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ABSTRACT

Is an Army of Robots Marching on Chinese Jobs?*

A handful of studies have investigated the effects of robots on workers in advanced economies. According to a recent report from the World Bank (2016), 1.8 billion jobs in developing countries are susceptible to automation. Given the inability of labor markets to adjust to rapid changes, there is a growing concern that the effect of automation and robotization in emerging economies may increase inequality and social unrest. Yet, we still know very little about the impact of robots in developing countries. In this paper we analyze the effects of exposure to industrial robots in the Chinese labor market. Using aggregate data from Chinese prefectural cities (2000-2016) and individual longitudinal data from the China Family Panel Study (2010-2016), we find a large negative impact of robot exposure on employment and wages of Chinese workers. Effects are concentrated in the state-owned sector and are larger among low-skilled, male, and prime-age and older workers. Furthermore, we find evidence that exposure to robots affected internal mobility and increased the number of labor-related strikes and protests.

JEL Classification: J23, J24, O33

Keywords: robots, labor markets, emerging economies

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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, 2018; Graetz and Michaels, 2018; Borjas and Freeman, 2018; Mokyr et al., 2015; Bessen et al., 2019), most analysis so far has been limited to advanced economies. However, 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. Many are worried about the inability of labor markets to adjust rapidly to the changes imposed by this technological revolution. Given the much higher share of workers with 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). Previous work has highlighted the risks of premature deindustrialisation and how automation may disrupt the income convergence process and hinder the ability of developing countries to exploit their labor-cost advantage to grow (Berg et al., 2018; Rodrik, 2016; Atolia et al., 2018; Palma, 2008). Without employment creation, automation, ditigalization and labor-saving technologies may foster inequality. In other words, new technologies that could potentially increase productivity might not lead to inclusive growth.[1] 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

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

significantly larger than those observed so far in the more developed countries (Schlogl and Sumner, 2018a).

Our main contribution is to provide, to the best of our knowledge, the first quantitative assessment of the effects of exposure to industrial robots in an emerging economy. 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 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) [2]. A stunning example is Foxconn, the massive producer of iPhone and many

[2] See also Knight (2016)

other electronic goods. Between 2012 and 2016, Foxconn has replaced more than 400,000 jobs with robots in China and is planning to achieve 30 percent automation by 2020. 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 (2018) to the Chinese context. 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.

In both aggregate- and individual-level analyses, we find large negative effects of robot exposure on employment and wages. For Chinese cities between 2000 and 2016, an increase by 1 standard deviation in robot exposure decreases a city's employment to population ratio in the state-owned sector by .3 standard deviation and reduces annual wage by 7.7 percent. Our result is consistent with recent evidence that innovation subsidies in China are preferentially allocated to state-owned firms and politically connected firms (Cheng et al., 2019).

Using individual-level data and exploiting within-individual variation in the exposure to robots over time, we show that an increase by 1 standard deviation in robot exposure lowers an individual's probability of being employed by 3 percent relative to the mean and reduces hourly wage by 7 percent. Exploring the heterogeneity of the effects among workers, we find that these effects are concentrated among low-skilled, male, and prime-age and older workers. Effects are also largely concentrated in cities with an initial high-density of manufacturing sector.

Another important peculiarity of the Chinese economy is the large number of internal migrants. Automation and robots may reduce significantly returns to migration, thus lowering the incentives to migrate. Consistent with this prior, we find that provinces with higher penetration of industrial robots experienced a decrease in the population share of migrants, suggesting that workers responded to the labor market changes.

Moreover, there is a growing concern that the rapid transition from human workers to robots may exacerbate inequality, which may cause economic hardships and even social unrest. Recent research shows evidence that exposure to automation may have contributed to the rise of polarization and populism in the US and Europe (Frey et al., 2017; Anelli et al., 2018). Over the last decade, China experienced an unprecedented surge in labor strikes and protests (see Figure 8). China Labor Bulletin, a Hong Kong-based NGO, reported a record-high of 2,774 incidents of labor strikes and protests in mainland China in 2015, doubling with respect to 2014. These strikes reflect a growing sense of insecurity among workers. Using data collected by China Labor Bulletin, we document a positive impact of exposure to robots on the number of labor strikes and protests. These results are driven by an increase in incidents motivated by layoffs and wage controversies.

Our results are not sensitive to the inclusion of controls for the offshoring of industries away from China, as measured by changes in foreign production and investments. Our results are also robust to the exclusion of one city at a time and to alternative ways of constructing the instrumental variable. Finally, we conduct a placebo test using lagged changes in our outcomes of interest and find no evidence of existing pre-trends, strengthening the causal interpretation of our findings.

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. In particular, our work is closely related to Acemoglu and Restrepo (2018) who provide 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 (2018) who compare the effect of immigration and robot exposure on employment. On the contrary, Graetz and Michaels (2015) use crosscountry 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. (2017) show that in Germany robots account for 23 percent of the decline in manufacturing jobs over the past two decades. However, to the best of our knowledge there is no empirical evidence on the effects of robot exposure in emerging economies. Our paper attempts to fill this gap in the literature.

Furthermore, while most of the previous papers use cross-sectional data, we are the first to integrate the aggregate analysis on the impact of robots with longitudinal panel data on individual workers. Using panel data enables us to shed light on the heterogeneous effects of robots across sectors and skill-groups. Finally, while several scholars have highlighted the potential effects of automation on social unrest (Schlogl and Sumner, 2018b; Avent, 2016), this is the first paper to estimate the effects of robot exposure on labor strikes and protests.

The paper is organized as follows. In Section 2 we describe our identification strategy. Data are discussed in Section 3. Section 4 presents the main results. Concluding remarks are in Section 5.

2 Empirical Strategy

2.1 Identification Strategy

Following Acemoglu and Restrepo (2018), 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 robots penetration in the Chinese labor market. 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) [3].

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

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

in different industries, and avoid any mechanical correlation or mean reversion with changes in overall or industry-level employment outcomes. 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:

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

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.

Figure 5 displays the increase in exposure to robots across Chinese prefectures between 2006 and 2016 based on the above measure. As seen in Figure 5, 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. We will exploit these variations in our analysis.

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 exploit 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, 2018). 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[4]. 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:

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

$$Exposure\ to\ Robots_{IV_{ct}} = \sum_{s \in S} \ell_{cs}^{2000} (\frac{R_{st}}{L_{s,2000}})_{EU_{Avg}} \tag{2}$$

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 usageamong European countries in sector s and year t[5].

2.2 Baseline specification

To identify the impact of robot exposure on our outcomes of interest, we first estimate the following long-difference equation at the city level:

$$\Delta^{2016-2000} Y_c = \Delta^{2016-2000} Exposure\ to\ Robots_c + X_{c,2000} + \epsilon_c \tag{3}$$

where $\Delta^{2016-2000} Y_c$ are the changes in city-level outcomes, such as employment to population ratio and the natural log of average annual wage, for city c between 2000 and 2016. $\Delta^{2016-2000} Exposure\ to\ Robots_c$ is the change in the city's exposure to robots between 2000 and 2016. $X_{c,2000}$ is a rich set of baseline (year 2000) city-level demographic controls for the natural log of population, the share of males, the share of married, the share of population aged 60 and above, the share of urban population, the shares of population with primary school, secondary school, and college education, the share of ethnic minorities (non-Han Chinese), and the share of migrants; city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west)[6]. Standard errors are clustered at the city level. The estimation sample is weighted using the size of the population of each city in 2000. We use a similar model to analyze province-level data on internal migration and labor strikes.

