# Robots, Routine Jobs and Rural Workers

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**Abstract**

We study how rural-to-urban workers adjust their employment and location choices to industrial robots in China. Constrained by the household registration system, rural workers in China often face significant labor market barriers, leading them to predominantly occupy routine jobs that require repetitive physical tasks and thus increasing their risk of displacement by automation. We find that robots solely replace rural workers in routine jobs, with a more pronounced effect in less efficient labor markets. After leaving routine jobs, about half of these rural workers shift to the agricultural sector within their local labor markets. The other half migrates to prefectures with a lower proportion of routine jobs, even though these areas are less economically developed than their previous places of residence. This study offers insights into the challenges posed by technological advancements to vulnerable workers in developing countries with labor market frictions.

# 1. Introduction

The growing usage of automation technologies, such as industrial robots, has encouraged extensive research into their displacement effects on employment (Acemoglu et al., 2022; Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Mandelman and Zlate, 2022). The literature demonstrates that automation primarily displace routine occupations which are characterized by repetitive and physical tasks (Acemoglu and Autor, 2011; Acemoglu et al., 2023; Autor et al., 2003; Dauth et al., 2021; Goos et al., 2014). However, the impact of automation on employment in developing countries is not well understood. These regions often face labor market frictions that restrict workers to certain jobs and locations (Donovan et al., 2023). On one hand, the agricultural sector remains an important source of employment in these countries, with 59% of the workforce in low-income and 29% in middle-income countries employed in agriculture in 2021, contrasting with 5% in high-income countries.[1] On the other hand, with economic develop, there is a significant migration of rural workers to urban areas, yet they are often restricted to routine jobs due to their limited skills and the imperfections of labor markets (Hu et al., 2024). As these countries begin to adopt automation following global technology trends, these workers become particularly vulnerable to displacement by automation and find it difficult to employ in other types of jobs in urban areas, potentially resulting in a return to the agricultural sector. Paradoxically, advancements in manufacturing, instead of reducing agricultural employment, may actually increase it in situations where labor markets are inefficient.

In this paper, we study how rural workers, who migrate from rural to urban areas, adjust to the industrial robots in China. Possessing the world's largest stock of industrial robots, China also struggles with persistent labor market frictions, largely attributed to its longstanding household registration (*hukou*) system. The system categorizes citizens into urban and rural residents by issuing them a certificate. Those without a local *hukou* certificate face constraints related to land use, education, and other social services in urban labor markets. As a result, rural workers, constrained by these systemic barriers, are frequently forced to accept occupations that require intensive physical and manual labor (Hu et al., 2024; Meng and Zhang, 2001; Zhang and Wu, 2017). Such occupations, being highly routine, are more susceptible to displacement by industrial robots. Thus, when robots replace human labor in these jobs, rural workers are disproportionately affected by them, not only because they represent a significant portion of the workforce in these jobs but also due to the challenges they face in transitioning to other occupations,

[1] The data comes from the International Labour Organization's "ILO modelled estimates database" (ILOSTAT).

exacerbated by their limited skills and the hurdles imposed by the urban labor market.

Figure 1 shows the trends among robots, routine jobs and rural workers. The number of industrial robots in China (represented by the red line) began to rise in 2005 and saw a more rapid increase after 2010. Meanwhile, the population of rural workers (blue line) continued to grow, with an average annual increase of 2.52% between 2005 and 2010. However, a decline in the number of routine occupations (green line) is observed from 2010 to 2015. This graphical representation emphasizes the relationship between automation technologies and labor market shifts over the decade. Given the constraints of our datasets, our analysis is focused on examining the impact of industrial robots on routine occupations and rural workers over the period from 2005 to 2015.

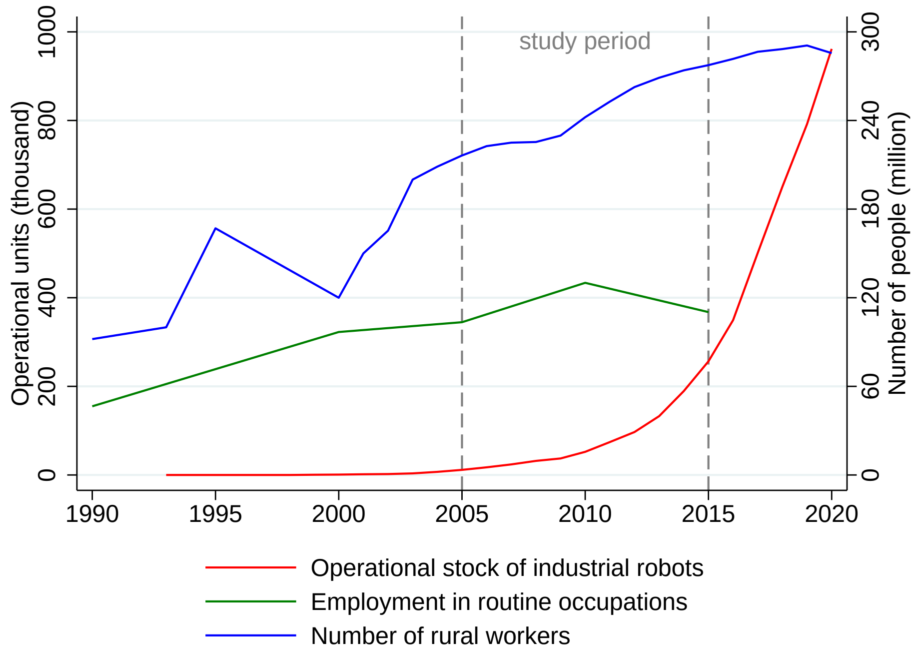


Figure 1: Robots, Routine Occupations, and Rural Workers, 1990-2020

Notes: The data sources are International Federation of Robotics (1993-2020), Population Census (1990-2015), and Migrant Workers Monitoring Survey Report (1990-2020).

Our empirical method is based on Acemoglu and Restrepo (2020). We construct a shift-share measure of exposure to robots at the prefecture level by combining the industry-level stock of robots with the employment structure in each industry. For a more causal interpretation, we instrument exposure to robots in each prefecture using industry-level robot adoption from other countries that show a similar increasing trend with China. To categorize the task content of each occupation, we follow Hu et al. (2024) and classify occupations as routine or non-routine based on job descriptions from Chinese *Occupation Classification Dictionary*. We use a long-difference specification to estimate the effects of robots on employment and occupation categories among both rural and urban workers from 2005 to 2015.

Using this strategy, we find a significant negative effect of industrial robots on the employment of workers in routine occupations in China. The effect is uniquely observed among rural workers, rather than urban workers. Specifically, the introduction of one more robot per thousand workers results in a 9.1 percentage point decrease in the employment-to-population ratio of rural workers engaged in routine occupations. This equates to the displacement of approximately 50.9 rural workers in a prefecture with average exposure to robotics. However, the displacement effects on rural workers are less pronounced in prefectures with a more open *hukou* system.

To investigate how rural workers adjust their employment and location in response to robots, we use a long-difference method similar to our baseline analysis and estimate the impact of robots on their employment choices and geographical mobility. When displaced from routine occupations by robots, rural workers face several decisions: whether to switch occupations or relocate, which locations to choose, and what occupations to find after relocation. To answer these questions, we first examine the influence of robots on the occupational categories and employment status of rural workers within prefectures. Then we construct a migration flow matrix between prefectures to track and analyze rural workers' relocation patterns and their characteristics in response to robots across different prefectures. Furthermore, we explore the occupational choices of rural workers in their new locations, taking into account various migration patterns.

Our findings indicate a significant trend of rural workers moving towards agricultural jobs or migrating out of the prefectures as a reaction to the robot shocks. In local labor markets, the introduction of an additional robot per thousand workers results in a 5.1 percentage point increase in the employment-to-population ratio in agriculture, which corresponds to approximately 28.8 rural workers. This trend is especially pronounced among rural workers with local *hukou* who own arable land in their local prefectures. In contrast, rural workers without local *hukou* tend to migrate out of their current prefectures, either returning to their hometowns or moving to new, less economically developed prefectures. In these new locations, they are more likely to take up non-agricultural occupations.

Finally, we use our estimates to quantify the magnitudes of the impacts of robots, interpreting these findings within the context of China. Our results indicate that 56% of rural workers choose to engage in agricultural jobs within their current work locations after leaving routine occupations due to the robot shocks. In contrast, a mere 2% transition into non-routine occupations. The remaining 42% choose to migrate out of their prefectures. Among these migrants, 55% return to their home prefectures, while 45% relocate to entirely new prefectures. After migrating, approximately half of them find employment in routine occupations, with the other half securing positions in non-routine occupations.

This paper contributes to multiple strands of literature. First, we extend the existing research regarding the employment effects of robots, particularly focusing on rural workers who are more vulnerable in imperfect urban labor markets of developing countries. Most literature concentrates on developed countries, such as the pioneering work by Acemoglu and Restrepo (2020), who find the negative effects of robot adoption on employment and wages at the commuting zone level in the US. Other studies, including Bonfiglioli et al. (2020), Dauth et al. (2021), Koch et al. (2021), Humlum (2022), Petit et al. (2023) and Acemoglu et al. (2023), estimate the employment effects at individual, firm, industry and district levels in European countries. These studies generally indicate significant negative impacts of robots on employment, especially for low-skilled, routine workers in production lines. Restrepo (2023) provides a detailed overview of the literature. Although Giuntella et al. (2022), Plumwongrot and Pholphirul (2023) and Brambilla et al. (2023) utilize data from developing countries, their focus is not on worker adjustment under labor market frictions. Our work investigates the effects of robots on a specific labor group in imperfect labor markets and offers insights for developing countries preparing for widespread automation adoption.

Second, our results relate to the substantial literature examining the migration response to a labor demand shock. Inspired by work of Bartik (1991) and Blanchard et al. (1992), a growing body of research has found that people tend to migrate under the influence of large and adverse labor demand shocks, including local employment decline (Foote et al., 2019; Wozniak, 2010), employment decline in connected locations (Borusyak et al., 2022; **?**), China shock (Autor et al., 2013), housing boom and manufacturing decline (Charles et al., 2019). Moreover, the migration response varies across different education, age, and immigrant groups (Bound and Holzer, 2000; Notowidigdo, 2020). Specifically, Cadena and Kovak (2016) find that low-skilled Mexican-born immigrants respond much more strongly than low-skilled natives. Faber et al. (2022) and Chen et al. (2022) focus on the migration response to robot shocks and find that robots reduce in-migration in the US and China respectively. Our paper regards robot adoption as a negative labor demand shock, particularly affecting routine occupations. We investigate the migration response among rural workers, including their choice of migration destinations and the types of employment they pursue after migrating.

Finally, we contribute to the literature by exploring how rural workers adjust to robots while struggling with barriers in urban labor markets under the *hukou* system. Rural workers in China, restricted in their access to social security and public services, often find themselves forced to accept jobs that urban workers reject (Meng, 2012; Meng and Manning, 2010; West and Zhao, 2000; Wu and Zhang, 2014; Zhao, 2000). Meng and Zhang (2001) find that 6% of rural migrants, who would have been eligible for white-collar jobs, were instead stuck in blue-collar positions during 1995-1996. Meng (2012) observes that over 89% of migrant workers are employed in unskilled positions within sales, service or production jobs. This occupational segregation negatively affects their wages. Zhang and Wu (2017) find that the earning disadvantages experienced by rural migrants can be largely attributed to occupational segregation, which is most severe in government agencies and state institutions. In the paper, we analyze the occupation and location choices of these rural workers influenced by robots, highlighting how the labor market frictions exacerbate the negative effects of robots.

The remainder of the paper is structured as follows. Section 2 introduces our data sources and empirical strategy. Section 3 presents our baseline results. Section 4 focuses on the adjustment behaviors of rural workers in response to robot shocks. Section 5 concludes.

# 2. Data and Methodology

## 2.1 Measuring Robots

The primary dataset for this study is drawn from the International Federation of Robotics (IFR), which includes information on the stock of robots at the industry-country level between 1993 and 2019. This data is collected through yearly surveys of robot suppliers across 50 countries and 25 industries, and has been widely used in previous research examining the impact of robots on employment (Acemoglu and Restrepo, 2020; Dauth et al., 2021; Graetz and Michaels, 2018). Based on the IFR's definition, an industrial robot is a "reprogrammable multipurpose manipulator programmable in three or more axes". In the paper, we analyze the impact of industrial robots used in manufacturing industries. To do so, we extract data on the stock of robots in 11 manufacturing industries from 2005 to 2015, including food and beverages, textiles, wood and furniture, paper and printing, chemical products, petroleum products, rubber and plastic, minerals, basic metals, metal products, industrial machinery, electrical, electronics, automotive, other transport equipment, and all other manufacturing branches.[2]

In our study, we aim to measure the stock of robots presented at the prefecture level. However, the IFR data only provides information on robot usage at the industry-country level. To address this issue, we follow the approach by Acemoglu and Restrepo (2020)

[2]Industry codes in the IFR data differ from those in the census data we use in our analysis, we translate the IFR industry code to the census industry code using the "International Standard Industrial Classification of All Economic Activities, Revision 4".

and construct a shift-share measurement for exposure to robots at the prefecture level.

$$EtR_{dt} = \sum_i \frac{L_{dit_0}}{L_{dt_0}} \times \frac{Robot_{it}}{L_{it_0}} \tag{1}$$

where $EtR_{dt}$ is exposure to robots in prefecture $d$ at year $t$. $\frac{L_{dit_0}}{L_{dt_0}}$ is the employment share of industry $i$ in prefecture $d$ at the base year $t_0$, which captures historical industry employment structure ("shares"). $\frac{Robot_{it}}{L_{it_0}}$ is the number of robots per thousand workers in industry $i$, which captures the labor shock across industries ("shift"). This measurement combines the industry-level stock of robots with the employment structure within each industry. By doing so, we can estimate the extent to which each prefecture's workforce is exposed to robots for our empirical estimation.

## 2.2 Measuring Routine Jobs

We classify non-agricultural occupations into routine and non-routine categories in Chinese context following the method proposed by Hu et al. (2024). They measure the level of routineness for each occupation and construct routine task intensities based on a task-based approach (Acemoglu and Autor, 2011; Autor and Dorn, 2013; Autor et al., 2003). In details, they use text data from the *Occupation Classification Dictionary* (OCD), which contains job descriptions for over 1,800 occupations, and *A Thesaurus of Modern Chinese*, which contributes to identifying the meaning of words in the descriptions. They measure routine task intensities for each occupation by calculating the frequencies of routine words defined by the thesaurus. Following Autor and Dorn (2013), they classify occupations as routine if the percentile of routine task intensity is larger than 66. The outcomes of this classification align well with empirical observations. For example, top three routine occupations are mechanical equipment repairers, mechanical and electricity assemblers, and rubber and plastic production workers. The top three non-routine occupations include teachers, functionaries of state organs, and functionaries of democratic parties and other people's organizations. The introduction of the method is detailed in the Appendix B.

## 2.3 Measuring Rural Workers

We use the individual-level Population Census as the main source of labor market data for five-year intervals from 2000 to 2015. The National Bureau of Statistics (NBS) of China conducted decennial population censuses in 1990, 2000, and 2010, as well as 1 percent sample surveys in 1995, 2005, and 2015. The census data provides valuable information including individuals' location, occupation, sector, migration status, *hukou* type, and other demographic characteristics. In the paper, we utilize the 2005 and 2015 Census data to establish our baseline results, and employ the 2000 and 2010 Census data for robustness checks.

