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ABSTRACT

We analyze the effects of exposure to industrial robots on labor markets and household behaviors, exploring longitudinal household data from China. We find that a one standard deviation increase in robot exposure led to a decline in labor force participation (-1%), employment (-7.5%), and hourly wages (-9%) of Chinese workers. At the same time, among those who kept working, robot exposure increased the number of hours worked by 14%. These effects were concentrated among the less educated and larger among men, prime-age, and older workers. We then explore how individuals and families responded to increased exposure to robots. We find that more exposed workers increased their participation in technical training and were significantly more likely to retire earlier. Despite the negative impact on wages and employment, we find no evidence of an effect on consumption or savings, which is explained by an increase in borrowing (+10%). While there is no evidence of an effect on marital behavior, we document that robot exposure led to a small decline in the number of children (-1%). Finally, we find that robot exposure increased family time investment in the education of children (+10%) as well as the investment in children's after-school academic and extra-curricular activities (+24%).

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1 Introduction

With the rise of new technologies such as artificial intelligence, machine learning, and robotics, policymakers are paying increasing attention to the labor market impacts of advanced automation. Despite a growing research interest in the effects of these automation technologies, and especially of robots (Acemoglu and Restrepo, 2020; Graetz and Michaels, 2018; Borjas and Freeman, 2019; Mokyr et al., 2015; Bessen et al., 2019), we still know relatively little about how workers and households may adjust to these labor market shocks (Dauth et al., 2021b). Exposure to robots may affect the training and retirement decisions of workers. In addition, while previous work investigated the effects of industrial robots on marital behavior and fertility (Anelli et al., 2021), we know less about other margins of adjustment of families. Whether exposure to robots affects family consumption and financial behaviors is an unexplored empirical question. New technologies may also influence family investment in children's human capital by changing the expected marginal returns to children's human capital and cognitive skills. Yet, these margins of adjustment at the worker and household levels have received so far limited attention.

Meanwhile, with most analysis so far focusing on advanced economies, it is largely unknown how emerging markets and developing economies are affected by the rise of new technologies. According to a recent World Bank (2016) estimate, 1.8 billion jobs or roughly two thirds of the labor force in developing countries are susceptible to automation (Peña-López et al., 2016). The implications of robotization in emerging markets for jobs, growth, and inequality could be profound. Given the different industry specializations 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 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,

[1]Previous work has highlighted the risks of premature deindustrialisation and how automation may

ditigalization and labor-saving technologies may foster inequality.[2] Consequently, developing countries may face new policy challenges and important economic trade-offs, such as the one between increased productivity and potential higher 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 analyzing the effects of exposure to industrial robots in an emerging economy and exploiting household longitudinal data to explore labor market adjustments and the dynamic response of workers and households more exposed 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 (2016-2020), the government has allocated billions of yuan for manufacturers to upgrade to technologies including robots and advanced machinery. Several Chinese provinces are also heavily subsidizing the adoption of robots. For instance, Guangdong province in southern China promised to spend $150 billion on industrial robots and new innovation centers dedicated to advanced automation. Cheng et al. (2019) show 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 US that have so far dominated the robot market both in terms of utilization 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 most number of industrial robots among all countries in the world, although in per capita terms China is still

disrupt the income convergence process and hinder the ability of developing countries to exploit their labor-cost advantage to grow (Berg et al., 2018; Rodrik, 2016; Atolia et al., 2018; Palma, 2008).

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

lagging behind the more advanced economies. The investment in robotics may boost China's manufacturing, which lately has been challenged by rising labor costs, an aging 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 Frey and Rahbari (2016) roughly 77 percent of Chinese jobs are highly susceptible to automation (Manyika, 2017; Chui et al., 2016) [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 percent automation within a few years. For all these reasons, China provides an extremely interesting context to explore the effects of automation on the labor 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. In particular, we exploit the variation in the pre-existing distribution of industrial employment across Chinese cities and use changes in the amount of robots across industries to create a measure of exposure to robots in China's labor market. Furthermore, we instrument the adoption of robots by Chinese industries using industry-level robot adoption from other economies (European countries). By doing so, we only identify off the variation resulting from industries that exhibited an increase in the use of robots in other economies.

Using panel data from the China Family Panel Studies (2010-2016) 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 by 1 standard deviation in robot exposure lowers an individual's probability of being employed by 6 percentage points (-7.5% with respect to the mean), increases the likelihood of leaving the labor force by 1 percentage point (+10.5% with respect to the mean), and increases the likelihood of reporting

[3] See also Knight (2016).

unemployment status by 5 percentage points (or 0.17 standard deviations). Robot exposure reduces hourly income on average (-9%), but with no significant effect on annual income, as individuals in areas that are more exposed work longer hours (+14%). These effects are concentrated among low-skilled, male, and prime-age and older workers.

Our results on the impact of robots on labor market outcomes are robust to a series of checks. The results remain similar when we control for region-specific shocks over time by including region-by-year fixed effects. The results are also robust to the inclusion of controls for the offshoring of industries away from China, as measured by changes in foreign production and investments. To address the concern that our results may be confounded by differential trends experienced by some industries, we calculate the Rotemberg weights following Goldsmith-Pinkham et al. (2020). We find that the electronics sector carries the largest weight in our identification strategy. Our results, however, are robust to controlling for the interactions between year dummies and the city's 2000 employment share in the electronics sector; the results also hold if we reconstruct the robot exposure measure by excluding the electronics sector. Moreover, the results are also robust to alternative ways of constructing the instrumental variable as well as to a number of other checks, further increasing our confidence in the causal interpretation of the results.

An important contribution of our study is to analyze how individuals and families respond to the increased exposure to robots in the labor 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. We then turn to analyze the impact of robot exposure on families' consumption decisions and financial behavior. Interestingly, we find no evidence of an effect on consumption or savings. While exposure to robots has negative effects on wages and employment opportunities, we document an increase in borrowing (+10%) that allows families to keep their consumption and savings constant.

In addition, we examine the effects of robot exposure on marital behavior, fertility, and educational investment in children. Previous studies have shown how labor demand shocks may affect family formation, divorce, and fertility behavior (Anelli et al., 2021; Autor and Hanson, 2019). While there is also no evidence of an effect on marital behavior, we find that robot exposure leads to a small decline in the number of children (-1.2%). Finally, we find that robot exposure increases family time investment in the education of children (+10%) as well as the investment in children's after-school academic and extra-curricular activities (+24%), including tutorial classes for core subjects such as math, Chinese, and English.

Our work speaks directly to a recent and growing literature on the labor market effects of robots, which has so far largely focused on advanced economies. Acemoglu and Restrepo (2020) provided evidence on large negative effects of robots adoption on employment and wages in the US. These results are consistent with recent findings by Borjas and Freeman (2019) who compare the effect of immigration and robot exposure on employment. On the contrary, Graetz and Michaels (2018) use cross-country data in a more macro approach and find positive effects of robots on productivity and wages, although they find negative effects on low-skilled workers. Dauth et al. (2021a) show that in Germany robots account for 23 percent 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 and households respond to the labor 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 analyzing robots 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., 2019); examined how robot adoption may create skill-biased development in firms' employment structure (Tang et al., 2021); and analyzed the effects of labor 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 (Carbonero et al., 2020; Maloney and Molina, 2019). Most of these studies, however, focus on the indirect effects of foreign robots in the developing countries (i.e., Mexico and Colombia) through their effects on trade and offshoring (Faber, 2020; Krenz et al., 2021; Artuc et al., 2019; Kugler et al., 2020). We contribute to these studies which 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 analyzing the impact of exposure to robots on training and retirement, highlighting potential channels of labor market adjustments, and exploring the effects on family consumption, financial behavior, and investment in children's human capital.

2 Empirical Strategy and Data

2.1 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 robots penetration in the Chinese local labor 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 specialization 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 the rise in industrial robots in China took place in the past few years, especially after 2010 (see Figure 1).[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 and multiply it by the city's baseline employment share in sector s and then sum over all sectors. Formally:

$$Exposure\ to\ Robots_{ct} = \sum_{s \in S} \ell_{cs}^{2000} \left(\frac{R_{st}}{L_{s,2000}}\right) \tag{1}$$

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

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. 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. Data on robot adoption in China at the sector-year level comes from the International Federation of Robotics (IFR), which we provide more details in the next section.

Figure A.1 displays the increase in exposure to robots across Chinese prefectures between 2006 and 2016 based on the above measure.[5] As seen in Figure A.1, cities most exposed to robots tend to be concentrated in the eastern part of China, which is also the more economically developed region. Yet, even within a region, there is variation in exposure to robots across cities. In addition, there is also variation in exposure to robots within each city over time. Our identification strategy exploits this variation in exposure over time while accounting for time-invariant characteristics at the city level.

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

$$Y_{ict} = \mathit{Exposure\ to\ Robots}_{ct} + X_{ict} + \eta_i + \lambda_c + \xi_t + \epsilon_{ict} \tag{2}$$

where Y_{ict} are outcomes of interest for individual i in city c and year t, including labor force participation, employment status and the natural log of income measures (hourly wage and annual earnings). $\mathit{Exposure\ to\ Robots}_{ct}$ is the exposure to robots of city c in year t. X_{ict} is a set of controls of individual characteristics, including gender, age and its quadratic term, and education level (dummy variables for no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above). η_i are

[5] In China, prefectures are administrative units below provinces and above counties. Most of the prefectures are prefecture-level cities (out of the 333 prefectures, 293 are prefecture-level cities, with the rest mostly consisting of autonomous prefectures which are historic homes of ethnic minorities). The household survey data used in our analysis also primarily comes from prefecture-level cities. For simplicity, we refer to prefecture-level administrative units simply as cities in this paper.

individual fixed effects, λ_c are city fixed effects, and ξ_t are year (survey wave) fixed effects. Standard errors are clustered at the city level. For the ease of interpretation, we standardize the robot exposure variable.

To further mitigate the concerns of confounding factors that may be correlated with both the industry-level spread of robots in China and labor 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 resulting from industries that exhibited an increase in the use of robots in these other economies. Our instrument is formally defined as follows:

$$Exposure\ to\ Robots_{IV_{ct}} = \sum_{s \in S} \ell_{cs}^{2000} \left(\frac{R_{st}}{L_{s,2000}}\right)_{EU_{Avg}} \tag{3}$$

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 $(\frac{R_{st}}{L_{s,2000}})_{EU_{Avg}}$ represents the average of robot usage among European countries in sector s and year t.[7]

2.2 Data

2.2.1 Robots Data

Data on the stock of robots by industry, country and year are drawn from the International Federation of Robotics (IFR). These data are based on yearly surveys of robot suppliers and contain information for 70 countries from 1993 to 2016, covering more than 90 percent of the industrial robot market. The IFR data provide the operational stock of "industrial robots", which are defined as "automatically controlled, reprogrammable, and multipurpose

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

[7] Our results are robust to using the median and other percentiles of European robot adoption to construct the instrument.