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

[6]We consider four regions in accordance with the definition used in the Twelfth Five-Year Plan for National Economic and Social Development of China.

As mentioned above, we integrate the aggregate analysis with longitudinal individual data. In the individual-level analysis we estimate:

$$Y_{ict} = Exposure\,to\,Robots_{ct} + X_{ict} + \eta_i + \lambda_c + \xi_t + \epsilon_{ict} \tag{4}$$

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). $Exposure\,to\,Robots_{ct}$ is the exposure to robots of city c in year t. X_{ict} includes a rich set of controls of individual characteristics, including gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* or household registration type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county). η_i are 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. The sample is restricted to individuals between 16 and 65 years old and regressions are weighted using individual weights in the survey.

3 Data

3.1 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 [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[7]; 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 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

[7] In our subsequent analysis for China, 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).

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.

3.2 City-Level Employment and Wage Data

For our aggregate analysis at the city level, we use the 2000 and 2016 *China City Statistical Yearbook*, a comprehensive annual statistical publication by the National Bureau of Statistics in China that reflects China's urban social and economic development. The *City Yearbook* covers all prefecture-level cities in China from 1985 onward and contains a wide range of information including population, labor force, industrial development, infrastructure, natural resources, investments, and social security etc. In particular, the *City Yearbook* reports for each city the annual employment in both state-owned and private sectors[8], the total wage bill paid to employed staff and workers in the state-owned sector[9], and the number of unemployed persons registered in the urban area at the end of the reporting year. Using these data, we constructed our main outcomes of interest at the city level: employment to population ratios (both overall and by ownership of the sector), registered urban unemployment rate, and the natural log of average annual wage[10]. A caveat is that in the *City Yearbook* the

[8]In the *City Yearbook*, the sector which we refer to as "state-owned" actually also includes foreign firms. However, based on national aggregate data released by China's National Bureau of Statistics, in 2000 only 5.5% of the employment in this category belong to foreign firms, while 94.5% of the employment in this category belong to state-owned or state-controlled entities (including both firms and non-commerical institutions); in 2016, roughly 85% of the employment in this category are in state-owned or state-controled entities. For simplicity, we refer to it as the state-owned sector hereafter. In comparison, the private sector consists of both private firms and self-employed individuals.

[9]In the *City Yearbook*, the total wage bill of employed staff and workers in the state-owned sector refers to the total remuneration payment to all employed staff and workers during the reporting year, including basic salary, performance salary, salary allowances and subsidies, and excluding the deductions for personal leave, sick leave and so on.

[10]Employment to population ratios are calculated by dividing the employment (overall or in a sector) by the city population. Registered urban unemployment rate is calculated by dividing the number of registered unemployed urban persons in each city by the city population. Average annual wage is calculated by dividing each city's total wage bill paid to workers in the state-owned sector by the number of workers in the state-

population measure corresponds to the end-of-year number of persons whose *hukou* (household registration) are registered in the city. As a result, this measure potentially excludes migrant workers who work in the city but do not have their *hukou* registered in the same city. A preferred measure of city population would have been the total number of people residing in the city, which would capture the size of the overall city population including migrant workers[11]. Another concern of this data set is that the official statistics on registered urban unemployed persons tend to understate the true unemployment level[12]. Due to these limitations of the *City Yearbook* data, our results on employment and unemployment at the city level should be interpreted with some caution.

Figure 6 shows the 261 prefecture-level cities that are covered by the *City Yearbook* and used in our aggregate analysis[13]. These cities are largely representative of urban China and of the areas with greater exposure to robots. In our sensitivity analysis, we also exclude two outlier cities (Shenzhen and Dongguan) that have the highest exposure to robots.

We also use the 2000 Census of China[14] to construct a rich set of city-level baseline demographic controls including the natural log of population, the share of males, the share of married, the share of population aged 60 and above, the share of urban population, the shares of population with primary school, secondary school, and college education, the share of ethnic minorities (non-Han Chinese), and the share of migrants. In addition, we use the 2000 Census to obtain a set of city-level broad industry share controls that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing.

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owned sector; wage paid to private sector workers is unavailable in the *City Yearbook* data set.

[11]To partially address this concern, we tried using province-level data from China's National Bureau of Statistics which report the total population of each province including migrants. The provincial results point to the same direction as our city-level results and are, if anything, larger in magnitude. Provincial results are available upon request.

[12]See this article: urlhttps://www.nber.org/digest/oct15/w21460.html

[13]The prefectures that are blank in Figure 6 are mostly autonomous regions of ethnic minority groups. They are prefecture-level administrative units but are not classified as prefectural *cities* in China's administrative system. There is no consistent employment or wage data on these prefectures from the *City Yearbook* and therefore they are not included in our city-level analysis.

[14]The 2000 Census is obtained from IPUMS International.

3.3 Individual Longitudinal Data

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, migration, and health. The 2010 baseline survey interviewed approximately 15,000 families and 30,000 individuals. Figure A.1 shows all the counties represented in the CFPS baseline survey. By mapping counties to cities, we assign each individual in each survey wave an robot exposure that corresponds to the robot exposure measure of the city in which the individual lives when the survey was conducted.

Given our focus on the labor market effects of automation, we restricted the sample to the working-age population (between 16 and 65 years old). Our main outcomes of interest are individual employment status (an indicator variable equal to 1 if an individual is employed and 0 otherwise), labor force participation (an indicator variable equal to 1 if an individual is in the labor force and 0 otherwise) and hourly wage[15]. However, a caveat is that information on individual hourly wage is only available for two (2010 and 2014) out of the four waves of surveys[16], which limits the sample size of our individual hourly wage analysis. We therefore supplement the hourly wage data with data on individual annual earnings which are available for all four waves of surveys[17]

[15]Hourly wage is obtained by dividing monthly or weekly wages by the number of hours worked. The hourly wage measurement here consists of only basic salary and does not include other forms of compensations such as floating wage or other benefits.

[16]The 2012 CFPS survey contains individuals' annual wage information but does not have information on hours worked, which prevents us from calculating hourly wage. The 2016 survey only has wage information for those individuals who changed their jobs since the 2014 survey and does not report wage information for individuals who did not change jobs since 2014.

[17]Similar to the problem of hourly wage in 2016, annual earnings in the 2016 survey were not collected from individuals who had the same jobs since 2014. Therefore, the 2016 annual earnings were imputed by

3.4 Data on Migration

We drew our data on migration at the province level from the Migrant Population Service Center of China's National Health Commission. This data set provides the number of migrants (both overall and by gender) within each of China's 31 provinces every five years since 2000 based on the Censuses[18]. The migrant population of each province consists of individuals who reside in a place that is different from the location of the individual's *hukou* and who have lived in the current place for over half a year.

