the prefecture level. This measure equals the ratio of robot installations in each industry to the number of workers employed in that industry, weighted by the baseline industry employment shares of each city.

Following the Bartik instrumental-variable approach, we construct a shift-share instrument that captures exogenous variation in local robot exposure driven by national trends in robot adoption across industries. The predicted robot exposure for city *j* in year *t* is given by:

$$Robot_{jt} = \sum_{s=1}^{S} \frac{employ_{sjt=2008}}{employ_{jt=2008}} \times \frac{Robot_{st}}{employ_{st=2008}} \tag{1}$$

where S denotes the set of all industries, j denotes the city, and t denotes the year. $Robot_{jt}$ represents the number of robots installed in city j in year t, while *employ* refers to employment. Specifically, $employ_{st=2008}$ denotes the number of employees in industry s in 2008, $employ_{jt=2008}$ denotes the total employment in city j in 2008, and $employ_{sjt=2008}$ denotes the number of employees in industry s in city j in 2008. We refer to this variable as *Robot*, measured as robot installations per million workers. It provides a consistent annual panel of city-level robot penetration matched to CHARLS respondents by city of residence.

Elderly reemployment is measured using a set of survey questions in CHARLS that capture both agricultural and non-agricultural work participation. Respondents are asked: (i) “Did you engage in agricultural work for at least 10 days in the past year for your own household? Agricultural work includes farming, forestry, fishing, animal production, and selling agricultural products produced by your own household.” (ii) “Did you work for other farmers/employers and get paid for at least ten days in the past year?” (iii) “Not including agricultural work, did you work for at least 1 h last week in paid work, individual business, or family business without getting paid?” (iv) “Are you currently engaged in any non-agricultural work but are on vacation, on sick or other leave, or in job training?” For each question, an affirmative (“Yes”) response is coded as one, and zero otherwise. We define *Reemp* as an indicator for any post-retirement work activity, while distinguishing between *Agri-reemp* and *Nonagri-reemp* depending on whether the reported activity is agricultural or non-agricultural.[4] The analysis sample is restricted to individuals who are retired at the time of the survey ,[5] ensuring that these outcomes capture post-retirement labor supply rather than continued pre-retirement employment. We further restrict the sample to individuals aged 45 to 70. The lower bound of 45 corresponds to the earliest institutional retirement age in China (applicable to employees in hazardous occupations or with work-related disabilities) and also aligns with the CHARLS sampling frame. The upper bound of 70 ensures that observed labor supply reflects behavioral responses to economic conditions rather than age-related health constraints. We assess sensitivity to both bounds in Section 3.3.

Our empirical specifications control for covariates at the individual, household, and city levels. At the individual level, we include age, age squared, gender, years of schooling, marital status, and a binary indicator of chronic health conditions. At the household level, the controls comprise a rural residence indicator, household size, and the number of children. At the city level, we include the logarithm of GDP, the share of secondary industry in GDP, and the unemployment rate. These controls account for observable differences in demographic composition, household structure, and local economic conditions that may jointly influence robot adoption and elderly reemployment.

Descriptive statistics for the study sample are reported in Table 1. About 42.5 percent of individuals report engaging in some form of work after retirement, with 35.2 percent in agricultural activities and 13.1 percent in non-agricultural work. City-level industrial robot density averages 3.640 units per million workers and ranges from 0.085 to 28.533, indicating considerable cross-city variation in automation exposure. The average respondent is approximately 59.4 years old. Men account for 41.1 percent of the sample, 89.6 percent have a spouse or partner, and 74.4 percent report at least one chronic condition. Nearly 58.0 percent reside in rural areas, and the average household has 3.45 members and 2.53 children. At the city level, mean log GDP is 6.52, the share of secondary industry in GDP is 48.8 percent, and the unemployment rate averages 4.26 percent.

2.2. Empirical strategy

We estimate the effect of industrial robot adoption on elderly reemployment using the following baseline specification:

$$Y_{ict} = \beta_0 + \beta_1 Robot_{ct} + \theta_1 X_{it} + \theta_2 X_{ct} + \varphi_c + \lambda_t + \varepsilon_{ict} \tag{2}$$

[4] We follow the CHARLS definition of work as activity undertaken to earn a livelihood. Under this definition, the agricultural reemployment indicator captures a range of agricultural activities, from market-oriented production and agricultural wage employment to household-oriented production whose output contributes to the respondent's livelihood. The decomposition of agricultural reemployment into self-employment and wage employment in Section 4.1 further allows us to distinguish between these forms of agricultural work participation.

[5] In this study, retirement is defined from respondents' self-reported status in CHARLS, which identifies individuals who have formally completed retirement procedures from their previous employment. This definition is consistent with the CHARLS questionnaire and includes retirees from government agencies, public institutions, enterprises, as well as those who retired under the urban or rural residents' pension systems.

Table 1
Summary statistics.

	Obs.	Mean	Std. Dev.	Min	Max
Reemployment outcomes					
Reemp (yes = 1)	16992	0.425	0.494	0	1
Agri-reemp (yes = 1)	16992	0.352	0.477	0	1
Nonagri-reemp (yes = 1)	16992	0.131	0.338	0	1
Industrial robots					
Robot (units/10000 people)	16992	3.640	3.939	0.085	28.533
Covariates					
Age	16992	59.359	6.594	45	70
Age^2	16992	3566.989	772.627	2025	4900
Gender (male = 1)	16992	0.414	0.493	0	1
Years of education	16992	5.066	4.686	0	22
Spouse (yes = 1)	16992	0.896	0.306	0	1
Ifchro (yes = 1)	16992	0.744	0.436	0	1
Rural (yes = 1)	16992	0.580	0.494	0	1
Family Size	16992	3.453	1.725	1	15
Number of children	16992	2.537	1.297	0	11
Ln(GDP)	16992	6.518	1.210	3.672	10.429
The proportion of secondary industry in GDP (%)	16992	48.82	10.286	18.630	74.78
Unemployment rate (%)	16992	4.257	2.082	1.087	8.796

Where Y_{ict} is alternatively defined as an indicator for (i) any post-retirement employment, (ii) agricultural reemployment, or (iii) non-agricultural reemployment for individual *i* in city *c* and year *t*. $Robot_{ct}$ denotes city-level robot adoption. X_{it} denotes a set of individual and household-level characteristics, while X_{ct} represents a vector of city-level control variables. All specifications include city fixed effects (φ_c) to absorb time-invariant local characteristics such as geography and historical development patterns, as well as year fixed effects (λ_t) that capture common shocks and nationwide trends. Standard errors are clustered at the city level.

