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HOW DO WORKERS ADJUST TO ROBOTS? EVIDENCE FROM CHINA*

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We analyse the effects of exposure to industrial robots on labour market adjustments, exploring longitudinal household data from China. We find that a one-standard-deviation increase in robot exposure led to a decline in labour force participation (−1%), employment (−7%) and hourly earnings (−8%) of Chinese workers. At the same time, among those who kept working, robot exposure increased the number of hours worked by 8%. These effects were concentrated among the less educated and larger among male, prime-age and older workers. We also find that more exposed workers increased their participation in technical training and were significantly more likely to retire earlier.

According to a recent World Bank Group (2016) estimate, 1.8 billion jobs or roughly two-thirds of the labour force in developing countries are susceptible to automation (World Bank Group, 2016). Despite a growing research interest in the effects of these automation technologies, and especially of robots (Mokyr *et al.*, 2015; Graetz and Michaels, 2018; Bessen *et al.*, 2019; Borjas and Freeman, 2019; Acemoglu and Restrepo, 2020), we still know relatively little about the impact of industrial robots in a developing country.

The implications of robotisation in emerging markets for jobs, growth and inequality could be profound. Given the different industry specialisations of developing countries, and the larger role of routine agricultural and manufacturing work as compared to service sector jobs, jobs in developing countries are more likely to be automated. With a much higher share of workers having only high school education or less, it will require time before workers acquire the skills needed to benefit from the complementarities brought up by smart machines and automation (Yusuf, 2017).[1] Without employment creation, automation, digitalisation and labour-saving technologies may foster inequality.[2] Consequently, developing countries may face new policy challenges and important economic trade-offs, such as that between increased productivity and potential higher

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The data and codes for this paper are available on the Journal repository. They were checked for their ability to reproduce the results presented in the paper. The authors were granted an exemption to publish parts of their data because access to these data is restricted. However, the authors provided the Journal with temporary access to the data, which enabled the Journal to run their codes. The codes for the parts subject to exemption are also available on the Journal repository. The restricted access data and these codes were also checked for their ability to reproduce the results presented in the paper. The replication package for this paper is available at the following address: https://doi.org/10.5281/zenodo.13760908.

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[1] Previous work has highlighted the risks of premature deindustrialisation and how automation may disrupt the income convergence process and hinder the ability of developing countries to exploit their labour-cost advantage to grow (Palma, 2008; Rodrik, 2016; Atolia *et al.*, 2018; Berg *et al.*, 2018).

[2] See also https://www.cgdev.org/publication/automation-ai-and-emerging-economies.

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economic inequality and social unrest (Avent, 2016). For all the reasons above, the effects of robots in emerging economies are likely to be significantly larger than those observed so far in the more developed countries (Schlogl and Sumner, 2018).

Our paper attempts to fill these gaps in the literature by analysing the effects of exposure to industrial robots in an emerging economy and exploiting individual longitudinal data to explore labour market adjustments and the dynamic response of workers to robot penetration. We focus on China, a country that over the last few years has massively invested in robots and automation. In 2014, China's President Xi Jinping called for a robot revolution to boost the country's manufacturing productivity. In the latest Five-Year Plan of China (2016–20), the government has allocated billions of yuan for manufacturers to upgrade to technologies including robots and advanced machinery. Several Chinese provinces are also heavily subsidising the adoption of robots. For instance, Guangdong province in southern China promised to spend $150 billion on industrial robots and new innovation centres dedicated to advanced automation. Cheng *et al.* (2019a) showed that innovation subsidies are preferentially allocated to state-owned firms and politically connected firms.

The ambition of the Chinese government is to transform China into a high-tech hub, challenging the leadership of countries like Germany, Japan and the United States that have so far dominated the robot market both in terms of utilisation and production. In fact, China has already become the largest market for industrial robots in the world since 2013 in terms of the number of robots purchased each year. At the moment, China also has the highest number of industrial robots among all countries in the world, although in per capita terms China is still lagging behind the more advanced economies. The investment in robotics may boost China's manufacturing, which has lately been challenged by rising labour costs, an ageing population and increased international competition. However, automation technologies such as robots can affect the prospects of hundreds of millions of Chinese workers in manufacturing and other sectors exposed to these technologies. Indeed, according to Rahbari and Frey (2016), roughly 77% of Chinese jobs are highly susceptible to automation (Chui *et al.*, 2016; Manyika, 2017).[3] A stunning example is Foxconn, the massive producer of iPhone and many other electronic goods. Between 2012 and 2016, Foxconn replaced more than 400,000 jobs with robots in China in an effort to achieve 30% automation within a few years. Another example is Zhejiang Province, which replaced two million workers with robots between just 2013 and 2015 (Yang, 2017). For all these reasons, China provides an extremely interesting context to explore the effects of automation on the labour market of emerging economies.

To identify the effects of robots, we use data from the International Federation of Robotics (IFR) and adapt the identification strategy proposed by Acemoglu and Restrepo (2020) to the Chinese context together with longitudinal individual data. Using panel data from the China Family Panel Studies (2010–16) and exploiting within-individual variation in exposure to robots over time, we find significant negative effects of robot exposure on employment and wages. We show that an increase of one SD in robot exposure lowers an individual's probability of being employed by 5 percentage points (−6.7% with respect to the mean), increases the likelihood of leaving the labour force by 1 percentage point (+12.6% with respect to the mean) and increases the likelihood of reporting unemployment status by 4 percentage points (or 0.15 SDs). Robot exposure reduces hourly wage on average (−8%), but with no significant effect on annual earnings, as individuals in areas that are more exposed work longer hours (+8%). These effects are concentrated among

[3] See also Knight (2016).