Figure 7 shows the migrant population in China between 2000 and 2017. It is evident from this figure that the migrant population has increased at a slower pace since 2008 and has even started to decline since 2014. This is the case in both absolute and percentage terms. The outcomes of interest for our analysis here are the shares of migrants in the population of each province, both overall and by gender.

To link the province-level migration data to robot exposure, we construct the exposure to robots measure for each province in an analogous fashion as we did for each city, utilizing the employment share of each province in 2000. Because the distribution of robots by sector is only available for China from 2006 onward, we construct the robot exposure of each province in 2010 and 2015 to match with the migration data of those two years. As a result, we end up with a two-year panel of 31 provinces for 2010 and 2015, linking each province's share of migrants in the population to its robot exposure.

3.5 Labor Strike and Protest Data

Because the Chinese government does not publish official statistics on labor strike or protest events, we measure labor unrest using the Strike Map database of China Labor Bulletin (CLB), a Hong Kong-based NGO that advocates labor rights in mainland China. Since

the CFPS team for each individual with these information missing. Our results are robust to excluding 2016 from the individual annual earnings analysis.

[18]The 2000 and 2010 data are based on the Censuses from those years, while the 2005 and 2015 data are based on the 1% mini-Censuses of those years.

2011, CLB has been recording labor strike and protest incidents in China and publishing these statistics on CLB's Strike Map database[19]. Between 2011 and 2017, CLB updates the Strike Map database daily through 24/7 monitoring, building on information usually posted on Chinese social media (e.g. Sina Weibo, Tianya, and WeChat) and occasionally in the official media. CLB reports for each labor incident the date, location, sector, number of participants, and a brief description on the nature and cause of the event.

We use the CLB Strike Map data for the period of 2011-2016, which consists of about 8,000 labor incidents in total. Figure 8 shows the number of labor strikes and protests recorded by CLB between 2011 and 2016. As seen in this figure, the total number of labor strikes and protests has risen drastically in recent years, increasing from 184 recorded events in 2011 to 2,664 in 2016.

We further categorize each incident by its cause. We classify an event as triggered by wage issues if a word related to wage or compensation is mentioned in the cause of the incident[20]. Similarly, we classify a strike or protest event as triggered by layoff if a word related to layoff or business closure is mentioned in the cause of the incident[21]. Figure 8 shows that wage issues contributed to most of the CLB strikes and protests during this period. The number of layoff-triggered incidents has been rising steadily in recent years as well, increasing from 7 recorded in 2011 to 385 in 2016. Besides, we also plot in Figure 8 the number of CLB events in manufacturing, which is the sector with the most recorded events (almost a third of the total) during this period.

For our regression analysis we aggregate the CLB data to the province-by-year level to create a province panel between 2011 and 2016. We measure the intensity of strikes and labor protests by the number of recorded CLB events per million of 2000 workers, which we use as our outcome of interest. Figure 9 maps out the total number of CLB events per million workers between 2011 and 2016 across provinces. It can be seen from this map

[19] The link to CLB's Strike Map is `https://maps.clb.org.hk/strikes/en`

[20] This list of words includes "wage", "pay", "salary", "compensation", "bonus", "benefit", "unpaid", as well as Chinese words of the same meanings.

[21] These words include "layoff", "closure", and "relocation".

that the eastern part of China has experienced the largest surge in labor strike and protest incidents in recent years. For our analysis we also construct similar measures of the intensity of strikes and labor protests by specific cause and sector. We relate the outcomes measuring each province's labor unrest to the province's robot exposure.

4 Main Results

4.1 City-level Analysis

First, we explore the impact of industrial robots on employment across Chinese cities. Table 1 analyzes the relationship between the change in the exposure to robots between 2000 and 2016 and the change in the employment to population ratio observed during the same period. All estimates include year 2000 baseline city-level demographic controls for the natural log of population, the share of males, the share of married, the share of population aged 60 and above, the share of urban population, the shares of population with primary school, secondary school, and college education, the share of ethnic minorities (non-Han Chinese), and the share of migrants; city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west). Standard errors, shown in parentheses, are clustered at the city level. The sample is restricted to the 261 prefectural cities covered in the *China City Statistical Yearbook* in 2000 and 2016. Our measure of robot exposure is standardized, and so are employment to population ratios and unemployment rates. Finally, the estimation sample is weighted using the population of each city.

Interestingly we find no evidence of significant effects on overall employment to population ratio[22]. However, interestingly this effect masks substantial heterogeneity across sectors

[22] We obtain the overall employment to population ratio by summing up the ratios in the state-owned and the private sectors.

(Panel A). Indeed, consistent with recent evidence suggesting that state-owned firms are more likely to receive innovation subsidies, Panel B shows that the effect of robot exposure in the state-owned sector is negative and significant. Based on the OLS estimate in Column 1 of Panel B, a 1 standard deviation change in robot exposure would yield a reduction of .2 standard deviation in employment to population ratio of the state-owned sector between 2000 and 2016. However, this effect is not precisely estimated. Column 2 reports the first-stage of our 2SLS estimate. Our instrument is strongly correlated with our endogenous measure of robot exposure, with the first-stage F-test statistic well above conventional levels. There is a strong negative reduced-form relationship between the instrument and the employment to population ratio (Column 3). Column 4 reports the 2SLS estimate, which is similar in magnitude to the OLS estimate and significant at the 10% level. According to the 2SLS estimate, a one standard deviation increase in robot exposure would decrease employment to population ratio by about .3 standard deviations in the state-owned sector. In the last column of Panel B, we report the 2SLS estimate after excluding the two cities (Shenzhen and Dongguan) that experienced the largest increase in exposure to robots between 2000 and 2016[23]. The 2SLS estimate becomes more precisely estimated after removing these two cities. This is likely due to the fact that Shenzhen and Dongguan, while being highly exposed to robots, experienced the largest increase in employment to population ratios as well. Therefore, the inclusion of these two cities tends to attenuate the negative impact of robots on employment and introduce more noise into our estimates. On the contrary we find no evidence of significant effects among private firms (Panel C).

To provide further support to the negative impact on employment found in Table 1, we next turn to the effects of industrial robots on measures of unemployment. Table 2 investigates the relationship between the change in the exposure to robots between 2000 and 2016 and the change in the registered urban unemployment rate observed in the same period. The OLS estimate in Column 1 is positive, although again marginally insignificant (p-value =

[23]Between 2000 and 2016, the change in the exposure to robots for Shenzhen is 5.5 based on our measure and that for Dongguan is 4.9, as compared to a mean of 0.76.

0.13). Based on the OLS estimate, a one standard deviation increase in robot exposure would increase urban unemployment by 0.37 standard deviation. The more precisely estimated IV result in Column 4 suggests that a one standard deviation increase in robot exposure would increase unemployment by .87 standard deviation. The effect becomes slightly smaller but still positive and statistically significant when we exclude the two outlier cities in Column 5. These coefficients are extremely large and may in part reflect the lack of precision of the data on the registered urban unemployed workers as well as the fact that the denominator does not include the migrant population potentially leading to a significant underestimation of the relevant population of reference in the labor market.