Our analysis focuses on individuals aged 45-70. This range captures cohorts approaching or having recently passed the statutory retirement age who typically retain substantial work capacity, while excluding the ages at which health constraints, rather than economic conditions, dominate labor supply. In robustness analyses, we assess sensitivity to alternative age cutoffs by progressively expanding the upper age limit.

3. Impact of robot adoption on elderly reemployment

In this section, we first present the baseline estimates of how robot adoption affects elderly reemployment across overall, agricultural, and non-agricultural sectors. We then address endogeneity concerns through an instrumental-variable approach, followed by a set of robustness checks to ensure that ensure the results are not driven by alternative specifications or sample definitions.

3.1. Main results

Table 2 reports the baseline estimates of Eq. (1) for post-retirement reemployment outcomes. Columns (1), (3), and (5) present specifications without individual, household, and city-level controls, while Columns (2), (4), and (6) include the full set of controls. The results reveal a clear shift in the sectoral composition of reemployment rather than a change in its overall level.

Columns (1) and (2) show that robot adoption has no statistically significant effect on overall reemployment among older individuals. The estimated coefficient is small and not statistically distinguishable from zero, indicating that increased robot exposure does not meaningfully change the aggregate likelihood of post-retirement labor force participation. Columns (3) and (4) reveal a significant sectoral response. Robot adoption is associated with an increase in the probability of agricultural reemployment of about 0.89 percentage points. Given that the baseline probability of agricultural reemployment is 35.2 percent (see Table 1), this estimate implies an increase of roughly 2.53 percent relative to the mean. By contrast, Columns (5) and (6) indicate that robot adoption significantly reduces non-agricultural reemployment. The estimated coefficient suggests a decline of approximately 0.51 percentage points. Relative to the baseline probability of 13.1 percent, this corresponds to a reduction of about 3.89 percent.

These results suggest that robot adoption does not change overall post-retirement reemployment but reshapes its sectoral composition, raising the share of retirees in agricultural work while reducing the share in non-agricultural work. We interpret these aggregate estimates as evidence of compositional change at the sectoral level rather than of individual-level transitions across sectors.

3.2. Endogeneity analysis

A potential concern in estimating the effect of robot adoption on elderly reemployment is endogeneity arising from omitted variables or measurement error. Local robot adoption may be correlated with unobserved demographic or economic conditions that independently shape older workers' reemployment decisions, biasing the OLS estimates. To address this issue, we construct a Bartik-type instrumental variable following Acemoglu and Restrepo (2020), based on industrial robot installations in China's five major

Table 2
Baseline results.

	Reemp		Agri-reemp		Nonagri-reemp	
	(1)	(2)	(3)	(4)	(5)	(6)
Robot	0.0081	0.0064	0.0100*	0.0089*	−0.0038**	−0.0051***
	(0.0052)	(0.0046)	(0.0053)	(0.0046)	(0.0018)	(0.0017)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	No	Yes	No	Yes	No	Yes
Observations	16,992	16,992	16,992	16,992	16,992	16,992
R-squared	0.2969	0.3580	0.3113	0.3714	0.0680	0.1385

Notes: Basic controls include individual- and household-level characteristics (age, age squared, gender, years of education, marital status, health status, rural residence, family size, and number of children) as well as city-level characteristics (log GDP, the share of secondary industry in GDP, and unemployment rate). City and year fixed effects are included in all specifications. Standard errors in parentheses are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

source countries (the United States, Japan, Germany, Sweden, and South Korea). The instrument is defined as:

$$Robot\_IV_{jt} = \sum_{s=1}^{S} \frac{employ_{sjt=2008}}{employ_{jt=2008}} \times \frac{Robot\_Import_{st}}{employ_{st=2008}} \tag{3}$$

Where $employ_{sjt=2008}/employ_{jt=2008}$ denotes the employment share of industry s in city j in the base year 2008, and $Robot\_Import_{st}/employ_{st=2008}$ denotes robot penetration in industry s in the source countries at time t. The instrument thus combines pre-sample local industrial composition with time-varying industry-level robot adoption in technologically advanced economies.

The instrument satisfies the relevance condition because a substantial share of industrial robots deployed in China are imported from these five source countries, so shifts in their robot adoption translate directly into variation in local robot exposure across Chinese cities. Identification relies on the exogeneity of the underlying shifts rather than that of the exposure shares. As emphasized by Goldsmith-Pinkham et al. (2020), shift-share designs can be justified by either source of variation. In our setting, the exogeneity of baseline employment shares is difficult to defend on its own, as local industrial composition may be correlated with long-run development patterns and demographic conditions that also influence post-retirement labor supply. We therefore follow Borusyak et al. (2022) and base identification on the exogeneity of the shifts instead. The industry-level shocks in our instrument derive from robot adoption in five technologically leading economies, whose deployment decisions are driven by their own technological frontiers, labor costs, and demographic pressures. These forces are unlikely to be shaped by post-retirement labor supply conditions in Chinese cities and can be interpreted as plausibly exogenous technology shifts that affect Chinese local labor markets only through city-level robot adoption. Fixing the employment shares at the 2008 baseline further mitigates the concern that shares are contaminated by contemporaneous shocks.

Table 3 reports the two-stage least squares estimates. The first-stage results confirm that the instrument strongly predicts local robot installation, with an F-statistic of 223.48, well above conventional thresholds and easing concerns about weak instruments. In the second stage, robot adoption has no statistically significant effect on overall reemployment, but significantly increases agricultural reemployment and significantly reduces non-agricultural reemployment. The signs and magnitudes of the coefficients are close to those in the baseline estimates, which indicates that addressing endogeneity does not alter the main empirical patterns.[6]

3.3. Robustness checks

To assess the robustness of our findings, we first re-measure local robot adoption using the cumulative stock of robots at the city level rather than the annual flow of installations. Columns (1)-(3) of Table 4 show that the main results are qualitatively unchanged. Robot adoption continues to have no statistically significant effect on overall reemployment among older individuals, while it significantly increases agricultural reemployment and significantly reduces non-agricultural reemployment. Our conclusions are therefore not sensitive to how robot adoption is defined.

Second, we replace city fixed effects with community fixed effects. This more demanding specification absorbs unobserved heterogeneity at a finer geographic level, thereby addressing the concern that local characteristics within cities may drive the results. As shown in Columns (4)-(6) of Table 4, the coefficients remain stable in both magnitude and significance. The estimated effects are thus not an artifact of the level at which fixed effects are defined.