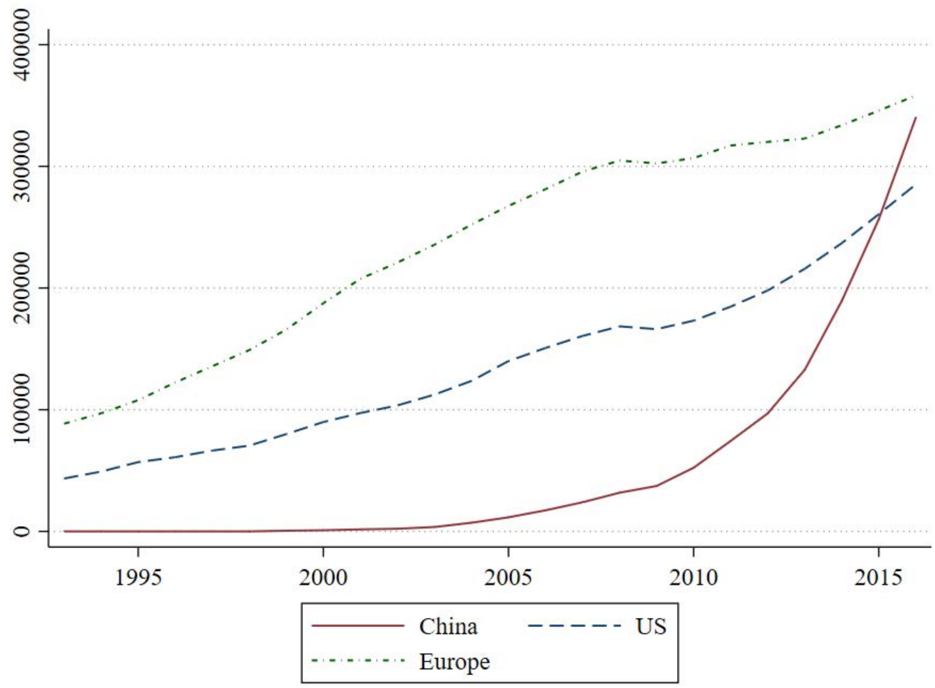
[machines]" (IFR, 2014). Basically, industrial robots are fully autonomous machines that are automatically controlled, do not need a human operator and can be programmed to perform several tasks such as welding, painting, assembling, carrying materials, or packaging.

There are several limitations of the IFR robot data. First, the information on the sectoral distribution of robots is limited and industry classifications are coarse. Within manufacturing, we have data on the operational stock of robots for 13 industrial sectors (roughly at the three-digit level), which include food and beverages; textiles; wood and furniture; paper; plastic and chemicals; glass and ceramics; basic metals; metal products; metal machinery; electronics; automotive; other vehicles[8]; and other manufacturing industries. Outside of manufacturing, data on the operational stock of robots are available for six broad categories (roughly at the two-digit level), which are agriculture, forestry and fishing; mining; utilities; construction; education, research and development; and other non-manufacturing industries (e.g., services). Besides, for China we only have information on the stock of industrial robots by sectors for the period 2006-2016. In fact, only a subsample of countries in the IFR dataset have data on the number of robots by sectors before 2006. Another drawback of the IFR data is the lack of information on the within-country distribution of robots. Despite these limitations which are shared by previous studies using the IFR data for the advanced economies, to our knowledge this is the best data available at the moment to study the effects of robot exposure in China. Figure 1 documents the rapid growth of industrial robots in China over the last decade. It is evident from Figure 1 that most of the increase in China's industrial robots took place within the last few years since 2010, in contrast to the more gradual increase in the US and Europe over decades.

Figure 2 shows the penetration of industrial robots in China in terms of the number of robots per thousand Chinese workers. Again, the sharp rise in China's robot penetration in

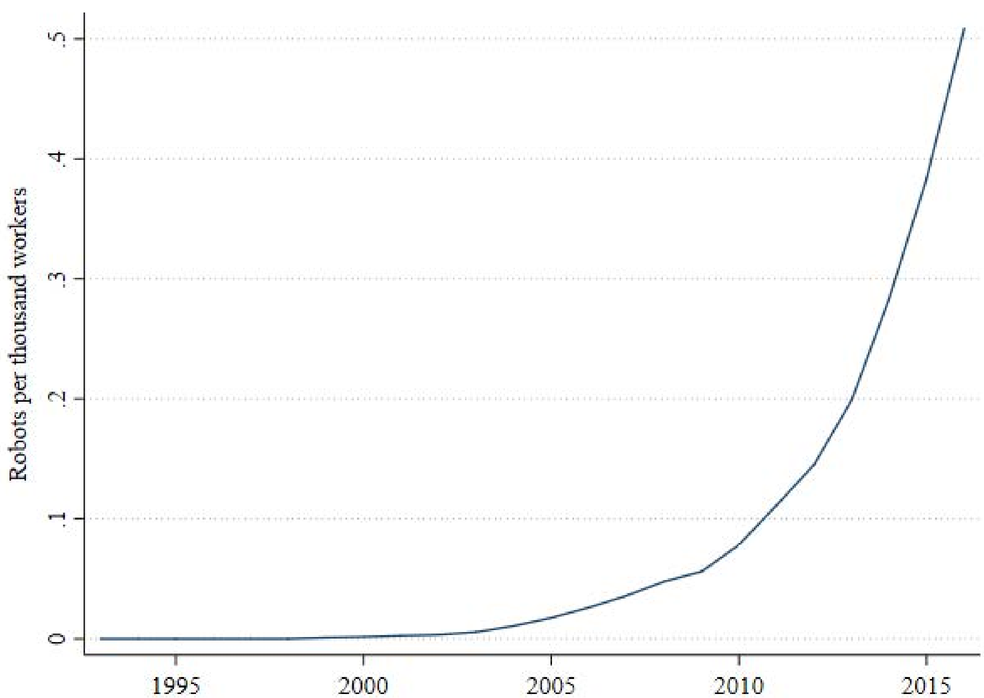
[8] In our analysis, we combine automotive and other vehicles as one industry. This is because China's 2000 Census reports these two sectors as one industry and therefore we are not able to distinguish workers in the automotive sector from workers in the sector of other vehicles (e.g., ships, trains, and aircrafts).

Figure 1: Operational Stock of Industrial Robots, 1993-2016



Notes - Data are drawn from the International Federation of Robotics (IFR).

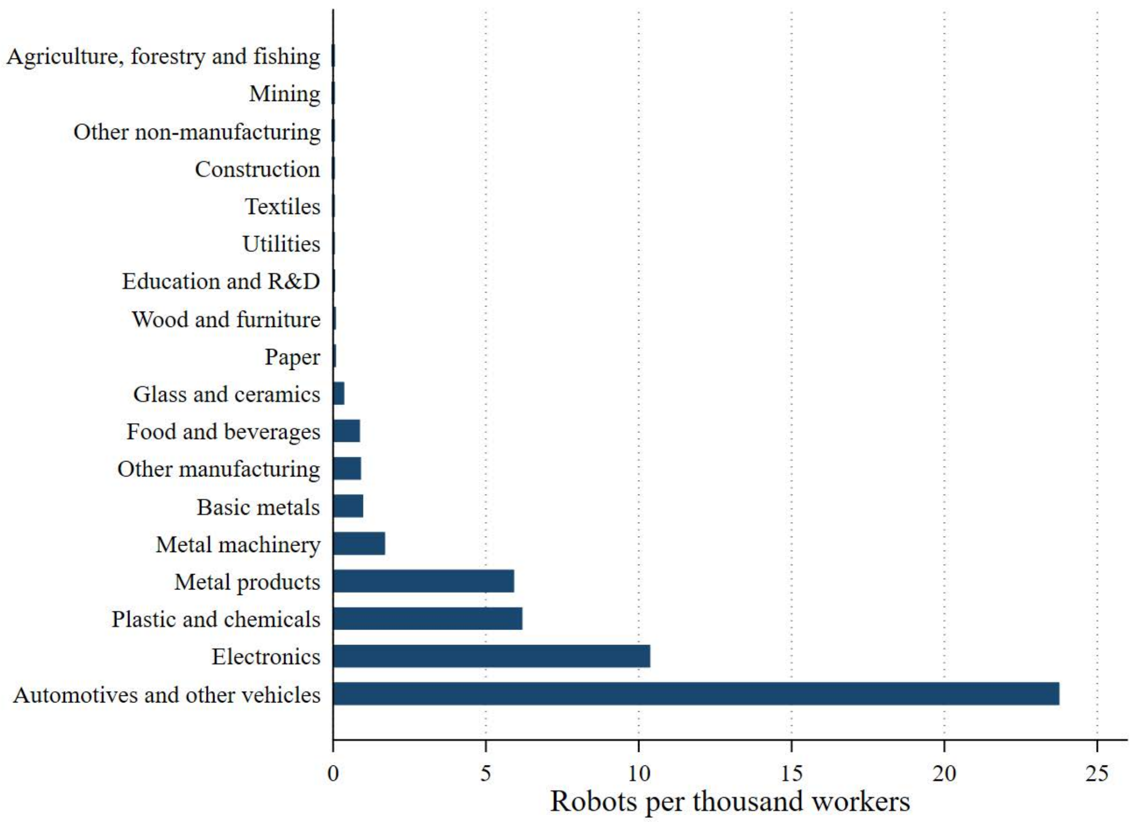
Figure 2: Penetration of Industrial Robots in China, 1993-2016



Notes - Data are drawn from the International Federation of Robotics (IFR).

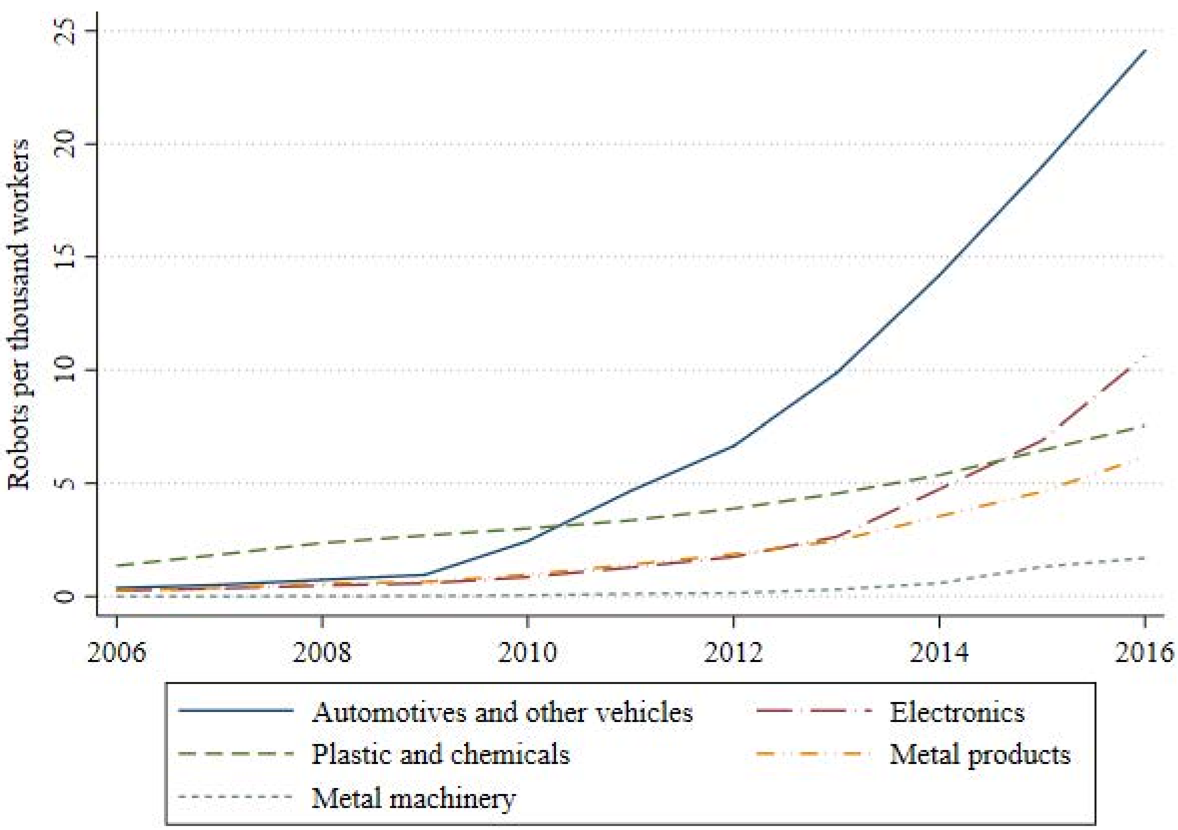
the past few years is noteworthy, although at the moment the number of industrial robots per thousand workers in China is still lower than those in the US and Europe. Figure 3 documents the extent of robot penetration by industrial sector between 2006 and 2016. As evident from the figure, the automotive sector is leading in robot adoption, followed by the electronics, the plastic and chemicals, and the metal products industry. Figure 4 further shows robot penetration by China's top five robot adopting sectors over time since 2006.