To identify the types of labor, we define "rural workers" and "urban workers" as individuals who possess agricultural *hukou* and non-agricultural *hukou* respectively. Our analysis focuses on the labor market outcomes for working-age individuals. So we include only individuals aged 16-65 years old, and exclude those who are currently studying or who have migrated for the purpose of studying. Then we use each individual's two-digit occupation code and identify whether their occupations are routine-intensive by matching the occupation classification codes from the census data with Hu et al. (2024).[3] Given that the census data separates agricultural occupations from non-agricultural ones, we consider agriculture as an independent occupation category.

To better understand the migration patterns of rural workers, we collect information on their place of registration, place of residence, and place of residence five years prior to the interview at the prefecture level in the 2015 Census.[4] Using this information, we create a matrix of migration flows between all Chinese prefectures during the period of 2010 to 2015.[5] Then we are able to determine which individuals have migrated from their previous location between 2010 and 2015. We define "location adjustment" as a change in individuals who report a current residence in a different prefecture from their residence five years ago. Three specific scenarios are considered: return migration (from non-home to home prefecture), new-city migration (from non-home to another non-home prefecture) and home departure (from home to non-home prefecture). Moreover, we use data on current employment status and occupation categories to identify the occupation mobility of workers after relocating. This information is then linked with characteristics of their previous residence to better understand the dynamics of labor market transitions.

## 2.4 Descriptive Statistics

Table 1 provide descriptive statistics for our key variables, grouped by total, rural, and urban workers at the prefecture level. In Panel A, we report changes in employment

[3]China has published five versions of the occupation classification code in 1986, 1999, 2009, 2015 and 2022. As the 1999 and 2009 versions are utilized in most census data and have few differences between them, we transformed the two-digit occupation codes of different years to the same 2009-year criterion.

[4]It is worth noting that while the 2005 and 2010 censuses also collected information about place of residence five years prior to the interview, this information was only available at the province level, which would be too rough for our research.

[5]An assumption underlying this matrix is that the population structure in 2010 is identical to the one deduced from the place of residence five years prior in the 2015 Census. Figure C1 in the Appendix provides support for this assumption, demonstrating a correlation between the actual share of migrants in 2010 and the predicted share of migrants derived from the 2015 Census. The findings indicate that the actual share is very close to the predicted share, providing support for the assumption.

outcomes within the local labor market. The data shows that there is a large decrease in the employment-to-population ratio among rural workers, whereas this ratio shows a minor increase among urban workers. Regarding employment categories, the proportion of rural workers employed in routine occupations remains relatively stable on average from 2005 to 2015 at the prefecture level, although there is substantial variation. The share of rural workers in agricultural jobs experienced a decline over the 10-year period, with significant variation as well. In contrast, for urban workers, changes in different employment categories are much less pronounced than for rural workers. The proportion of workers engaged in routine occupations decreased, while the opposite trend was observed for non-routine occupations.[6]

Table 1: Summary Statistics

| | Total | | Rural workers | | Urban locals | |
|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd |
| **Panel A: local labor market outcomes (N=285)** | | | | | | |
| 2005-15 point change in employment/population ratio | -0.106 | 0.058 | -0.138 | 0.088 | 0.003 | 0.062 |
| 2005-15 point change in emp/pop ratio, routine jobs | -0.000 | 0.078 | 0.004 | 0.068 | -0.014 | 0.024 |
| 2005-15 point change in emp/pop ratio, non-routine jobs | 0.091 | 0.052 | 0.059 | 0.044 | 0.014 | 0.032 |
| 2005-15 point change in emp/pop ratio, agricultural jobs | -0.196 | 0.118 | -0.201 | 0.123 | 0.002 | 0.025 |
| 2005-15 point change in unemployment/population ratio | 0.018 | 0.020 | 0.015 | 0.014 | 0.002 | 0.009 |
| 2005-15 point change in non-LFP/population ratio | 0.039 | 0.045 | 0.030 | 0.037 | 0.004 | 0.033 |
| **Panel B: migration outcomes (N=276)** | | | | | | |
| 2010-2015 location adjustment/pop | 0.023 | 0.021 | 0.016 | 0.016 | 0.007 | 0.006 |
| 2010-2015 return migration/pop (from non-home to home) | 0.009 | 0.015 | 0.007 | 0.013 | 0.002 | 0.003 |
| 2010-2015 new-city migration/pop (from non-home to non-home) | 0.002 | 0.005 | 0.001 | 0.004 | 0.000 | 0.001 |
| 2010-2015 hometown departure/pop (from home to non-home) | 0.012 | 0.009 | 0.008 | 0.008 | 0.004 | 0.003 |
| **Panel C: exposure to robots (N=285)** | | | | | | |
| 2005-15 change in exposure to Chinese robots | 0.411 | 0.331 | 0.411 | 0.331 | 0.411 | 0.331 |
| 2005-15 change in exposure to foreign robots | 2.114 | 1.635 | 2.114 | 1.635 | 2.114 | 1.635 |
| 2010-15 change in exposure to Chinese robots | 0.395 | 0.267 | 0.395 | 0.267 | 0.395 | 0.267 |
| 2010-15 change in exposure to foreign robots | 2.118 | 1.407 | 2.118 | 1.407 | 2.118 | 1.407 |

Notes: This table reports the observation, mean and standard deviation of prefecture-level variables for total workers, rural workers and urban workers. The term "Non-LFP" denotes non-labor force participation. The outcome variables in Panel A and B are aggregated at the prefecture level calculated from the individual Census.
Source: IFR, and 2005-2015 Census.

Panel B presents changes in migration outcomes from 2010 to 2015. The period differs from Panel A due to the absence of panel data in the census. Therefore, we must rely on the variable "place of residence five years prior'' to analyze the impact of robots on migration. The statistics show an increase in the proportion of total workers who choose to migrate out of the prefecture, and the share of location adjustment is more substantial for rural workers compared to urban workers. Among the three migration patterns, home departure constitutes the largest share, followed by return migration,

[6] Table C1 and Figure C2 in the Appendix provide further evidence of employment differences between rural and urban workers, and we observe that rural workers are primarily employed in routine occupations.

with new-city migration being the least common, for both rural and urban workers.[7]

Panel C reports descriptive statistics of change in exposure to robots at the prefecture level between 2005 and 2015. It shows an average increase of 0.41 robots per thousand workers during this period, with the growth being more pronounced from 2010 to 2015. Considering the enormous size of China's population, this indicates a significant rise in the robot usage across Chinese prefectures.[8]

## 2.5 Empirical Strategy

To capture the average effects of robots on local labor markets and migrants' behaviors, we estimate the impact on employment status, occupation adjustment and migration patterns at the prefecture level. The model is constructed as follows:

$$\Delta y_d = \beta_0 + \beta_1 \Delta EtR_d + \boldsymbol{\alpha}\mathbf{x_d'} + \varepsilon_d \tag{2}$$

where $\Delta y_d$ are changes in outcomes for prefecture $d$, including the employment-to-population ratio and the ratios in various occupation categories and migration patterns. $\Delta EtR_d$ is change in exposure to robots for prefecture $d$. In the vector $\mathbf{x_d'}$, we control for broad district dummies and prefecture-level demographic characteristics in the base year (log of population density; the share of female; the share of population aged 65 and above; the share of married; the share of ethnic minorities; the share of urban population; the shares of population with primary school, junior high school, senior high school and college degrees). To control the effect of industry composition and other technological shocks on employment, we also incorporate employment shares of 7 broad industry groups in the base year (the shares of employment in agriculture (reference), mining, manufacturing, electricity, construction, traditional services and modern services) and change in exposure to ICT technologies (changes in the usage ratios of mobile phones and broadband internet). The data is from the census data aggregated at the prefecture level and Statistics Yearbook. Standard errors are clustered at the province level, and each prefecture is weighted by the population at baseline.

In Equations (2), $EtR_d$ is designed using the shift-share method, as defined in Equation (1). Recent research has shown that obtaining consistent estimates in shift-share designs requires exogeneity of either the shares or shifts (Adão et al., 2019; Borusyak et al., 2022; Goldsmith-Pinkham et al., 2020). However, in our setting, the industry em-

[7]Figure C3 in the Appendix indicates that rural workers tend to migrate within their registered prefecture, suggesting a tendency for return migration.

[8]Figure A1 in the Appendix provides a visual representation of the geographic distribution of robot exposure. We observe high concentrations of robot usage in some eastern and central cities of China, particularly those with highly developed manufacturing industries.

ployment structure (shares) is endogenous to employment outcomes, and the exposure to robots (shifts) is also likely to be endogenous due to potential labor demand or supply shocks that may drive robot adoption in a prefecture. To address this endogeneity challenge, we adopt an instrumental variable strategy in the spirit of Acemoglu and Restrepo (2020), which leverages variation in the number of robots across countries instead of population characteristics. Specifically, we employ the average number of robots in five countries — the US, Korea, Portugal, Netherlands and Poland — that exhibit a similar growth trend in robot deployment as China. We construct our instrument for exposure to robots as follows:

$$EtR_{dt}^{IV} = \frac{1}{5}\sum_{j}\sum_{i}\frac{L_{dit_0}}{L_{dt_0}} \times \frac{Robot_{ijt}}{L_{ijt_0}} \tag{3}$$

$$j = \{\text{US, Korea, Portugal, Netherlands, Poland}\}$$

To test the identification assumption, we examine the relationship between prefecture-level demographics and exposure to robots in Table E1 in the Appendix. We find no significant association between demographics (such as employment, gender, age, and education) and exposure to either Chinese or foreign robots, suggesting that our identification strategy is not confounded by differential sorting of workers across prefectures. We report the results of our first-stage regressions in Table E2 in the Appendix. The estimates indicate that exposure to Chinese robots is significantly positively correlated with exposure to foreign robots, and their F-statistics are well above the conventional threshold of 10. This finding confirms that our instrument is valid and satisfies the relevance criterion necessary for obtaining consistent estimates of the causal effect of robots on labor outcomes.

Finally, to address the potential correlation of outcomes across prefectures with similar industry employment structures, we employ a method proposed by Adão et al. (2019) to adjust standard errors in shift-share designs. This adjustment allows us to obtain more accurate statistical inference and mitigate the risk of erroneous findings. In our analysis, we apply this method and present the adjusted standard error in our results to ensure the validity of our estimates.

# 3. Baseline Results

## 3.1 Employment effects

Understanding the effects of robots on employment in China is crucial, especially with regards to whether it has stronger displacement effects on rural workers due to the vulnerability imposed by the *hukou* system. To evaluate the differential employment impacts of robots on rural and urban workers, we estimate various versions of Equation (2) by utilizing the employment-to-population ratio, as well as the ratios in routine and non-routine occupations among total, rural and urban workers at the prefecture level. Table 2 presents 2SLS estimates for long-differences specifications between 2005 and 2015, and we also include the shift-share standard errors using the method proposed by Adão et al. (2019).[9] Given the unique significance of agriculture, especially for rural workers in China, this section will focus on non-agricultural employment, and the adjustment to agriculture will be discussed in the following section.

Columns 1 and 2 of Panel A shows the effects of robots on overall employment-to-population ratio. Column 1 controls prefecture-level demographic characteristics, industry shares and district fixed effects. The coefficient is estimated to be significantly negative. Column 2 adds exposure to ICT technologies using changes in the usage ratios of mobile phones and broadband internet between 2005 and 2015. This adjustment results in a marginal change in coefficient, yet the negative effects are remaining and strong. Specifically, the introduction of one more robot per thousand workers results in a 2.9 percentage point decrease in the employment-to-population ratio. This translates to the displacement of approximately 16.4 workers in a prefecture subjected to the mean level of robotic exposure.[10] Comparing the findings from Acemoglu and Restrepo (2020) and Dauth et al. (2021), it was found that 7.9 manufacturing workers were displaced in the local labor market regions exposed to the mean level of robots in Germany, and 3.4 workers were displaced in the commuting zone exposed to the mean level of robots in the US. This comparison suggests that the negative impact of robots on employment in China is substantially greater than in these two countries.

We further categorize occupations into routine and non-routine, and then estimate the impact of robots on both categories. Columns 3 and 4 reveal a negative and statistically significant effect on routine jobs, indicating a clear trend of robotic replacement

[9] The OLS results are reported in Table E3 in the Appendix, and they exhibit similar patterns.

[10] We calculate the magnitude of displacement using the method employed by Dauth et al. (2021). Consider two time points, where $E_t$ represents the level of employment at time $t$, $R$ exposure to robots, and $Pop$ population. The difference in the employment-to-population ratio between these two time periods can be expressed as:

$$\frac{E_2}{Pop_2} - \frac{E_1}{Pop_1} = \beta \left( \frac{R_2 - R_1}{E_1} \right)$$

Assuming a constant population over the two periods simplifies the equation to:

$$E_2 - E_1 = \beta \left( \frac{R_2 - R_1}{E_1 / Pop_1} \right)$$

Drawing from the descriptive statistics reported in Tables 1 and 2, the average change in robot exposure from 2005 to 2015 is 0.41 robots per thousand workers, and an employment-to-population mean is 0.74 in the baseline year of 2005. These values enable the calculation of the employment displacement.

Table 2: Effects of Robots on Employment

| | Total Employment | | Routine jobs | | Non-routine jobs | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: total workers** | | | | | | |
| $\Delta$ Exposure to robots | -0.028 | -0.029 | -0.080 | -0.084 | 0.001 | 0.003 |
| | (0.011)** | (0.011)** | (0.016)*** | (0.015)*** | (0.012) | (0.011) |
| | [0.012]** | [0.012]** | [0.017]*** | [0.016]*** | [0.010] | [0.010] |
| Baseline mean of E/P | 0.738 | 0.738 | 0.139 | 0.139 | 0.196 | 0.196 |
| Effect of mean robot | -15.4 | -16.4 | -44.8 | -46.8 | 0.6 | 1.6 |
| **Panel B: rural workers** | | | | | | |
| $\Delta$ Exposure to robots | -0.039 | -0.038 | -0.089 | -0.091 | 0.001 | 0.003 |
| | (0.023)** | (0.023)** | (0.019)*** | (0.018)*** | (0.011) | (0.011) |
| | [0.018]** | [0.018]** | [0.018]*** | [0.017]*** | [0.009] | [0.009] |
| Baseline mean of E/P | 0.568 | 0.568 | 0.096 | 0.096 | 0.079 | 0.079 |
| Effect of mean robot | -21.7 | -21.3 | -49.4 | -50.9 | 0.5 | 1.4 |
| **Panel C: urban workers** | | | | | | |
| $\Delta$ Exposure to robots | 0.013 | 0.009 | 0.004 | 0.003 | 0.004 | 0.003 |
| | (0.017) | (0.017) | (0.006) | (0.006) | (0.010) | (0.010) |
| | [0.013] | [0.013] | [0.004] | [0.004] | [0.008] | [0.008] |
| Baseline mean of E/P | 0.170 | 0.170 | 0.043 | 0.043 | 0.117 | 0.117 |
| Effect of mean robot | 7.2 | 5.2 | 2.0 | 1.5 | 2.3 | 1.6 |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry shares | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $\Delta$ ICT technologies | | ✓ | | ✓ | | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for total workers, rural workers and urban workers. The estimates are based on 285 prefectures in China. Dependent variables are the 2005-15 change in employment-to-population ratios. Column 1, 3 and 5 control for prefecture-level demographic variables (log of population density; the share of female; the share of population aged 65 and above; the share of married; the share of ethnic minorities; the shares of population with primary school, junior high school, senior high school and college degrees in 2005), employment shares of 7 broad industry groups (the shares of employment in agriculture (reference), mining, manufacturing, electricity, construction, traditional services and modern services in 2005) and broad district dummies (east (reference), northeast, central, west). Column 2, 4 and 6 add change in exposure to ICT technologies (changes in the usage ratios of mobile phones and broadband internet between 2005 and 2015). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

within this category. The preferred estimate in column 4 illustrates that an average-level robotic exposure in a prefecture results in the replacement of approximately 46.8 workers. In contrast, the coefficients presented in columns 5 and 6 do not suggest any significant impact on non-routine occupations, implying that robots have not substantially influenced on this occupation category.