Third, we examine the sensitivity of the results to alternative age restrictions. We vary both the lower and upper bounds of the

[6] To further assess the robustness of our shift-share design, we implement three diagnostic exercises drawn from the recent shift-share literature. They comprise a Rotemberg-weight decomposition (Goldsmith-Pinkham et al., 2020), a leave-own-city-out construction, and an alternative-baseline-year weighting scheme using 2010 industry shares (Borusyak et al., 2022). The qualitative pattern of signs and significance across all three exercises is consistent with our baseline estimates. We do not report the detailed results here due to space constraints, though they are available from the authors upon request.

Table 3
2SLS estimation.

	First stage	Second stage		
	Robot	Reemp	Agri-reemp	Nonagri-reemp
	(1)	(2)	(3)	(4)
Robot		0.0014	0.0057**	−0.0081***
		(0.0065)	(0.0023)	(0.0025)
Robot_IV	0.7767***			
	(0.0519)			
F statistic	223.48			
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	16,992	16,992	16,992	16,992
R-squared		0.0875	0.0885	0.0758

Notes: Columns (1) present the first-stage regression results of the 2SLS estimation, with F-statistics exceeding 10, indicating no weak instrument problem. Columns (2)-(4) report the second-stage regression results. All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 4
Robust check I

	Changing explanatory variables			Finer Fixed Effects		
	Reemp	Agri-reemp	Nonagri-reemp	Reemp	Agri-reemp	Nonagri-reemp
	(1)	(2)	(3)	(4)	(5)	(6)
Robot				0.0076	0.0105**	−0.0056***
				(0.0047)	(0.0047)	(0.0018)
Stock	0.0008	0.0013***	−0.0010***			
	(0.0009)	(0.0003)	(0.0003)			
City FE	Yes	Yes	Yes	No	No	No
Community FE	No	No	No	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,992	16,992	16,992	16,991	16,991	16,991
R-squared	0.3578	0.3710	0.1385	0.3999	0.4250	0.1706

Notes: All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

baseline age window to ensure that our conclusions do not hinge on the specific choice of 45-70. At the lower end, we raise the cutoff to 50, which corresponds to the statutory retirement age for female workers in China and therefore excludes individuals eligible only under early-retirement provisions. At the upper end, we progressively extend the sample to include individuals up to ages 75, 80, and 85. Because labor supply decisions at more advanced ages are increasingly shaped by health constraints rather than economic considerations, we restrict the upward-extended samples to individuals reporting good or very good self-rated health, so that reemployment remains a feasible economic choice. The results, reported in Table 5, are again qualitatively unchanged. Robot adoption continues to have no significant effect on overall reemployment, while it significantly raises agricultural reemployment and reduces non-agricultural reemployment. The baseline age cutoff therefore does not drive our findings.

Fourth, we address the possibility that individuals who simultaneously engage in agricultural and non-agricultural activities contaminate the classification of outcomes, and we exclude this small subset of dual participants. Removing these cases mitigates potential biases in the classification of reemployment outcomes and ensures a cleaner separation between agricultural and non-agricultural labor. The results, reported in Columns (1)-(3) of Table 6, remain highly consistent with the baseline estimates, confirming that the main findings are not driven by this group.

Fifth, given the rapid expansion of the digital economy and the emergence of new employment forms that may shape older workers' labor market opportunities, we further account for city-level digital development. We construct a composite index using the entropy method, incorporating internet penetration, employment and output in computer services and software, mobile phone penetration, and measures of digital inclusive finance. Controlling for this index addresses the possibility that digitalization, rather than robot adoption itself, drives reemployment dynamics. As shown in Columns (4)-(6) of Table 6, the estimated effects of robots remain robust to the inclusion of these controls.

4. Further analyses

In this section, we conduct additional analyses to clarify the mechanisms behind the compositional change in post-retirement reemployment. Reemployment decisions after retirement operate along two distinct margins that respond to different economic

Table 5
Robust check II

	Reemp	Agri-reemp	Nonagri-reemp	Reemp	Agri-reemp	Nonagri-reemp
	Age 50-70			Age 45-75		
	(1)	(2)	(3)	(4)	(5)	(6)
Robot	0.0066	0.0079*	−0.0037**	0.0055	0.0084**	−0.0055***
	(0.0045)	(0.0045)	(0.0017)	(0.0043)	(0.0042)	(0.0018)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,369	15,369	15,369	13,750	13,750	13,750
R-squared	0.3500	0.3670	0.1291	0.3743	0.3853	0.1457
	Age 45-80			Age 45-85		
	(7)	(8)	(9)	(10)	(11)	(12)
Robot	0.0054	0.0083**	−0.0053***	0.0054	0.0081**	−0.0048***
	(0.0042)	(0.0041)	(0.0016)	(0.0042)	(0.0041)	(0.0016)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,029	15,029	15,029	15,745	15,745	15,745
R-squared	0.3781	0.3796	0.1476	0.3814	0.3782	0.1476

Notes: All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 6
Robust check III

	Excluding Overlapping Employment			Adding control variables		
	Reemp	Agri-reemp	Nonagri-reemp	Reemp	Agri-reemp	Nonagri-reemp
	(1)	(2)	(3)	(4)	(5)	(6)
Robot	0.0075	0.0106**	−0.0031**	0.0070	0.0093**	−0.0050***
	(0.0046)	(0.0046)	(0.0014)	(0.0043)	(0.0045)	(0.0017)
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,003	16,003	16,003	16,969	16,969	16,969
R-squared	0.3296	0.3488	0.0983	0.3589	0.3720	0.1386

Notes: All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

forces. The participation margin governs whether retirees engage in the labor market at all and is shaped primarily by economic necessity, including pension adequacy, household financial obligations, and intergenerational support (Blundell et al., 2016; French, 2005). The sectoral allocation margin determines where retirees work conditional on participation and depends on the match between their accumulated human capital and the distribution of job opportunities across sectors.

Within this framework, and consistent with the task-based perspective of Acemoglu and Restrepo (2018b, 2020), automation disproportionately displaces routine tasks concentrated in non-agricultural activities, whereas agricultural work, which has lower

Table 7
Robot adoption and post-retirement reemployment by employment type.

	(1)	(2)	(3)	(4)
	Agri-self-reemp	Agri-wage-reemp	Nonagri-self-reemp	Nonagri-wage-reemp
Robot	0.0062*	0.0001	−0.0008*	−0.0022**
	(0.0033)	(0.0005)	(0.0004)	(0.0009)
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control variables	Yes	Yes	Yes	Yes
Observations	16,992	16,992	16,992	16,992
R-squared	0.3848	0.0391	0.0487	0.1269

Notes: The dependent variables distinguish four types of post-retirement reemployment: agricultural self-employment, agricultural wage employment, non-agricultural self-employment, and non-agricultural wage employment. All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

technology intensity and fewer entry barriers, is less exposed. Automation may therefore reshape the composition of employment without affecting overall participation. The analyses below evaluate this interpretation along several dimensions. We first disaggregate reemployment by detailed employment type to identify which forms of work absorb the sectoral shift. We then examine whether changes in non-agricultural labor demand contribute to the decline in non-agricultural reemployment. We further explore the roles of skill-related adjustment frictions and economic pressure in shaping retirees' reemployment choices, corresponding respectively to the allocation and participation margins. Finally, we assess the earnings consequences of the shift across sectors to evaluate whether it entails meaningful differences in income prospects.