Figure 3: Penetration of Industrial Robots in China by Sector between 2006 and 2016



Notes - Data are drawn from the International Federation of Robotics (IFR).

Figure 4: Penetration of Robots in China's Top Robot Adopting Sectors, 2006-2016



Notes - Data are drawn from the International Federation of Robotics (IFR).

2.2.2 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, 2010-2016). This is a nationally representative, biennial longitudinal survey of individuals and households which was launched in 2010 by the Institute of Social Science Survey (ISSS) of Peking University, China. The CFPS is modeled on the Panel Study of Income Dynamics (PSID) of the US. The surveys contain detailed socioeconomic information on households' and individuals' economic activities, education outcomes, family dynamics and relationships, and health. The 2010 baseline survey interviewed approximately 15,000 families and 30,000 individuals. Figure A.2 shows all the counties represented in the CFPS baseline survey. 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.[9]

Given our focus on the labor market effects of automation, we focus on the sample of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey and follow them over time.[10] Our outcomes of interest in the baseline analysis are individual employment status, labor force participation, wage, and the number of hours worked in a month.[11] A caveat, however, is that information on wage is missing for a large share of the sample in the 2016 survey.[12] As a result, our analysis on wage focuses on the period 2010-2014, while we examine employment and labor force participation for the entire period 2010-2016. Table

[9] 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.

[10] 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.

[11] 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 labor force if the individual is neither employed nor unemployed. We calculate one's hourly wage by dividing one's monthly or weekly wage by the number of hours worked in the corresponding period. For wage 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.

[12] Due to a technical problem, the 2016 CFPS survey did not collect wage information from those individuals who did not change jobs since 2014.

A.1 provides summary statistics of these variables.

3 Labor Market Effects of Robots

Using the China Family Panel Studies (CFPS), we analyze the labor market effects of robot exposure. We start by examining the effects on employment status, labor market participation, and unemployment status in Table 1. Columns 1-2 of the table include controls for individual characteristics, including gender, age and its quadratic term, ethnicity (a dummy for Han Chinese), and education level (dummies for no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above). All estimates include city and year fixed effects. Column 3 also controls for individual fixed effects, thereby exploiting only within-worker variation in exposure to robots over time. Standard errors are clustered at the city level. The outcome variable is an indicator variable equal to 1 if an individual is employed (Panel A), or out of the labor force (Panel B), or unemployed (Panel C) and 0 otherwise.

The OLS estimate suggests a significant negative relationship between robot exposure and the likelihood of being employed (column 1, Panel A). In terms of magnitude, an increase by 1 standard deviation in robot exposure lowers an individual's probability of being employed by 6 percentage points (or 7.5% of the mean of the dependent variable). Column 2 reports the 2SLS estimate which is only marginally larger than the OLS estimate. Effects are stable when accounting for individual fixed effects (column 3). Panel B shows that at least part of the employment effects is explained by a decline in labor force participation, which decreases by approximately 1%. However, the effect on labor force participation is less precisely estimated when including individual fixed effects (column 3, p-value=0.18).

Finally, Panel C shows that a 1 standard deviation increase in robot exposure increases the likelihood of becoming unemployed by 5 percentage points. These effects are, if anything, larger and more precisely estimated when using 1982 as the base year to construct our

Table 1: Robot Exposure, Employment, and Labor Force Participation, Individual-Level Analysis

	(1) OLS	(2) 2SLS	(3) 2SLS
	Panel A. Employed		
Robot exposure	-0.061***	-0.063***	-0.062***
	(0.015)	(0.012)	(0.014)
Observations	25,354	25,354	23,999
Mean of Dep. Var.	0.809	0.809	0.811
Std.Dev. of Dep. Var.	0.393	0.393	0.392
First-stage F stat		373.6	270.2
	Panel B. Out of Labor Force		
Robot exposure	0.009*	0.012*	0.010
	(0.005)	(0.006)	(0.007)
Observations	25,354	25,354	23,999
Mean of Dep. Var.	0.0900	0.0900	0.0951
Std.Dev. of Dep. Var.	0.286	0.286	0.293
First-stage F stat		373.6	270.2
	Panel C. Unemployed		
Robot exposure	0.051***	0.052***	0.051***
	(0.012)	(0.008)	(0.010)
Observations	25,354	25,354	23,999
Mean of Dep. Var.	0.101	0.101	0.0944
Std.Dev. of Dep. Var.	0.302	0.302	0.292
First-stage F stat		373.6	270.2
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the estimates of the impact of exposure to robots on individual employment status and labor force participation. The sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time during 2010-2016. The outcome variable is an indicator variable equal to 1 if an individual is employed (Panel A), or out of the labor force (Panel B), or unemployed (Panel C) and 0 otherwise. All estimates include city fixed effects, year (survey wave) fixed effects, and individual sociodemographic controls for gender, age and its quadratic term, ethnicity (dummy for Han Chinese), and education level (dummies for no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above). Column 3 also controls for individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

instrumental variable (see Table A.9). Overall, these results suggest that exposure to robots had negative effects on employment, leading some workers to drop out of the labor force and increasing unemployment.[13]

In Table 2, we turn to examine the effects on wages (both hourly and annual) and hours worked in a month, conditional on the worker being employed. We find that, conditional on being employed, a 1 standard deviation increase in robot exposure lowers an individual's hourly wage by 7.7% (column 1, Panel A). 2SLS estimates point at an even larger effect (-11.5%, column 2, Panel A). When including individual fixed effects, the coefficient declines slightly, pointing at a 8.9% reduction in hourly wage. In contrast with the decrease in hourly wage, we find no significant effect on annual wage (Panel B). Instead, we find a significant increase in the average number of hours worked ranging between 12.6% and 14.2% (Panel C, columns 1-3) among those who kept working. The results therefore suggest that workers in cities more exposed to robots are working longer to make up for the reduction in hourly wages.

3.1 Robustness Checks

Tables A.3-A.4 show the robustness of our main results to a battery of robustness checks. Overall, our estimates on employment, labor force participation, and unemployment status are substantially unchanged. Specifically, 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.[14] The results are largely similar. Besides, the rising labor 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

[13]Reduced-form estimates are reported in Table A.2.

[14]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.

Table 2: Robot Exposure, Income, and Working Hours, Individual-Level Analysis

	(1) OLS	(2) 2SLS	(3) 2SLS
	Panel A. log(Hourly Wage)		
Robot exposure	-0.077***	-0.115***	-0.089**
	(0.017)	(0.029)	(0.043)
Observations	12,104	12,104	9,310
Mean of hourly income (yuan)	19.18	19.18	19.55
Std.Dev. of hourly income (yuan)	133.6	133.6	135.9
First-stage F stat		19.22	12.55
	Panel B. log(Annual Wage)		
Robot exposure	-0.007	-0.014	0.051
	(0.040)	(0.061)	(0.089)
Observations	12,595	12,595	9,749
Mean of annual income (yuan)	28749	28749	29944
Std.Dev. of annual income (yuan)	31504	31504	31542
First-stage F stat		19.05	12.47
	Panel C. log(Monthly Hours)		
Robot exposure	0.126***	0.131***	0.142***
	(0.021)	(0.029)	(0.032)
Observations	13,810	13,810	10,946
Mean of monthly hours worked	221.7	221.7	220.4
Std.Dev. of monthly hours worked	81.52	81.52	79.81
First-stage F stat		21.55	13.95
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2014). The table presents the estimates of the impact of exposure to robots on income and working hours of employed workers. The sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time and employed during 2010-2014. The outcome variable in Panel A is the natural log of hourly wage at one's primary job. The outcome in Panel B is the natural log of annual earnings from the primary job. The outcome in Panel C is the natural log of monthly working hours at the primary job. All estimates include city fixed effects, year (survey wave) fixed effects, and baseline individual sociodemographic controls as in column 1 of Table 1. Column 4 also controls for individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

home. The offshoring of industries away from China could be correlated with our measure of exposure to robots, and it could suppress employment and wages in China, which would bias our estimates downward and make our results look more negative. We address this concern by controlling for time-varying measures of foreign production and investment across Chinese cities. Specifically, we obtain data on foreign direct investments and output value of foreign industrial enterprises at the city-year level during 2010-2016 from China City Statistical Yearbook and control for these variables in column 2 of each table. The results are substantially the same with these additional controls.

A natural question is whether our results may be affected by attrition in the panel. While there is attrition and the sample of workers observed in all four survey waves during 2010-2016 appears to be older, less educated, more likely to work in manufacturing, and had lower annual wage in 2010 (as seen in column 2 of Table A.5), in Table A.6 we show that the main results hold when restricting to individuals whose estimated propensity scores of being observed in all four survey waves fall in the middle 50 percentile (i.e., we drop those whose propensity of being observed in all waves fall in the lower and upper quartile).[15] We also report the balance of our main covariates for this sample (column 4 of Table A.5).[16]

To address the concern that our results may be confounded by differential trends experienced by some industries, we calculate the Rotemberg weights following the methodology described in Goldsmith-Pinkham et al. (2020). We find that the electronics sector carries the largest weight in our identification strategy, as shown in Table A.7. 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 Table A.3 and Table A.4. As a further check, we also reconstruct the robot exposure measure by excluding the electronic sector. Columns 4 in both tables present the estimates based on this alternative measure of robot exposure.

[15]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.

[16]While the baseline years of education remains lower among individuals who were non-missing during all four waves in this sample, our results are robust to controlling for educational attainment.

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 Figure 3), we also conduct a robustness check similar to that in column 4 of Tables A.3 and A.4 by reconstructing the robot exposure measure with the "automotives and other vehicles" sector removed. Columns 5 of both tables show 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 population and the population shares of men, urban population, working-age population, university-educated population, and migrants), which allows each of the baseline city characteristics to exert a differential effect over time. The results on wages and hours worked remain qualitatively similar, suggesting that robot exposure was unlikely confounded by other potential local shocks.[17] While in the baseline analysis we focus on income from one's primary job, Table A.8 shows a similar null effect on annual income when examining total annual income from all jobs combined.[18]

We also replicate the main estimates using an earlier Census year, 1982 (instead of 2000), as the base year to construct the measure of exposure to robots across Chinese cities (Tables A.9 and A.10). Using 1982 as the base year to construct our instrumental variable, the effects on employment and unemployment status are largely unchanged (Panel A and C, Table A.9), while the increase in the likelihood of leaving the labor force is larger and more precisely estimated (Panel B). The effects on hourly wages are overall similar to our baseline estimates (see columns 1-3 of Table A.10), although the coefficient is less precisely estimated and slightly smaller in magnitude (-4.6%) when controlling for individual fixed effects. We

[17]We have also tried using alternative ways to construct the 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.