Panel B and C of Table 2 show the differential effects of robots on employment among rural and urban workers. Columns 1 and 2 in both panels reveal that robots have strong and negative effects on rural workers' employment, while the effects on urban workers are positive but insignificant. The estimated coefficient magnitude in column 2 of Panel B suggests that, within a prefecture receiving an average level of robotic exposure, approximately 21.3 rural workers were replaced. Further results in columns 3 and 4 focus on the effects on routine occupations, showing that an average prefectural robot shock is associated with the displacement of 50.9 rural workers from routine jobs. In contrast, the effects on urban workers remain statistically insignificant. Consistent with earlier findings, columns 5 and 6 reveal no significant impact on either rural or urban workers in terms of quitting from or transitioning into non-routine occupations during the period. The findings underscore the displacement effects of robots as being disproportionately borne by rural workers in China.

## 3.2 Heterogeneity by Institutions

Prefectures with varying levels of labor market institutions may exhibit different effects of robots on employment. For instance, in a more efficient labor market, the displacement of rural workers by robots might be less pronounced due to reduced occupational segregation between rural and urban workers. Moreover, more flexible labor market institutions tend to correlate with increased labor market flows (Donovan et al., 2023; Engbom, 2022). We anticipate a greater transition to non-routine occupations in response to the displacement by robots. Therefore, we reexamine how labor market institutions interact with the effect of robots on employment.

To measure labor market institutions, we construct a *hukou* index for each prefecture following the method proposed by Fan (2019), which acts as a proxy for labor market flexibility.[11] Fan (2019) collects official news, laws and regulations using combinations of keywords "*hukou*" or "*huji*" and "*gaige*" (reform) or "*guanli*" (management). He then reviews these documents and rates each prefecture on a scale from 0 to 6.[12] A rating of

[11] In 2014, the Chinese government implemented *hukou* reforms with the aim of relaxing restrictions on granting *hukou* to migrants. During the study period, 74.7% of prefectures exhibited an increase in their hukou index, indicating a transition towards more flexible hukou systems.

[12] Fan (2019) rates *hukou* policies based on three criteria for migrants: (1) job prospects and stability, (2) residential conditions, and (3) contributions to the local social security system.

0 indicates strict *hukou* control, while a rating of 6 denotes an open policy that grants *hukou* to anyone with legal residence and employment in a prefecture. Fan (2019) covers *hukou* policies from 1997 to 2010. We follow his methodology and extend the hukou index from 2011 to 2015. See Table E4 in the Appendix for details.

We conduct a regression analysis to examine the interaction effects between changes in robots and the hukou index. Table 3 shows distinct impacts on rural and urban workers in prefectures with more open hukou systems. In such prefectures, rural workers in routine occupations are less negatively impacted by robots and more likely to transition to non-routine occupations. The magnitudes show that for each unit increase in the hukou index, there is a reduction of 10.2 rural workers displaced from routine occupations in prefectures with an average level of robotic exposure, accompanied by a transition of 4.1 rural workers to non-routine occupations. In contrast, urban workers in routine occupations face a higher likelihood of displacement by robots in prefectures with more open hukou systems. For each unit increase in the hukou index, there is an increase of 2.2 displaced urban workers in routine occupations in these prefectures. Although the number is smaller compared to the displacement of rural workers, it indicates that the negative effects of robotics are not limited to rural workers alone. Our findings suggest that more efficient labor market institutions, as reflected in open hukou systems, can mitigate the negative impacts of robots on vulnerable labor groups and facilitate their faster reallocation to different occupations. The openness of hukou system is reflected not only in the granting of local residency permits but also in a more friendly labor market, leading to reduced discrimination and less occupational segregation in non-routine occupations.

Table 3: Effects of Robots on Employment, Interacting with Hukou Index

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total (1) | Routine (2) | Non-Routine (3) | Total (4) | Routine (5) | Non-Routine (6) |
| Δ Exposure to robots × Δ Hukou index | 0.011 | 0.018 | 0.007 | -0.005 | -0.004 | -0.001 |
| | (0.008) | (0.006)*** | (0.004)* | (0.005) | (0.001)*** | (0.004) |
| Δ Exposure to robots | -0.049 | -0.106 | -0.005 | 0.017 | 0.008 | 0.004 |
| | (0.022)** | (0.021)*** | (0.010) | (0.017) | (0.006) | (0.010) |
| Δ Hukou index | -0.003 | -0.006 | -0.001 | 0.001 | 0.001 | -0.002 |
| | (0.005) | (0.004) | (0.002) | (0.003) | (0.001)* | (0.002) |
| Baseline mean of E/P | 0.568 | 0.096 | 0.079 | 0.170 | 0.043 | 0.117 |
| Effect of mean robot × hukou index | 6.1 | 10.2 | 4.1 | -2.9 | -2.2 | -0.5 |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers. The estimates are based on 285 prefectures in China. Dependent variables are 2005-15 change in employment-to-population ratio and ratios for routine and non-routine occupations. The change in *hukou* index reflects labor market flexibility. The more flexible the process is to obtain a local *hukou*, the lower the labor market frictions. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, Statistical Yearbook, and Fan (2019).

## 3.3 Robustness checks

We perform several robustness checks of Table 2 and display the results in the Appendix E. We first estimate long differences between the years 2005-2010 and 2010-2015 separately, and then stack two periods together to estimate using stacked differences. The results in Table E5 and E6 remain robust when separating periods and using stacked differences.

We also show our results are robust to using exposure to US robots as our alternative instrumental variable in Table E7. Then we change our outcome variables to percent change in the number of employment between 2005 and 2015. Since the Census data selected sample in different ratio in each year, we weight sample by the sampling rate released by NBS. The coefficients in Table E8 stay the same direction as the baseline results.

We then consider the large differences in educational structures between rural and urban workers. As shown in Table C1, only 1% of rural workers have college degrees, compared to 24% of urban workers. This large disparity in educational attainment may lead to self-selection into different occupations. We narrow our analysis to low-educated workers, those with primary and high school degrees, and examine the differential impacts of robots on these two groups. The results, presented in Table E9, confirm the robustness of our findings: there continues to be no significant effect of robots on urban workers.

There are concerns that pre-exiting trend influence the outcome variables. Table E1 shows that exposure to robots is not correlated with pre-period changes in demographics, and Table E10 further shows that our results are also robust when we control for pre-period change in employment-to-population ratios.

We also use two ways to address potential issues with our estimates stemming from the spatial proximity. One is a spatial autoregressive model, where we use distance as our spatial weight to consider the influence of employment changes in nearby prefectures on the outcomes in the target prefectures. Another is adjusting standard error for spatial correlation following Conley (1999). Both methods show that the results are robust detailed in Table E11 and E12.

Finally, we use a complementary data — the China Labor Dynamics Survey (CLDS) panel data at the individual level — to provide a mutually supportive research approach.[13] We regress the individual-level outcome variables on prefecture-level exposure to robots, and control for time-varying individual and prefectural characteristics, as well as individual and year fixed effects. The results in Table E13 show the similar direction of effects on employment and occupations using individual-level panel data.

[13]In Appendix D, we provide a comprehensive overview of CLDS data, and present the statistics and facts derived from the datasets in detail.

# 4. Adjustments of Rural Workers to Robots

The previous section indicates that robots have a negative effect on routine occupations, especially affecting rural workers. In this section, we focus on examining how robots influence rural workers' adjustment behaviors. When rural workers are displaced from routine occupations by robots, their first adjustment decision involves choosing between transitioning to non-routine occupations or the agricultural sector within their current prefectures. If they are unable to find new jobs in the current prefectures, they need to consider relocating to other prefectures for employment opportunities. After relocating, their occupational choices in the new prefectures are also crucial. Therefore, rural workers displaced from routine occupations likely face three levels of adjustments concerning occupation and location. In this section, we employ the same empirical specifications to investigate these adjustment behaviors among rural workers.

## 4.1 Employment adjustment within prefectures

In the initial step of adjustments, rural workers decide whether to transition to different occupations within their current prefectures. Table 4 presents the impact of robots on various employment categories, which include routine, non-routine and agricultural occupations, as well as unemployment and non-labor participation. Moreover, we categorize non-routine occupations into professional, administrative and commercial jobs based on the *Occupation Classification Dictionary* (OCD) taxonomy.

Table 4: Effects of Robots on Employment, Rural Workers

| | Employed | | | | | | Unemployed | No LFP |
|---|---|---|---|---|---|---|---|---|
| | Total | Routine | Profess | Admin | Commercial | Agriculture | Total | Total |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Δ Exposure to robots | -0.038 | -0.091 | 0.021 | -0.001 | -0.018 | 0.051 | -0.003 | -0.003 |
| | (0.023)** | (0.018)*** | (0.009)*** | (0.001) | (0.007)*** | (0.020)*** | (0.005) | (0.007) |
| | [0.018]** | [0.017]*** | [0.007]*** | [0.002] | [0.007]*** | [0.019]*** | [0.003] | [0.008] |
| Baseline mean of E/P | 0.568 | 0.096 | 0.023 | 0.005 | 0.051 | 0.393 | 0.009 | 0.120 |
| Effect of mean robot | -21.3 | -50.9 | 11.6 | -0.4 | -10.0 | 28.2 | -1.8 | -1.9 |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers. The estimates are based on 285 prefectures in China. Dependent variables are the 2005-15 change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Columns 1 and 2 in Table 4, identical to columns 2 and 4 in Panel B of Table 2, exhibit pronounced negative impacts on the employment of rural workers, particularly those employed in routine occupations. Columns 3 to 5 show their occupation reallocation in non-routine occupations. The results reveal that a small part of rural workers transition into professional jobs in response to robot shocks, with 11.6 rural workers in the prefecture with the mean level of robotic exposure. While entry into administrative positions is absent. Surprisingly, we find a negative spillover effect of robots on commercial occupations, implying that increased robot adoption may reshape the occupation structure within the prefecture.

Given that the majority of rural workers own agricultural land in their *hukou* registered villages under the household contract responsibility system in China, we examine their choices on the agricultural sector in column 6. The coefficient shows an increase of one robot per thousand workers correlates with a 5.1 percentage point rise in the agriculture-to-population ratio among rural workers, equating to 28.2 workers in an average prefecture exposed to robots. This indicates that the introduction of robots may drive rural workers to return to agricultural employment, which is a unique phenomenon in developing countries. Rural workers migrate from rural to urban areas in pursuit of better employment opportunities, while retaining their arable land in the rural area as a form of "insurance" against risks in non-agricultural labor markets. Our results validate this phenomenon.

The adjustment behaviors among rural workers vary according to their demographics. As depicted in Figure 2, we categorize rural workers into three age groups: young (aged 16-30), middle-aged (aged 31-45), and older (aged 46-65), to assess the impact of robots on these different groups. The figure reveals that younger rural workers, typically with less experience and lower human capital, are more negatively affected by robots compared to their middle-aged counterparts. Besides experiencing different levels of robot influence, they also exhibit distinct adjustment behaviors. The proportion of middle-aged rural workers leaving routine occupations is nearly identical to those transitioning to the agricultural sector. This suggests that middle-aged workers displaced from routine jobs predominantly shift to agricultural work, a trend less evident among younger workers. As for young workers, robots significantly lower their employment-to-population ratios, indicating a higher likelihood of them migrating out of their prefectures. This could be due to lower migration costs for younger workers, who are less likely to have established families or extensive social networks in their current residences (Chen et al., 2022; Schwartz, 1976).[14]

Another critical factor influencing whether rural workers return to agriculture is the possession of a local *hukou*. To illustrate this, Figure 3 divides rural workers into two groups: those working in their home prefectures (termed as "rural locals") and those employed outside their home prefectures (termed as "rural migrants"). The findings

[14]Figure E1 in the Appendix E further examines the impact of robots on rural workers' adjustment behaviors by education levels. Rural workers with lower education are more impacted by robotic exposure, tend to choose agricultural work or migration due to barriers in accessing non-routine occupations.

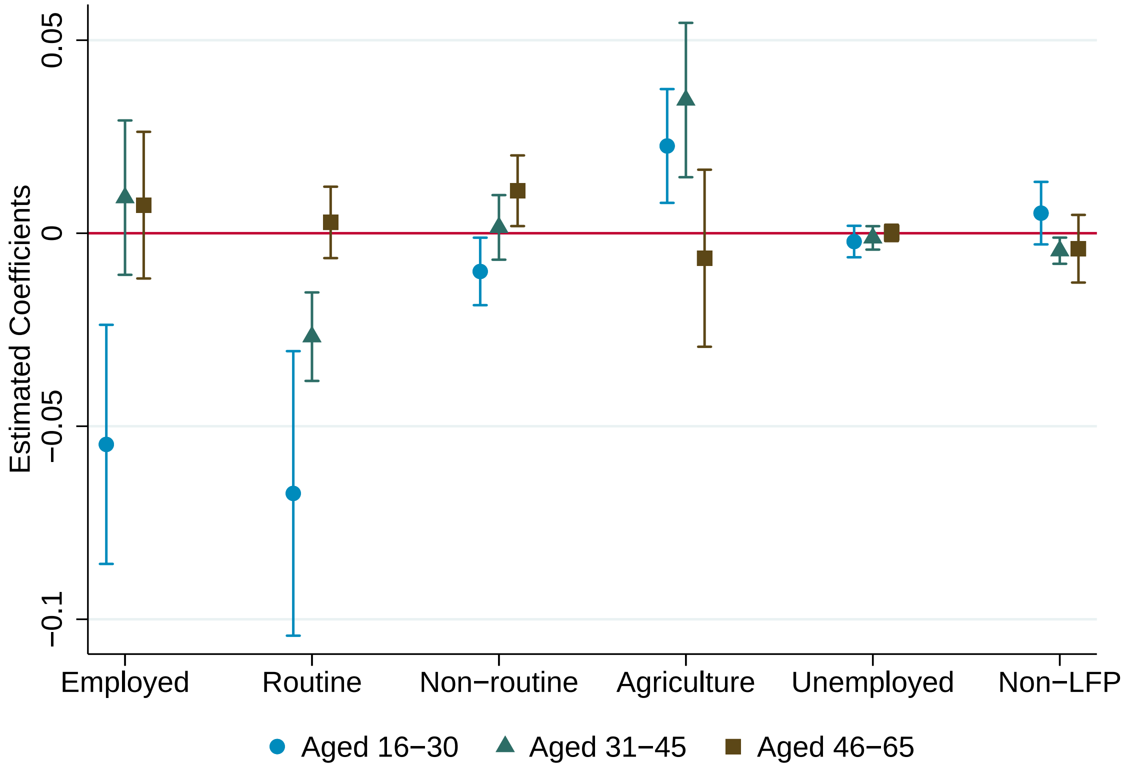


Figure 2: Effects of Robots on the Share of Population in Employment Categories: by Age Group

Notes: The figure reports the estimated coefficient and the associated p-value of Equation (2) by 2SLS for rural workers by age groups. The estimates are based on 285 prefectures in China. Dependent variables are the 2005-15 change in employment-to-population ratios in different employment categories. See Table 2 for more details.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

indicate that robots significantly displace routine occupations for both groups, yet their responses vary. Rural locals primarily transition to agricultural jobs, with robots having minimal impact on their employment-to-population ratio. In contrast, the employment-to-population ratio for rural migrants decreases substantially, suggesting that a significant majority of them opt for migration. A key factor in this divergence is the ownership of a local *hukou* by rural locals, which typically grants them potential access to agricultural land under China's household contract responsibility system. This land acts as a form of insurance against disruptions in the non-agricultural sector for rural locals (Moschini and Hennessy, 2001). When faced with urban labor market upheavals, such as those induced by robots, they use this "insurance" to protect their livelihoods. However, for rural migrants without a local *hukou*, transitioning to agriculture is mostly unfeasible. Thus, when they lose routine jobs and struggle to find non-routine ones, migrating becomes their preferred alternative. Following this, we explore their migration patterns in response to the robot-induced changes.