4.1. Reemployment by type of employment

Table 7 further decomposes post-retirement reemployment by sector and employment type. The results reveal that the effects of robot adoption are highly uneven across employment forms. Column (1) shows that robot adoption significantly increases agricultural self-employment among retirees. Column (2) shows no statistically significant effect on agricultural wage employment, which suggests that the expansion of agricultural reemployment operates almost entirely through self-employment rather than hired agricultural jobs. Turning to non-agricultural reemployment, Columns (3) and (4) indicate that robot adoption significantly reduces both self-employed and wage-based non-agricultural reemployment, with the contraction more pronounced for wage employment. Automation thus disproportionately crowds out non-agricultural jobs that rely on employer-employee matches, while also discouraging self-employment outside agriculture.

To identify which non-agricultural jobs are most affected by robot adoption, we further decompose non-agricultural wage reemployment by employment type. As shown in Table 8, robot adoption significantly reduces both contract-based employment and casual or part-time employment among retirees, while having no statistically significant effect on dispatch-based employment. This pattern suggests that automation primarily substitutes for standard employment relationships that rely on well-defined tasks and stable labor input, as the decline in contract employment reflects. The reduction in casual and part-time jobs indicates that changes in production organization following robot adoption also lower demand for flexible and non-standard labor arrangements. By contrast, robot adoption has no significant effect on dispatch employment. This contrast reflects a difference in task content. Casual and part-time jobs are concentrated in production-related activities directly exposed to robot adoption, whereas dispatch positions are largely confined to logistical and auxiliary functions that automation neither replaces nor expands.

4.2. Labor demand responses in non-agricultural sectors

Changes in local labor demand may shape post-retirement employment by altering the availability and composition of job opportunities available to older workers. To assess whether the decline in non-agricultural reemployment reflects changes on the demand side, Table 9 examines the relationship between robot adoption and the total number of non-agricultural job vacancies at the city level. The estimates reveal no statistically significant association between robot adoption and overall non-agricultural hiring. The reduction in non-agricultural reemployment among retirees is therefore unlikely to be driven by a contraction in aggregate labor demand, which suggests that robot adoption does not operate through a quantity-based demand channel at the city level.

4.3. Adjustment constraints in non-agricultural reemployment

Given that robot adoption does not reduce overall non-agricultural hiring, a natural concern is whether automation reshapes job requirements and work organization in ways that constrain older workers' ability to adjust. A key friction may arise from the digital divide, which affects how older workers access and navigate non-agricultural jobs under automation. So, we examine the role of the digital divide in shaping the non-agricultural reemployment responses to robot adoption. Following Lythreatis et al. (2022), the digital divide can be conceptualized along two dimensions, the access divide and the usage divide. The access divide refers to disparities in basic digital infrastructure such as broadband internet and electronic devices, while the usage divide reflects heterogeneity in individuals' ability to engage effectively with digital technologies, commonly proxied by education (Lythreatis et al., 2022; Pandey et al., 2003). We use household internet connectivity in the initial 2011 wave to capture the access dimension and educational attainment to capture usage capacity. We classify individuals with senior high school education or above as high-skilled and those with junior high school education or below as low-skilled, an adaptation of standard binary skill classifications in the labor literature (Lordan & Neumark, 2018) that accommodates the relatively low rate of college-level education among older Chinese cohorts.

Fig. 3 shows that the reemployment responses to robot adoption are closely tied to older workers' digital and skill constraints. Robot adoption has no statistically significant effect on agricultural reemployment among households without internet access, but it significantly reduces their non-agricultural reemployment. For older individuals in households with internet access, it significantly reduces agricultural reemployment and shows no significant effect on non-agricultural reemployment. A similar pattern emerges along the skill dimension. Robot adoption significantly increases agricultural reemployment among low-skilled older workers, with a significantly negative effect on non-agricultural reemployment, while showing no significant effect among high-skilled workers. The evidence points to adjustment constraints as a key mechanism behind the decline in non-agricultural reemployment. Older workers with limited digital access or lower skill levels face greater difficulty remaining in non-agricultural jobs, and the share of retirees in agricultural activities rises correspondingly under stronger automation exposure, where adjustment requirements are less demanding.

Digital access and skill differences point to the importance of adjustment capacity in mediating older workers' employment responses to automation. Table 10 provides more direct evidence by incorporating an indicator for participation in vocational or

Table 8
Robot adoption and non-agricultural reemployment by employment type.

	(1)	(2)	(3)
	Dispatch-emp	Contract-emp	Part-time-emp
Robot	−0.0002	−0.0005*	−0.0021***
	(0.0002)	(0.0003)	(0.0007)
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	16,992	16,992	16,992
R-squared	0.0193	0.0384	0.0825

Notes: The dependent variables capture different types of non-agricultural reemployment among retired individuals, classified according to the form of employment relationship. Specifically, non-agricultural reemployment is further divided into dispatch-based employment, contract-based employment, and casual or part-time employment. All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 9
Robot adoption and non-agricultural labor demand.

	(1)	(2)
	Num-position	Num-position
Robot	514.7802	505.1815
	(560.3685)	(556.9079)
City FE	Yes	Yes
Year FE	Yes	Yes
City FE×Year FE	No	Yes
Control variables	Yes	Yes
Observations	1317	1317
R-squared	0.9366	0.9367

Notes: The dependent variable is the total number of non-agricultural job postings at the city-year level. Job posting data are collected from *51job*, the largest online recruitment platform in China, covering the period from 2014 to 2018. All specifications control for city-level characteristics, including the logarithm of GDP, the share of secondary industry in GDP, and the unemployment rate. Column (1) includes city fixed effects and year fixed effects. Column (2) further incorporates city-by-year fixed effects to flexibly control for time-varying unobserved heterogeneity at the city level. Standard errors are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

technical training and its interaction with robot adoption. Consistent with the baseline results, robot exposure reduces non-agricultural reemployment. This adverse effect is significantly weaker among individuals who have received job-related training, as the positive and statistically significant interaction term shows. By contrast, training does not meaningfully affect agricultural reemployment responses. These findings suggest that the contraction in non-agricultural reemployment primarily reflects limitations in adaptive capacity rather than a uniform reduction in employment opportunities. Formal training appears to cushion the impact of automation by improving older workers' ability to meet evolving job requirements.