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

also confirm the lack of significant effects on annual income (Panel B) and the increase in monthly hours (+12%, Panel C). Overall, the robustness of our results to the battery of checks increases our confidence in the causal interpretation of the results.

3.2 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, age, and gender. Table A.11 shows the estimated effects by workers' skill, as measured by education level. We find that the effects on labor force participation and employment are larger among the least skilled (Panel A, column 1). A 1 standard deviation increase in robot exposure reduces employment by 8.7 percentage points (approximately a 11% 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 a 1 standard deviation increase in robot exposure implies a 4% 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 3-year college or more (Panel C, column 1). Columns 2-4 show that the effects of robots on labor 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 3-year college degree or more. In addition, there is evidence of a similar increase in working hours across the skill groups (Panel A-C, column 5). This contributes to explaining the lack of significant effects on annual income (column 6). These findings are consistent with the prior that low-skilled workers are more directly exposed to robots' competition.

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 labor force and retire earlier, while younger workers may invest in new skills by training or looking for different jobs. Table A.12 illustrates the heterogeneity of the effects by age. A 1 standard deviation increase in robot exposure leads to a 4.5 percentage points decline in employment (-6%, column 1, Panel

A) among the 16-24 years old; a 5 percentage points decline among the 25-44 (-6%, column 1, Panel B); and a 8.3 percentage points decline among the 45-59 (-11%, 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 labor force (-15%, column 2, Panel A) in areas more exposed to robot penetration. In contrast, among older workers, robot exposure increases by 3.2 percentage points the share of workers leaving the labor force (+20%, column 2, Panel C). Across the different skill-groups, robot exposure increases the likelihood of unemployment (column 3).

Moreover, there is no evidence of a significant effect on the hourly wage of young workers (Panel A, column 4), while the effects are larger and statistically significant among prime-age (-11%, Panel B) and older workers (-8%, Panel C). In addition, the increase in working hours was larger among younger workers (Panel A, column 5). Overall, these results again suggest that prime-age and in particular older workers suffer more from the negative effects of robots on labor market opportunities.

Turning to examine the effects by gender in Table A.13, we find that overall the effects on employment and wages 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 labor 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 4), while the number of hours worked increases more among women (column 5).

4 Adjustment by the Workers and Households

4.1 Effects on Training and Retirement

While we have documented the effects of robot exposure on employment and income in China, a key question is how workers would respond to the negative effects. In this section, we explore Chinese workers' response 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 labor 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 labor 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.[19] In Panel A of Table 3, we explore the effects of robot exposure on workers' participation in technical or work-related training. Across different specifications, we find that exposure to robots significantly increases workers' participation in such training. Specifically, based on the 2SLS estimate with individual fixed effects in column 3, a 1 standard deviation increase in robot exposure increases participation in technical or work-related training by 1.4 percentage points, which is about 34% relative to the mean (or 0.07 of a standard deviation).

In contrast, as a placebo test, Panel B of the Table shows that robot exposure has no effect on participation in "ideological" or political training that does not directly impart working skills. Moreover, we explore heterogeneity of the effects by age group in Table A.14 and find that the increase in participation in technical or work-related training was driven by younger workers, consistent with the expectation that younger workers tend to have greater returns to human capital investment.

Next, we examine the effects of robot exposure on workers' retirement decisions in Panel C of Table 3. We find evidence that robot exposure significantly increases the likelihood of

[19] 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."

early retirement, defined as retiring before age 50 for women and before age 60 for men.[20] Specifically, based on column 3, a 1 standard deviation 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 a standard deviation). Not surprisingly, we show in the last two columns of Table A.14 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 labor force.

4.2 Effects on Household Consumption, Savings and Borrowing

So far, our analysis has explored the effects of exposure to robots on individual Chinese workers, focusing on their labor market outcomes and adjustments. A natural question to explore is how exposure to robots affects Chinese households, such as their consumption and financial behaviors. An advantage of the CFPS surveys is that it also contains detailed information on household economic behaviors and characteristics. In this section, we turn to examine the impact of exposure to robots on household consumption, savings, and borrowing.

To be consistent with our baseline individual-level analysis, we focus on the households of all the workers in our baseline analysis and obtain household-level data for these workers from the 2010-2016 CFPS surveys. We run similar regressions as in our baseline analysis, except now at the household level, focusing on per capita household consumption, savings, and borrowing.

Table 4 presents our findings. In Panel A, the outcome is the natural log of household consumption expenditures per capita over the past 12 months. The coefficients are small, positive, and not statistically significant across the OLS and 2SLS estimates, suggesting that robot exposure has little effect on household consumption expenditures. In Panel B, we look at savings and the outcome is the natural log of household savings per capita. The

[20] During 2010-2016, the statutory retirement age in China is 60 for males and 50-55 for females, depending on whether one is a female cadre or worker (55 years for female cadres and 50 years for female workers).

Table 3: Robot Exposure, Training, and Early Retirement, Individual-Level Analysis (2SLS)

	(1) OLS	(2) 2SLS	(3) 2SLS
	Panel A. Participated in Technical Training		
Robot exposure	0.013***	0.013***	0.014***
	(0.003)	(0.003)	(0.004)
Observations	25,354	25,354	23,999
Mean of Dep. Var.	0.0389	0.0389	0.0411
Std.Dev. of Dep. Var.	0.193	0.193	0.198
First-stage F stat		373.6	270.2
	Panel B. Participated in Political or Ideological Training		
Robot exposure	0.001	0.001	0.001
	(0.002)	(0.002)	(0.003)
Observations	25,354	25,354	23,999
Mean of Dep. Var.	0.00856	0.00856	0.00904
Std.Dev. of Dep. Var.	0.0921	0.0921	0.0947
First-stage F stat		373.6	270.2
	Panel C. Retired Early		
Robot exposure	0.001	0.002**	0.002**
	(0.001)	(0.001)	(0.001)
Observations	25,354	25,354	23,999
Mean of Dep. Var.	0.00390	0.00390	0.00413
Std.Dev. of Dep. Var.	0.0624	0.0624	0.0641
First-stage F stat		373.6	270.2
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the estimates of the impact of exposure to robots on one's training participation and early retirement decisions. The sample consists of all the baseline workers as in Table 1. In Panel A, the outcome variable is an indicator variable that equals 1 if an individual participated in technical or skill-based training over the past 12 months and 0 otherwise. In Panel B, the outcome variable is an indicator variable that equals 1 if an individual participated in ideological or political training over the past 12 months and 0 otherwise. In Panel C, the outcome variable is an indicator variable that equals 1 if an individual retired early (i.e., retired before reaching 50 years old for females and before reaching 60 years old for males). All estimates include city fixed effects, year (survey wave) fixed effects, and baseline individual sociodemographic controls as in column 1 of Table 1. Column 3 also controls for individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

coefficients are positive and relatively larger, although again statistically indistinguishable from zero, suggesting that exposure to robots has limited effect on household savings.

Given what we find in Panels A and B of the Table, it is natural to wonder how Chinese households manage to maintain the levels of their consumption and savings in spite of the negative labor market effects from exposure to robots. One possibility is that the households may resort to borrowing to maintain their standards of living. We formally test this hypothesis in Panels C and D of the Table. In Panel C, the outcome is a dummy variable that equals 1 if a household has any non-housing debts, defined as any debts outside of home mortgage. Across the OLS and 2SLS estimates in Panel C, we find that exposure to robots increases the likelihood that a household has any non-housing debts. Specifically, based on the 2SLS estimate with household fixed effects in column 3, a 1 standard deviation increase in robot exposure increases the probability of having non-housing debts by about 1.9 percentage points, which is about 9.7% of the mean or 0.048 of a standard deviation. We find similar evidence when we look at the amount of non-housing debts in Panel D, where the estimates suggest that a 1 standard deviation increase in robot exposure increases per capita household debts by about 10-11%. The results therefore show that exposure to robots has increased Chinese households' non-housing debts on both the extensive and intensive margins.[21]

4.3 Effects on Marriage and Fertility

Having studied the effects of exposure to robots on individual training participation, retirement decisions, and household consumption and financial behaviors, we now turn to the impact of robot exposure on individual marital and fertility outcomes, which might also adjust in response to the negative labor market shocks. Table 5 presents our findings. To be consistent with the rest of our analysis, we again focus on the baseline sample of workers. In Panel A of the Table, we examine the impact of robot exposure on marital stability among

[21] Further analysis in Table A.15 shows that the sources of the debts include borrowing from both banks and from friends and relatives.

Table 4: Robot Exposure and Household Per Capita Consumption, Savings, and Borrowing

	(1) OLS	(2) 2SLS	(3) 2SLS
Panel A.	log(Consumption Expenditures)		
Robot exposure	0.010	0.009	0.024
	(0.009)	(0.011)	(0.015)
Observations	16,578	16,578	15,253
Mean of Dep. Var. (without log, in yuan)	15,186	15,186	15,073
Std.Dev. of Dep. Var. (without log, in yuan)	19,378	19,378	18,684
First-stage F stat		349.5	241.6
Panel B.	log(Savings)		
Robot exposure	0.079	0.141	0.169
	(0.079)	(0.096)	(0.114)
Observations	18,005	18,005	16,784
Mean of Dep. Var. (without log, in yuan)	13,504	13,504	13,588
Std.Dev. of Dep. Var. (without log, in yuan)	46,831	46,831	46,409
First-stage F stat		349.7	247.3
Panel C.	Has Non-Housing Debts		
Robot exposure	0.018***	0.019***	0.019**
	(0.004)	(0.005)	(0.007)
Observations	18,089	18,089	16,863
Mean of Dep. Var.	0.194	0.194	0.195
Std.Dev. of Dep. Var.	0.395	0.395	0.397
First-stage F stat		347.6	245.5
Panel D.	log(Non-Housing Debts)		
Robot exposure	0.101**	0.110**	0.113
	(0.040)	(0.049)	(0.070)
Observations	17,918	17,918	16,685
Mean of Dep. Var. (without log, in yuan)	2,811	2,811	2,816
Std.Dev. of Dep. Var. (without log, in yuan)	17,747	17,747	17,389
First-stage F stat		348.4	246.6
City FE and year FE	Yes	Yes	Yes
Household FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the estimates of the impact of robot exposure on household consumption, saving, and borrowing behaviors. The sample consists of the households of all the baseline workers as in Table 1. The outcome variable in Panel A is the natural log of household per capita consumption expenditures over the past 12 months. The outcome in Panel B is the natural log of household savings per capita. The outcome in Panel C is an indicator variable equal to 1 if a household has any non-housing debts and 0 otherwise. The outcome in Panel D is the natural log of the amount of non-housing debts per capita. All estimates include city fixed effects and year (survey wave) fixed effects. Column 3 also controls for household fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

baseline workers who were already married at the time of the 2010 survey. The outcome is a dummy variable that equals 1 if an individual is divorced and 0 otherwise. In both OLS and 2SLS regressions, we find no evidence that greater exposure to robots affects the likelihood of divorce among those already married in the baseline. In Panel B, we focus on baseline workers who were never married at the time of the 2010 survey, and the outcome is a dummy variable that equals 1 if the person is married. We find that exposure to robots also has little effect on the likelihood of getting married among those who were never married in the baseline. The results from Panels A and B therefore suggest that exposure to robots had little effect on the marital status among the baseline workers.