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low-skilled, male, prime-age and older workers. An important contribution of our study is to also analyse how individuals respond to the increased exposure to robots in labour markets. We find that robot penetration significantly increases early retirement, especially among older workers, while younger workers are more likely to participate in technical or work-related training in response to robot competition.

Our work speaks directly to a recent and growing literature on the labour market effects of robots, which has so far largely focused on advanced economies. Acemoglu and Restrepo (2020) provided evidence on large negative effects of robot adoption on employment and wages in the United States. These results are consistent with recent findings by Borjas and Freeman (2019), who compared the effect of immigration and robot exposure on employment. On the contrary, Graetz and Michaels (2018) used cross-country data in a more macro approach and found positive effects of robots on productivity and wages, although they found negative effects on low-skilled workers. Koch *et al.* (2021) examined panel data on Spanish manufacturing firms and found that robots increase firm productivity, reduce labour cost share and lead to net job creation. Dauth *et al.* (2021) showed that in Germany robots account for 23% of the decline in manufacturing jobs over the past two decades. However, there is only limited evidence on the effects of robot exposure in emerging economies. We also know very little about how workers respond to the labour market shocks brought by robots. Our paper attempts to fill these gaps in the literature.

In particular, our paper contributes to a handful of studies analysing robot adoption and the impact of robots in China. These previous studies documented the adoption of robots by China's manufacturers using aggregate industry-level and firm-level data (Cheng *et al.*, 2019b), examined how robot adoption may create skill-biased development in firms' employment structures (Tang *et al.*, 2021) and analysed the effects of labour costs on the adoption of robots (Fan *et al.*, 2021). More generally, we relate to a recent set of studies exploring the impact of foreign and domestic robots in emerging economies (Maloney and Molina, 2019; Carbonero *et al.*, 2020). Most of these studies, however, focus on the indirect effects of foreign robots in developing countries (i.e., Mexico and Colombia) through their effects on trade and offshoring (Artuc *et al.*, 2019; Faber, 2020; Kugler *et al.*, 2020; Krenz *et al.*, 2021). We contribute to these studies that largely relied on cross-sectional data by exploring longitudinal data on Chinese workers, which enables us to directly examine the impacts of robot exposure on Chinese workers, as well as to shed further light on the heterogeneous effects of robots across demographics and skill groups. Moreover, we provide novel evidence by analysing the impact of exposure to robots on training and retirement, highlighting potential channels of labour market adjustments.

1. Empirical Strategy and Data

1.1. *Identification Strategy*

Following Acemoglu and Restrepo (2020), we exploit variations in the pre-existing distribution of industrial employment across Chinese cities and changes in the amount of robots across industries to create a measure of robot penetration in the Chinese local labour market. By relying on pre-existing industrial composition of cities before the recent increase in adoption of robots, we focus on historical differences in the specialisation of Chinese cities in different industries, and avoid any mechanical correlation or mean reversion with changes in overall or industry-level employment outcomes. We choose our baseline year to be 2000, since most of

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the rise in industrial robots in China took place in the past few years, especially after 2010 (see Figure 1(a)).[4]

To measure the exposure to robots for a city, we calculate the ratio of robots to employed workers in industry sector s at the national level, multiply it by the city's baseline employment share in sector s and then sum over all sectors. In other words, our measure of robot exposure is normalised with respect to the city employment population. Formally,

$$\textit{Exposure to Robots}_{ct} = \sum_{s \in S} \ell_{cs}^{2000} \left(\frac{R_{st}}{L_{s,2000}} \right),$$

where ℓ_{cs}^{2000} is the 2000 share of city c's employment in industry sector s, R_{st} is the total number of robots in use in sector s and year t, and $L_{s,2000}$ is the total number of workers (in thousands) employed in sector s in 2000. For each city, our employment share across sectors was normalised with respect to the city's own employment size (and not the total national industry employment). We measure China's city-level employment shares across sectors, as well as the overall employment across sectors in 2000 using public-use microdata from China's 2000 census (Ruggles *et al.*, 2024). Data on robot adoption in China at the sector-year level comes from the IFR, which we provide more details on in the next section.[5]

To identify the impact of robot exposure on our outcomes of interest, we use longitudinal data from the China Family Panel Studies (CFPS) to estimate

$$Y_{ict} = \textit{Exposure to Robots}_{ct} + \lambda_c + \xi_t + \eta_i + \epsilon_{ict},$$

where the Y_{ict} are outcomes of interest for individual i in city c and year t, including labour force participation, employment status and the natural log of income measures (hourly and annual earnings); $\textit{Exposure to Robots}_{ct}$ is the exposure to robots of city c in year t. In our baseline specification, we account for time-invariant heterogeneity at the city level that may be correlated with our measure of robot exposure by including city fixed effects λ_c; we include year (survey-wave) fixed effects ξ_t to account for common shocks that may be correlated with both the trends in robot adoption and our outcomes of interest; finally, we exploit the longitudinal nature of the data by including individual fixed effects that allow us to capture the potential confounding role of time-invariant characteristics at the individual level (η_i). In the Online Appendix, we also check the sensitivity of our results to the inclusion or removal of individual fixed effects and controls for individual characteristics. SEs are clustered at the city level. For ease of interpretation, we standardise the robot exposure variable with respect to the city-year variation in exposure.

To further mitigate the concerns of confounding factors that may be correlated with both the industry-level spread of robots in China and labour market outcomes, we construct an instrument by exploiting the industry-level spread of robots in other economies, which are meant to proxy improvements in the world technology frontier of robots (Acemoglu and Restrepo, 2020). In particular, we use the average industry-level spread of robots in the nine European countries that are available in the IFR data over the same period of time.[6] Thus, we exploit only the variation

[4] In the Online Appendix, we also report estimates obtained using 1982 as a base year.