Cities that were more exposed to robot penetration between 2000 and 2016 also experienced a marked decline in wages. We find that a one standard deviation increase in robot exposure decreased wages by 6.8% (column 1 of Table 3). Again, the 2SLS estimate is, if anything, larger in absolute value pointing to a 7.7% reduction in wages (column 4).

Overall, our IV estimates show more negative effects of robots than the OLS estimates across our city-level results. This is consistent with the idea that the OLS estimates may be upward biased, as economic growth is likely correlated with both robots adoption and increased labor demand in Chinese cities. There may also be measurement errors in our Chinese data, which tend to attenuate our results towards zero. The IV strategy mitigates these potential sources of bias.

Interestingly, investigating the results separately for cities whose baseline (2000) employment share in manufacturing was above the median versus those that were below the median, we find that negative effects are largely concentrated on cities specialized in manufacturing and non-significant in other cities (see Table 4). This finding supports the intuition that cities with larger baseline shares of manufacturing jobs are more affected by the adoption of robots.

4.2 Individual Analysis

The aggregate analyis documents a large negative effects of robots exposure on employment and wages. However, this evidence and in particular the magnitude of the effects should be interpreted with caution due to the lack of reliability of aggregate data on employment and unemployment at the prefecture level. While it is worth noting that we find similar effects when examining province-level data, to further strengthen the analysis and investigate the underlying mechanisms of these labor market effects, we turn to the use of individual longitudinal data. Furthermore, CFPS data allows us to shed further light on the heterogeneity of the effects among workers.

Table 5 reports the effects of robot exposure on employment status and labor market participation. Columns 1-3 controls for individual characteristics, including gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county). Column 4 also controls for individual fixed effects, thereby exploiting only within worker variation in exposure to robots. Standard errors are clustered at the city level. All estimates use individual weights in the survey. The outcome variable is an indicator variable equal to 1 if an individual is employed (Panel A), or reported to be in the labor force (Panel B), or unemployed (Panel C) and 0 otherwise.

The individual-level analysis of the effects on employment substantially confirms what we find in the city-level data (Panel A). The OLS estimate suggests a significant negative relationship between robot exposure and the likelihood of being employed. In terms of magnitude, an increase by 1 standard deviation in robot exposure lowers an individual's probability of being employed by 2.9 percentage points. Effects are, if anything, larger when accounting for individual fixed effects (column 4). These effects are driven by a decline in labor force participation (Panel B). Restricting the sample to individual in the labor force (Panel C), we find that a one standard deviation increase in robot exposure reduces the likelihood of reporting unemployed status by 0.08 percentage points (a 22 % reduction with respect to the mean). However, the point-estimate becomes only marginally significant (column 5, p-value=0.13).

Similarly, Table 6 analyzes the effects on hourly wages, hours worked, and annual earnings. We find that a 1 standard deviation increase in robot exposure lowers an individual's hourly wage by 7 percent (column 4, Panel A). At the same time we found no evidence of significant changes in the number of hours worked (Panel B), although the average working hours, if anything, increased for those who did not lose a job. Examining annual earnings for the entire population (including the non-employed to which we assign an earning equal to zero), we find that annual earnings decreased by 14% in cities that were more exposed to robot penetration (see Panel C). [24].

4.3 Heterogeneity by skill, age, and gender

4.3.1 Effects by Education

Exploring the heterogeneity of the effects by skill, Table A.1 shows that effects on labor force participation and employment are larger among the low-skilled. A one standard deviation increase in robot exposure reduces labor force participation by 3.7 percentage points (approximately a 5% reduction with respect to the mean) among workers with a middle school education or below. Effects are considerably smaller among workers with a college degree or more, for whom a 1 standard deviation increase in robot exposure implies a 2.4% reduction with respect to the mean. We find instead no significant differences on the likelihood of being unemployed, although all coefficients are statistically insignificant. Finally, the income effects are concentrated among the low-skilled for whom a 1 standard deviation increase in robot exposure reduces annual income by 22.6%.

[24]These effects are substantially unchanged when using 1982 as the base year to construct our instrumental variable (see Tables A.6 and A.7 in the Appendix).

4.3.2 Effects by Age

Furthermore, we find that the effect of robot exposure is concentrated among prime-age and older workers (Table A.2). In particular, Panel A and B show that, if anything, the younger workers (16-24) are more likely to participate in the labor force and to be employed (column 1) in areas that were more exposed to robot penetration. In constrast, the effects on labor force participation and employment are negative among prime-age workers and those over 45 (columns 2 and 3). In particular, there is evidence of a large negative effect on labor force participation of the 45-65 years old. A one standard deviation increase in robot exposure decreases their labor force participation by 4.7 percentage points (a 6.6% reduction with respect to the mean). Robot exposure increases the risk of unemployment among prime-age workers (25-44), who are less likely than the over 45 to drop from the labor force (Panel C, column 2). Interestingly, among the over 45 who kept their job, those working in cities that were more exposed to robot penetration are working longer hours (+ 6%, Panel D, column 3). Finally, robot penetration reduces by 15% (14%) the annual income of prime-age (over 45) workers (Panel E).

4.3.3 Effects by Gender

Robot exposure affects men and women's labor force participation and employment rates similarly (columns 1 and 2 of Table A.3). However, the effects on unemployment and income (columns 3 and 5) are significant only among men and larger in absolute value. A one standard deviation increase in robot exposure increased the risk of unemployment by 28% with respect to the mean, while the effect on women is three times smaller in magnitude and not statistically different from zero. Similarly we find that the effect on income is concentrated among men for whom a 1 standard deviation increase in robot exposure would reduce income by 16.8% , while it is smaller and less precisely estimated among women. At the same time our results indicate that among women a 1 standard deviation increase in robot exposure increased hours worked by 5.4%, while there is no significant effect among men.

4.4 Effects on Internal Migration

To analyze the effects of robot exposure on internal migration we drew province-level data from the Migrant Population Service Center of China's National Health Commission. As mentioned above, since 2008 there has been a decline in the growth rate of the migrant population which has begun declining since 2014. Robot penetration and automation may affect internal migration. Indeed, we would expect individuals to react to the change in labor market returns. Using a panel of 31 Chinese provinces in 2010 and 2015, we find that robot exposure reduces net migrant inflow (Table 7). A one standard deviation increase in robot exposure reduces by .13 standard deviation the population share of migrants in a province. Effects are slightly larger among women (.16 standard deviation decrease).

4.5 Social Unrest

To investigate the effects of robot exposure on social unrest we use data drawn from the Strike Map database of China Labor Bulletin (CLB) for the period 2011-2016. As shown in Figure 8, strikes have been increasing significantly over the last few years. Using a province-year level measure of the intensity of labor strikes and protests, we examine the effects of robot exposure on province-year labor unrest (Table 8).

We find that a one standard deviation increase in robot exposure led to a .3 standard deviation increase in the overall rate of strikes and protests (column 1) . The effects are particularly large when focusing on layoff-related strikes (.6 standard deviation increase) and larger in the manufacturing sector (columns 4-6). While we found no evidence of significant effects in construction.

These effects should be interpreted cautiously as the measure of strike intensity is likely to be noisy and imperfect. Yet, these results support the rising concerns that automation and the robotization of work in developing countries may increase social unrest (Yusuf, 2017;

Avent, 2016).