In Panel C, we turn to the effects of robot exposure on fertility. The sample consists of all baseline workers who are in the fertile age (i.e., below 49 years old) and the outcome variable is one's number of children. Both the OLS and 2SLS estimates suggest that exposure to robots reduces fertility. Specifically, based on the 2SLS estimates with individual fixed effects in column 3, a 1 standard deviation increase in robot exposure reduces the number of children by 0.013, which is about a 1.2% decrease relative to the mean.[22] The finding is consistent with the notion that the adverse labor market shocks associated with industrial robots reduces one's ability to afford a larger number of children.

4.4 Effects on Parenting and Investment in Children

Our analysis so far has explored the effects of robot exposure on Chinese workers and their households. A large number of the workers in our baseline analysis are also parents, and one could wonder whether exposure to robots may affect how the workers raise their children, such as their investment in the children's future. The effects of robot exposure on parental investment in children, however, is not *a priori* clear. On the one hand, the negative labor market effects and loss in income may lower the workers' ability to spend on their children's

[22]Focusing on the baseline workers who had no child in the 2010 survey, we show in Table A.16 that individuals more exposed to robots during 2010-2016 also had their first child at an older age. Given the relatively small sample size associated with this subset of baseline workers, we interpret the finding as suggestive evidence.

Table 5: Robot Exposure, Marriage and Fertility Outcomes, Individual-Level Analysis

	(1) OLS	(2) 2SLS	(3) 2SLS
	Panel A. Divorced Sample: Already married in baseline		
Robot exposure	-0.000	-0.000	-0.000
	(0.001)	(0.001)	(0.001)
Observations	20,529	20,529	19,564
Mean of Dep. Var.	0.00799	0.00799	0.00838
Std. Dev. of Dep. Var.	0.0890	0.0890	0.0912
First-stage F stat		380	279.2
	Panel B. Married Sample: Never married in baseline		
Robot exposure	0.006	0.005	-0.004
	(0.010)	(0.009)	(0.013)
Observations	3,923	3,923	3,599
Mean of Dep. Var.	0.272	0.272	0.296
Std. Dev. of Dep. Var.	0.445	0.445	0.457
First-stage F stat		297.8	211
	Panel C. Number of Children Sample: Individuals in fertile age		
Robot exposure	-0.016***	-0.010	-0.013**
	(0.005)	(0.007)	(0.006)
Observations	19,336	19,336	17,752
Mean of Dep. Var.	1.079	1.079	1.087
Std. Dev. of Dep. Var.	0.791	0.791	0.787
First-stage F stat		345.3	247.6
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the estimates of the impact of exposure to robots on individual marital and fertility outcomes. Panel A consists of baseline workers who were already married at the time of the 2010 baseline survey, and the outcome variable is an indicator variable equal to 1 if an individual is divorced and 0 otherwise. Panel B consists of baseline workers who were never married at the time of the 2010 baseline survey, and the outcome variable is an indicator variable equal to 1 if an individual is married and 0 otherwise. In Panel C, the outcome variable is one's number of children, and the sample consists of all baseline workers in the fertile age (i.e., below 49 years old). All estimates include city fixed effects, year (survey wave) fixed effects, and baseline individual sociodemographic controls as in column 1 of Table 1. Column 3 also controls for individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

education. On the other hand, the competition posed by robots may offer the workers stronger incentives to prepare their children for the future. A nice feature of our data is that the CFPS also surveys the children in each household, which allows us to empirically study the parents' educational and time investment in their children in response to robot exposure.

To be consistent with our baseline individual-level analysis, we focus on the children of the workers in our baseline analysis and obtain longitudinal data for each child from the 2010-2016 CFPS surveys. We then run similar regressions as in our baseline analysis, except now at the child level, focusing on the parents' educational and time investment in the child.

Table 6 presents our findings. In Panel A, we focus on monetary investment in a child's education and the outcome is the parents' educational expenses (in natural log) for the child over the past 12 months. The coefficients are negative but not statistically distinguishable from zero, suggesting limited effect on monetary investment in the child's education. In Panel B, we turn to time investment in the child. Specifically, we look at the average number of hours per week that family members tutored the child's homework over the last semester. The coefficients are positive and statistically significant in both the OLS and 2SLS estimates (columns 1-2). The coefficient is of comparable magnitude, although less precisely estimated, when we also control for child fixed effects in column 3, likely because of the smaller sample size. In terms of magnitude, the estimates in Panel B suggest that a 1 standard deviation increase in robot exposure increases the number of hours per week that family members tutor a child's homework by 0.3-0.4 hours (as compared to a mean of about 4.5 hours per week).

In China, children's caretaking is frequently shared between parents and grandparents. In Panel C, we therefore examine the average number of days per week that a child could see his or her parents as an alternative measure of parental time investment in children. We find a positive and statistically significant effect across different specifications. Specifically, based on column 3, the estimate suggests that a 1 standard deviation increase in robot exposure increases the average number of days per week that a child could see his or her parents by about 0.4, which is about 6.5% of the mean. We show in columns 1-2 of Table A.17 that the result is likely explained by parents replacing grandparents as a child's primary caretakers. The results in both Panels B and C of Table 6 therefore suggest that exposure to robots in China is associated with greater parental time investment in children.

Lastly, in Panel D of Table 6, we examine another measure of parents' investment in their children's human capital, namely the enrollment of children in tutorial and extracurricular classes. In China, enrollment in after-school tutorial and extracurricular classes is widely seen by parents as a way to augment a child's skill sets and competitiveness in the future. We find strong evidence that exposure to robots increases the likelihood that a child is enrolled in such classes. Based on column 3 of the Panel, a 1 standard deviation increase in robot exposure increases the probability that a child is enrolled in any after-school tutorial or extracurricular classes by 4.3 percentage points, which is about 24% of the mean (or 0.11 of a standard deviation). We further provide evidence in columns 3-4 of Table A.17 that the result is primarily driven by an increase in the enrollment in academic tutorial classes, such as math, Chinese, and English tutorials. The results are consistent with the idea that, in response to the greater competition from robots, Chinese parents resort to additional academic and extracurricular training for their children to stay competitive in the future labor market.

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 labor market effects of these new automation technologies, we still know relatively little about how the labor markets and households may adjust to these labor market shocks. Furthermore, we have so far limited empirical evidence on the impact of robots from developing countries and emerging economies.

Table 6: Effects on Educational and Time Investment in Children, Child-Level Analysis

	(1) OLS	(2) 2SLS	(3) 2SLS
Panel A.	log(Educational Expenses)		
Robot exposure	-0.028	-0.048	-0.025
	(0.049)	(0.056)	(0.085)
Observations	9,190	9,190	8,068
Mean of educational expenses (yuan)	2,942	2,942	3,036
Std.Dev. of educational expenses (yuan)	5,223	5,223	5,321
First-stage F stat		269.4	173.9
Panel B.	Hours Per Week Tutored Homework by Family Members		
Robot exposure	0.436***	0.395***	0.289
	(0.112)	(0.132)	(0.198)
Observations	6,502	6,502	5,465
Mean of Dep. Var.	4.501	4.501	4.683
Std.Dev. of Dep. Var.	5.552	5.552	5.630
First-stage F stat		314.4	181.7
Panel C.	Days Per Week Seeing Parents		
Robot exposure	0.228***	0.266***	0.391***
	(0.057)	(0.079)	(0.136)
Observations	8,614	8,614	7,147
Mean of Dep. Var.	6.086	6.086	6.024
Std.Dev. of Dep. Var.	2.171	2.171	2.236
First-stage F stat		319	184.2
Panel D.	Enrolled in Any Tutorial or Extracurricular Classes		
Robot exposure	0.027***	0.027***	0.043***
	(0.008)	(0.009)	(0.012)
Observations	9,490	9,490	8,362
Mean of Dep. Var.	0.175	0.175	0.176
Std.Dev. of Dep. Var.	0.380	0.380	0.380
First-stage F stat		340.5	224.3
Child controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Child FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the estimates of the impact of robot exposure on parents' educational and time investment in their children. The sample consists of children aged 0-15 of the baseline workers as in Table 1. The outcome variable in Panel A is the natural log of educational expenses for the child over the past 12 months. The outcome in Panel B is the average number of hours per week that family members spent tutoring the child's homework over the last semester. The outcome variable in Panel C is the average number of days per week over the last month that a child saw his or her parents. In Panel D, the outcome is an indicator variable that equals 1 if a child is enrolled in any tutorial or extracurricular classes. All estimates include city fixed effects, year (survey wave) fixed effects, and controls for child gender and age dummies. Column 3 also controls for child fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

In this study, we investigate the effects of industrial robots on the Chinese labor market. We find that an increase by one standard deviation in robot exposure lowers an individual's probability of being employed by 7.5% with respect to the mean and reduces hourly wages by 8.9%. Results hold to the inclusion of individual fixed effects, exploiting within-worker changes in exposure to robots over time. In addition, the effects are concentrated among the less educated and larger among men, 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. Households respond to the increased exposure to industrial robots in the labor markets by increasing borrowing. We find no evidence of any change in consumption, saving patterns, and marital behavior, and only a modest decline in fertility. In addition, robot exposure leads to an increase in time spent in children's education and in their after-school academic and extra-curricular activities.

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 labor 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 labor market. Households responded to the negative shock by increasing borrowing to keep savings and consumption constant. At the same time, more exposed households increased investment in the human capital of their children.

Future research could shed light on whether exposure to robots is affecting educational and career choices of young adults in developing economies so far characterized by a heavy specialization in manufacturing industries. Whether productivity gains in the long-run translate into employment growth or what will be the political consequences of the labor market effects of automation and digitization are important questions that demand further scientific investigation.