[5] Unfortunately, we have only limited information on sectoral occupation (one-digit level), which does not allow us to use the sectoral information of each individual to build a measure of exposure to robots at the individual level. Our measure of robot exposure at the regional level also has the advantage of allowing us to capture the local general equilibrium effects of robot exposure in each city.

[6] These European countries are Denmark, Finland, France, Germany, Italy, Norway, Spain, Sweden and the UK.

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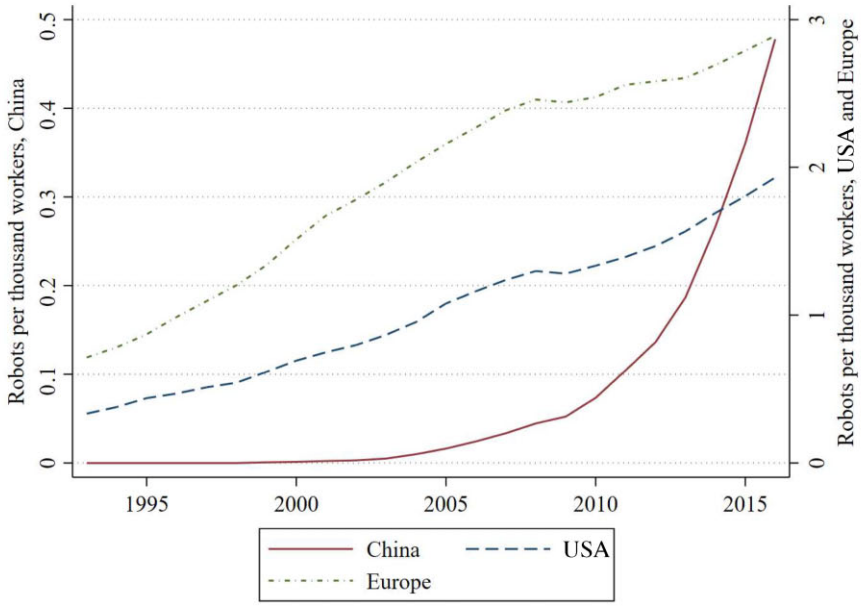
(a) Robot Penetration in China, USA and Europe, 1993–2016



(b) Robot Penetration in China's Top Robot-Adopting sectors, 2006–2016

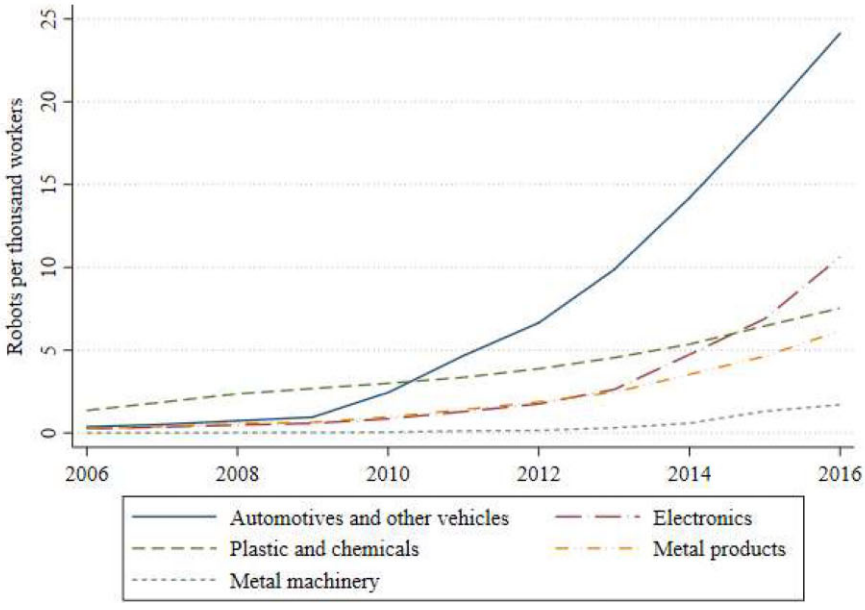


Fig. 1. *Penetration of Industrial Robots.*
Notes: Data are drawn from the IFR. Robot penetration is measured by the number of industrial robots per thousand workers. Panel (a) describes robot penetration in China, USA and Europe. Panel (b) describes robot penetration in China's top robots adopting sectors.

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resulting from industries that exhibited an increase in the use of robots in these other economies. Our instrument is formally defined as

$$Exposure\ to\ Robots_{IV_{ct}} = \sum_{s \in S} \ell_{cs}^{2000} \left(\frac{R_{st}}{L_{s,2000}} \right)_{EU_{Avg}},$$

where the sum runs over all sectors in the IFR data, ℓ_{cs}^{2000} is the 2000 share of city c employment in sector s, as computed from China's 2000 census, and $(R_{st}/L_{s,2000})_{EU_{Avg}}$ represents the average of robot usage among European countries in sector s and year t.

1.2. *Data*

1.2.1. *Robot data*

Data on the stock of robots by industry, country and year are drawn from the International Federation of Robotics (IFR, 2016). These data are based on yearly surveys of robot suppliers and contain information for seventy countries from 1993 to 2016, covering more than 90% of the industrial robot market. The IFR data provide the operational stock of 'industrial robots', which are defined as 'automatically controlled, reprogrammable, and multipurpose [machines]' (Jurkat *et al*., 2022). In the Online Appendix, we discuss the data and their limitations in more detail. Figure 1 shows the penetration of industrial robots in terms of the number of robots per thousand workers and documents the rapid growth of industrial robots in China.[7] It is evident from Figure 1(a) that most of the increase in China's industrial robots took place in recent years since 2010, in contrast to the more gradual increase in the United States and Europe over decades, although at the moment the number of robots per thousand workers in China is still lower than those in the United States and Europe.