4.6 Robustness Checks

Our results are robust to several robustness checks. First, we show that the point-estimates of the effects on wages and employment at the city-level are not sensitive to the removal of one city at a time from the sample. These checks are shown graphically in Figures A.2 and A.3, which verifies that our results are not driven by any particular city in China.

Second, one may be concerned about other potential confounding factors at play. One potential confounding factor is the offshoring of industries away from China. 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 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 measures of offshoring away from China in our regressions as a robustness check. In particular, in our city-level long-difference regressions, we control for the changes between 2000 and 2016 in the amount of foreign direct investments and in the value of output by foreign industrial enterprises (including Hong Kong, Macau, and Taiwan firms) in each city. In our individual regressions, we also include time-varying controls for foreign direct investments and output value of foreign industrial enterprises as a robustness check. Table A.4 and A.5 report our baseline results after adding in these controls. As shown in these tables, our results are robust to the inclusion of these controls for off-shoring away from China and, if anything, become larger in magnitude and more precisely estimated (especially for individual wage results, see columns 3 and 4 of Table A.5).

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[25].

As a robustness check, in the Appendix we replicated the main estimates using 1982 as the base year to construct the measure of exposure to robots across Chinese cities. Overall we confirm the main results. However, due to the changes in the boundaries that occurred between 1982 and 2000, we do lose some identification power and as a result the aggregate estimates are somehow less precise and larger in magnitude. On the contrary, individual estimates are practically unchanged (Tables A.6-A.7).

Finally, in a placebo test (Table 9) we examined the effect of robot exposure between 2006 and 2016 on lagged values of labor market outcomes. In practice, we regressed changes in employment, unemployment and wage between 1990 and 2000 on the exposure to robots between 2006 and 2016. Reassuringly, we find no evidence of pre-trends in both employment and wage.

5 Conclusions

The utilization 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 have so far little or no empirical evidence from developing countries. Our paper attempts to fill this gap in the literature.

In this study, we investigate the effects of industrial robots on Chinese employment and wages. We find that an increase by 1 standard deviation in robot exposure lowers an individual's probability of being employed by 5% with respect to the mean and reduces hourly wages by 7%. Our evidence suggests that the negative effects on employments are largely driven by the state-owned sector. Effects are concentrated among low-skilled workers and larger on men and prime-age and older workers. Furthermore, cities with an initial higher specialization in manufacturing suffer significantly higher losses in terms of workers'

[25] These results are available upon request.

employment and wages. Results hold to the inclusion of individual fixed effects, exploiting within-worker changes in exposure to robots over time. We find that in areas that were most exposed to the adoption of industrial robots, in-migration flows reduced significantly. We also show that robot exposure led to increased labor unrest. Furthermore, our results are not sensitive to the inclusion of controls for offshoring away from China. Finally, we find no evidence of pre-trends supporting the validity of our identification strategy.

New technologies, AI and automation may have positive impacts on growth and productivity which could eventually increase demand for higher-skilled workers. Yet, 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.

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 in employment growth or what will be the political consequences of the labor market effects of automation and digitalisation are important questions that demand further scientific investigation.

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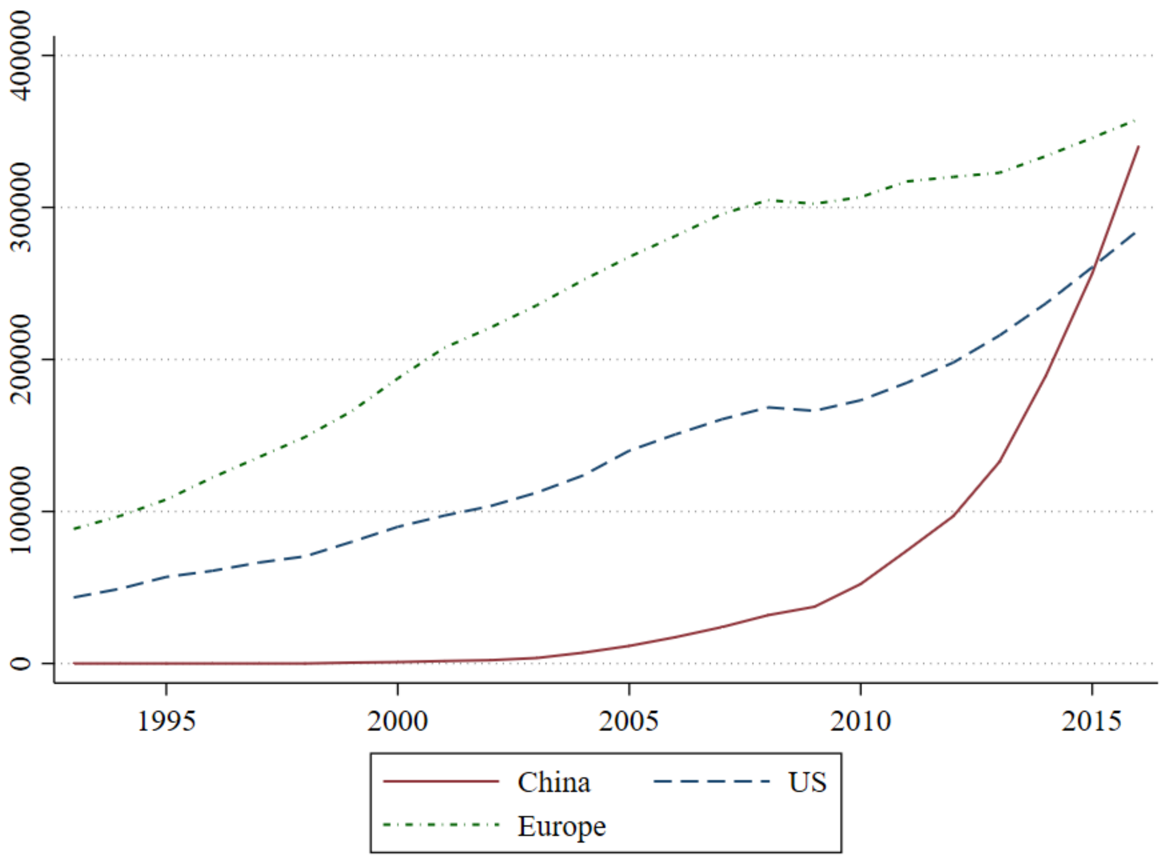
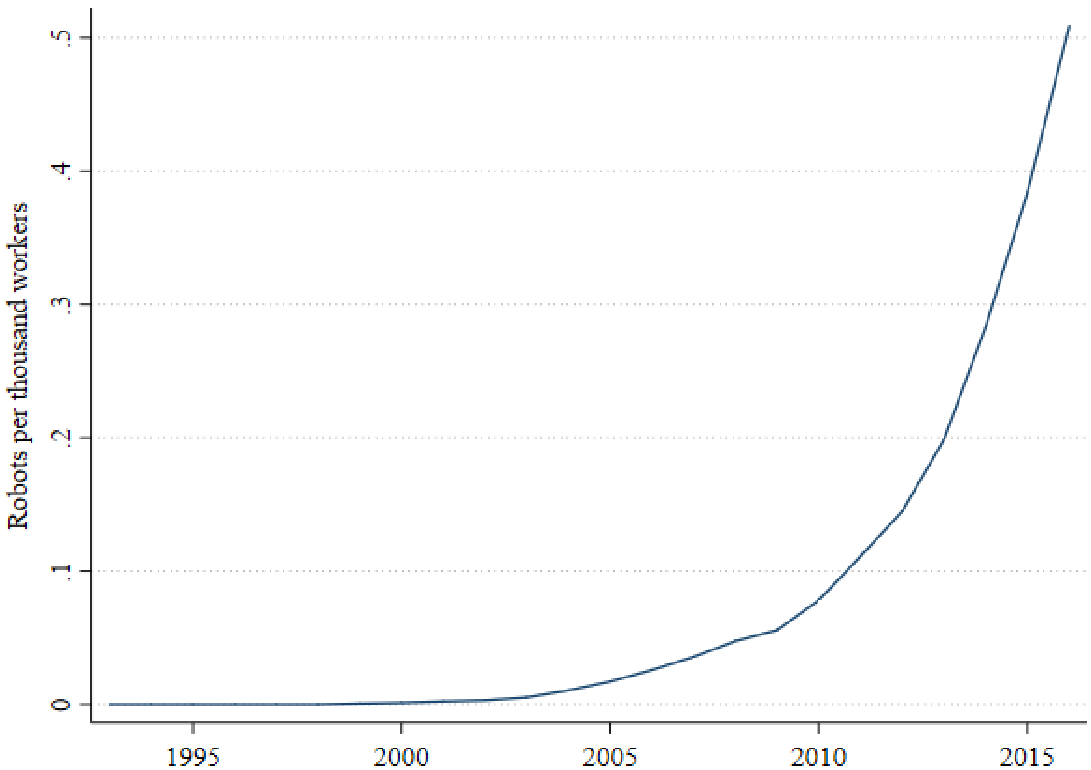
Figure 1: Operational Stock of Industrial Robots, 1993-2016