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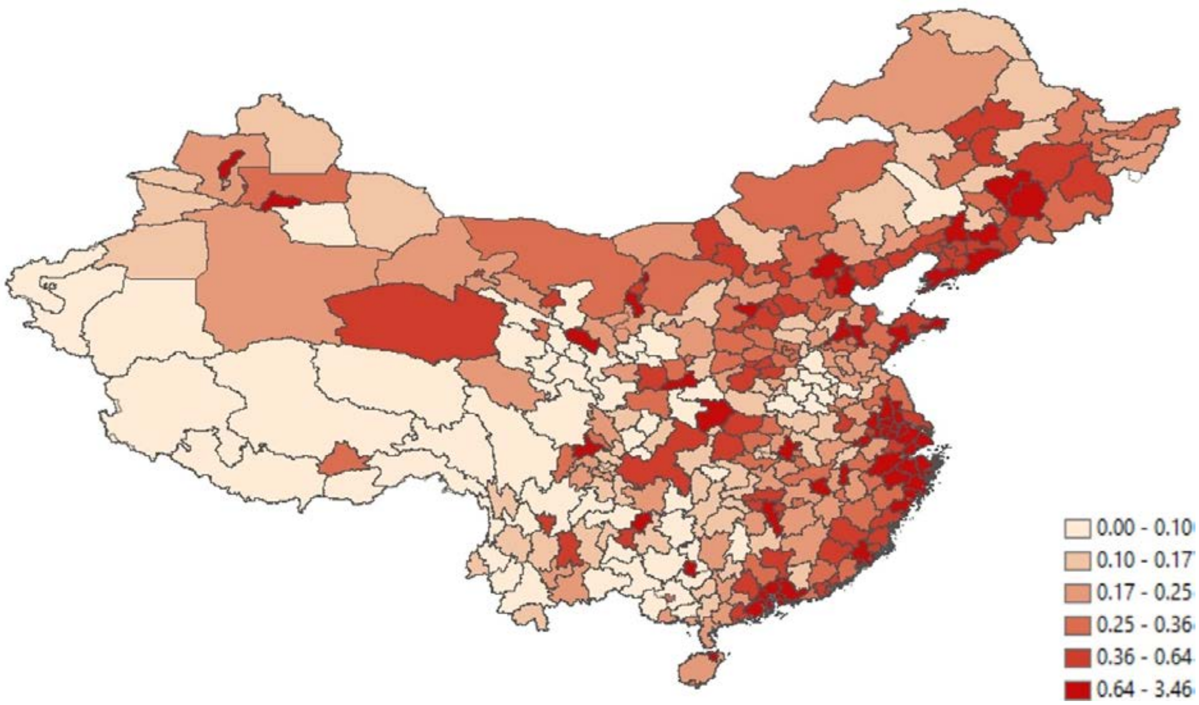
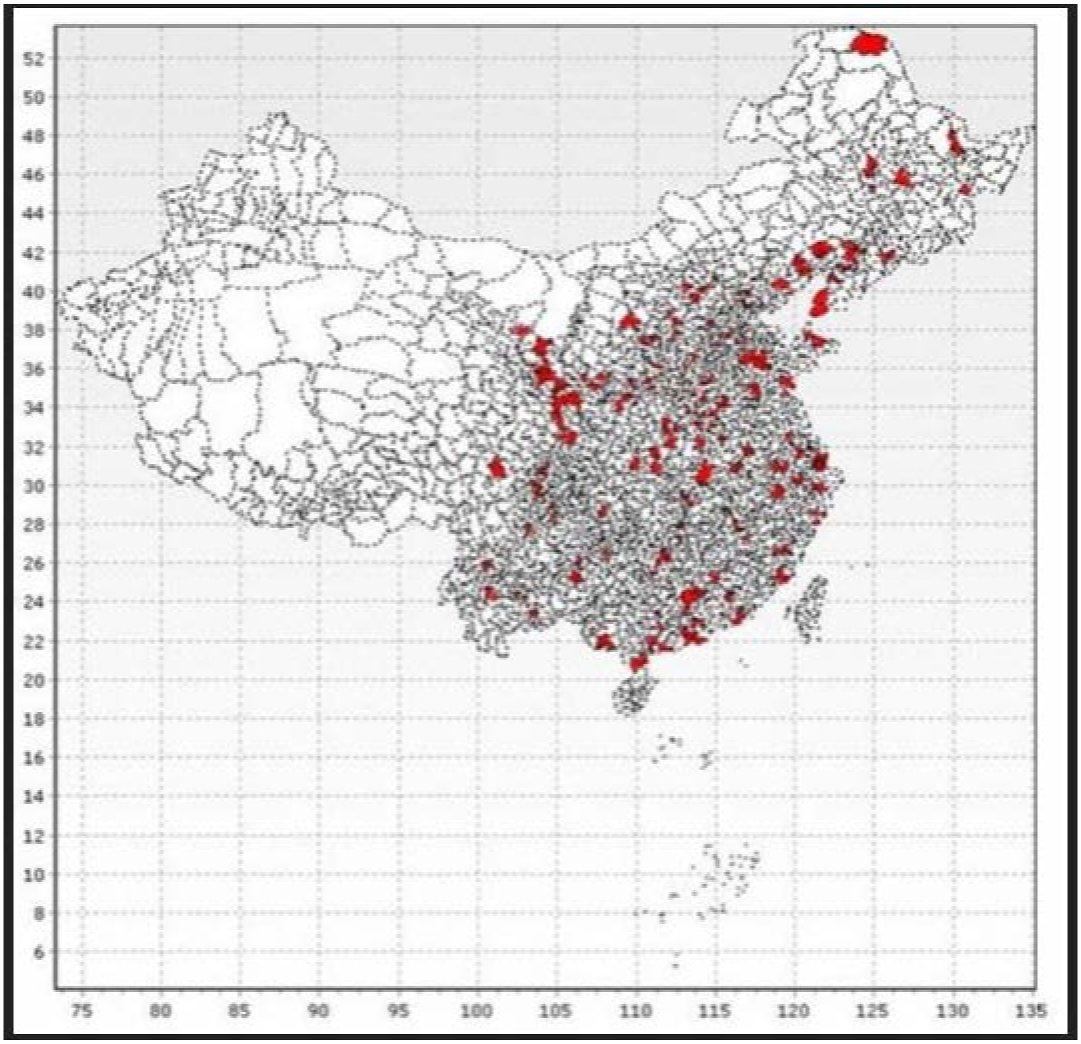
Appendix: Supplemental Figures and Tables

Figure A.1: Exposure to Robots Across Prefectures between 2006 and 2016



Notes - Data are drawn from the International Federation of Robotics (IFR) and China's 2000 Census.

Figure A.2: Counties in the CFPS Sample



Notes - Source: China Family Panel Studies (CFPS)

Table A.1: Summary Statistics

	Years covered	(1) N	(2) Mean	(3) SD	(4) Min	(5) Max
Male	2010-2016	25,355	0.585	0.493	0	1
Age	2010-2016	25,354	40.54	11.16	16	66
Han Chinese	2010-2016	25,355	0.954	0.210	0	1
Educational level: Primary school	2010-2016	25,355	0.156	0.363	0	1
Educational level: Secondary school	2010-2016	25,355	0.329	0.470	0	1
Educational level: High school	2010-2016	25,355	0.218	0.413	0	1
Educational level: 3-Year college	2010-2016	25,355	0.115	0.319	0	1
Educational level: 4-Year college or above	2010-2016	25,355	0.0797	0.271	0	1
Employed	2010-2016	25,355	0.809	0.393	0	1
Unemployed	2010-2016	25,355	0.101	0.302	0	1
Out of labor force	2010-2016	25,355	0.0900	0.286	0	1
Participated in technical or work-related training	2010-2016	25,355	0.0389	0.193	0	1
Participated in ideological & political training	2010-2016	25,355	0.00856	0.0921	0	1
Retired early	2010-2016	25,355	0.00390	0.0624	0	1
Hourly wage (primary job)	2010-2014	12,105	19.18	133.6	0	12,512
Annual wage (primary job)	2010-2014	12,596	28,749	31,503	0	1,241,940
Hours worked in a month (primary job)	2010-2014	13,811	206.6	73.67	0.400	744
Total annual earnings (all jobs)	2010-2014	12,656	29,753	32,489	0	1,241,940

Notes - Data are from the China Family Panel Studies (CFPS, 2010—2016). Each observation is an individual.

Table A.2: Robot Exposure and Labor Market Effects: Reduced-Form Estimates

	(1)	(2)	(3)
	Panel A. Employment		
	Employed	Out of LF	Unemployed
Robot exposure	-0.446***	0.083*	0.364***
	(0.084)	(0.046)	(0.054)
Observations	25,354	25,354	25,354
Mean of Dep. Var.	0.809	0.0900	0.101
Std.Dev. of Dep. Var.	0.393	0.286	0.302
	Panel B. Income and Hours		
	ln(Hourly Wage)	ln(Annual Wage)	ln(Monthly Hours)
Robot exposure	-0.775***	-0.094	0.905***
	(0.144)	(0.402)	(0.270)
Observations	12,104	12,595	13,810
Mean of hourly income (yuan)	19.18	28749	221.7
Std.Dev. of hourly income (yuan)	133.6	31504	81.52
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes

Notes - The table presents the reduced-form estimates of the impact of exposure to robots on individual labor market outcomes. In Panel A, data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time during 2010-2016. The outcome variable is an indicator variable equal to 1 if an individual is employed (column 1), or out of the labor force (column 2), or unemployed (column 3) and 0 otherwise. In Panel B, data are drawn from the China Family Panel Studies (CFPS, 2010—2014). The sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time and employed during 2010-2014. The outcome variable in column 1 is the natural log of hourly wage at one's primary job. The outcome in column 2 is the natural log of annual earnings from the primary job. The outcome in column 3 is the natural log of monthly working hours at the primary job. All estimates include city fixed effects, year (survey wave) fixed effects, and individual sociodemographic controls for gender, age and its quadratic term, ethnicity (dummy for Han Chinese), and education level (dummies for no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above). Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Robustness Checks: Employment and Labor Force Participation Results (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
			Panel A. Employed			
Robot exposure	-0.066***	-0.063***	-0.096***	-0.070***	-0.057***	-0.099***
	(0.016)	(0.014)	(0.021)	(0.014)	(0.016)	(0.037)
Observations	23,999	22,278	23,999	23,999	23,999	23,183
First-stage F stat	193.2	314.2	103.3	278.6	95.93	52.49
Mean of Dep. Var.	0.811	0.812	0.811	0.811	0.811	0.812
Std.Dev. of Dep. Var.	0.392	0.391	0.392	0.392	0.392	0.391
			Panel B. Out of Labor Force			
Robot exposure	0.010	0.010	0.016	0.011	0.010	-0.004
	(0.009)	(0.008)	(0.011)	(0.008)	(0.009)	(0.019)
Observations	23,999	22,278	23,999	23,999	23,999	23,183
First-stage F stat	193.2	314.2	103.3	278.6	95.93	52.49
Mean of Dep. Var.	0.0951	0.0956	0.0951	0.0951	0.0951	0.0946
Std.Dev. of Dep. Var.	0.293	0.294	0.293	0.293	0.293	0.293
			Panel C. Unemployed			
Robot exposure	0.056***	0.054***	0.079***	0.059***	0.047***	0.103***
	(0.012)	(0.010)	(0.016)	(0.011)	(0.011)	(0.028)
Observations	23,999	22,278	23,999	23,999	23,999	23,183
Full baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes					
FDI and foreign output controls		Yes				
2000 city electronic share x year dummies			Yes			
Excluding electronics from robot exposure				Yes		
Excluding automotives from robot exposure					Yes	
2000 city characteristics x year dummies						Yes
First-stage F stat	193.2	314.2	103.3	278.6	95.93	52.49
Mean of Dep. Var.	0.0944	0.0928	0.0944	0.0944	0.0944	0.0935
Std.Dev. of Dep. Var.	0.292	0.290	0.292	0.292	0.292	0.291

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents robustness checks on the baseline estimates of the impact of robot exposure on individual employment status and labor force participation. The sample and outcome variables are the same as those in Table 1. All estimates include the full baseline controls for city fixed effects, year (survey wave) fixed effects, individual characteristics, and individual fixed effects as in column 3 of Table 1. In addition, column 1 controls for region-by-year fixed effects. Column 2 controls for the natural log of the value of Foreign Direct Investment (FDI) and foreign production (including those of Hong Kong, Macau, and Taiwan firms). Column 3 controls for the interactions between year dummies and the city's 2000 employment share in the electronics sector. Column 4 reconstructs robot exposure by excluding the electronics sector. Column 5 reconstructs robot exposure by excluding the"automotive and other vehicles" sector. Column 6 controls for the interactions between year dummies and the city's 2000 characteristics (natural log of population and the population shares of men, urban population, working-age population, university-educated population, and migrants). Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: Robustness Checks: Income and Working Hours Results (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel A. log(Hourly Wage)					
Robot exposure	-0.078	-0.095**	-0.086	-0.072**	-0.157**	-0.128
	(0.068)	(0.045)	(0.056)	(0.034)	(0.072)	(0.084)
Observations	9,310	8,703	9,310	9,310	9,310	9,030
First-stage F stat	8.630	11.06	23.73	43.68	5.331	29.25
Mean of Dep. Var.	19.55	19.89	19.55	19.55	19.55	19.68
Std.Dev. of Dep. Var.	135.9	140.5	135.9	135.9	135.9	138
	Panel B. log(Annual Wage)					
Robot exposure	0.043	0.062	0.068	0.038	0.096	0.087
	(0.141)	(0.094)	(0.115)	(0.076)	(0.135)	(0.239)
Observations	9,749	9,116	9,749	9,749	9,749	9,460
First-stage F stat	8.532	10.97	23.93	43.99	5.213	29.27
Mean of Dep. Var.	29944	30313	29944	29944	29944	30111
Std.Dev. of Dep. Var.	31542	32226	31542	31542	31542	31912
	Panel C. log(Monthly Hours)					
Robot exposure	0.130***	0.152***	0.154***	0.125***	0.200***	0.154**
	(0.047)	(0.038)	(0.036)	(0.025)	(0.064)	(0.064)
Observations	10,946	10,244	10,946	10,946	10,946	10,626
Full baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
Region-by-year FE	Yes					
FDI and foreign output controls		Yes				
2000 city electronic share x year dummies			Yes			
Excluding electronics from robot exposure				Yes		
Excluding automotives from robot exposure					Yes	
2000 city characteristics x year dummies						Yes
First-stage F stat	9.824	12.68	25.41	48.08	6.153	29.82
Mean of Dep. Var.	220.4	220.3	220.4	220.4	220.4	220.5
Std.Dev. of Dep. Var.	79.81	79	79.81	79.81	79.81	79.11