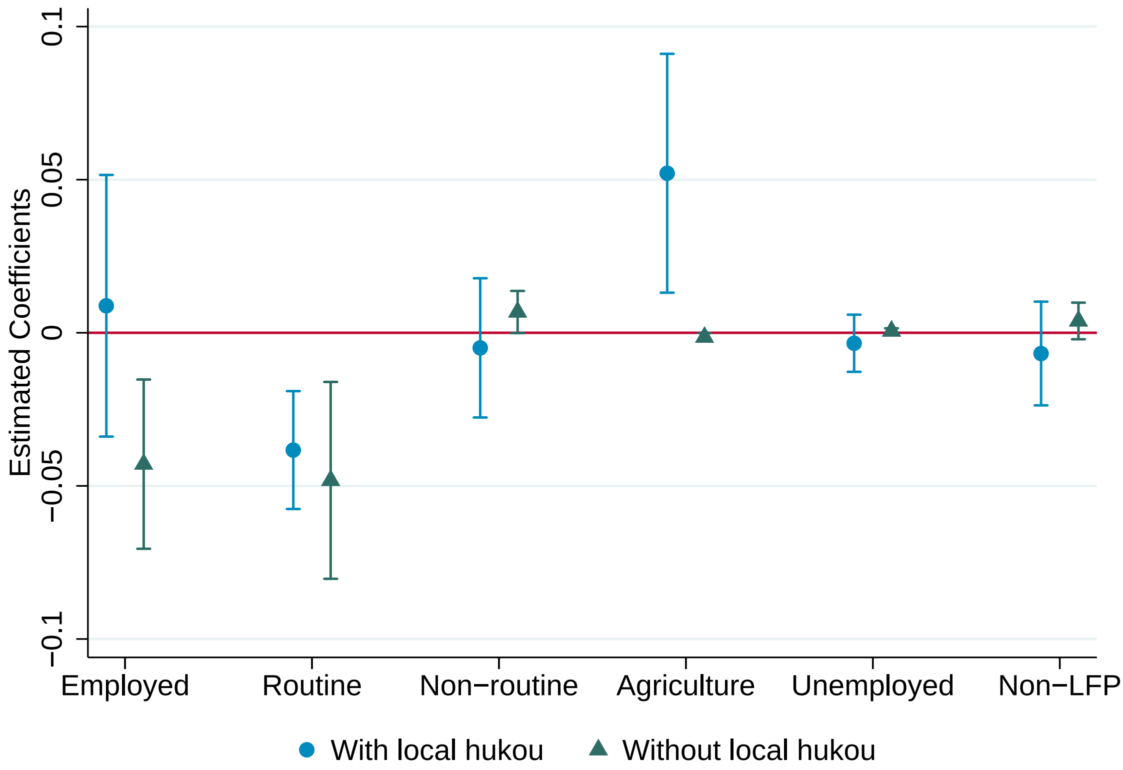


Figure 3: Effects of Robots on the Share of Population in Employment Categories: by *Hukou* Type

Notes: The figure reports the estimated coefficient and the associated p-value of Equation (2) by 2SLS for rural workers by *hukou* type. The estimates are based on 285 prefectures in China. Dependent variables are the 2005-15 change in employment-to-population ratios in different employment categories. See Table 2 for more details.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

## 4.2 Location adjustment across prefectures

To investigate the impact of robots on migration, we utilize data from the 2015 Census, which includes information on rural workers' current and previous residences five years prior. We define "location adjustment" as the change in a worker's residence from one prefecture to another over a five-year period. This methodology enables us to create a migration flow matrix for all Chinese prefectures from 2010 to 2015.[15] Using Equation (2), we then analyze the effects of robots on migration during this period. The results are presented in Table 5. Additionally, we categorize these workers into three distinct

[15]Since census data does not provide panel data, it is impossible to track individual samples in each year. So estimating long difference from 2005 to 2015 is infeasible. However, by utilizing responses to the question "Where did you live five years ago?", we can identify patterns of location adjustment from 2010 to 2015.

groups based on their migration patterns: return migrants who moved back to their home prefectures from other locations (column 2); rural workers who relocated from one non-home prefecture to another (column 3); and those who migrated from their home prefectures to different ones (column 4).

Table 5: Effects of Robots on Migration

| | Total | Return migration | New-city migration | Hometown departure |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Exposure to robots | 0.013 | 0.008 | 0.007 | -0.001 |
| | (0.006)*** | (0.004)** | (0.002)*** | (0.002) |
| | [0.005]*** | [0.004]** | [0.002]*** | [0.002] |
| Mean of outcomes | 0.016 | 0.007 | 0.001 | 0.008 |
| Effect of mean robot | 7.3 | 4.3 | 3.7 | -0.8 |
| Observations | 276 | 276 | 276 | 276 |
| District FE | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports the effects of changes in robots on the 2010-2015 return migration, new-city migration and hometown departure by 2SLS for rural workers. The estimates are based on 276 prefectures in China. Dependent variables are the number of rural workers reporting a current residence in a city different from their residence five years ago, divided by the population of the city five years ago. Return migration is defined as the situation where an individual lived in a city five years ago and now resides in their home prefectures. New-city migration is defined as the situation where an individual lived in a city five years ago, and now resides in a different non-home prefecture. Hometown departure is defined as the situation where an individual lived in their home prefectures and now resides in a non-home prefecture. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2010. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2010-2015 Census, and Statistical Yearbook.

Column 1 of Table 5 presents the impact of robots on the proportion of rural workers who adjust their location. The results indicate that robots encourage rural workers to migrate out of their prefectures. The introduction of one additional robot per thousand workers leads to a 1.3% increase in location adjustment. Columns 2 to 4 further highlight that a significant proportion of rural migrants, previously employed in prefectures with higher robot exposure five years earlier, tend to either return to their hometowns or move to new prefectures. The magnitude of return migration induced by robot-related changes involves approximately 4.3 workers, a figure nearly equivalent to the 3.7 workers opting for migration to new prefectures. In contrast, the trend of rural workers moving away from their home prefectures does not appear to be significantly influenced by the robotic exposure in their home prefectures.

Table 6 sheds light on the impact of robots on the characteristics of prefectures that rural workers migrate to. The analysis involves comparing the current characteristics of the workers' residence prefectures with those from five years prior, with a focus on changes in robot exposure, GDP per capita, and population. Given that robots do not significantly affect rural workers leaving their home prefectures, as shown in Table 5, the following tables exclude this group from our analysis. Columns 1 and 2 of Table 6 show that both return migrants and new-city migrants tend to relocate to prefectures with lower robot exposure if they worked in prefectures with higher robot exposure five years earlier. Columns 3 and 4 highlight that the current prefectures where these migrants settle generally have a lower GDP per capita compared to their previous robot-intensive prefectures. In columns 5 and 6, the results reveal no significant correlation between the population size of return migrants' hometowns and the robot exposure in their previous prefectures. While for migrants relocating to new cities, a higher proportion move to less populous prefectures if they previously resided in high robot exposure areas. These findings indicate that rural migrants more impacted by robots are more likely to migrate to prefectures with not only lower robot exposure but also lower economic development. Essentially, robots are influencing a migration pattern from economically richer to relatively poorer areas, effectively leading to a downgrade in location for these migrants.

Table 6: Effects of Robots on Migration: The Characteristics of Destinations

| | Δ Exposure to robots | | GDP per capita | | Population | |
|---|---|---|---|---|---|---|
| | Higher | Lower | Higher | Lower | Higher | Lower |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: return migration** | | | | | | |
| Δ Exposure to robots | -0.007 | 0.015 | -0.002 | 0.009 | 0.001 | 0.007 |
| | (0.002)*** | (0.003)*** | (0.001)* | (0.004)** | (0.001) | (0.004) |
| | [0.002]*** | [0.003]*** | [0.001]* | [0.004]** | [0.001] | [0.004] |
| Mean of outcomes | 0.002 | 0.005 | 0.002 | 0.005 | 0.003 | 0.004 |
| Effect of mean robot | -3.8 | 8.2 | -0.9 | 5.3 | 0.5 | 3.8 |
| **Panel B: new-city migration** | | | | | | |
| Δ Exposure to robots | 0.000 | 0.006 | 0.002 | 0.004 | 0.002 | 0.004 |
| | (0.001) | (0.002)*** | (0.001) | (0.001)*** | (0.001)* | (0.001)*** |
| | [0.001] | [0.001]*** | [0.001] | [0.002]*** | [0.001]* | [0.002]*** |
| Mean of outcomes | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 | 0.001 |
| Effect of mean robot | 0.2 | 3.4 | 1.3 | 2.4 | 1.2 | 2.5 |
| Observations | 276 | 276 | 276 | 276 | 276 | 276 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports the effects of changes in robots on the selection of destination prefectures by 2SLS for rural workers. The estimates are based on 276 prefectures in China. Dependent variables are the number of rural workers who have relocated to cities with either higher or lower change in exposure to robots, GDP per capital and population relative to their residence five years ago, divided by the population of the city five years ago. For detailed definitions of return migration and new-city migration, please refer to Table 5. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2010. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2010-2015 Census, and Statistical Yearbook.

The analysis of migration effects can also be conducted using individual panel data. However, the panel data in CLDS are carried out at the prefecture level, making it challenging to track individuals who migrate out of the prefectures over extended periods. Nonetheless, we identify relevant variables in the CLDS that reflect rural workers' willingness to live locally, acquire a local *hukou*, and give up land in their hometown. We present the results in Table E14 in the Appendix. The results show that robots reduce rural workers' willingness to obtain local *hukou* and give up land in their hometowns, suggesting that they may have an inclination to migration.

### 4.3 Employment adjustment after migration

Existing literature has studied the impact of robots on occupation or population structure within the local labor market (Chen et al., 2022; Dauth et al., 2021; Faber et al., 2022; Giuntella et al., 2022). However, few studies have investigated the impact of such shocks on workers' occupational choices after they leave the labor market. By utilizing the census question regarding their place of residence five years ago, we can investigate how exposure to robots in their previous place of residence influences their current employment statuses.

Table 7 presents the results of the impact of robots on their subsequent employment choices after adjusting location. We construct a set of dependent variables that include the proportion of employment, unemployment, non-labor participation and each occupation category across return migrants and new-city migrants in the total population of their residence five years prior. These variables can reflect the employment and occupational structures within each migration group, providing a comprehensive overview of the dynamic labor market outcomes of migrants in relation to robot adoption.

In column 1 of Panel A, we observe that return migrants from non-home prefectures with higher exposure to robots are more likely to find employment in their home prefectures. This suggests that workers from robot-intensive cities may possess a stronger incentive to work and therefore have a greater likelihood of finding new employment opportunities after relocating. The magnitude indicates that 4.0 workers return home and find employment if they are from a prefecture with average robot exposure five years earlier. Columns 2 to 4 detail the occupational choices of return migrants, showing a tendency to engage in both routine and non-routine occupations, though the coefficient for non-routine occupations is not sufficiently significant.

Panel B replicates the analysis for individuals relocating to new prefectures and reveals a similar trend. Columns 1 to 3 show that a higher number of robots in their previous place of residence increases the likelihood of their employment, especially in routine and non-routine occupations. Columns 5 to 6 indicate that the influence of robots on their unemployment and non-labor force participation is statistically significant. This suggests that rural workers who relocate to new urban environments may encounter a risk of non-employment, while the magnitude of these effects is relatively small.

Table 7: Effects of Robots on Employment After Migration

| | Employed | | | | Unemployed | No LFP |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-routine | Agriculture | Total | Total |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: return migration** | | | | | | |
| Δ Exposure to robots | 0.007 | 0.004 | 0.003 | 0.000 | 0.000 | 0.000 |
| | (0.003)** | (0.001)** | (0.002) | (0.000) | (0.000) | (0.000) |
| | [0.003]** | [0.001]** | [0.002] | [0.000] | [0.000] | [0.000] |
| Mean of outcomes | 0.006 | 0.001 | 0.004 | 0.000 | 0.000 | 0.001 |
| Effect of mean robot | 4.0 | 2.0 | 1.7 | 0.2 | 0.0 | 0.2 |
| **Panel B: new-city migration** | | | | | | |
| Δ Exposure to robots | 0.006 | 0.003 | 0.002 | 0.000 | 0.000 | 0.001 |
| | (0.002)*** | (0.001)*** | (0.001)*** | (0.000) | (0.000)*** | (0.000)*** |
| | [0.001]*** | [0.001]*** | [0.001]*** | [0.000] | [0.000]*** | [0.000]*** |
| Mean of outcomes | 0.001 | 0.000 | 0.001 | 0.000 | 0.000 | 0.000 |
| Effect of mean robot | 3.2 | 1.8 | 1.3 | 0.0 | 0.1 | 0.3 |
| Observations | 276 | 276 | 276 | 276 | 276 | 276 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| City-level controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports the effects of changes in robots on the selection of new occupations after migration by 2SLS for rural workers. The estimates are based on 276 prefectures in China. Dependent variables are the number of rural workers who have transfer to different employment statuses and occupation categories, divided by the population of the city they resided five years ago. For detailed definitions of return migration and new-city migration, please refer to Table 5. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2010. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2010-2015 Census, and Statistical Yearbook.

Referring back to Figure 3, it is evident that the majority of rural workers with local *hukou* transition from routine occupations to the agricultural sector. This occupational shift, however, contrasts sharply with the patterns observed among these workers who return to their hometowns and regain the benefits of local *hukou* status. A minority of them engage in agricultural work. Instead, they primarily seek employment in routine occupations, akin to the type of work they engaged in at their previous residences. This occupational difference suggests two key implications. First, the fact that these return migrants initially chose to migrate five years ago signifies a higher level of capability, possibly due to the selection effects of migration (Bryan and Morten, 2019; Nakamura et al., 2022). Therefore, they are more inclined to pursue more skilled non-agricultural occupations compared to those locals who have never migrated beyond their prefecture during the five-year period. This selection effect appears to be more pronounced among migrants moving to new prefectures, who, by choosing to migrate again rather than return home, may demonstrate an even greater level of capability. In new prefectures, these migrants are likely to find opportunities in non-routine occupations, which typically demand higher skill levels than routine jobs. Second, the experience and skills gained by return migrants in their previous working prefectures are valuable (Roca and Puga, 2017). By working in a more economically developed environment, they are likely to have accumulated more experience and skills, enhancing their human capital and making them better suited for routine occupations, as opposed to agricultural work. A similar case applies to new-city migrants.

## 4.4 Magnitude

Table 2 indicates that an average level of robotic exposure in a prefecture leads to the displacement of 50.9 rural workers in routine occupations. To assess the magnitude of adjustment among rural workers caused by robots, we employ the coefficients from Tables 4, 5 and 7 to derive the number of individuals affected by average robotic exposure levels. Then we calculate the proportion of rural workers whose location and occupational decisions are influenced by this exposure. Figure 4 illustrates the decision-making processes among rural workers.