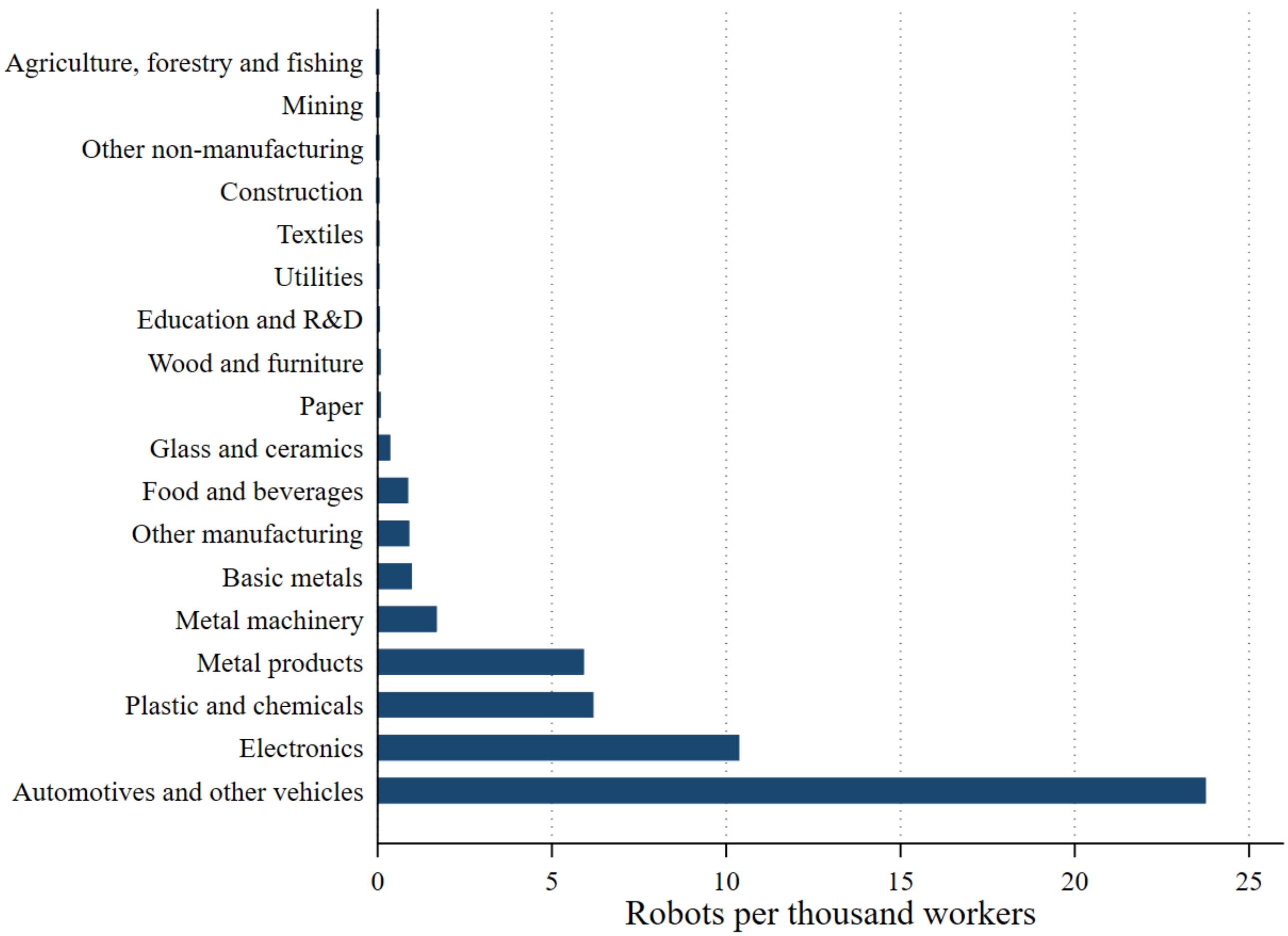
Notes - Data are drawn from the International Federation of Robotics (IFR).