Online Appendix Figure A.2 documents the extent of robot penetration by industrial sector between 2006 and 2016. As evident from the figure, the automotive sector is leading in robot adoption, followed by the electronics, plastic and chemicals, and metal products industries. Figure 1(b) further shows robot penetration by China's top five robot-adopting sectors over time since 2006.

In the Online Appendix, we discuss the robustness of our results to control for specific time trends in areas with high/low shares of the industries with the highest Rotemberg weights (electronics sector and automotive sector). Online Appendix Table A.1 lists the Chinese cities with the highest and lowest changes in robot penetration during 2010–16. Online Appendix Figure A.3 illustrates the change in robot exposure across Chinese prefectures between 2006 and 2016.

1.2.2. *The China Family Panel Studies dataset*

To exploit the variation in the exposure to robots while accounting for time-invariant individual heterogeneity, we exploit the China Family Panel Studies dataset (CFPS, 2010; 2012; 2014; 2016). The CFPS is a nationally representative, biennial longitudinal survey of individuals and households that was launched in 2010 by Peking University's Institute of Social Science Survey (ISSS). It is designed to collect individual-, family- and community-level longitudinal data in contemporary China and focuses on the economic, as well as the non-economic, well-being of the Chinese population. Modelled on the United States's Panel Study of Income Dynamics (PSID), the CFPS surveys contain detailed socioeconomic information on households' and individuals'

[7] The total operational stock of industrial robots follows a similar pattern and is shown in Online Appendix Figure A.1.

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Table 1. *Summary Statistics of CFPS Cities and Sample Workers.*

Panel A. CFPS cities, 2010	(1) *N*	(2) Mean	(3) SD
Population (thousands)	127	8,153	4,241
Average age	127	42.52	3.201
% Male	127	50.44	3.272
% Han	127	91.03	20.45
% Urban	127	47.91	31.57
% Married	127	75.96	5.354
% Secondary school educated	127	31.56	7.634
% High school educated	127	14.65	7.652
% Three-year college educated	127	4.714	4.308
% University educated	127	3.015	4.089
% Employed	127	49.28	14.77
% Agricultural sector	127	40.98	29.38
% Manufacturing sector	127	15.35	12.00
Average monthly hours	127	147.1	73.46
Average annual earnings	127	12,224	9,598
Panel B. CFPS sample workers, 2010–16	Years covered	Mean	SD
Male	2010–16	0.588	0.492
Age	2010–16	40.80	11.11
Han	2010–16	0.954	0.209
Secondary school educated	2010–16	0.330	0.470
High school educated	2010–16	0.216	0.411
Three-year college educated	2010–16	0.114	0.317
University educated	2010–16	0.077	0.266
Employed	2010–16	0.811	0.392
Out of the labour force	2010–16	0.095	0.293
Unemployed	2010–16	0.094	0.292
Participated in technical training	2010–16	0.041	0.198
Participated in ideological or political training	2010–16	0.009	0.095
Retired early	2010–16	0.004	0.064
Hourly earnings (primary job; yuan)	2010–14	19.55	135.9
Hours worked in a month (primary job)	2010–14	219.9	75.66
Annual earnings (primary job; yuan)	2010–14	30,483	31,696
Total annual earnings (all jobs; yuan)	2010–14	31,640	32,965

Notes: For panel A, data are from CFPS (2010). The summary statistics are for cities in the CFPS adult sample in 2010. The variables are weighted averages across individuals in each city using the individual survey weights in the CFPS. For panel B, data are from CFPS (2010; 2012; 2014; 2016). The summary statistics are across individuals and years. Our main sample consists of 24,000 observations (7,098 individuals) across 2010–16. For the variables on earnings and monthly hours, the sample includes only employed individuals during 2010–14, which consists of 9,310 observations (3,874 individuals).

economic activities, education outcomes, family dynamics and relationships, and health. The 2010 baseline survey interviewed approximately 15,000 families and 30,000 individuals across 127 counties. By mapping counties to cities, we measure each individual's robot exposure in each survey wave based on the robot exposure of the city that the individual resided in when the survey was conducted.[8] Panel A of Table 1 provides descriptive statistics for cities in the 2010 CFPS baseline survey.

Given our focus on the labour market effects of automation, we focus on the sample of non-agricultural wage workers aged between sixteen and fifty-nine in the 2010 CFPS survey, a

[8] In China, counties are administrative units that are below cities. We cannot measure robot exposure at the county level because the microdata from China's 2000 census does not contain county identifiers, which prevents us from computing employment shares and robot exposure at the county level.