4.4. *Economic incentives for agricultural reemployment*

Intergenerational transfers constitute an important source of economic pressure shaping older workers' labor supply decisions. Financial obligations to, and financial support from, younger generations may alter the need for continued labor market participation under automation. Fig. 4 illustrates how these transfer-based incentives shape sectoral reemployment responses to robot adoption. Robot adoption increases agricultural reemployment in both low- and high-burden groups, with a substantially stronger response among individuals facing heavier financial obligations.[7] By contrast, non-agricultural reemployment declines only for those with lower burden, while the effect is statistically indistinguishable from zero among those with higher burden. Greater downward transfer obligations strengthen the need to remain economically active and channel labor supply adjustments toward agricultural work when non-agricultural opportunities contract.

A related contrast emerges along the support dimension. Among individuals receiving limited financial support from younger generations, robot adoption raises agricultural reemployment and reduces non-agricultural reemployment. For those with stronger intergenerational support, robot exposure has no statistically discernible effect in either sector. Access to family-based support thus alleviates economic pressure and dampens the sectoral response in reemployment.

[7] We formally test the difference in agricultural reemployment coefficients between the high- and low-burden groups. The estimated difference is −0.0093 and is statistically significant at the 1 percent level.

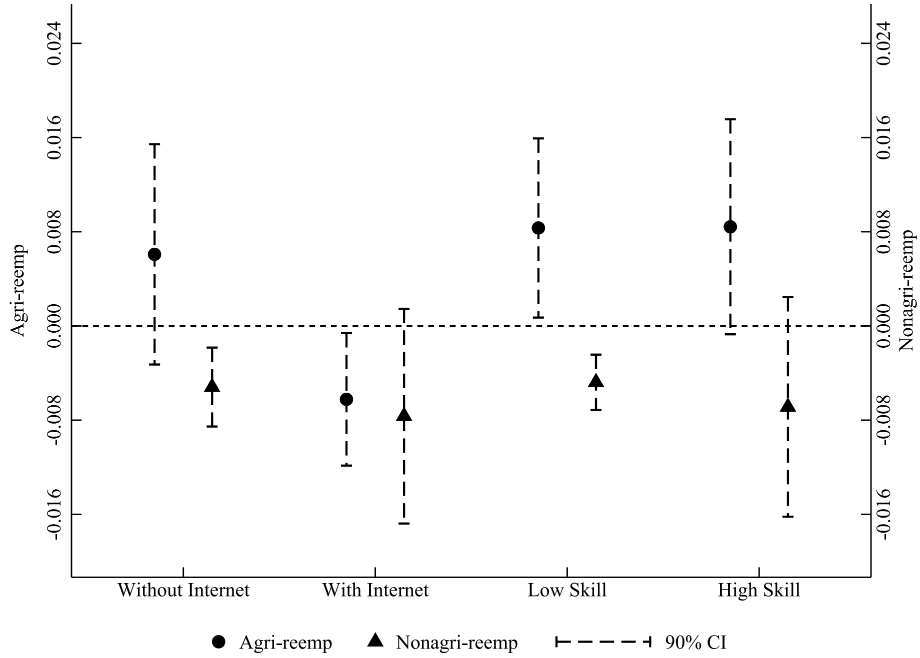

Fig. 3. Digital divide and sectoral reemployment responses to robot adoption
Notes: This figure reports coefficient estimates from regressions illustrating the role of the digital divide in shaping post-retirement reemployment responses to robot adoption. Circles denote the estimated coefficients for agricultural reemployment, corresponding to the left vertical axis, while triangles denote the estimated coefficients for non-agricultural reemployment, corresponding to the right vertical axis. Vertical bars indicate 90 percent confidence intervals. All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 10
Skill investment and reemployment responses to robot adoption.

	(1)	(2)
	Agri-reemp	Nonagri-reemp
Robot	0.0053*	0.0007
	(0.0028)	(0.0023)
Train	−0.0498	0.0174
	(0.0699)	(0.0771)
Train×Robot	0.0122	0.0243**
	(0.0093)	(0.0109)
City FE	Yes	Yes
Year FE	Yes	Yes
Control variables	Yes	Yes
Observations	4666	4666
R-squared	0.1169	0.1104

Notes: Train is an indicator for participation in vocational or technical training and equals one if the respondent reports having attended any job-related training program, and zero otherwise. Information on training participation is available only in the 2015 and 2018 waves of CHARLS, resulting in a smaller estimation sample in columns (3) and (4). All specifications include the same set of control variables as in the baseline regressions. Standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

Economic pressure may also depend on the availability of household resources that buffer income shocks. Household net assets and savings in the initial 2011 wave provide an additional margin along which the necessity of reemployment can vary. Fig. 5 presents the results. Robot adoption increases agricultural reemployment among individuals from low-asset households, while the effect is statistically insignificant for those from high-asset households. On the non-agricultural side, robot adoption reduces reemployment among the high-asset group, with no discernible effect among the low-asset group. Wealth scarcity therefore strengthens the rise in agricultural reemployment, whereas greater asset holdings are associated with a decline in non-agricultural reemployment.

When households are grouped by baseline savings, the adjustment margin differs from that along the asset dimension. Robot adoption does not significantly affect agricultural reemployment in either savings group, indicating that liquidity alone does not