After exiting routine occupations, their subsequent decision-making involves whether to stay in their current location or relocate. Our results, illustrated in Figure 4, show that 58% choose to remain in their current work locations, while the remaining 42% choose to move. Interestingly, this distribution closely mirrors the proportions of rural workers who have local *hukou* (59%) and those without (41%), as reported in the 2005 census data. This finding confirms again that *hukou* status plays a significant role in influencing decision-making: rural workers with local *hukou* tend to stay, while those without are

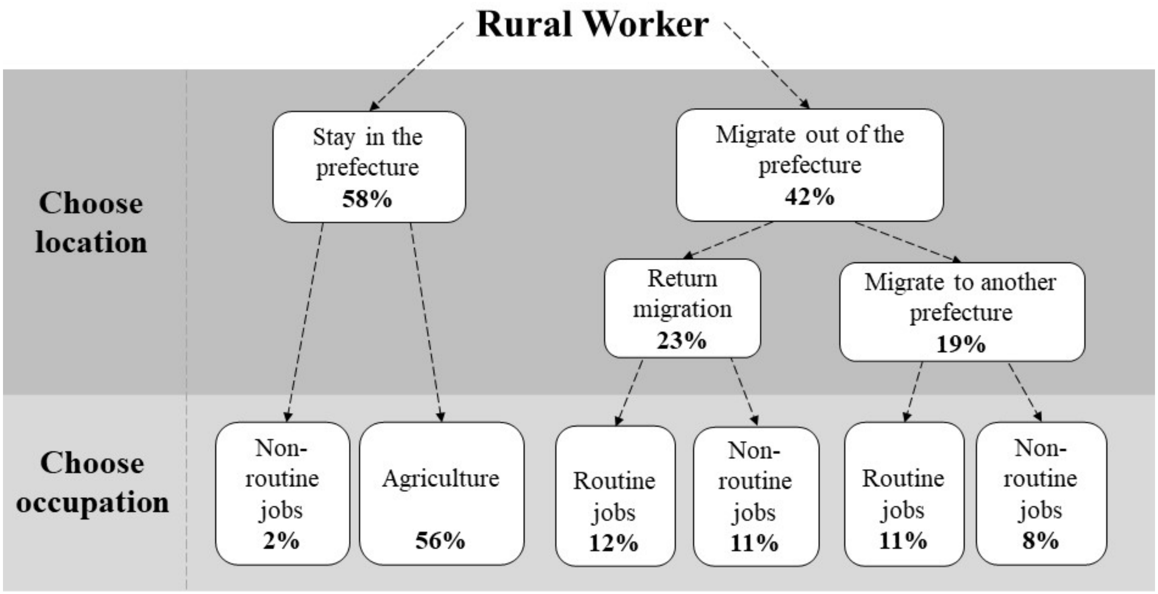


Figure 4: Adjustment Magnitude of Rural Workers

Notes: The figure shows the proportion of rural workers' location and occupation decisions influenced by exposure to robots, as determined by our point estimates.

more inclined to relocate. Specifically, of the workers who migrate, 55% (23 out of 42) return to their home prefectures, and 45% (19 out of 42) move to entirely new prefectures.

After choosing location, rural workers then face the choice of a new occupation. The data shows that among those who stay in the same prefecture, a vast majority of 97% (56 out of 58) move into agricultural jobs, while only a small fraction, 3%, transition into non-routine occupations. Despite the presence of industrial robots being indicative of a growing manufacturing sector, our findings suggest that in China, nearly all rural workers who leave routine occupations due to robots and choose to stay locally, transition back to the agricultural sector. Paradoxically, advancements in manufacturing could lead to a decline in agricultural productivity due to an excess of employment in the sector. This finding represents a unique phenomenon observed in developing countries.

Conversely, those who either return to their home prefectures or move to new ones tend to engage in non-agricultural occupations. Among return migrants, 52% (12 out of 23) choose routine jobs, while 48% (11 out of 23) opt for non-routine occupations. A similar trend is observed among new-city migrants: 58% (11 out of 19) engage in routine jobs, and 42% (8 out of 19) work in non-routine jobs. Their occupational choices are likely influenced by both the selection effects of migration and the experiential learning acquired across different prefectures. This pattern also suggests that the introduction of robots in one labor market may drive workers towards other labor markets, consequently affecting both the employment and demographic structures of those areas.

# 5. Conclusion

This paper investigates how the rise of industrial robots influences rural workers' decisions regarding employment, migration behaviors, and their selection of new occupations following migration. While a growing body of literature has explored how robots influence employment and location choices in developed countries, research on developing countries remains limited. We focus on the adjustment behaviors of rural workers in China, who face labor market barriers such as occupation segregation and limited social security in urban labor markets under the *hukou* system in China. This strategy enables us to illuminate the effects of robots on vulnerable labor groups within inefficient labor markets.

Our findings show that robots have a negative employment effect on rural workers, particularly those in routine occupations. For every additional robot per thousand workers, there is a 9.1% decline in the employment-to-population ratio for rural workers in routine occupations. This corresponds to the displacement of 50.9 rural workers from routine occupations in a prefecture with average exposure to robots. This effect does not apply to urban workers. Moreover, the displacement effect on rural workers is less pronounced in prefectures with more open *hukou* systems. An increase of one unit in the hukou index, which represents more flexible labor market institutions, leads to 10.2 fewer rural workers being displaced from routine occupations and 4.1 more rural workers transitioning into non-routine occupations.

We then analyze rural workers' adjustments involving their three decisions: employment adjustments within prefectures, location adjustments across prefectures, and employment adjustments after migration. Our findings indicate that an additional robot per thousand workers results in a 5.1% increase in the employment-to-population ratio of rural workers employed in agriculture. Calculating the magnitudes from our estimates, this equates to 56% of the rural workers displaced by robots. This trend is more pronounced among workers with local *hukou* who have access to local farmland. On the other hand, rural workers frequently face challenges in entering non-routine occupations, with only 2% successfully making this transition. The remaining 42% of rural workers choose to migrate away from prefectures with high robot adoption. These workers either return to their home prefectures or move to new but less economically developed prefectures, and they are more likely to engage in non-agricultural occupations after migration.

This study offers insights into the challenges posed by technological advancements to vulnerable workers in developing countries with labor market frictions. It highlights that while robots bring benefits to productivity, they also exert negative impacts on employment. Such effects are likely more serious in developing countries characterized by imperfect labor institutions and a substantial reliance on agriculture. These displaced workers might find themselves compelled to either return to the agricultural sector or relocate to less economically developed areas. Our findings emphasize the importance of implementing policies aimed at alleviating labor market frictions, thereby mitigating the negative effects of automation on these vulnerable labor groups.

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# Appendix A. Robot Data

To provide a visual representation of the geographic distribution of robot exposure, we present Figure A1. This figure shows that the number of robots per thousand workers varies significantly across different cities, ranging from 0.03 to 1.95. Notably, we observe high concentrations of robot usage in some eastern and central cities of China, particularly those with highly developed manufacturing industries.

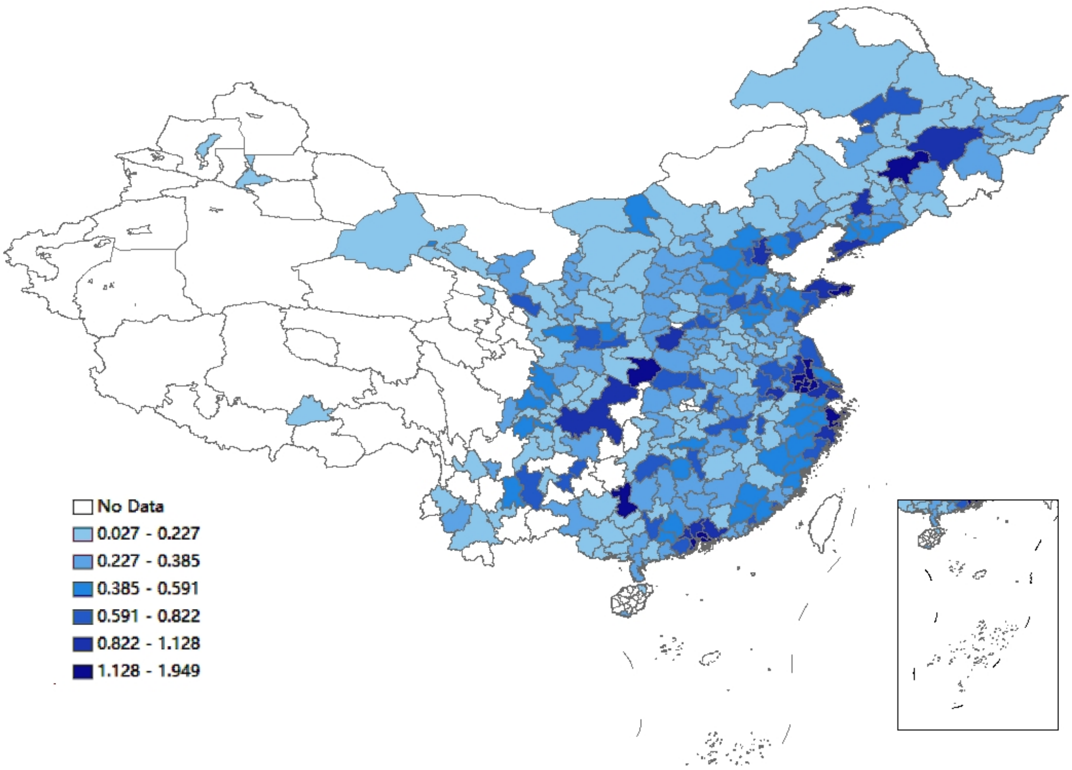


Figure A1: Geographic Distribution of Exposure to Robots, 2005-2015

Notes: The figure shows exposure to robots in our 285 sample prefectures, which is measured as the 2005-15 change in robots per thousand workers calculated by Equation (1). Sources: IFR.

# Appendix B. Occupation Data

The key challenge of our study is the classification of routine occupations based on their job nature and task content. While it is feasible to classify US occupations using established databases such as Occupational Information Network (O*NET) and Dictionary of Occupational Titles (DOT), which offer scores such us Finger Dexterity and Set Limit, Tolerances, or Standards to measure routine tasks, there is no equivalent occupational-level database for China.[16] Moreover, it would be imprecise to match Chinese occupations with those in O*NET due to significant differences in the occupational systems between two countries. For example, China's occupational structure features a more detailed classification of production-line workers that categorizes roles based on product types and production flows. Additionally, even identical occupations can have varied task content, working methods, and skill requirements in the two countries due to differences in their developmental stages. Therefore, directly applying routine task measurements from the US to Chinese occupations is impractical. This emphasizes the necessity of measuring routine tasks in China for a comprehensive study of occupational development.

To address this gap, Hu et al. (2024) propose a methodology to quantify routine tasks in China by analyzing text data from Chinese occupational descriptions. The primary datasets include text sourced from the *Occupation Classification Dictionary* (OCD), containing task descriptions for over 1,800 occupations, and *A Thesaurus of Modern Chinese*, which contributes to identifying the meaning of words in the descriptions. In Section B.1, we begin by cleaning and processing the text data to extract effective words from the OCD. In Section B.2, we use the thesaurus as a standard reference to identify the skill attributes of each word. Finally, in Section B.3, we match the thesaurus with the OCD to measure the routine intensity levels in each occupation and define routine occupation. This approach resembles that of Michaels et al. (2019), who use occupational descriptions and Roget's Thesaurus to quantify the interactiveness of an occupation.

## B.1 Processing Text Data

The *Occupation Classification Dictionary* was originally released in 1999 by the Ministry of Labor and Social Security, the General Administration of Quality Supervision, Inspection and Quarantine, and the National Bureau of Statistics in China. The releasing is motivated by the "Labor Law" in China that regulates that the nation should establish

[16]DOT was a publication by the United States Department of Labor, which contained detailed definitions and job descriptions of over 13,000 occupations. It was replaced by an online database O*NET, which grades different skills for each occupation based on DOT, such as language abilities, social skills and physical skills. The two databases are widely used in the literature (Acemoglu and Autor, 2011; Atalay et al., 2020; Autor et al., 2003; Deming, 2017; Michaels et al., 2019).

occupational classifications, formulate professional skill standards for specified occupations, and implement a system of occupational qualification certificates. To achieve the goal, thousands of people from 50 divisions of governments, research institutions, colleges and enterprises participated in the writing. Therefore, the job descriptions in the OCD are comprehensive, objective and precise compared with other data.

The OCD has been published in three versions, respectively in 1999, 2015, and 2022. Given its significant influence during our study period (2005-2015), we use the 1999 edition of OCD as the basic text files to analyze occupational descriptions. The OCD 1999 classifies occupations into 8 one-digit occupations, 66 two-digit occupations, 413 three-digit occupations, and 1,838 four-digit occupations, providing detailed job descriptions that outline the skills and knowledge required, work procedures, and work environments, enabling us to understand and analyze the task and skill attributes of different occupations.

The methodology begins by employing natural language processing techniques to clean the text and extract verbs and nouns from the OCD. To prepare the text for analysis, we eliminate highly frequent words known as "stopwords" such as "to" and "of". Next, we utilize a Chinese tokenizer, *jieba*, to conduct word segregation and part-of-speech tagging, allowing us to isolate only the verbs and nouns from occupational descriptions (Zhang and LeCun, 2015; Zhang et al., 2015).[17] For instance, consider the occupational description of an lathe machnist (four-digit occupation) translated into English below:

> 6-04-01-01 Lathe Machinist
>
> Personnel who <u>operate</u> <u>lathes</u> for <u>cutting</u> and <u>machining</u> the <u>rotating</u> <u>surfaces</u> of <u>workpieces</u>.
>
> The main tasks include: (1) <u>installing</u> <u>fixtures</u>, <u>adjusting</u> the <u>lathe</u>, and <u>clamping</u> the <u>workpieces</u>. (2) <u>Maintaining</u> and <u>sharpening</u> <u>lathe</u> <u>cutting tools</u>. (3) <u>Operating</u> horizontal <u>lathes</u>, vertical <u>lathes</u>, and <u>computer numerical control</u> <u>lathes</u> to <u>cut</u> and <u>machine</u> <u>rotating</u> <u>surfaces</u> such as <u>cylinders</u>, <u>cylindrical holes</u>, <u>cones</u>, <u>conical holes</u>, <u>stepped surfaces</u>, <u>end faces</u>, uniquely shaped <u>surfaces</u>, internal and external <u>cylindrical surfaces</u>, <u>grooves</u>, as well as <u>drilling</u>, <u>reaming</u>, and various <u>forms</u> of <u>threading</u>. (4) <u>Maintaining</u> and <u>servicing</u> <u>machine tools</u> and <u>technological equipment</u>, and <u>troubleshooting</u> general <u>malfunctions</u> encountered during <u>operation</u>.

where the words detected as verbs and nouns by *jieba* are underlined. It should be noted that there are significant differences between English and Chinese grammar, particularly with regards to verbs and nouns. First, in the Chinese language, there is no distinction

[17] See https://github.com/fxsjy/jieba.

between first-person singular, third-person singular, and present participle forms of verbs such as *cut*, *cuts*, and *cutting*, which all share the same word. Second, Chinese nouns do not have a plural form, so words like *machine* and *machines* are represented by the same word. Third, in some cases, there is no differentiation between verbs and nouns in Chinese, as exemplified by words such as *operate* and *operation*, which share the same word in the Chinese language. Lastly, sometimes certain English phrases comprising an adjective and a noun may be represented solely as a noun in Chinese. For instance, the term "cylindrical holes" from the job description is recognized as a singular noun by *jieba*.