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Table 2. *Robot Exposure and Labour Market Outcomes (2SLS).*

	(1) Employed	(2) Out of the labour force	(3) Unemployed	(4) ln(annual earnings)	(5) ln(hourly earnings)	(6) ln(monthly hours)
Robot exposure	−0.054***	0.012	0.043***	0.068	−0.078**	0.080***
	(0.012)	(0.007)	(0.008)	(0.059)	(0.036)	(0.019)
Observations	24,000	24,000	24,000	9,310	9,310	9,310
City FEs and year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
First-stage *F*-statistic	269	269	269	12.39	12.39	12.39
Mean of dep. var.	0.811	0.0951	0.0944	9.946	2.540	5.317
SD of dep. var.	0.392	0.293	0.292	1.236	0.798	0.469

Notes: Data are drawn from CFPS (2010; 2012; 2014; 2016). The table presents the 2SLS estimates of the impact of exposure to robots on individual labour market outcomes. For columns (1)–(3), the sample consists of non-agricultural wage workers aged between sixteen and fifty-nine in the 2010 CFPS survey, who are followed over time during 2010–16. The outcome variable is an indicator variable equal to 1 if an individual is employed (column (1)), or out of the labour force (column (2)), or unemployed (column (3)) and 0 otherwise. For columns (4)–(6), the sample consists of non-agricultural wage workers aged between sixteen and fifty-nine in the 2010 CFPS survey, who are followed over time and employed during 2010–14. The outcome variables are one's primary job annual earnings (column (4)), hourly earnings (column (5)) and monthly working hours (column (6)), all in natural logs. All estimates include city fixed effects, year (survey-wave) fixed effects and individual fixed effects. Exposure to robots is standardised. SEs, reported in parentheses, are clustered at the city level. *** $p < .01$, ** $p < .05$.

total of 7,098 individuals, and follow them over time.[9] Our outcomes of interest in the baseline analysis are individual employment status, labour force participation, earnings and the number of hours worked in a month.[10] A caveat, however, is that information on earnings is missing for a large share of the sample in the 2016 survey.[11] As a result, our analysis on earnings focuses on the period 2010–14, while we examine employment and labour force participation for the entire period 2010–16. Panel B of Table 1 provides summary statistics of these variables. Online Appendix Figure A.4 reports the distribution of hours and earnings.

2. Labour Market Effects of Robots

2.1. *Effects on Employment, Earnings and Hours Worked*

Using the CFPS data, we analyse the labour market effects of robot exposure (Table 2). While we focus on the 2SLS estimates in this table, the OLS estimates are broadly similar and reported in Online Appendix Table A.2. All estimates include city fixed effects, year fixed effects and individual fixed effects.[12] By including individual fixed effects, we exploit only within-worker variation in exposure to robots over time. SEs are clustered at the city level.

[9] Our main results are qualitatively the same and still statistically significant at similar levels if we relax the sample to include all workers across sectors and age groups.

[10] We consider that an individual is unemployed if the individual is without a job at the time of the survey, but was searching for jobs over the past one month. We consider that an individual is out of the labour force if the individual is neither employed nor unemployed. We calculate one's hourly earnings by dividing one's monthly or weekly earnings by the number of hours worked in the corresponding period. For earnings and working hours, we focus on one's primary job, because such information is most detailed and complete for one's primary job. We do, however, consider one's total annual earnings from all jobs as a robustness check.

[11] Because of a technical problem, the 2016 CFPS survey did not collect income information from those individuals who did not change jobs since 2014.

[12] We also report 2SLS estimates without individual fixed effects in Online Appendix Table A.3 and show the robustness of our results to the inclusion of individual sociodemographic controls in Section 3 below.

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We start by examining the effects on employment and labour force participation (columns (1)–(3)). We find that robot exposure reduces employment and labour force participation and increases unemployment. Specifically, a one-SD increase in robot exposure reduces the probability of being employed by 5.4 percentage points (column (1)), decreases labour force participation by approximately 1% (p-value = .107; column (2)), although the effect is not precisely estimated, and increases the likelihood of becoming unemployed by 4.3 percentage points (column (3)).[13]

Next, we turn to examine the effects on income and work hours among those who were employed (columns (4)–(6)).[14] We find no evidence of significant effects on annual earnings (column (4)). This is explained by the fact that while exposure to robots has a significant negative effect on individual hourly earnings, hours worked increases substantially, offsetting the impact on the hourly earnings among those who kept working. Specifically, among those who remain employed, a one-SD increase in robot exposure leads to a 7.8% reduction in hourly earnings (column (5)) and increases monthly hours worked by 8% (column (6)). Results on hourly earnings are substantially larger, ranging between a 13% and 24% decline, when including individuals who are not employed and reporting zero earnings (see Online Appendix Table A.7).[15] It is worth noting, however, that our survey data on earnings and work hours are self-reported and may contain noise, as shown in Online Appendix Figure A.4.

Taken together, these results suggest that exposure to robots has negative effects on employment, leading some workers to drop out of the labour force and increasing unemployment. Those who keep working have to respond to the reduction in hourly wages and the heightened risk of unemployment by working longer hours. We believe that these results are consistent with a backward bending labour supply. Income effects may be stronger than substitution effects that may contribute to explaining the increase in working hours, particularly if shocks are perceived as permanent (Giupponi, 2019; Golosov *et al.*, 2021). Our results suggest that, similar to what Acemoglu and Restrepo (2020) found for the United States, robots led to significant substitution effects in the labour markets in China, at least in the short run.

2.2. *Heterogeneity by Skill, Age and Gender*

Having documented the overall effects of exposure to robots, we turn to explore the heterogeneity of the effects by workers' skill, ages and genders. Online Appendix Table A.8 shows the estimated effects by workers' skill, as measured by education level. We find that the effects on employment are larger among the least skilled (panel A, column (1)). A one-SD increase in robot exposure reduces employment by 7.2 percentage points (approximately a 9% reduction with respect to the mean) among workers with a middle school education or below. Effects are considerably smaller among workers with a high school degree, for whom the same increase in robot exposure implies a 3.5% reduction with respect to the mean (panel B, column (1)). There is instead no evidence of a significant effect on employment among those with a three-year college degree or more (panel C, column (1)).

[13] Reduced-form estimates are reported in Online Appendix Table A.4.

[14] The sample size becomes smaller for this analysis partly because of the shorter sample period (2010–14), but also because the analysis is conditional on still being employed in a waged job and having non-missing values for all three of the outcomes in columns (4)–(6).