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



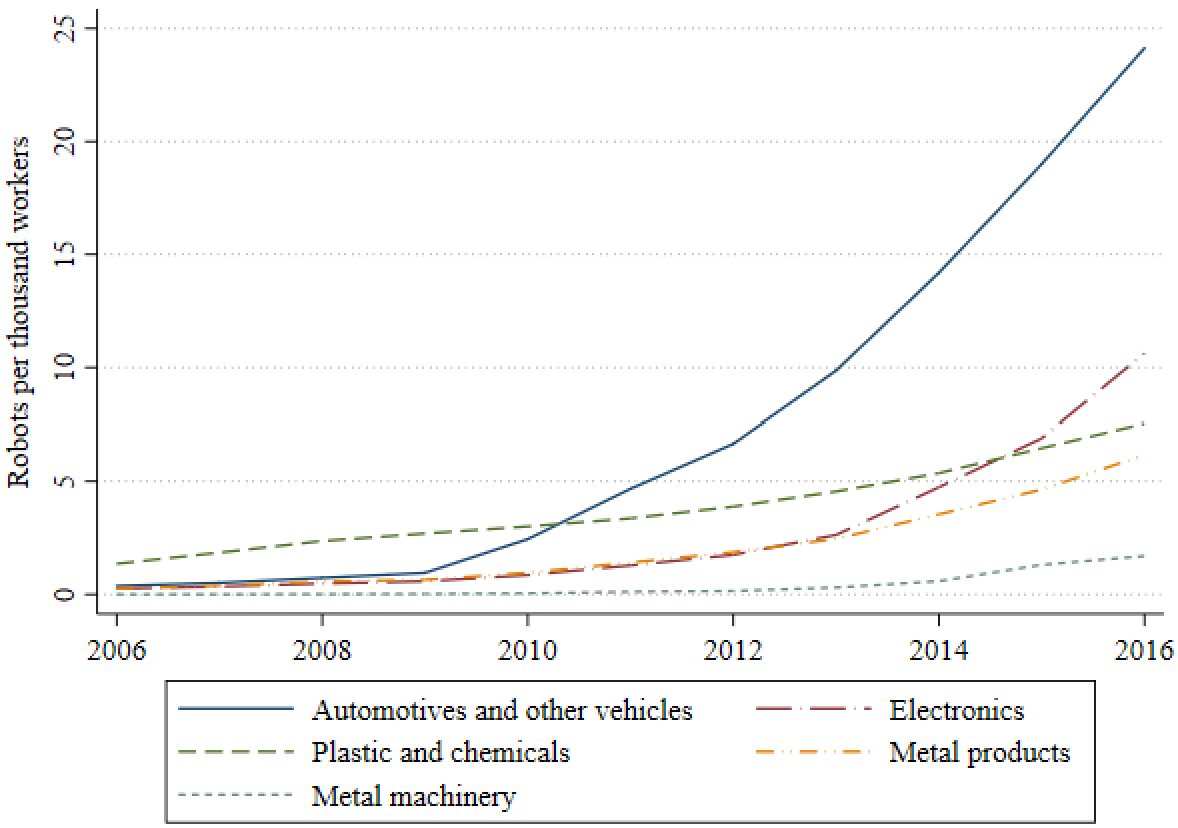
Notes - Data are drawn from the International Federation of Robotics (IFR).

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



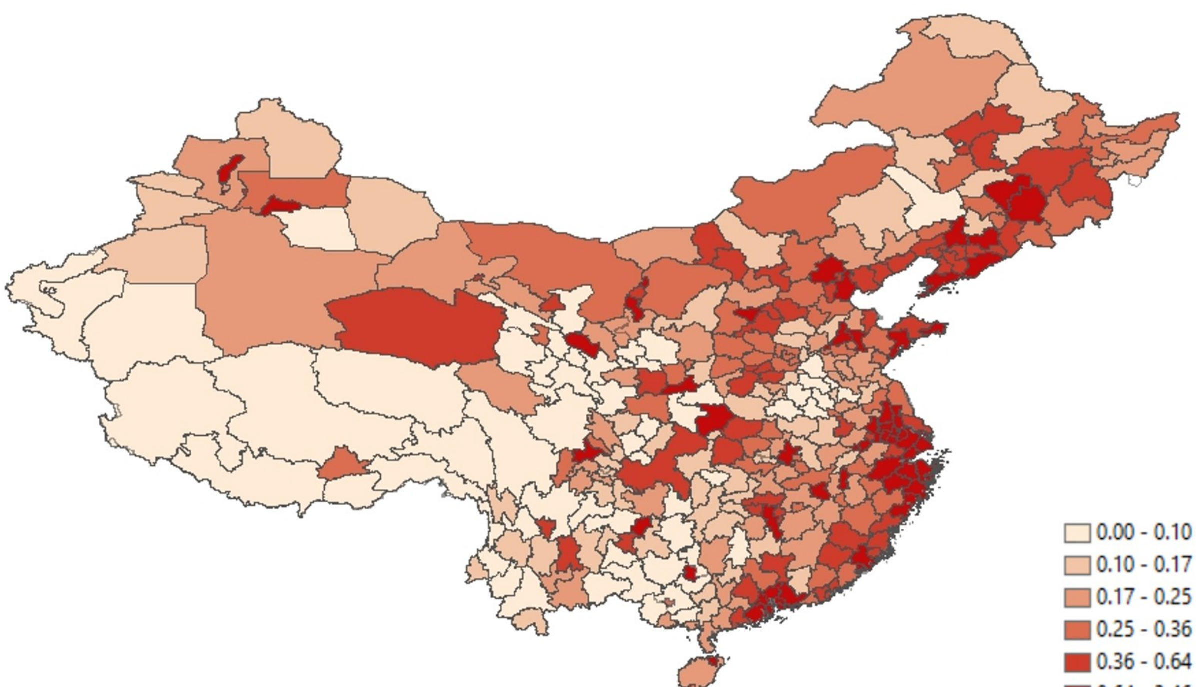
Notes - Data are drawn from the International Federation of Robotics (IFR).

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



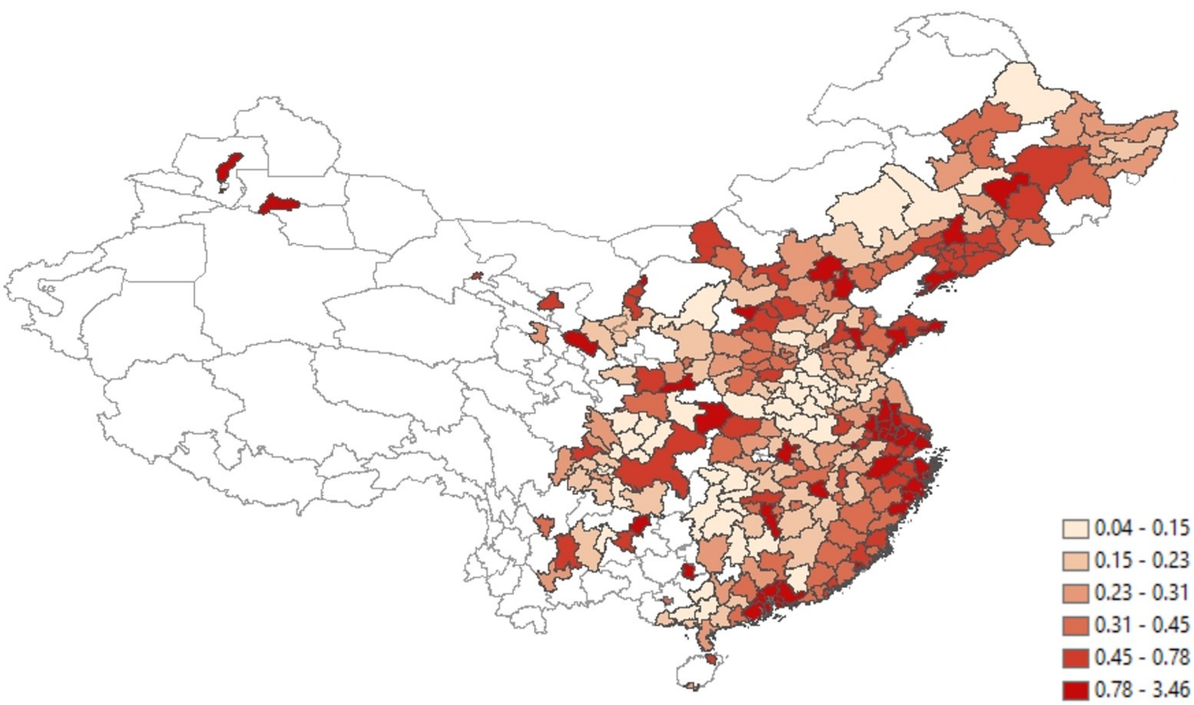
Notes - Data are drawn from the International Federation of Robotics (IFR).