## B.2 Selecting Measures of Tasks

In order to establish a quantitative measure of the meanings of words in occupational descriptions, we use *A Thesaurus of Modern Chinese* published by the Commercial Press (Su, 2013) as a standard reference for word usage. This thesaurus classifies 83,146 Chinese words into 9 classes, 62 divisions, and 514 categories. The classification system is designed to reflect the nature and characteristics of common Chinese words. The nine classes are as follows: Class I (Creature) includes humans, animals, plants, and other forms of life. Class II (Concrete) includes objects such as materials, tools, and food. Class III (Matter) addresses the physical world and humankind's perception. Class IV (Space) focuses on order and time. Class V (Action) encompasses specific actions and facial expressions. Class VI (Social Activity) covers specified social activities, such as management, trade, and production. Class VII (Motion) ranges from cosmic space motion to individual living existence and variance. Class VIII (Character) consists of qualities that can be attributed to humans or objects. Finally, Class IX (Auxiliary) includes modal particles, prepositions, mimetic words, and other similar elements.

For the purposes of analyzing occupational descriptions, we focus on three specific classes as a standard reference: Class II (Concrete), Class V (Action) and Class VI (Social Activity). Furthermore, to determine the divisions within the thesaurus that best approximate our task constructs, we select three categories most closely related to routine tasks within the three classes. The correspondence between these divisions and the skill attributes of routine tasks is shown in Table B1. Specifically, we utilize a measure of manual and physical skills, selecting the TOOL division to measure manual activities where machines are commonly employed, and the LIMB MOVEMENT and PRODUCTION categories as references for repetitive and physical activities. These categories are chosen for their close relation to routine task contents, including the tools utilized in particular work settings, concrete working activities, and different movements involved in working. Other divisions and classes that are less related to working settings are not included. Through a rigorous classification of words, we are able to identify the routine task associated with the verbs and nouns extracted from the occupational descriptions.

Table B1: Definition of Routine Task from the Thesaurus

| Class | Division | Word count | Word example |
|---|---|---|---|
| II Concrete | 4 Tool | 2122 | machine, drilling rig, crane, cable |
| V Action | 1 Limb Movement | 1603 | pick, wring, scrape, dig |
| VI Social Activity | 3 Production | 886 | repair, install, process, smelt |

Notes: The table reports the correspondence between the divisions in the thesaurus and the skill attributes of routine tasks. In each division, we report the word frequencies and examples to show its size and attributes. *A Thesaurus of Modern Chinese*—the standard reference for word usage—divides 83,146 Chinese words into 9 classes and 62 divisions. We select Class II (Concrete), Class V (Action) and Class VI (Social Activity) that are closely related to occupations, within which we select 3 divisions to identify the routine task.

## B.3 Measuring Routine Intensities

In the previous section, we define routine tasks using a dictionary-based method developed in the field of computational linguistics. Using this approach, we pre-select a list of words from the thesaurus and match it with words extracted from occupational descriptions. Table B2 lists ten words with the highest frequencies in each division of the thesaurus. Our findings demonstrate that this method is capable of providing both intrinsic and behavioral significance to occupational descriptions, thereby facilitating the quantification of routine task intensities.

Table B2: Ten Words that Appear Most Frequently

| Tool | | Limb movement | | Production | |
|---|---|---|---|---|---|
| Word | Frequency | Word | Frequency | Word | Frequency |
| Tools | 446 | Repair | 151 | Operate | 1878 |
| Instrument | 238 | Package | 117 | Produce | 616 |
| Machinery | 193 | Filtrate | 84 | Process | 497 |
| Measuring Tool | 124 | Cleaning | 65 | Inspect | 471 |
| Aircraft | 100 | Clamp | 56 | Verify | 368 |
| Gauge | 95 | Wash | 51 | Install | 362 |
| Engine | 94 | Grind | 50 | Assemble | 304 |
| Ships | 76 | Stir | 47 | Manufacture | 300 |
| Implement | 65 | Load | 46 | Test | 278 |
| Locomotives | 58 | Extrude | 37 | Function | 249 |

Notes: The table reports ten words with the highest frequencies for each division. The words are verbs and nouns extracted from occupational descriptions which match the thesaurus's words. Note that some verbs and nouns share the same words in Chinese (for example, "operate" and "operation" are represented by the same word). Additionally, the term "measuring tool" is just one word in Chinese.

Next, we assume that the frequencies of successful word matches with the thesaurus for each given task attribute can serve as a measure of the routine task's importance within a given occupation. This allows us to quantify the routine task intensities for each occupation. Specifically, we begin by defining a dictionary, denoted as $\mathbb{D}$, that represents all words in the thesaurus, and $\mathbb{D}_r$ to represent the subset of words categorized under the "routine" divisions as defined in Table B1. We similarly decompose the words extracted from each occupational description into a list of words $b = B(1), \cdots, B(j)$ where $j$ represents a three-digit occupation. From this point, we count the number of successfully matched words within $\mathbb{D}_r$, dividing it by the total number of words matched with the dictionary:

$$\text{RoutineShare}_j = \frac{\sum_{b=B(1)}^{B(j)} \mathbb{I}[b \in \mathbb{D}_r]}{\sum_{b=B(1)}^{B(j)} \mathbb{I}[b \in \mathbb{D}]} \tag{B.1}$$

where $\mathbb{I}[\cdot]$ is the indicator function. The numerator corresponds to the count of words that have been successfully matched with dictionary $\mathbb{D}_r$ for occupation $j$. The denominator represents the total number of words that have been matched across all the dictionaries.

In the second step, we aim to reduce potential measurement error and expand the applicability of our methodology by deriving routine task intensities for two-digit occupations through the weighting of three-digit occupations.[18] We utilize employment shares calculated by the Population Census in the base year 2000 as weights:

$$\text{RoutineShare}_J = \sum_j w_j^J \text{RoutineShare}_j \tag{B.2}$$

where $w_j^J$ denotes the employment share of three-digit occupations $j$ within two-digit occupations $J$ in 2000.

Finally, we standardize the share of word frequencies on a scale of 0 to 10. As a result, the standardized outcomes can be interpreted as the routine task intensity. Figure B1 provides a comparison between our task measures and the corresponding measures derived from O*NET, as developed by Acemoglu and Autor (2011). The correlations between the two sets of measures for routine tasks are 0.77. These results suggest that our task measures are in line with other established measures in this area.

Table B3 presents the routine task intensities of the top ten and bottom ten occupations ranked by employment shares in 2005. According to our measure, some physical and manual occupations, such as mechanical equipment repairers, construction workers

[18] It is worth noting that the 1 percent sample survey conducted in 2005 solely surveyed two-digit occupations, whereas some micro-surveys, such as China Labor-force Dynamics Survey (CLDS) and China Family Panel Studies (CFPS), collected information on respondents' three-digit occupations.

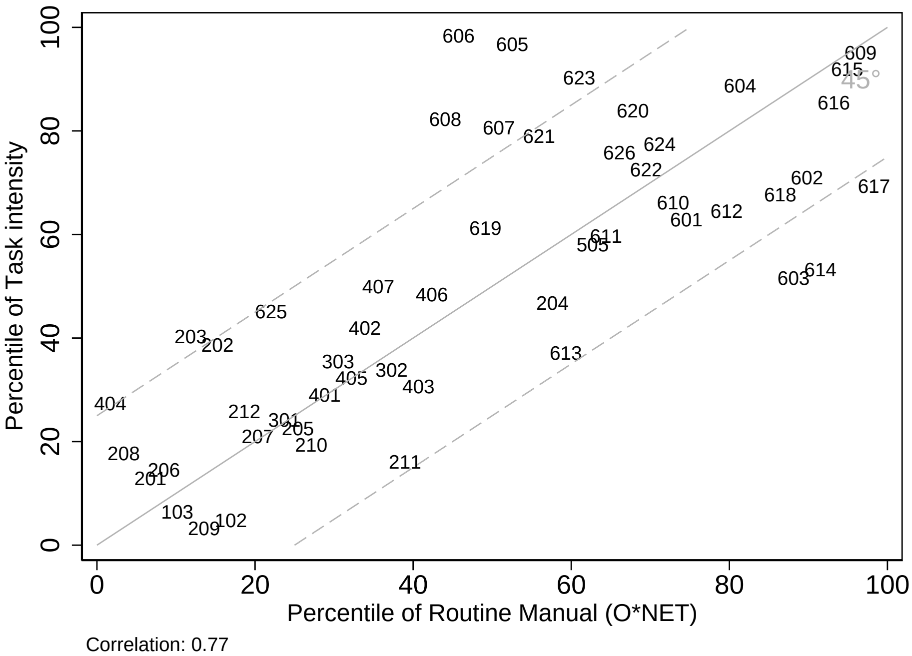


Figure B1: Our Routine Task Intensity and the Corresponding Measures from O*NET

Notes: The measures from O*NET are from Acemoglu and Autor (2011). We convert the task measure into percentiles to improve comparability.

and packers, are routine-intensive. While salesmen, administrative staff and teachers are identified as non-routine occupations, with teachers displaying the lowest level of routine intensity.

A crucial input in our study is occupation categories based on their routine task intensities. Following Autor and Dorn (2013), we determine whether the occupation is routine-intensive by the following definition:

$$\text{RoutineCategory}_J = \mathbb{I}[\text{RoutineIntensity}_J > \text{RoutineIntensity}^{P66}] \tag{B.3}$$

where $\text{RoutineIntensity}_J$ is the intensity for occupation $J$ calculated by Equation (B.2). $\mathbb{I}[\cdot]$ is the indicator function, which takes the value of one if the percentile of task intensity is larger than 66 (corresponding to a numerical value of 5.64).

Table B3: Most and Least Routine Occupations

| Occupations | Routine Intensity |
|---|---|
| **Panel A: top ten routine-intensive occupations** | |
| Mechanical equipment repairers | 10.00 |
| Mechanical and electricity assemblers | 9.01 |
| Rubber and plastic production workers | 8.49 |
| Packers, pump operators, etc. | 8.28 |
| Wood production workers | 7.89 |
| Construction workers | 7.47 |
| Mechanical manufacturing workers | 6.98 |
| Paper production workers | 6.77 |
| Printers | 6.66 |
| Electronic manufacturing workers | 6.55 |
| **Panel B: bottom ten routine-intensive occupations** | |
| Teachers | 0.07 |
| Functionaries of state organs | 0.07 |
| Functionaries of democratic parties and other people's organizations | 0.33 |
| Enterprise executives | 0.40 |
| Functionaries of CPC Central and Local Committees | 0.51 |
| Staff of public institutions | 0.56 |
| Scientific researchers | 0.88 |
| Accountants, auditors, etc. | 0.96 |
| Athletes, sports instructors and officials | 1.04 |
| Legal professionals | 1.12 |

Notes: The table reports the ten occupations with the highest and lowest routine intensity measured by the proportion of word frequencies within the divisions of Tool, Limb movement, and Production in the thesaurus.

# Appendix C. Census Data

## C.1 Characteristics of Different Types of Workers

Table C1 categorizes all workers into four groups based on their *hukou* type (rural or urban *hukou*) and migration status (locals or migrants). The findings suggest that these groups exhibit distinct characteristics across several dimensions. First, migrants tend to be younger than locals, with the average age of migrants being less than 35 years, while local workers have an average age exceeding 35 years. Second, urban workers generally have higher levels of education compared to rural workers. The data reveals that individuals with rural *hukou* are more likely to possess primary and junior high school degrees, whereas urban workers are more likely to have completed senior high school and college degrees. Third, these groups display varying sectoral concentrations. Rural local workers are more concentrated in the agricultural sector, while rural migrants are notably more engaged in the manufacturing sector than the other groups. Both urban locals and migrants exhibit a strong presence in the service sector, respectively accounting for over 70% of each group's composition. Lastly, rural migrants are more likely to be employed in routine occupations, comprising 42% of all rural migrants, whereas the proportion of urban locals engaged in routine occupations is significantly lower at only 14%.

## C.2 Assumption Underlying the Mobility Matrix

To study the migration patterns within our study sample, we gather data on individuals' place of registration, current place of residence, and their place of residence five years ago in the 2015 Census. With this information, we can construct a migration flow matrix from 2010 to 2015, which tracks movements between Chinese prefectures.

A key assumption underlying this matrix is that the demographic composition in 2010 mirrors that deduced from individuals' places of residence five years prior to the 2015 Census. In Figure C1, we present evidence supporting this assumption by illustrating a correlation between the actual share of migrants in 2010 and the predicted share of migrants derived from the 2015 Census. The data reveals that the actual share just slightly exceeds the predicted share. This suggests that the actual influence of robots on migration may be more substantial than our initial estimates suggest.

## C.3 Stylized Facts

Using census data, we provide two stylized facts about rural workers' employment and migration in China. We highlight the first fact related to employment by making compar-

Table C1: Migrant Selection

| | Rural-*hukou* locals | Rural-*hukou* migrants | Urban-*hukou* locals | Urban-*hukou* migrants |
|---|---|---|---|---|
| Age | 38.74 | 31.40 | 39.29 | 33.49 |
| Female | 0.51 | 0.51 | 0.49 | 0.49 |
| Married | 0.81 | 0.69 | 0.81 | 0.65 |
| Education: | | | | |
| *Primary school* | 0.35 | 0.21 | 0.09 | 0.06 |
| *Junior high school* | 0.45 | 0.57 | 0.32 | 0.28 |
| *Senior high school* | 0.09 | 0.16 | 0.33 | 0.32 |
| *Tertiary education* | 0.01 | 0.02 | 0.24 | 0.33 |
| Industry: | | | | |
| *Agriculture* | 0.66 | 0.07 | 0.04 | 0.01 |
| *Manufacturing* | 0.06 | 0.35 | 0.11 | 0.21 |
| *Construction* | 0.02 | 0.07 | 0.02 | 0.04 |
| *Wholesale and retail trade* | 0.01 | 0.02 | 0.03 | 0.02 |
| *Other Service* | 0.24 | 0.48 | 0.77 | 0.70 |
| Occupation: | | | | |
| *Routine* | 0.09 | 0.42 | 0.14 | 0.18 |
| *Non-routine* | 0.08 | 0.30 | 0.39 | 0.51 |

Notes: The table reports descriptive statistics on different types of labor by their *hukou* type and migration status. All variables except *Age* are dummy-coded. The sample is restricted to labor aged 16-65.
Sources: 2005 Census.

isons between rural and urban workers. Additionally, we present the changes in migration flows as captured by the second fact, which documents rural workers' migration direction.

**FACT 1: Employment Gap** — Rural workers are primarily employed in routine occupations, however, there is a substantial decline in their share of routine occupations.