[15] In Online Appendix Table A.5, we follow Chen and Roth (2024) and use Poisson regressions to examine the effects on hours and earnings in levels and then obtain the implied effects in percentage changes. Overall, the results from this exercise are qualitatively similar to our baseline findings. In addition, Online Appendix Table A.6 shows the robustness of our results when winsorising the top 1% of hourly earnings and monthly hours.

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Columns (2)–(5) show that the effects of robots on labour force participation, unemployment status and hourly wage are also significantly larger among the low skilled, with no evidence of significant effects among those with a three-year college degree or more. In addition, there is evidence of a similar increase in working hours across the skill groups (panels A–C, column (6)). This contributes to explaining the lack of significant effects on annual earnings (column (4)). These findings are consistent with the prior that low-skilled workers are more directly exposed to competition from robots.

Age may also mediate the impact of exposure to robots in important ways. One may expect older workers to have stronger incentives to leave the labour force and retire earlier, while younger workers may invest in new skills by training or looking for different jobs. Online Appendix Table A.9 illustrates the heterogeneity of the effects by age. A one-SD increase in robot exposure leads to a 3.7-percentage-point decline in employment (−5%, column (1), panel A) among the 16–24 year olds; a 4.1-percentage-point decline among the 25–44 year olds (−5%, column (1), panel B) and a 6.9-percentage-point decline among the 45–59 year olds (−9%, column (1), panel C). Consistent with our prior, reduction on employment is larger among older workers.

In addition, younger workers (16–24) are less likely to leave the labour force (−12%, column (2), panel A) in areas more exposed to robot penetration. In contrast, among older workers, robot exposure increases by 2.6 percentage points the share of workers leaving the labour force (+16%, column (2), panel C). Across the different age groups, robot exposure increases the likelihood of unemployment (column (3)).

Moreover, there is no evidence of a significant effect on the hourly earnings of young workers (panel A, column (5)), while the effects are larger and statistically significant among prime-age (−8.9%, panel B) and older workers (−6.6%, panel C). In addition, the increase in working hours was larger among younger workers (panel A, column (6)). Overall, these results again suggest that prime-age and, in particular, older workers suffer more from the negative effects of robots on labour market opportunities.

Turning to examine the effects by gender in Online Appendix Table A.10, we find that overall the effects on employment and earnings are larger (in absolute value) among men. In particular, we find that among men (panel A) robot exposure has larger negative effects on the likelihood of being employed, and, albeit not precisely estimated, on the probability of leaving the labour force (column (2)). The effects on unemployment status are substantially identical across gender (column (3)). There is instead a significantly larger reduction in hourly wage among men (column (5)), while the number of hours worked increases more among women (column (6)).

3. Robustness Checks

In this section, we summarise a large battery of robustness checks on our main results on labour market outcomes. Overall, the evidence confirms our baseline findings. First, Table 3 goes beyond relying on yearly variations in robot exposure and provides long-difference estimates of our main results, which complement and confirm our baseline findings. To further strengthen inference, we also calculated the AKM confidence intervals as suggested by Adao *et al.* (2019), which affirm the statistical significance of the baseline estimates. Online Appendix Figure A.5 further illustrates the long-difference relationship at the city level between robot exposure and our main outcomes of interest.

Next, we consider the role of trade and offshoring as potential confounders. In particular, one could be concerned that a city's robot exposure might be correlated with its openness to trade,

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Table 3. *Long-Difference Estimates for Individual Labour Market Outcomes.*

	(1)	(2)	(3)	(4)	(5)	(6)
	Δ Employed		Δ Out of the labour force		Δ Unemployed	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel A: effects on employment and labor market participation						
Δ Robot exposure	−0.082***	−0.101***	0.011*	0.014**	0.072***	0.087***
	(0.018)	(0.017)	(0.006)	(0.006)	(0.015)	(0.015)
Observations	5,196	5,196	5,196	5,196	5,196	5,196
First-stage *F*-statistic		312.9		312.9		312.9
	Δ ln(annual earnings)		Δ ln(hourly earnings)		Δ ln(monthly hours)	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
Panel B: effects on earnings and work hours						
Δ Robot exposure	0.028	0.038	−0.021**	−0.034**	0.039***	0.049***
	(0.024)	(0.032)	(0.010)	(0.016)	(0.006)	(0.009)
Observations	2,312	2,312	2,312	2,312	2,312	2,312
First-stage *F*-statistic		23.74		23.74		23.74

Notes: The table presents the long-difference estimates of the impact of exposure to robots on individual labour market outcomes. Data are drawn from CFPS (2010; 2012; 2014; 2016). For panel A, the sample consists of the baseline sample workers who are observed in both 2010 and 2016 and who stayed in their original cities. The outcome variable is the change in one's employment status between 2010 and 2016 for being employed (columns (1)–(2)), out of the labour force (columns (3)–(4)) or unemployed (columns (5)–(6)). For panel B, the sample consists of the baseline sample workers who are observed and employed in both 2010 and 2014 and who stayed in their original cities. The outcome variables are the changes in one's primary job annual earnings (columns (1)–(2)), hourly earnings (columns (3)–(4)) and monthly hours (columns (5)–(6)), all measured in natural logs, between 2010 and 2014. The explanatory variable in each panel is the change in exposure to robots during the sample period (2010–16 for panel A and 2010–14 for panel B) and is standardised. The odd columns present the OLS estimates and the even columns the 2SLS estimates. SEs, reported in parentheses, are clustered at the city level. *** $p < .01$, ** $p < .05$, * $p < .1$.

which might also affect the outcomes. In addition, the rising labour cost in China in recent years has led an increasing number of foreign companies to move production away from China to other emerging economies (such as Southeast Asian countries) or back home. The offshoring of industries away from China might be correlated with both our measure of robot exposure and the labour market outcomes. We address these concerns in Online Appendix Table A.11 by controlling for the natural logs of import and export volumes (panel A), as well as foreign production and investments (panel B) across Chinese cities.[16] The results stay substantially the same with these additional controls.