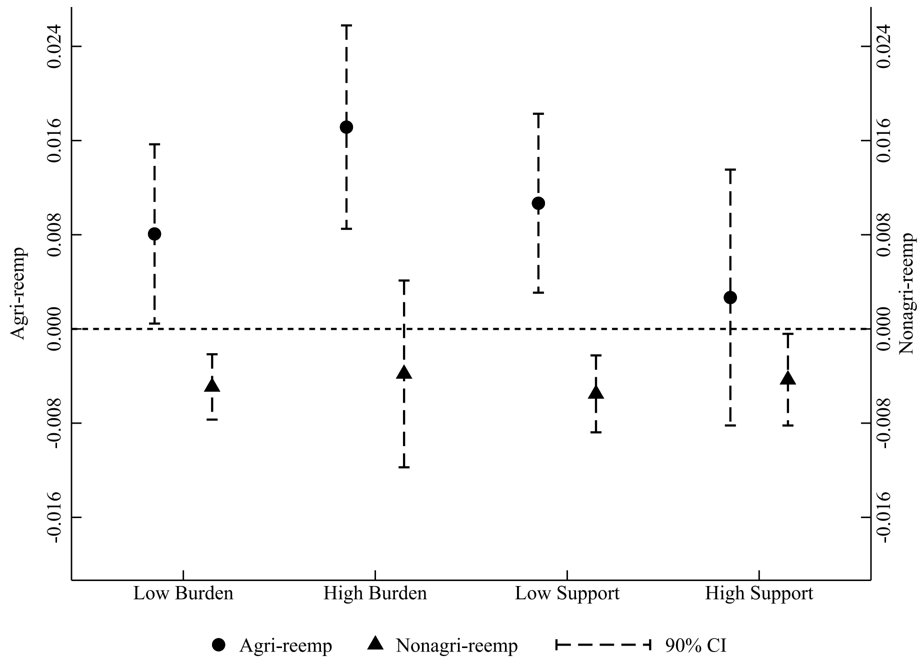

Fig. 4. Intergenerational transfers and sectoral reemployment responses to robot adoption
Notes: This figure reports coefficient estimates from regressions examining how intergenerational transfers shape sectoral reemployment responses to robot adoption. Individuals are classified into high- and low-burden groups based on whether financial transfers provided to younger generations exceed the sample mean, and into high- and low-support groups based on whether financial transfers received from younger generations exceed the sample mean. Circles denote the estimated coefficients for agricultural reemployment, corresponding to the left vertical axis, while triangles denote the estimated coefficients for non-agricultural reemployment, corresponding to the right vertical axis. Vertical bars indicate 90 percent confidence intervals. All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

induce compensatory entry into agriculture. The response instead appears in non-agricultural reemployment, which declines among individuals with higher savings and remains unchanged among those with lower savings. Higher savings thus relax the need to sustain non-agricultural employment in response to automation, while leaving agricultural reemployment patterns largely unchanged. The asymmetric response is consistent with savings affecting whether retirees remain in non-agricultural work rather than inducing a direct reallocation from non-agricultural to agricultural employment.

Overall, reemployment responses to automation reflect the interaction between economic pressure and household financial capacity. Binding constraints amplify the agricultural margin's expansion, whereas greater wealth and liquidity loosen the necessity of non-agricultural reemployment.

4.5. *Earnings consequences of sectoral recomposition*

A further question is whether post-retirement reemployment represents a viable economic adjustment or merely a low-return fallback. The preceding sections show that robot adoption shifts older workers across sectors, but whether this shift translates into meaningful earnings differences remains unclear.

Table 11 reports the corresponding wage effects. Columns (1) and (2) use the full panel and allow wage trajectories to differ by post-retirement employment status. The average wage response to robot adoption is modest. The relevant variation arises from the differential responses across reemployment types captured by the interaction terms. Non-agricultural reemployment is associated with significant wage gains under greater automation exposure, both in hourly terms (Column 1) and in daily terms (Column 2), whereas agricultural reemployment shows no comparable wage gains and yields significantly lower daily earnings as automation intensifies (Column 2). The evidence points to asymmetric price effects across sectors rather than uniform wage changes. Column (3) focuses only on retirees who reenter employment and compares earnings across sectors directly. Relative to non-agricultural reemployment, agricultural reemployment is associated with significantly lower annual wage income as robot adoption intensifies. Conditional on working, sectoral wage differentials widen under greater automation exposure.

Taken together, the results suggest that post-retirement adjustment is accompanied by differentiated earnings consequences. Automation appears to reinforce wage premia in non-agricultural activities while leaving agricultural reemployment comparatively less remunerative. Sectoral recomposition therefore entails not only shifts in employment status but also divergent income prospects across sectors, with welfare implications for retirees engaged in lower-return activities under greater automation exposure.

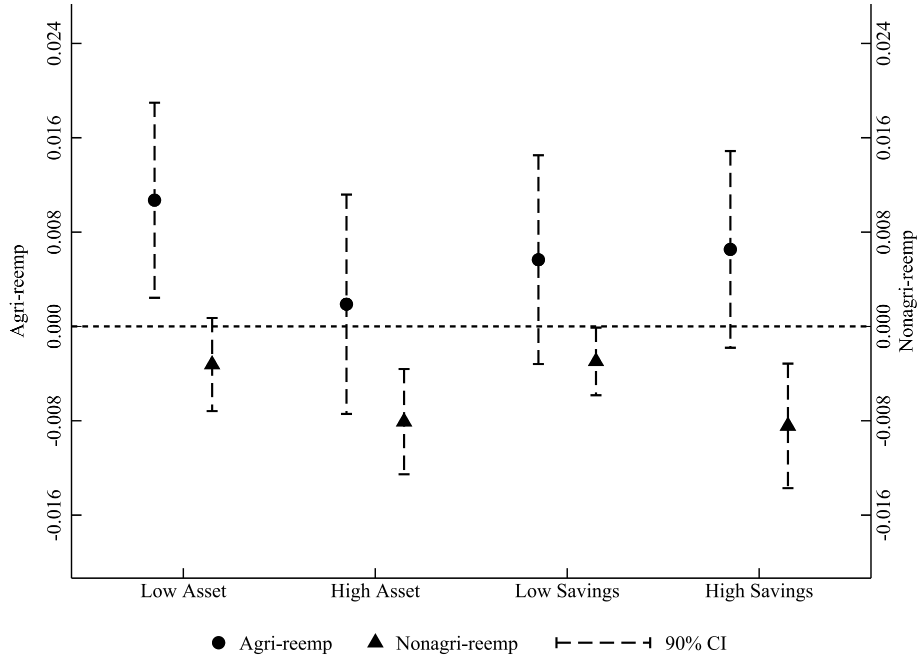

Fig. 5. Household financial resources and sectoral reemployment responses to robot adoption
Notes: This figure reports coefficient estimates from regressions examining how household wealth and savings condition sectoral reemployment responses to robot adoption. Individuals are classified into high- and low-asset groups based on whether baseline household net assets exceed the sample median, and into high- and low-savings groups based on whether baseline household savings exceed the sample median. Circles denote the estimated coefficients for agricultural reemployment, corresponding to the left vertical axis, while triangles denote the estimated coefficients for non-agricultural reemployment, corresponding to the right vertical axis. Vertical bars indicate 90 percent confidence intervals. All specifications include the same set of control variables as in the baseline regressions, and standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

Table 11
Effects of robot adoption on wage outcomes by reemployment type.