To establish the fact, we measure the employment gaps across routine and non-routine occupations. we use a regression analysis approach on samples of rural and urban workers from the 2000-2015 Census data. Following Hurst et al. (2021) who construct racial "task gaps'', we regress individual occupation choices on their *hukou* types for each occupation category and year:

$$\text{Categ}_{it}^{k} = \alpha_t^k + \beta_t^k \text{Rural}_{it} + \Gamma_t^k X_{it} + \varepsilon_{it}^k \tag{C.1}$$

where $\text{Categ}_{it}^{k}$ is a dummy variable indicating whether the occupation of individual $i$ in period $t$ is classified as routine and non-routine occupations. $\text{Rural}_{it}$ is a dummy variable that takes the value of 1 if individual $i$ in period $t$ is a rural worker. $X_{it}$ denotes a set of individual-level control variables, including dummies for five-year age, education levels

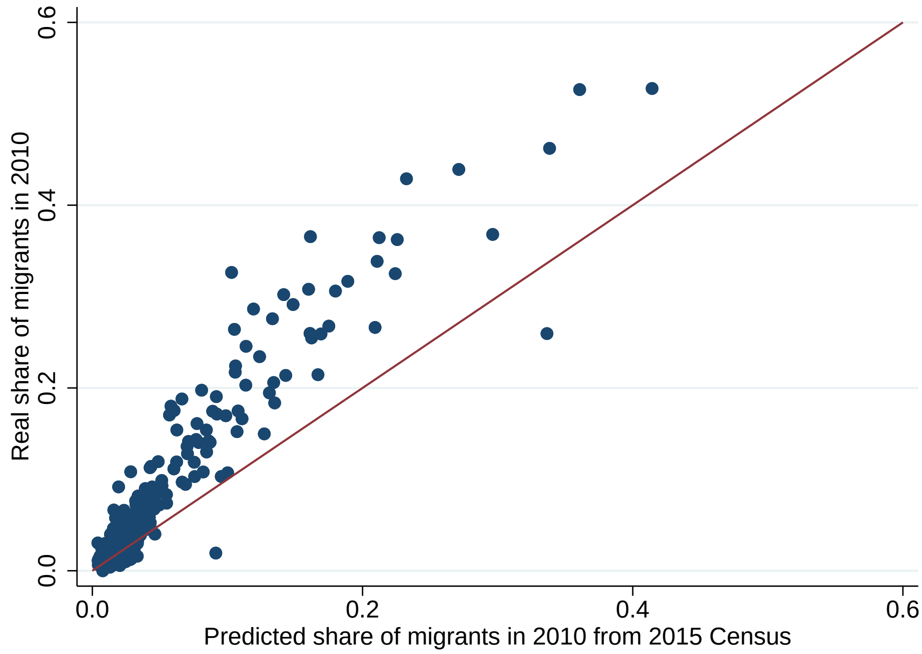


Figure C1: Real and Predicted Share of Migrants in 2010

Notes: The X-axis represents the actual share of migrants in 2010 at the prefecture level, calculated using data from the 2010 Census. The Y-axis represents the predicted share of migrants at the prefecture level in 2010, based on information about the place of residence five years prior from the 2015 Census. The red line corresponds to the 45-degree line.
Sources: 2010-2015 Census.

(never attended school, primary school, junior school, senior school, junior college, college, more than college), gender, 7 broad industry groups (agriculture, mining, manufacturing, electricity, construction, traditional services and modern services) and province. The coefficient $\beta_t^k$ represents the employment gap for each occupation category between rural and urban workers. Figure C2 plots the coefficients from 2000 to 2015.

Figure C2 shows both the level difference in employment gaps between rural and urban workers across occupation categories and the temporal evolution of these differences over the period. As shown in the figure, rural workers are more likely to be employed in routine jobs, while less likely to work in non-routine jobs. In the year 2000, the employment gap between rural and urban workers was substantially large. Specifically, rural workers' probability of being employed in routine jobs was 7.7 percentage points higher than that of urban workers. Conversely, their probability of working in non-routine jobs was 9.1 percentage points lower. The employment gap remained stable from 2000 to 2010, and started to decrease thereafter. By 2015, the differential in the probability of rural workers working in routine jobs versus urban workers had reduced to 2.8 percentage points, and the differential for non-routine jobs had lessened to 4.3 percentage points.

**FACT 2: Migration Flows** — Rural migrants exhibit a tendency to migrate

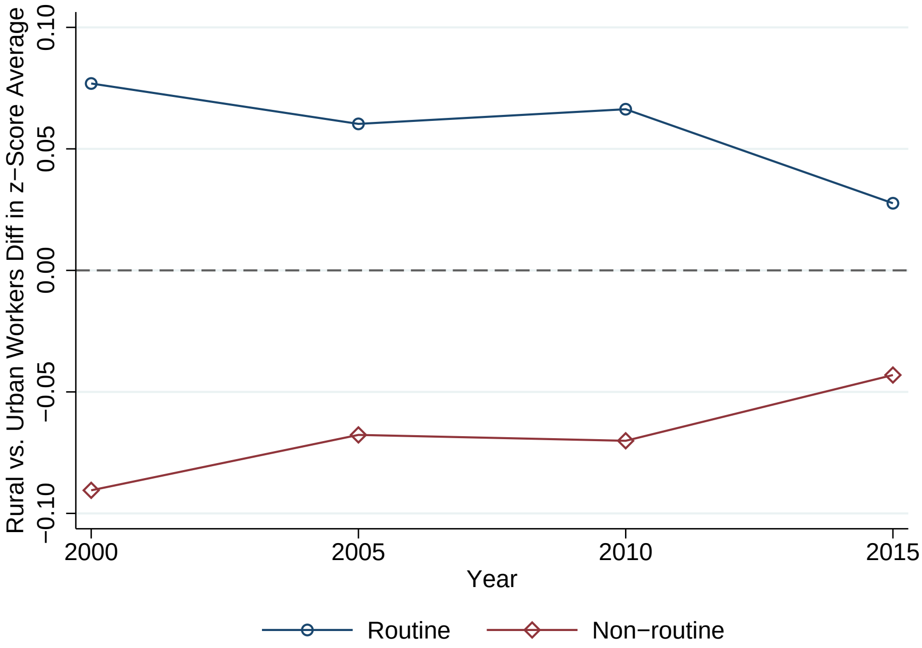


Figure C2: Employment Gaps between Rural and Urban Workers

Notes: The figures show estimates $\beta_t^k$ from Equation (C.1), representing the employment gap in occupation categories between rural and urban workers. The sample is restricted to working-age population aged 16-65. All main variables have standard errors of less than 0.01 in all years.
Sources: 2000-2015 Census.

within their registered prefecture rather than to another prefecture or province.

We document the fact by examining the direction of migration for rural migrants in each year using census data. Specifically, rural migrants are asked about their place of registration and residence in the 2000-2015 Census, and we utilize this information to identify their migration directions (cross-town, cross-county, cross-prefecture, and cross-province). We then calculate the share of each migration type and present our findings in Figure C3. Our results indicate that in 2000, half of rural migrants chose to migrate cross-province, with cross-prefecture migration ranking second (27.9%). By 2005, the share of cross-province migration had peaked at 61.0%, but decreased dramatically by 24.0 percentage points thereafter. During the same period, the share of cross-county and cross-town migration increased from 23.1% in 2005 to 48.0% in 2015. These findings suggest that rural migrants are more likely to migrate within their registered prefecture than outside of it or to a different province, which may reflect the availability of employment opportunities in the local labor market. Given that the mobility costs associated with moving to another prefecture or province are higher, it is more appealing for workers to migrate within the same prefecture.

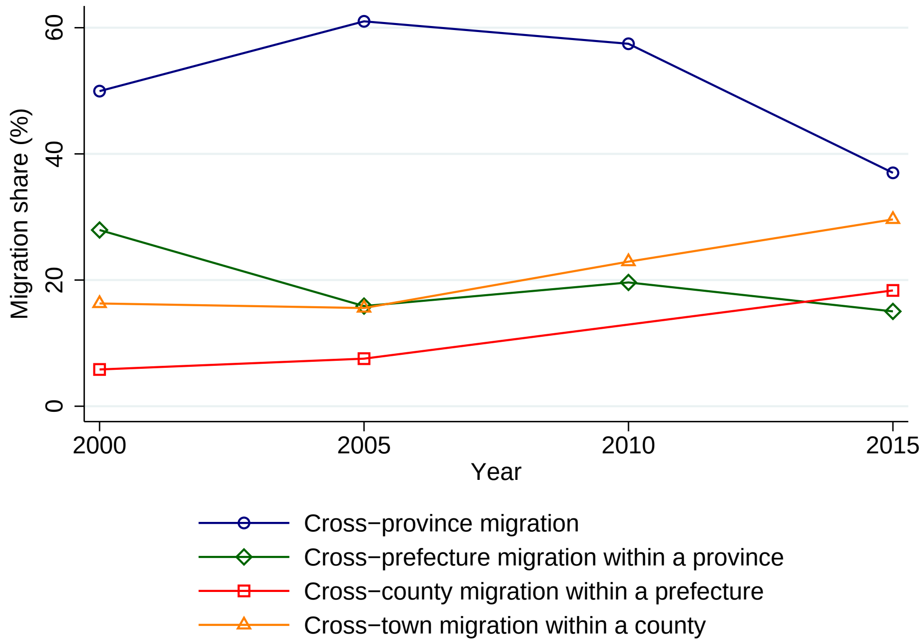


Figure C3: The Distribution of Migration Flows in Four Directions, 2000-2015

Notes: The figure shows the proportion of rural migrants for each migration direction from 2000 to 2015. The sample is restricted to rural migrants aged 16-65. The year 1990 is not included because the informaiton is not complete in the 1990 Census.
Sources: 2000-2015 Census.

# Appendix D. Individual-level Data

## D.1 China Labor-Force Dynamics Survey

We use individual panel data from the China Labor-Force Dynamics Survey (CLDS) to present stylized facts and provide supporting evidence for the impact of robots on individual labor outcomes. Conducted biennially from 2012 to 2018 by the Center for Social Survey at Sun Yat-sen University, this longitudinal survey covers 29 mainland provinces (excluding Tibet and Hainan) and includes a sample size of 44,024 individuals, 25,067 households, 598 villages, and 309 cities. The survey focuses on employment, migration and labor rights of the working-age population and addresses the limitations of tracking surveys in census data. It provides detailed information on individuals' two-digit occupations, which can be matched with task intensities and categories we measure. To mitigate sampling selection concerns, the survey design is based on birthplace rather than current residence, and each sample is followed for four consecutive rounds (six years) before being replaced by a new rotating sample. In our analysis, we retain only the working-age population aged 16-65 whose surveyed rounds are more than two, resulting in a total of 38,660 valid samples after excluding observations with missing key data. Table D1 presents descriptive statistics of key variables at the individual level, including employment status and the distribution of routine, non-routine and agricultural occupations. We observe that urban workers enjoy higher non-routine occupations, and lower routine occupations than rural workers, highlighting the significant disparities in labor market outcomes across different groups within China's workforce.

## D.2 Occupational Mobility

We analyze occupational mobility for rural and urban workers through two matrices in our panel data CLDS. Table D2 displays the transition shares among five employment statuses over a six-year span (2012-2018) for both rural and urban workers, thus enabling a direct comparative evaluation across the two groups. The findings demonstrate a notable disparity in post-routine job transitions: a substantial 46.3% of urban workers progress to non-routine occupations, as opposed to only 23.4% of rural workers. Similarly, the proportions of workers transitioning from agriculture, unemployment, and non-labor force participation to non-routine jobs are all higher for urban workers than for rural workers. This suggests a potentially higher mobility barrier for rural workers transitioning into non-routine occupations. Furthermore, the retention rates within employment statuses, as represented by the diagonal entries of our matrices, point to a pronounced stability among urban workers in non-routine jobs, with a retention rate of 52.2%, contrasted with

Table D1: Summary Statistics at the Individual Level

| | Rural workers | | Urban workers | |
|---|---|---|---|---|
| | mean | sd | mean | sd |
| **Panel A: employment outcomes** | | | | |
| 1 if employed | 0.691 | 0.462 | 0.854 | 0.353 |
| 1 if working in routine occupation | 0.247 | 0.432 | 0.394 | 0.489 |
| 1 if working in non-routine occupation | 0.430 | 0.495 | 0.186 | 0.389 |
| 1 if working in agricultural occupation | 0.014 | 0.118 | 0.274 | 0.446 |
| 1 if unemployed | 0.009 | 0.093 | 0.007 | 0.083 |
| 1 if leaving the labor market | 0.309 | 0.462 | 0.146 | 0.353 |
| **Panel B: migration outcomes** | | | | |
| Willingness to live locally | - | - | 0.521 | 0.448 |
| Willingness to obtain a local hukou | - | - | 0.327 | 0.418 |
| Willingness to drop land in the hometown | - | - | 0.268 | 0.404 |
| **Panel C: exposure to robots** | | | | |
| Change in exposure to Chinese robots | 0.205 | 0.163 | 0.208 | 0.163 |
| Change in exposure to foreign robots | 0.948 | 0.627 | 1.026 | 0.659 |

Notes: This table reports the mean and standard deviation of individual-level outcome variables and prefecture-level exposure to robots for rural workers and urban workers.
Source: IFR and 2012-2018 CLDS.

a lower 39.6% for rural workers. This differential reveals the challenges faced by rural workers in securing sustained employment in non-routine occupations.

Table D2: Occupational Mobility Matrices

| Employment status in time $t$ | Employment status in time $t+2$ | | | | |
|---|---|---|---|---|---|
| | Routine | Non-routine | Agriculture | Unemployed | Non-LFP |
| **Panel A: rural workers** | | | | | |
| Routine | 32.12 | 23.36 | 22.73 | 3.62 | 18.17 |
| Non-routine | 19.54 | 39.59 | 14.55 | 4.07 | 22.25 |
| Agriculture | 25.62 | 19.04 | 4.78 | 2.78 | 47.78 |
| Unemployed | 21.29 | 25.72 | 24.19 | 6.98 | 21.81 |
| Non-LFP | 14.58 | 18.67 | 24.94 | 2.89 | 38.91 |
| **Panel B: urban workers** | | | | | |
| Routine | 18.82 | 46.33 | 2.59 | 4.45 | 27.82 |
| Non-routine | 12.88 | 52.15 | 0.95 | 3.88 | 30.15 |
| Agriculture | 19.71 | 41.61 | 1.46 | 2.92 | 34.31 |
| Unemployed | 14.16 | 40.66 | 0.60 | 7.53 | 37.05 |
| Non-LFP | 9.16 | 30.34 | 0.74 | 3.44 | 56.32 |

Notes: The table presents the distribution of employment status changes among rural and urban workers from 2012 to 2018. The sample is restricted to working-age population aged 16-65 whose surveyed rounds are more than two. “Non-LFP” represents non-labor force participation.
Source: 2012-2018 CLDS.

# Appendix E. Additional Results on Empirics

Table E1: Balance Test for Prefectural Characteristics in 2005

| | % Change in E/P | % female | % age>65 | % low skilled | % high skilled |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| **Panel A: Change in exposure to Chinese robots** | | | | | |
| Δ Exposure to robots | 0.005 | 0.002 | -0.006 | -0.012 | 0.012 |
| | (0.006) | (0.003) | (0.004) | (0.010) | (0.010) |
| **Panel B: Change in exposure to foreign robots** | | | | | |
| Δ Exposure to robots | 0.001 | 0.001 | -0.002** | -0.001 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.002) | (0.002) |
| Observations | 260 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry shares | ✓ | ✓ | ✓ | ✓ | ✓ |
| Δ ICT technologies | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: Dependent variables include the 2000-05 change in employment-to-population ratios, the 2005 share of female, the 2005 share of population aged 65 and above, the 2005 share of population with low skills (primary and junior high school) and high skills (senior high school and above). Sample includes 285 prefectures in China. All the specifications control for a series of variables except for its own dependent variables, including prefecture-level demographic variables, employment shares of broad industry groups, change in exposure to ICT technologies and broad district dummies. All the regressions are weighted by population in 2005. Standard errors (in parentheses) are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.
Sources: IFR, 2000-2005 Census, and Statistical Yearbook.