A natural question is whether our results using the China Family Panel Studies are representative and whether they may be affected by attrition in the panel. Online Appendix Table A.12 shows that our results are not affected by the use of survey weights. Regarding attrition, we show in Online Appendix Table A.13 that the main results hold when we weigh the estimates by the inverse of one's propensity score of being observed at least twice (panel A) or in all four survey waves (panel B) during 2010–16.[17]

Selective internal migration may confound our analysis and affect the interpretation of our findings. To address this concern, in Online Appendix Table A.14, we examine one's work location

[16] We obtain custom data on city-level import and export volumes during 2010–16. For the same period, we obtain data on foreign direct investments and the output value of foreign industrial enterprises across cities from the *China City Statistical Yearbooks*.

[17] We predict the propensity score based on one's gender, age, years of education, marital status, employment status, income, a dummy for agricultural Hukou, a dummy for local Hukou and a dummy for working in manufacturing, all measured in the 2010 baseline survey.

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as an outcome and show no evidence of significant effects of robot exposure on migration, nor any differences when examining migration patterns by age and education.

Next, Online Appendix Tables A.16–A.17 show the robustness of our main results to a series of additional controls and to using alternative ways to construct the robot exposure measure. In column 1 of each table, we add to our baseline specification region-by-year fixed effects to account for any potential shocks to specific regions that might also be correlated with robot exposure, such as the different pace of economic development across regions.[18] The results remain largely similar. In column 2, we show that the main results are not sensitive to controlling for the interactions between individual baseline characteristics (gender, age and its quadratic term, ethnicity and education level in 2010) and year dummies, which allows each of the characteristics to exert a differential effect on the outcomes over time.

To address the concern that our results might be confounded by differential trends experienced by some industries, we calculate the Rotemberg weights following the methodology described by Goldsmith-Pinkham *et al.* (2020). We find that the electronics sector carries the largest weight in our identification strategy, as shown in Online Appendix Table A.15. Therefore, as a robustness check, we control for each city's 2000 employment share in the electronics sector interacted with year dummies in columns 3 of Online Appendix Tables A.16 and A.17. As a further check, we also reconstruct the robot exposure measure by excluding the electronics sector. Column 4 in both tables presents the estimates based on this alternative measure of robot exposure. The results remain qualitatively similar with both exercises.

Furthermore, since the 'automotives and other vehicles' sector experienced the greatest penetration of robots than other sectors (as shown in Online Appendix Figure A.2), we also conduct a robustness check similar to that in column 4 of Online Appendix Tables A.16 and A.17 by reconstructing the robot exposure measure with the 'automotives and other vehicles' sector removed. Column 5 of both tables shows that the estimates based on this alternative measure of robot exposure are again qualitatively similar, suggesting that the results are unlikely driven by potential confounding shocks to the automotive and other vehicle sector.

Moreover, in column 6 of each table, we include controls for the interactions between year dummies and the city's 2000 characteristics (natural log of the population and the population shares of men, the urban population, the working-age population, the university-educated population and migrants) to allow each of the baseline city characteristics to exert a differential effect over time. The results remain qualitatively similar, suggesting that robot exposure was unlikely confounded by other potential local shocks.[19] While in the baseline analysis we focus on income from one's primary job, Online Appendix Table A.18 shows a similar null effect on total annual earnings from all jobs combined.[20] As a further check, in Online Appendix Table A.19, we estimate our main results at the industry-year level using the approach proposed by Borusyak *et al.* (2022), which largely confirms our baseline findings.[21]

[18] We follow China's National Bureau of Statistics and classify China into four regions: Northeast, East, Central and West. The baseline results are also largely similar and statistically significant when we control for province-by-year fixed effects, although some estimates become less precisely estimated, possibly because of the relatively small number of cities within each province.

[19] We have also tried using alternative ways to construct the instrumental variable (IV). Instead of using the European average of robot adoption, we have tried using the median and other percentiles to construct the instrument. Our 2SLS results are largely robust to these alternative ways of constructing our IV. These results are available upon request.

[20] We cannot do the analogous exercise for hourly earnings or total hours worked from all jobs because information on hours worked is largely incomplete for jobs other than one's primary job.

[21] We use the 'ssaggregate' Stata command provided by Borusyak *et al.* (2022) for this exercise.

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Table 4. *Robot Exposure, Training and Early Retirement (2SLS).*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Participated in technical training				Retired early		
	All	Age 16–24	24–44	45–59	All	Age ≤ 44	45–59
Robot exposure	0.011***	0.042***	0.014***	−0.002	0.002**	−0.000	0.004***
	(0.003)	(0.009)	(0.005)	(0.003)	(0.001)	(0.000)	(0.002)
Observations	24,000	3,331	13,134	7,535	24,000	16,465	7,535
City FEs and year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage *F*-statistic	269	197.8	260.7	266.9	269	253.9	267
Mean of dep. var.	0.0411	0.0342	0.0512	0.0265	0.00413	0.00134	0.0102
SD of dep. var.	0.198	0.182	0.220	0.161	0.0641	0.0365	0.101

Notes: Data are drawn from CFPS (2010; 2012; 2014; 2016). The table presents the 2SLS estimates of the impact of exposure to robots on one's training participation and early retirement decisions. The sample consists of non-agricultural wage workers aged between sixteen and fifty-nine in the 2010 CFPS survey, who are followed over time during 2010–16. In columns (1)–(4), the outcome variable is an indicator variable that equals 1 if an individual participated in technical or skill-based training over the past twelve months and 0 otherwise. In columns (5)–(7), the outcome variable is an indicator variable that equals 1 if an individual retired early (i.e., retired before reaching fifty years old for females and before reaching sixty years old for males). Columns (2)–(4) and (6)–(7) split the sample by age group based on workers' ages in 2010. All estimates include city fixed effects, year (survey-wave) fixed effects and individual fixed effects. Exposure to robots is standardised. SEs, reported in parentheses, are clustered at the city level. *** $p < .01$, ** $p < .05$.