	(1)	(2)	(3)
	Hourly wage	Daily wage	Wage
Robot	0.1328	1.4392	0.0697
	(0.1072)	(1.3192)	(0.0835)
Robot×Agri-reemp	−0.1364	−2.6187**	−0.2473***
	(0.1123)	(1.2839)	(0.0576)
Robot×Nonagri-reemp	0.4214***	2.8727*	
	(0.1197)	(1.5581)	
Agri-reemp	1.2723	5.4431	−0.0381
	(0.9570)	(10.0931)	(0.0816)
Nonagri-reemp	−0.0178	−0.7873	
	(1.0540)	(10.1003)	
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control variables	Yes	Yes	Yes
Observations	29,616	30,078	6685
R-squared	0.0399	0.0299	0.4669

Notes: Columns (1) and (2) use the full panel sample and examine wage outcomes before and after retirement. The omitted group consists of individuals who do not engage in post-retirement reemployment. Column (1) uses hourly wage as the dependent variable, and column (2) uses daily wage. Column (3) restricts the sample to individuals who are reemployed after retirement. The dependent variable is the logarithm of annual wage income. The omitted category is non-agricultural reemployment. All specifications include the same set of control variables as in the baseline regressions. Standard errors are clustered at the city level. ***p < 0.01, **p < 0.05, *p < 0.1.

5. Conclusion

This paper provides new empirical evidence on how technological change shapes labor market outcomes later in the life cycle. Using individual-level data from CHARLS combined with regional variation in industrial robot adoption, we find no evidence that robot adoption alters overall post-retirement reemployment among older individuals. Robot adoption instead shifts the sectoral composition of reemployment, with agricultural participation rising and non-agricultural employment declining. Technological change therefore operates through sectoral recomposition rather than through changes in overall post-retirement labor supply.

Our additional analyses yield four main insights. First, robot adoption increases agricultural self-employment among retirees, while it reduces both self-employed and wage-based non-agricultural reemployment. Second, we find no evidence that robot adoption significantly affects overall non-agricultural hiring, which indicates that supply-side adjustments alone do not drive the observed employment changes. Third, reemployment responses to automation are shaped by both skill and digital constraints as well as economic pressures. Older workers with limited digital proficiency or job-related training are more vulnerable to non-agricultural displacement, and those facing heavier financial obligations, lower intergenerational support, or fewer household assets concentrate disproportionately in agricultural work. Finally, non-agricultural reemployment is associated with notable wage gains, particularly in hourly earnings, whereas agricultural reemployment shows little improvement and yields significantly lower daily and annual wages relative to non-agricultural work. Sectoral recomposition rather than uniform wage decline therefore drives the income disparities that emerge under increasing robot exposure.

These findings carry important implications for inequality in aging labor markets, and they bear directly on China's reform to gradually raise statutory retirement ages. As technological change accelerates alongside population aging, policies promoting extended working lives may interact with automation in ways that amplify existing vulnerabilities. Whether longer working lives translate into effective reemployment depends on older workers' capacity to adjust as automation reshapes the jobs available to them. When non-agricultural reemployment is constrained by limited digital proficiency or skill gaps, older workers are more likely to enter lower-quality agricultural employment rather than exiting the labor force. The institutional context of China amplifies these patterns, as the unequal coverage between the Urban Employee Pension and the Urban-Rural Resident Basic Pension leaves retirees in vulnerable categories with weaker financial buffers to absorb such adjustments.

For longer working lives to draw older human capital into productive use rather than into low-return fallback work, the reform needs three complementary supports. First, retirement-age extension should be paired with age-specific digital and vocational training. Our results show that job-related training significantly weakens the displacement effect of automation on non-agricultural reemployment, so reskilling geared to the digital and task requirements of automated workplaces can make longer working lives feasible in practice rather than nominal. Second, the reform should support sectoral transitions and flexible employment within non-agricultural work. Channels such as job-matching services, transition subsidies, and the integration of platform-based work into the social insurance system can help older workers remain in non-agricultural employment rather than moving into agriculture. Third, the pace of retirement-age extension should be aligned with pension adequacy for the most exposed groups. Targeted assistance for workers facing heavier economic or caregiving burdens, together with a narrowing of the coverage gap between the two pension systems, would relieve the economic pressure that drives financially constrained retirees back into work. These supports matter most where automation expands faster than the institutional capacity to absorb its effects, and more broadly the results underscore the need to weigh post-retirement labor supply and sectoral recomposition when assessing the distributional consequences of technological change in later life.

CRediT authorship contribution statement

Mengxuan Wu: Writing – original draft, Validation, Methodology, Formal analysis, Conceptualization. **Weiwei Zheng:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Wei Wang:** Writing – review & editing, Validation.

Consent to publish

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Ethical approval

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Competing interests

The authors declare that they have no competing interests.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.telpol.2026.103278.

Data availability

The authors do not have permission to share data.

References

Abeliansky, A. L., Beulmann, M., & Prettner, K. (2024). Are they coming for us? Industrial robots and the mental health of workers. *Res. Policy, 53*, Article 104956. https://doi.org/10.1016/j.respol.2024.104956

Acemoglu, D., Koster, H. R. A., & Ozgen, C. (2023). *Robots and workers: evidence from the Netherlands*. https://doi.org/10.3386/w31009. Working Paper Series.

Acemoglu, D., & Restrepo, P. (2018a). Low-skill and high-skill automation. *Journal of Human Capital, 12*, 204–232. https://doi.org/10.1086/697242

Acemoglu, D., & Restrepo, P. (2018b). The race between man and machine: implications of technology for growth, factor shares, and employment. *The American Economic Review, 108*, 1488–1542. https://doi.org/10.1257/aer.20160696

Acemoglu, D., & Restrepo, P. (2019). Automation and new tasks: how technology displaces and reinstates labor. *The Journal of Economic Perspectives, 33*, 3–30. https://doi.org/10.1257/jep.33.2.3

Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: evidence from US labor markets. *Journal of Political Economy, 128*, 2188–2244. https://doi.org/10.1086/705716

Acemoglu, D., & Restrepo, P. (2024). A task-based approach to inequality. *Oxf Open Econ, 3*, i906–i929. https://doi.org/10.1093/ooec/odad082

Akerman, A., Gaarder, I., & Mogstad, M. (2015). The skill complementarity of broadband internet. *Quarterly Journal of Economics, 130*, 1781–1824. https://doi.org/10.1093/qje/qjv028

Autor, D., Chin, C., Salomons, A., & Seegmiller, B. (2024). New frontiers: The origins and content of new work, 1940–2018. *Quarterly Journal of Economics, 139*, 1399–1465. https://doi.org/10.1093/qje/qjae008

Autor, D. H., & Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the US labor market. *The American Economic Review, 103*, 1553–1597. https://doi.org/10.1257/aer.103.5.1553

Autor, D. H., Dorn, D., & Hanson, G. H. (2015). Untangling trade and technology: Evidence from local labour markets. *Econ J, 125*, 621–646. https://doi.org/10.1111/ecoj.12245

Autor, D. H., Katz, L. F., & Krueger, A. B. (1998). Computing inequality: Have computers changed the labor market? *Quarterly Journal of Economics, 113*, 1169–1213. https://doi.org/10.1162/003355398555874

Blau, D. M., & Goodstein, R. M. (2016). Commitment in the household: evidence from the effect of inheritances on the labor supply of older married couples. *Labour Economics, 42*, 123–137. https://doi.org/10.1016/j.labeco.2016.08.003

Blundell, R., French, E., & Tetlow, G. (2016). Retirement incentives and labor supply. In *Handbook of the economics of population aging* (pp. 457–566). North-Holland. https://doi.org/10.1016/bs.hespa.2016.10.001.