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2014). The table presents robustness checks on the baseline estimates of the impact of robot exposure on income and working hours of employed workers. The sample and outcome variables are the same as those in Table 2. All estimates include the full baseline controls for city fixed effects, year (survey wave) fixed effects, individual characteristics, and individual fixed effects as in column 3 of Table 1. In addition, column 1 controls for region-by-year fixed effects. Column 2 controls for the natural log of the value of Foreign Direct Investment (FDI) and foreign production (including those of Hong Kong, Macau, and Taiwan firms). Column 3 controls for the interactions between year dummies and the city's 2000 employment share in the electronics sector. Column 4 reconstructs robot exposure by excluding the electronics sector. Column 5 reconstructs robot exposure by excluding the"automotive and other vehicles" sector. Column 6 controls for the interactions between year dummies and the city's 2000 characteristics (natural log of population and the population shares of men, urban population, working-age population, university-educated population, and migrants). Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5: Accounting for Sample Attrition with the Propensity Score of Being Matched

	Baseline sample		Propensity score restricted sample	
	Mean (S.D.) (1)	Coefficient (2)	Mean (S.D.) (3)	Coefficient (4)
Male	0.580	0.015	0.578	-0.007
	(0.494)	(0.011)	(0.494)	(0.014)
Age	37.37	2.914***	37.58	0.258
	(10.95)	(0.317)	(9.797)	(0.285)
Han Chinese	0.951	0.007	0.948	0.004
	(0.215)	(0.005)	(0.221)	(0.007)
Years of education	9.838	-0.521***	10.29	-0.326**
	(4.177)	(0.144)	(3.947)	(0.137)
Non-agricultural Hukou	0.504	-0.009	0.640	0.022
	(0.500)	(0.014)	(0.480)	(0.015)
Manufacturing	0.234	0.023***	0.210	0.007
	(0.423)	(0.008)	(0.407)	(0.010)
Employed	0.734	0.006	0.776	0.008
	(0.442)	(0.011)	(0.417)	(0.012)
Hourly wage	8.579	-0.492	9.214	0.039
	(28.21)	(0.743)	(37.18)	(0.787)
Monthly hours	151	1.431	158.7	4.251
	(115.9)	(2.745)	(110.1)	(3.481)
Annual wage	18136	-2,206.852**	18631	-382.598
	(26872)	(878.763)	(22552)	(599.316)
N	8,453	8,453	4,213	4,213

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents balance tests between workers observed in all four survey waves and those with missing observations in both the baseline sample (columns 1-2) and the subsample of workers whose propensity scores of being observed in all four waves fall in the middle 50 percentile (columns 3-4). Columns 1 and 3 show the mean (and standard deviation) of individual characteristics in 2010 for each sample. In columns 2 and 4, each coefficient comes from a separate regression, in which the individual characteristic is regressed on a dummy variable that equals 1 if the individual is observed in all four waves and 0 otherwise. Each regression also includes city fixed effects. The sample for column 2 consists of all baseline workers in 2010, while that for column 4 removes workers whose propensity score of being observed in all four waves fall in the bottom or the upper quartile. Standard errors, shown in parentheses in columns 2 and 4, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6: Estimates from the Propensity Score Restricted Sample

	(1) Employed	(2) Out of Labor Force	(3) Unemployed	(4) ln(Hourly Wage)	(5) ln(Annual Wage)	(6) ln(Monthly Hours)
Robot exposure	-0.047***	0.008	0.039***	-0.078	0.082	0.130***
	(0.011)	(0.006)	(0.009)	(0.063)	(0.101)	(0.038)
Observations	12,251	12,251	12,251	5,322	5,506	6,066
Full baseline controls	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F stat	247.4	247.4	247.4	11.58	11.77	12.42
Mean of Dep. Var.	0.829	0.0913	0.0801	2.578	9.906	5.236
Std.Dev. of Dep. Var.	0.377	0.288	0.271	0.741	1.514	0.469

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the 2SLS estimates of the labor market impact of robot exposure for individuals whose propensity scores of being observed in all four survey waves fall in the middle 50 percentile. All estimates include city fixed effects, year (survey wave) fixed effects, individual sociodemographic controls, and individual fixed effects as in column 3 of Table 1. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.7: Rotemberg Weights

Sector	Rotemberg weight
Electronics	0.374245
Construction	0.232338
Metal product	0.152321
Glass and ceramic	0.103267
Automotives and other vehicles	0.072878
Basic metal	0.064979
Agriculture, forestry, and fishery	0.049526
Paper	0.038372
Plastic and chemicals	0.017836
Mining	0.007382
Food and beverages	0.005413
Utilities	0.003621
Wood and furniture	0.003062
Other non-manufacturing	0.001348
Education and R&D	0.001097
Other manufacturing	0.000881
Metal machinery	-0.03468
Textiles	-0.09388

Notes - This table shows the Rotemberg weight associated with each sector following the procedure introduced by Goldsmith-Pinkham et al. (2020). We calculated Rotemberg weights by sector and year. Here we report the average weight of each sector throughout the period of the analysis.

Table A.8: Robot Exposure and Total Annual Income from All Jobs

	(1) OLS	(2) 2SLS	(3) 2SLS
	Log(Total Annual Income)		
Robot exposure	-0.001	-0.021	0.049
	(0.037)	(0.064)	(0.097)
Observations	12,655	12,655	9,800
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes
Mean of annual income (yuan)	29753	29753	31038
Std. Dev. of annual income (yuan)	32490	32490	32715
First-stage F stat		19.24	12.57

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2014). The table presents the estimates of the impact of exposure to robots on total annual income of employed workers. The sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey and employed during 2010-2014. The outcome variable is the natural log of one's total annual income from all jobs. All estimates include city fixed effects, year (survey wave) fixed effects, and individual sociodemographic controls for gender, age and its quadratic term, ethnicity (dummy for Han Chinese), and education level (dummies for no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above). Column 3 also controls for individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.9: Robot Exposure, Employment, and Labor Force Participation, Individual-Level Analysis (1982 IV)

	(1) OLS	(2) 2SLS	(3) 2SLS
	Panel A. Employed		
Robot exposure	-0.061***	-0.078***	-0.077***
	(0.015)	(0.014)	(0.017)
Observations	25,354	25,354	23,999
R-squared	0.143	0.082	0.027
Mean of Dep. Var.	0.809	0.809	0.811
Std.Dev. of Dep. Var.	0.393	0.393	0.392
First-stage F stat		81.21	55.64
	Panel B. Out of Labor Force		
Robot exposure	0.009*	0.024***	0.023***
	(0.005)	(0.005)	(0.007)
Observations	25,354	25,354	23,999
R-squared	0.151	0.083	0.023
Mean of Dep. Var.	0.0900	0.0900	0.0951
Std.Dev. of Dep. Var.	0.286	0.286	0.293
First-stage F stat		81.21	55.64
	Panel C. Unemployed		
Robot exposure	0.051***	0.054***	0.054***
	(0.012)	(0.011)	(0.013)
Observations	25,354	25,354	23,999
R-squared	0.222	0.030	0.019
Mean of Dep. Var.	0.101	0.101	0.0944
Std.Dev. of Dep. Var.	0.302	0.302	0.292
First-stage F stat		81.21	55.64
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table reproduces Table 1 when using 1982 (instead of 2000) as the base year to construct the instrument for robot exposure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.10: Robot Exposure, Income, and Working Hours, Individual-Level Analysis (1982 IV)

	(1) OLS	(2) 2SLS	(3) 2SLS
	Panel A. Log(Hourly Wage)		
Robot exposure	-0.077***	-0.084***	-0.046
	(0.017)	(0.024)	(0.037)
Observations	12,104	12,104	9,310
R-squared	0.315	0.151	0.010
Mean of hourly income (yuan)	19.18	19.18	19.55
Std.Dev. of hourly income (yuan)	133.6	133.6	135.9
First-stage F stat		48.32	29.55
	Panel B. Log(Annual Wage)		
Robot exposure	-0.007	-0.001	0.107
	(0.040)	(0.060)	(0.071)
Observations	12,595	12,595	9,749
R-squared	0.129	0.061	0.014
Mean of annual income (yuan)	28749	28749	29944
Std.Dev. of annual income (yuan)	31504	31504	31542
First-stage F stat		49.31	29.41
	Panel C. Log(Monthly Hours)		
Robot exposure	0.126***	0.115***	0.127***
	(0.021)	(0.028)	(0.033)
Observations	13,810	13,810	10,946
R-squared	0.145	0.028	0.009
Mean of monthly hours worked	221.7	221.7	220.4
Std.Dev. of monthly hours worked	81.52	81.52	79.81
First-stage F stat		49.84	32.61
Individual controls	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes
Individual FE			Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2014). The table reproduces Table 2 when using 1982 (instead of 2000) as the base year to construct the instrument for robot exposure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.11: Robot Exposure and Labor Market Effects by Education Level (2SLS)