Finally, we have replicated the main estimates using an earlier census year, 1982 (instead of 2000), as the base year to construct the instrument for robot exposure (Online Appendix Table A.20). The instrument derived from a base year further back in time before the recent rise of robots is even more likely to be exogenous and less susceptible to endogeneity concerns regarding the Bartik IV approach. Overall, the robustness of our results to the battery of checks increases our confidence in the causal interpretation of the results.

4. Workers' Responses to Robot Exposure

While we have documented the effects of robot exposure on employment and income in China, a key question is how workers respond to the negative effects. In this section, we explore Chinese workers' responses to robots, focusing on workers' participation in training and their retirement decisions. Exposure to competition from robots may induce some workers to invest in human capital to keep their jobs or stay competitive in the labour market. This may be particularly true among younger workers who enjoy longer returns from these investments. In addition, among older workers—who may have higher costs and lower expected benefits from training—the labour market effects of robot exposure may induce them to retire earlier.

An advantage of our data is that the CFPS surveys individuals about their participation in training, including technical or work-related training, as well as 'ideological' or political training.[22] In columns (1)–(4) of Table 4, we explore the effects of robot exposure on workers' participation in technical or work-related training. We find that exposure to robots significantly increases workers' participation in such training. Specifically, column (1) shows that a one-SD increase

[22] According to the CFPS, common examples of technical or work-related training include 'training or tutorial for certificates in foreign language, computer skills, business administration, finance and accounting, judicial exam, driving and maintenance, etc, as well as adult continuing education; such training can be self-paying or sponsored by the company/institution'. In contrast, the CFPS notes that 'the main content of ideological and political education is the basic theory and knowledge of Marxism, Mao Zedong Thought and Deng Xiaoping Theories, as well as patriotism, collectivism, and morality, discipline and law awareness under socialism'.

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in robot exposure increases participation in technical or work-related training by 1.1 percentage points, which is about 26.8% relative to the mean (or 0.05 of an SD). The effects are concentrated among workers aged 16–24 (4.2 percentage points, column (2)) and those aged 24–44 years old (1.4 percentage points, column (3)), while we find no effect on older workers. The results are consistent, with the expectation that younger workers tend to have greater returns to human capital investment. In contrast, as a placebo test, Online Appendix Table A.21 shows that robot exposure has no effect on participation in 'ideological' or political training that does not directly impart working skills.

Next, we examine the effects of robot exposure on workers' retirement decisions in columns (5)–(7) of Table 4. We find evidence that robot exposure significantly increases the likelihood of early retirement, defined as retiring before age fifty for women and before age sixty for men.[23] Specifically, based on column (5), a one-SD increase in robot exposure is associated with a 0.2-percentage-point increase in early retirement, which is about a 50% increase with respect to the mean (or 0.03 of an SD). Not surprisingly, we show in the last two columns of Table 4 that the effect on early retirement is entirely driven by older workers. Overall, the results in this section show that workers may respond to greater competition from robots through participating in technical training programs or retiring earlier and dropping out of the labour force.[24]

5. Conclusions

The adoption of advanced automation technologies and robots is increasing at a very rapid pace in emerging economies. Despite the growing debate on the labour market effects of these new automation technologies, we still know relatively little about how the labour markets may adjust to these shocks. Furthermore, we have so far limited empirical evidence on the impact of robots from developing countries and emerging economies. In this study, we investigate the effects of industrial robots on the Chinese labour market. We find that an increase of one SD in robot exposure lowers an individual's probability of being employed by 6.7% with respect to the mean and reduces hourly wages by 7.8%. In addition, the effects are concentrated among the less educated and larger among male, prime-age and older workers. Moreover, we also find that in areas most exposed to the adoption of industrial robots, workers are more likely to respond by participating in technical training or retiring early.

New technologies, AI and automation may have positive impacts on growth and productivity, which could eventually increase demand for higher-skilled workers. Our results suggest that in the short run the labour market may not adjust to such a rapid and dramatic change. As income inequality increases in many emerging economies, this may pose further challenges to governments facing increased dissatisfaction in the population, and particularly among those who are most exposed to the competition with new technologies. However, we also document how workers responded to the shock by increasing early retirement and technical training, highlighting the role of these channels of adjustment in the labour market.

Future research could shed light on whether exposure to robots is affecting educational and career choices of young adults in developing economies so far characterised by a heavy specialisation in manufacturing industries. Whether productivity gains in the long run

[23] During 2010–16, the statutory retirement age in China was sixty for males and 50–5 for females, depending on whether the individual is a female cadre or worker (fifty-five years for female cadres and fifty years for female workers).

[24] Online Appendix Table A.22 provides consistent evidence on the training and retirement results from long-difference specifications.

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translate into employment growth or what will be the political consequences of the labour market effects of automation and digitisation are important questions that demand further scientific investigation.

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Additional Supporting Information may be found in the online version of this article:

Online Appendix
Replication Package

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