Borusyak, K., Hull, P., & Jaravel, X. (2022). Quasi-experimental shift-share research designs. *Rev. Econom. Stud., 89*, 181–213. https://doi.org/10.1093/restud/rdab030

Bratberg, E., Holmås, T. H., & Thøgersen, Ø. (2004). Assessing the effects of an early retirement program. *Journal of Population Economics, 17*, 387–408. https://doi.org/10.1007/s00148-003-0165-y

Capatina, E. (2015). Life-cycle effects of health risk. *J. Monet. Econ., 74*, 67–88. https://doi.org/10.1016/j.jmoneco.2015.06.002

Chen, K., Feinerman, K., & Haggag, K. (2025). Flexible pay and labor supply: evidence from uber's instant pay. *Manage. Sci.*. https://doi.org/10.1287/mnsc.2024.05301

Chen, Y., & Zhao, Y. (2022). The timing of first marriage and subsequent life outcomes: evidence from a natural experiment. *Journal of Comparative Economics, 50*, 713–731. https://doi.org/10.1016/j.jce.2022.04.005

Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). The adjustment of labor markets to robots. *Journal of the European Economic Association, 19*, 3104–3153. https://doi.org/10.1093/jeea/jvab012

Dixon, J., Hong, B., & Wu, L. (2019). The employment consequences of robots: Firm-level evidence. *SSRN Electronic Journal*, 1–39. https://doi.org/10.2139/ssrn.3422581

Engels, B., Geyer, J., & Haan, P. (2017). Pension incentives and early retirement. *Labour Economics, 47*, 216–231. https://doi.org/10.1016/j.labeco.2017.05.006. EALE conference issue 2016.

Fadlon, I., & Nielsen, T. H. (2021). Family labor supply responses to severe health shocks: evidence from danish administrative records. *American Economic Journal: Applied Economics, 13*, 1–30. https://doi.org/10.1257/app.20170604

French, E. (2005). The effects of health, wealth, and wages on labour supply and retirement behaviour. *The Review of Economic Studies, 72*, 395–427. https://doi.org/10.1111/j.1467-937X.2005.00337.x

Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technol. Forecasting Social Change, 114*, 254–280. https://doi.org/10.1016/j.techfore.2016.08.019

Giuntella, O., Lu, Y., & Wang, T. (2025). How do workers adjust to robots? Evidence from China. *Econ. J., 135*, 637–652. https://doi.org/10.1093/ej/ueae086

Goldsmith-Pinkham, P., Sorkin, I., & Swift, H. (2020). Bartik instruments: What, when, why, and how. *The American Economic Review, 110*, 2586–2624. https://doi.org/10.1257/aer.20181047

Graetz, G., & Michaels, G. (2018). Robots at work. *The Review of Economics and Statistics, 100*, 753–768. https://doi.org/10.1162/rest_a_00754

Hampton, M., & Totty, E. (2023). Minimum wages, retirement timing, and labor supply. *J. Public Econ., 224*, Article 104924. https://doi.org/10.1016/j.jpubeco.2023.104924

Inderbitzin, L., Staubli, S., & Zweimüller, J. (2016). Extended unemployment benefits and early retirement: Program complementarity and program substitution. *Am. Econ. J.: Econ. Policy, 8*, 253–288. https://doi.org/10.1257/pol.20130315

Khanna, G., Lay, M. J., Lee, S., & Thompson, B. (2025). Female labor supply and rural pension eligibility in Brazil. *J. Public Econ., 245*, Article 105352. https://doi.org/10.1016/j.jpubeco.2025.105352

Kolsrud, J., Landais, C., Reck, D., & Spinnewijn, J. (2024). Retirement consumption and pension design. *The American Economic Review, 114*, 89–133. https://doi.org/10.1257/aer.20221426

Lordan, G., & Neumark, D. (2018). People versus machines: The impact of minimum wages on automatable jobs. *Labour Economics, 52*, 40–53. https://doi.org/10.1016/j.labeco.2018.03.006

Lythreatis, S., Singh, S. K., & El-Kassar, A.-N. (2022). The digital divide: A review and future research agenda. *Technol. Forecasting Social Change, 175*, Article 121359. https://doi.org/10.1016/j.techfore.2021.121359

Ma, W., Ouimet, P., & Simintzi, E. (2025). Mergers and acquisitions, technological change, and inequality. *Journal of Financial Economics, 172*, Article 104136. https://doi.org/10.1016/j.jfineco.2025.104136

Mason, P. L. (2021). Computerization and occupational change: Assessing the impact of automation on racial and gender employment densities. *The Review of Black Political Economy*. https://doi.org/10.1177/00346446211055203

Pandey, S. K., Hart, J. J., & Tiwary, S. (2003). Women's health and the internet: Understanding emerging trends and implications. *Social Science & Medicine, 56*, 179–191. https://doi.org/10.1016/S0277-9536(02)00019-9

Peng, F., Anwar, S., & Kang, L. (2017). New technology and old institutions: An empirical analysis of the skill-biased demand for older workers in Europe. *Econ. Model., 64*, 1–19. https://doi.org/10.1016/j.econmod.2017.03.004

Somanathan, E., Somanathan, R., Sudarshan, A., & Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy, 129*, 1797–1827. https://doi.org/10.1086/713733

Wang, R., Shi, J., & Ye, B. (2022). Can robots reshape gender role attitudes? *China Economic Review, 75*, Article 101852. https://doi.org/10.1016/j.chieco.2022.101852

Wang, T., Zhang, Y., & Liu, C. (2024). Robot adoption and employment adjustment: Firm-level evidence from China. *China Economic Review, 84*, Article 102137. https://doi.org/10.1016/j.chieco.2024.102137

Zhang, L., Gan, T., & Fan, J. (2023). Do industrial robots affect the labour market? Evidence from China. *Econ. Transit. Institutional Change, 31*, 787–817. https://doi.org/10.1111/ecot.12356