Table E2: IV First Stage Regressions: Prefecture Level

| | Δ Exposure to Chinese robots | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Δ Exposure to foreign robots | 0.184*** | 0.184*** | 0.186*** | 0.190*** |
| | (0.025) | (0.020) | (0.019) | (0.019) |
| Observations | 285 | 285 | 285 | 285 |
| R-squared | 0.82 | 0.85 | 0.85 | 0.86 |
| F-statistic | 23.4 | 96.4 | 91.8 | 235.4 |
| District FE | ✓ | ✓ | ✓ | ✓ |
| Demographics | | ✓ | ✓ | ✓ |
| Industry shares | | | ✓ | ✓ |
| Δ ICT technologies | | | | ✓ |

Notes: Dependent variables are change in exposure to Chinese robots between 2005 and 2015. The first stage regressions are long-difference equations for our prefecture-level estimation. Column 1 includes only broad district dummies. Column 2 adds demographic characteristics. Column 3 adds employment shares of broad industry groups. Column 4 adds change in exposure to ICT technologies. All the regressions are weighted by population in 2005. Standard errors (in parentheses) are clustered at the province level. *** p<0.01, ** p<0.05, * p<0.1.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E3: Effects of Robots on Employment: OLS Estimate

| | Total Employment | | Routine jobs | | Non-routine jobs | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: total workers** | | | | | | |
| Δ Exposure to robots | -0.028 | -0.028 | -0.053 | -0.053 | 0.002 | 0.002 |
| | (0.008)*** | (0.008)*** | (0.016)*** | (0.016)*** | (0.010) | (0.010) |
| | [0.010]*** | [0.010]*** | [0.015]*** | [0.015]*** | [0.009] | [0.009] |
| **Panel B: rural workers** | | | | | | |
| Δ Exposure to robots | -0.028 | -0.027 | -0.053 | -0.053 | 0.003 | 0.003 |
| | (0.017)* | (0.017)* | (0.017)*** | (0.016)*** | (0.009) | (0.009) |
| | [0.015]* | [0.015]* | [0.015]*** | [0.015]*** | [0.008] | [0.008] |
| **Panel C: urban workers** | | | | | | |
| Δ Exposure to robots | 0.005 | 0.003 | -0.001 | -0.001 | 0.003 | 0.002 |
| | (0.014) | (0.013) | (0.005) | (0.004) | (0.008) | (0.008) |
| | [0.011] | [0.010] | [0.003] | [0.003] | [0.006] | [0.006] |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Demographics | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Industry shares | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Δ ICT technologies | | ✓ | | ✓ | | ✓ |

Notes: This table reports results of Equation (2) by OLS for total workers, rural workers and urban workers. The estimates are based on 285 prefectures in China. Dependent variables are the 2005-15 change in employment-to-population ratios. Column 1, 3 and 5 control for prefecture-level demographic variables, employment shares of 7 broad industry groups and broad district dummies. Column 2, 4 and 6 add change in exposure to ICT technologies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** $p<0.01$, ** $p<0.05$, * $p<0.10$.

Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E4: Summary Statistics of Hukou Index

| Year | Hukou index | | Δ Hukou index | |
|---|---|---|---|---|
| | mean | sd | mean | sd |
| 2005 | 2.462 | 1.234 | 0.044 | 0.318 |
| 2006 | 2.553 | 1.227 | 0.091 | 0.407 |
| 2007 | 2.738 | 1.266 | 0.185 | 0.557 |
| 2008 | 2.782 | 1.297 | 0.044 | 0.400 |
| 2009 | 3.150 | 1.341 | 0.368 | 1.021 |
| 2010 | 3.315 | 1.455 | 0.165 | 0.689 |
| 2011 | 3.415 | 1.490 | 0.100 | 0.746 |
| 2012 | 3.574 | 1.575 | 0.159 | 0.677 |
| 2013 | 3.738 | 1.616 | 0.165 | 0.777 |
| 2014 | 3.876 | 1.666 | 0.138 | 0.701 |
| 2015 | 4.600 | 1.686 | 0.724 | 1.372 |

Notes: This table reports the mean and standard deviation of *hukou* index and the annual change in the *hukou* index compared to the previous year. The *hukou* index from 2005 to 2010 comes from Fan (2019), who collects official news, laws and regulations related to *hukou* reforms and rates every city on a scale of 0-6. We use the same method to extend the *hukou* index from 2011 to 2015.

Table E5: Effects of Robots on Employment, 2005-2010 and 2010-2015

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: 2005-2010** | | | | | | |
| Δ Exposure to robots | -0.329 | -0.477 | 0.109 | -0.055 | -0.038 | -0.022 |
| | (0.115)*** | (0.113)*** | (0.123) | (0.056) | (0.022) | (0.049) |
| | [0.106]*** | [0.112]*** | [0.086] | [0.059] | [0.023] | [0.056] |
| **Panel B: 2010-2015** | | | | | | |
| Δ Exposure to robots | -0.023 | -0.071 | -0.018 | 0.006 | 0.006 | 0.004 |
| | (0.011)** | (0.013)*** | (0.011)* | (0.013) | (0.002) | (0.008) |
| | [0.011]** | [0.012]*** | [0.009]* | [0.014] | [0.004] | [0.009] |
| Observations | 276 | 276 | 276 | 276 | 276 | 276 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers. There are two time periods: 2005-2010 (Panel A) and 2010-2015 (Panel B). The estimates are based on 276 prefectures in China. Dependent variables are change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E6: Effects of Robots on Employment, Stacked Differences

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -0.090 | -0.109 | 0.001 | 0.023 | 0.006 | 0.015 |
| | (0.014)*** | (0.016)*** | (0.009) | (0.012)** | (0.003) | (0.008)** |
| | [0.014]*** | [0.012]*** | [0.009] | [0.011]** | [0.004] | [0.008]** |
| Observations | 552 | 552 | 552 | 552 | 552 | 552 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Period FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers using stacked-differences method. The estimates are based on 276 prefectures in China. Dependent variables are change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies, broad district dummies (See Table 2 for more details) and period dummies. All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E7: Effects of Robots on Employment, Instrumented by Change in Exposure to US Robots

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -0.029 | -0.078 | 0.003 | 0.008 | -0.002 | 0.003 |
| | (0.019)* | (0.017)*** | (0.010) | (0.016) | (0.005) | (0.009) |
| | [0.016]* | [0.017]*** | [0.009] | [0.012] | [0.004] | [0.007] |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers using change in exposure to US robots as an instrument. The estimates are based on 285 prefectures in China. Dependent variables are 2005-15 change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E8: Effects of Robots on Percent Change in Employment

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -1.463 | -1.113 | -1.997 | 0.397 | 0.206 | 0.375 |
| | (0.775)** | (0.516)* | (1.390) | (0.243) | (0.188) | (0.221) |
| | [0.609]** | [0.655]* | [1.258] | [0.280] | [0.191] | [0.271] |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers. The estimates are based on 285 prefectures in China. Dependent variables are 2005-15 percent change in employment. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E9: Effects of Robots on Low-educated Employment

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -0.043 | -0.093 | -0.001 | 0.005 | 0.002 | -0.001 |
| | (0.023)** | (0.018)*** | (0.010) | (0.015) | (0.006) | (0.007) |
| | [0.017]** | [0.017]*** | [0.008] | [0.011] | [0.004] | [0.006] |
| Baseline mean of E/P | 0.565 | 0.095 | 0.077 | 0.116 | 0.039 | 0.068 |
| Effect of mean robot | -24.0 | -51.7 | -0.7 | 2.6 | 1.1 | -0.5 |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers with primary and high school degrees. The estimates are based on 285 prefectures in China. Dependent variables are 2005-15 change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.

Table E10: Effects of Robots on Employment, Controlling for Pre-trends

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -0.039 | -0.090 | 0.006 | 0.011 | 0.003 | 0.004 |
| | (0.023)** | (0.018)*** | (0.010) | (0.018) | (0.006) | (0.011) |
| | [0.018]** | [0.017]*** | [0.008] | [0.013] | [0.004] | [0.008] |
| Δ in emp/pop (2000-2005) | 0.120 | -0.097 | -0.003 | -0.240 | -0.040 | -0.128 |
| | (0.132) | (0.086) | (0.068) | (0.128)* | (0.030) | (0.076)** |
| | [0.143] | [0.077] | [0.074] | [0.125]* | [0.027] | [0.059]** |
| Observations | 260 | 260 | 260 | 260 | 260 | 260 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers. The estimates are based on 260 prefectures in China. Dependent variables are 2005-15 change in employment-to-population ratios. All the specifications control for 2000-05 change in employment-to-population ratios, prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. Shift-share standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2000-2015 Census, and Statistical Yearbook.

Table E11: Effects of Robots on Employment, Spatial Autoregressive Model

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -0.025 | -0.034 | -0.007 | 0.010 | 0.005 | 0.004 |
| | (0.012)** | (0.010)*** | (0.007) | (0.010) | (0.003) | (0.005) |
| Observations | 552 | 552 | 552 | 552 | 552 | 552 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Period FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) using spatial autoregressive model for rural workers and urban workers. The spatial lag control are created with inverse distance between prefectures. The estimates are based on 276 prefectures in China. Dependent variables are 2005-10 and 2010-15 change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies, broad district dummies (See Table 2 for more details) and period dummies. All the regressions are weighted by population in 2005. Standard errors clustered at the province level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, Statistical Yearbook and Baidu Map.

Table E12: Effects of Robots on Employment, Adjusting Standard Error for Spatial Correlation

| | Rural workers | | | Urban workers | | |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-Routine | Total | Routine | Non-Routine |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Δ Exposure to robots | -0.038 | -0.091 | 0.003 | 0.009 | 0.003 | 0.003 |
| | (0.020)* | (0.022)*** | (0.009) | (0.013) | (0.005) | (0.009) |
| Observations | 285 | 285 | 285 | 285 | 285 | 285 |
| District FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: This table reports results of Equation (2) by 2SLS for rural workers and urban workers. The estimates are based on 285 prefectures in China. Dependent variables are 2005-15 change in employment-to-population ratios. All the specifications control for prefecture-level demographic variables, employment shares of 7 broad industry groups, change in exposure to ICT technologies and broad district dummies (See Table 2 for more details). All the regressions are weighted by population in 2005. Standard errors allow for arbitrary spatial correlation with prefectures within 300 kilometers following Conley (1999). *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2005-2015 Census, Statistical Yearbook and Baidu Map.

Table E13: Effects of Robots on Employment: Individual Level

| | Employed | | | | Unemployed | No LFP |
|---|---|---|---|---|---|---|
| | Total | Routine | Non-routine | Agriculture | Total | Total |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| **Panel A: rural workers** | | | | | | |
| Δ Exposure to robots | -0.135 | -1.056*** | -0.313** | 1.233*** | 0.026 | 0.135 |
| | (0.150) | (0.250) | (0.158) | (0.195) | (0.036) | (0.150) |
| Mean of outcomes | 0.854 | 0.394 | 0.186 | 0.274 | 0.007 | 0.146 |
| Observations | 10342 | 10342 | 10342 | 10342 | 10342 | 10342 |
| **Panel B: Urban workers** | | | | | | |
| Δ Exposure to robots | 0.021 | 0.285 | -0.547 | 0.283*** | 0.068 | -0.021 |
| | (0.292) | (0.359) | (0.391) | (0.096) | (0.075) | (0.292) |
| Mean of outcomes | 0.691 | 0.247 | 0.430 | 0.014 | 0.009 | 0.309 |
| Observations | 2516 | 2516 | 2516 | 2516 | 2516 | 2516 |
| Individual FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |

Notes: The table reports the effects of prefecture-level exposure to robots on individual employment and occupation choices in the local labor markets. Samples are restricted to working-age population in the same city during the periods. Dependent variables are dummy variables indicating whether individuals are employed, unemployed, leaving the labor market, and their choices of occupation, including routine, non-routine and agricultural jobs. Panel A focuses on a sample of rural workers, and Panel B focuses on urban workers. All the specification control individual and year fixed effects, as well as worker-level variables (five-year age dummies and education levels) and prefecture-level variables (log of population density; employment shares of 7 broad industry group; the usage ratios of mobile phones and broadband internet). Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2012-2018 CLDS and Statistical Yearbook.

Table E14: Effects of Robots on Willingness to Migration: Individual Level

| | Willingness to | | |
|---|---|---|---|
| | live locally | obtain *hukou* | drop land |
| | (1) | (2) | (3) |
| $\Delta$ Exposure to robots | -0.912 | -3.206* | -4.245** |
| | (1.150) | (1.808) | (1.904) |
| Mean of outcomes | 0.521 | 0.327 | 0.268 |
| Observations | 604 | 604 | 356 |
| Individual FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| Individual controls | ✓ | ✓ | ✓ |
| Prefectural controls | ✓ | ✓ | ✓ |

Notes: The table reports the effects of prefecture-level exposure to robots on individual willingness to migration. Samples are restricted to rural workers. Dependent variables are willingness to live locally, obtain a local *hukou* and drop land in the hometown (1 for "willing", 0.5 for "not sure", 0 for "not willing"). All the specification control individual and year fixed effects, as well as worker-level variables (five-year age dummies and education levels) and prefecture-level variables (log of population density; employment shares of 7 broad industry group; the usage ratios of mobile phones and broadband internet). Standard errors clustered at the individual level in parentheses. *** p<0.01, ** p<0.05, * p<0.10.
Sources: IFR, 2012-2018 CLDS and Statistical Yearbook.

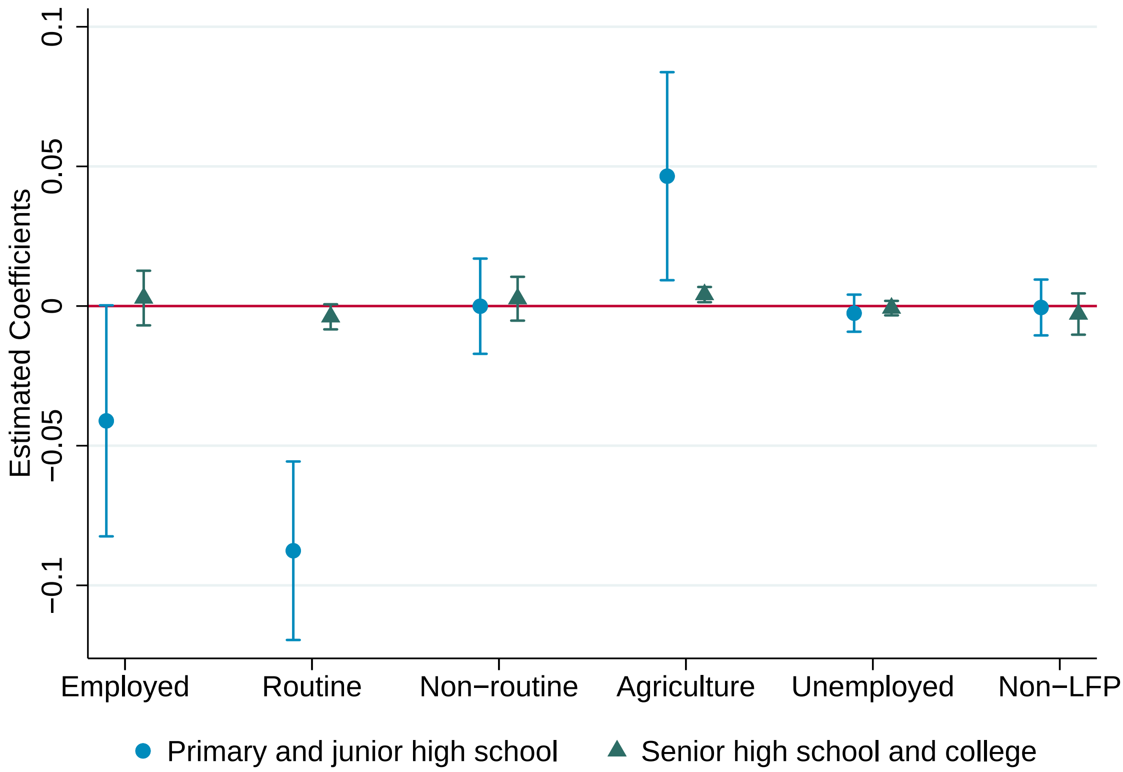


Figure E1: Effects of Robots on the Share of Population in Employment Categories: by Education Levels

Notes: The figure reports the estimated coefficient and the associated p-value of Equation (2) by 2SLS for rural workers by education levels. The estimates are based on 285 prefectures in China. Dependent variables are the 2005-15 change in employment-to-population ratios in different employment categories. See Table 2 for more details.
Sources: IFR, 2005-2015 Census, and Statistical Yearbook.