	(1) Employed	(2) Out of Labor Force	(3) Unemployed	(4) ln(Hourly Wage)	(5) ln(Monthly Hours)	(6) ln(Annual Wage)
			Panel A. Middle school or below			
Robot exposure	-0.087***	0.023*	0.064***	-0.150***	0.141***	-0.006
	(0.019)	(0.012)	(0.012)	(0.055)	(0.033)	(0.147)
Observations	13,615	13,615	13,615	4,230	5,380	4,481
First-stage F stat	258.3	258.3	258.3	15.62	18.33	16.06
Mean of Dep. Var.	0.770	0.111	0.119	2.307	5.372	9.572
Std.Dev. of Dep. Var.	0.421	0.314	0.323	0.717	0.572	1.690
			Panel B. High school			
Robot exposure	-0.034**	0.007	0.027***	-0.047	0.137**	-0.053
	(0.014)	(0.010)	(0.010)	(0.062)	(0.066)	(0.190)
Observations	4,845	4,845	4,845	2,069	2,332	2,145
First-stage F stat	197.7	197.7	197.7	7.996	8.006	7.783
Mean of Dep. Var.	0.823	0.105	0.0720	2.555	5.249	9.825
Std.Dev. of Dep. Var.	0.382	0.306	0.259	0.804	0.535	1.507
			Panel C. 3-Year college or above			
Robot exposure	-0.017	0.011	0.006	-0.023	0.125***	0.168
	(0.012)	(0.008)	(0.006)	(0.067)	(0.047)	(0.188)
Observations	4,393	4,393	4,393	2,524	2,700	2,607
First-stage F stat	349.7	349.7	349.7	13.10	13.31	12.78
Mean of Dep. Var.	0.931	0.0405	0.0287	2.921	5.217	10.23
Std.Dev. of Dep. Var.	0.254	0.197	0.167	0.776	0.386	1.564
City FE and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the 2SLS estimates of the labor market impact of exposure to robots on individuals by education level (i.e., for individuals with a middle school degree or below in Panel A, a high school degree or equivalent in Panel B, and a 3-year college degree or above in Panel C). For columns 1-3, the sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time during 2010-2016. The outcome variable is an indicator variable equal to 1 if an individual is employed (column 1), or out of the labor force (column 2), or unemployed (column 3) and 0 otherwise. For columns 4-6, the sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time and employed during 2010-2014. The outcome variables are the natural logs of hourly wage at one's primary job (column 4), monthly working hours at the primary job (column 5), and annual earnings from one's primary job (column 6). All estimates include city fixed effects, year (survey wave) fixed effects, and individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.12: Robot Exposure and Labor Market Effects by Age Group (2SLS)

	(1) Employed	(2) Out of Labor Force	(3) Unemployed	(4) ln(Hourly Wage)	(5) ln(Monthly Hours)	(6) ln(Annual Wage)
			Panel A. Age 16-24			
Robot exposure	-0.045*	-0.016*	0.061***	-0.023	0.196**	0.231
	(0.024)	(0.010)	(0.020)	(0.122)	(0.082)	(0.334)
Observations	3,331	3,331	3,331	881	1,160	999
First-stage F stat	197.7	197.7	197.7	14.02	18.95	15.02
Mean of Dep. Var.	0.757	0.105	0.137	2.539	5.360	9.303
Std.Dev. of Dep. Var.	0.429	0.307	0.344	0.826	0.541	2.517
			Panel B. Age 25-44			
Robot exposure	-0.050***	0.001	0.049***	-0.107*	0.146***	-0.047
	(0.012)	(0.005)	(0.010)	(0.061)	(0.038)	(0.123)
Observations	13,134	13,134	13,134	5,693	6,624	5,907
First-stage F stat	260.7	260.7	260.7	9.432	10.41	9.733
Mean of Dep. Var.	0.863	0.0547	0.0823	2.559	5.324	9.887
Std.Dev. of Dep. Var.	0.344	0.227	0.275	0.776	0.470	1.572
			Panel C. Age 45-59			
Robot exposure	-0.083***	0.032*	0.052***	-0.080**	0.119**	0.074
	(0.021)	(0.017)	(0.010)	(0.036)	(0.051)	(0.110)
Observations	7,535	7,535	7,535	2,736	3,162	2,845
First-stage F stat	266.9	266.9	266.9	32.14	20.31	17.74
Mean of Dep. Var.	0.743	0.161	0.0964	2.502	5.244	9.814
Std.Dev. of Dep. Var.	0.437	0.368	0.295	0.833	0.614	1.488
City FE and year FE	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the 2SLS estimates of the labor market impact of exposure to robots on individuals by one's age in the 2010 baseline survey (i.e., for individuals aged between 16 and 24 in Panel A, between 25 and 44 in Panel B, and between 45 and 59 in Panel C). For columns 1-3, the sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time during 2010-2016. The outcome variable is an indicator variable equal to 1 if an individual is employed (column 1), or out of the labor force (column 2), or unemployed (column 3) and 0 otherwise. For columns 4-6, the sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time and employed during 2010-2014. The outcome variables are the natural logs of hourly wage at one's primary job (column 4), monthly working hours at the primary job (column 5), and annual earnings from one's primary job (column 6). All estimates include city fixed effects, year (survey wave) fixed effects, and individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.13: Robot Exposure and Labor Market Effects by Gender (2SLS)

	(1) Employed	(2) Out of Labor Force	(3) Unemployed	(4) ln(Hourly Wage)	(5) ln(Monthly Hours)	(6) ln(Annual Wage)
			Panel A. Men			
Robot exposure	-0.070***	0.019	0.051***	-0.112**	0.129***	0.054
	(0.018)	(0.012)	(0.011)	(0.055)	(0.039)	(0.110)
Observations	14,096	14,096	14,096	5,689	6,824	5,957
First-stage F stat	259.3	259.3	259.3	12.01	13.44	12.12
Mean of Dep. Var.	0.844	0.0651	0.0914	2.610	5.321	9.928
Std.Dev. of Dep. Var.	0.363	0.247	0.288	0.800	0.541	1.605
			Panel A. Women			
Robot exposure	-0.056***	0.005	0.051***	-0.066	0.161***	-0.101
	(0.014)	(0.009)	(0.010)	(0.047)	(0.044)	(0.136)
Observations	9,872	9,872	9,872	3,605	4,103	3,778
First-stage F stat	276.7	276.7	276.7	11.66	12.94	11.55
Mean of Dep. Var.	0.763	0.138	0.0984	2.433	5.276	9.614
Std.Dev. of Dep. Var.	0.425	0.345	0.298	0.783	0.495	1.777

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the 2SLS estimates of the labor market impact of exposure to robots on individuals by gender (i.e., men in Panel A and women in Panel B). For columns 1-3, the sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time during 2010-2016. The outcome variable is an indicator variable equal to 1 if an individual is employed (column 1), or out of the labor force (column 2), or unemployed (column 3) and 0 otherwise. For columns 4-6, the sample consists of non-agricultural wage workers aged between 16 and 59 in the 2010 CFPS survey, who are followed over time and employed during 2010-2014. The outcome variables are the natural logs of hourly wage at one's primary job (column 4), monthly working hours at the primary job (column 5), and annual earnings from one's primary job (column 6). All estimates include city fixed effects, year (survey wave) fixed effects, and individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.14: Effects on Training Participation and Early Retirement by Age Group (2SLS)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Participated in							
	Technical training			Ideological training			Retired Early	
	Age 16-24	24-44	45-59	Age 16-24	24-44	45-59	Age≤44	45-59
Robot exposure	0.046***	0.016***	-0.001	0.011	0.000	-0.003	-0.001	0.005**
	(0.011)	(0.006)	(0.004)	(0.007)	(0.004)	(0.002)	(0.000)	(0.002)
Observations	3,331	13,133	7,535	3,331	13,133	7,535	16,464	7,535
City FE and year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
First-stage F stat	214.3	265.1	275.3	214.3	265.1	275.3	254.3	275.3
Mean of Dep. Var.	0.034	0.051	0.027	0.005	0.012	0.006	0.00134	0.0102
Std. Dev. of Dep. Var.	0.182	0.220	0.161	0.071	0.107	0.079	0.0365	0.101

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the 2SLS estimates of the impact of exposure to robots on one's training participation and early retirement decisions by age group, where age is measured in the 2010 survey. The sample consists of all the baseline workers as in Table 1. In columns 1-3, the outcome is an indicator variable that equals 1 if an individual participated in technical or skill-based training over the past 12 months and 0 otherwise. In columns 4-6, the outcome is an indicator variable that equals 1 if an individual participated in ideological or political training over the past 12 months and 0 otherwise. In columns 7-8, the outcome is an indicator variable that equals 1 if an individual retired early (i.e., retired before reaching 50 years old for females and before reaching 60 years old for males). All estimates include city fixed effects, year (survey wave) fixed effects, baseline individual sociodemographic controls as in column 1 of Table 1, and individual fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.15: Robot Exposure and Household Debts by Sources

	(1) OLS	(2) 2SLS	(3) 2SLS
	Outcome: log(Non-Housing Debts)		
Panel A.	Owed to Banks		
Robot exposure	0.105***	0.122***	0.123**
	(0.034)	(0.042)	(0.054)
Observations	12,358	12,358	11,187
Mean of Dep. Var.	0.468	0.468	0.460
Std.Dev. of Dep. Var.	2.040	2.040	2.024
First-stage F stat		389.7	244.2
Panel B.	Owed to Relatives and Friends		
Robot exposure	0.136**	0.115*	0.103
	(0.054)	(0.064)	(0.087)
Observations	12,237	12,237	11,068
Mean of Dep. Var.	1.331	1.331	1.319
Std.Dev. of Dep. Var.	3.166	3.166	3.152
First-stage F stat		393	248.1
City FE and year FE	Yes	Yes	Yes
Household FE		Yes	Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the estimates of the impact of robot exposure on household debts by sources. The sample consists of the households of all the baseline workers as in Table 1. The outcome in Panel A is the natural log of the amount of non-housing debts per capita owed to banks. The outcome in Panel B is the natural log of the amount of non-housing debts per capita owed to relatives and friends. All estimates include city fixed effects and year (survey wave) fixed effects. Column 3 also controls for household fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.16: Robot Exposure and Age at First Child Birth, Individual-Level Analysis

	Outcome: Age at First Child Birth			
	OLS	OLS	2SLS	2SLS
Δ Robot exposure, 2010-2016	0.780***	0.405**	0.641**	0.347
	(0.205)	(0.196)	(0.290)	(0.248)
Observations	407	407	407	407
Individual controls		Yes		Yes
Mean of Dep. Var.	26.76	26.76	26.76	26.76
Std. Dev. of Dep. Var.	4.530	4.530	4.530	4.530
First-stage F stat			12.72	13.78

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The outcome is the age when one had his or her first child. The data in this Panel is cross-sectional and consists of baseline workers who had no child in the 2010 baseline survey but who subsequently had at least one child by the 2016 survey. The explanatory variable in Panel B is the change in exposure to robots during 2010-2016, and the IV used in columns 3-4 of the Panel is the change in robot exposure IV during the same period. Columns 1 and 3 of Panel B includes no control, while columns 2 and 4 of the Panel include individual sociodemographic controls for gender, ethnicity (dummy for Han Chinese), and education level (dummies for no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above). The explanatory variables in both panels are standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.17: Additional Results from Child-Level Analysis (2SLS)

	(1)	(2)	(3)	(4)
	Caretakers are		Extracurricular Classes	
	Parents	Grandparents	Academic	Non-academic
Robot exposure	0.054***	-0.038***	0.027***	0.022
	(0.014)	(0.013)	(0.009)	(0.014)
Observations	7,943	7,943	8,917	8,917
Child fixed effects	Yes	Yes	Yes	Yes
Child age dummies	Yes	Yes	Yes	Yes
City FE and year FE	Yes	Yes	Yes	Yes
First-stage F stat	233.5	233.5	229.6	229.6
Mean of Dep. Var.	0.466	0.289	0.109	0.0827
Std.Dev. of Dep. Var.	0.499	0.453	0.312	0.275

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010—2016). The table presents the 2SLS estimates of the impact of robot exposure on additional child-level outcomes. The outcome variable in column 1 is an indicator variable equal to 1 if a child's primary caretakers are his or her parents, while the outcome in column 2 is an indicator variable equal to 1 if a child's primary caretakers are his or her grandparents. The outcome variable in column 3 is an indicator variable equal to 1 if a child is enrolled in any academic tutorial classes, while the outcome in column 4 is an indicator variable equal to 1 if a child is enrolled in any non-academic extracurricular activities. All estimates include city fixed effects, year (survey wave) fixed effects, child gender and age dummies, as well as child fixed effects. Exposure to robots is standardized. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$