Figure 5: Exposure to Robots Across Prefectures between 2006 and 2016



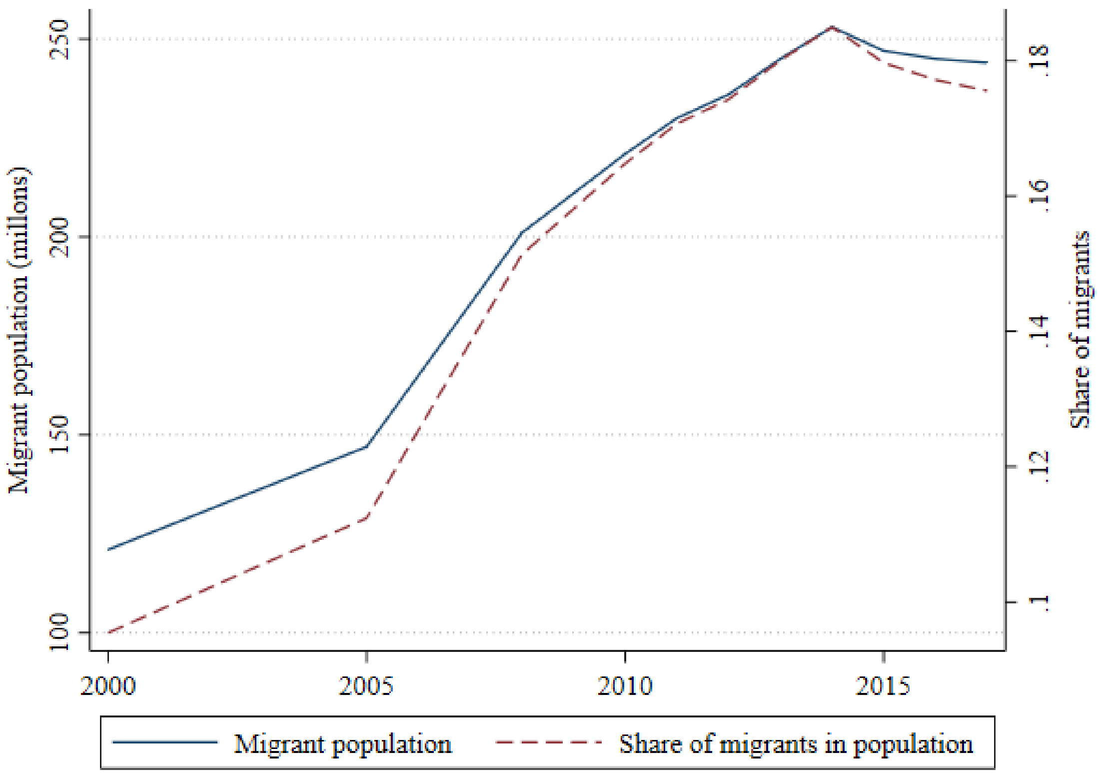
Notes - Data are drawn from the International Federation of Robotics (IFR) and China's 2000 Census.

Figure 6: Exposure to Robots Across Prefecture-level Cities between 2006 and 2016



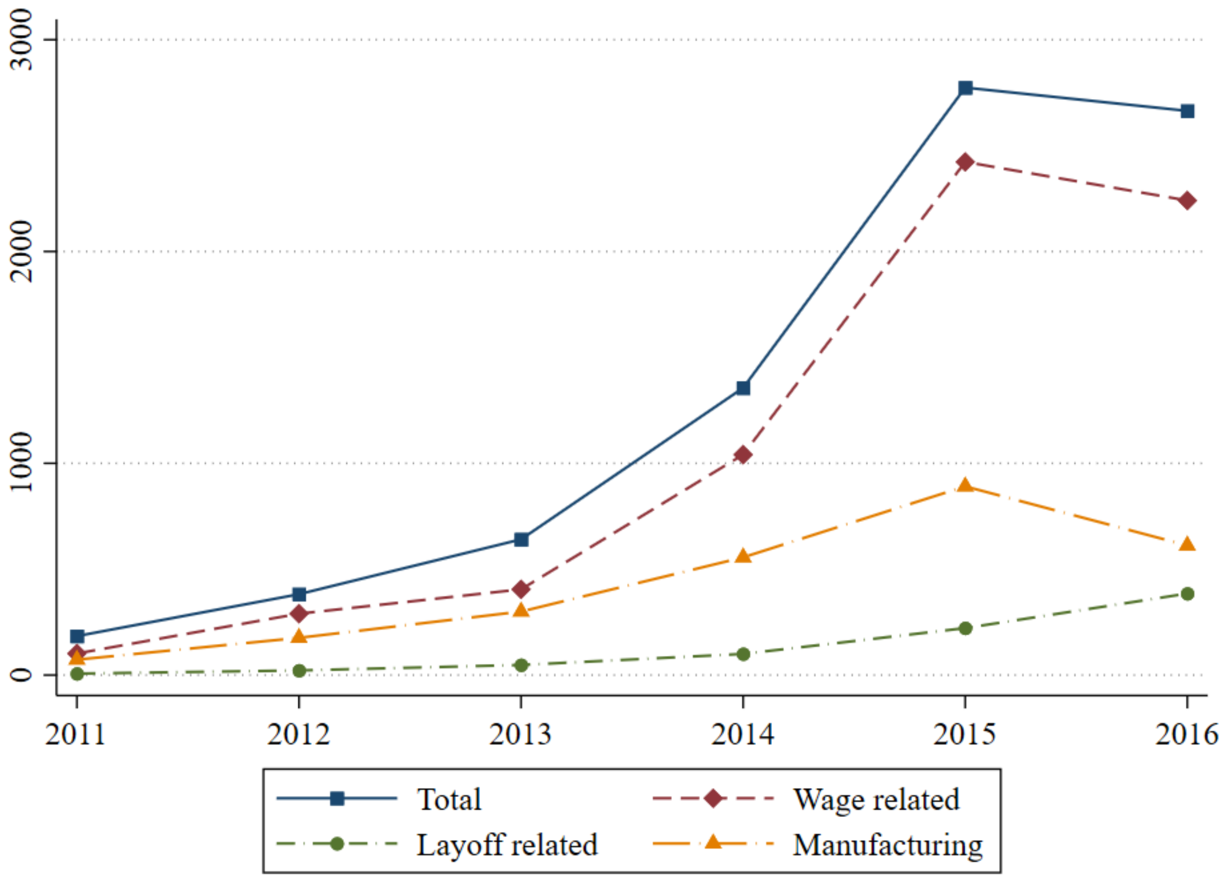
Notes - Data are drawn from the International Federation of Robotics (IFR) and China's 2000 Census.

Figure 7: Migrant Population in China, 2000-2017



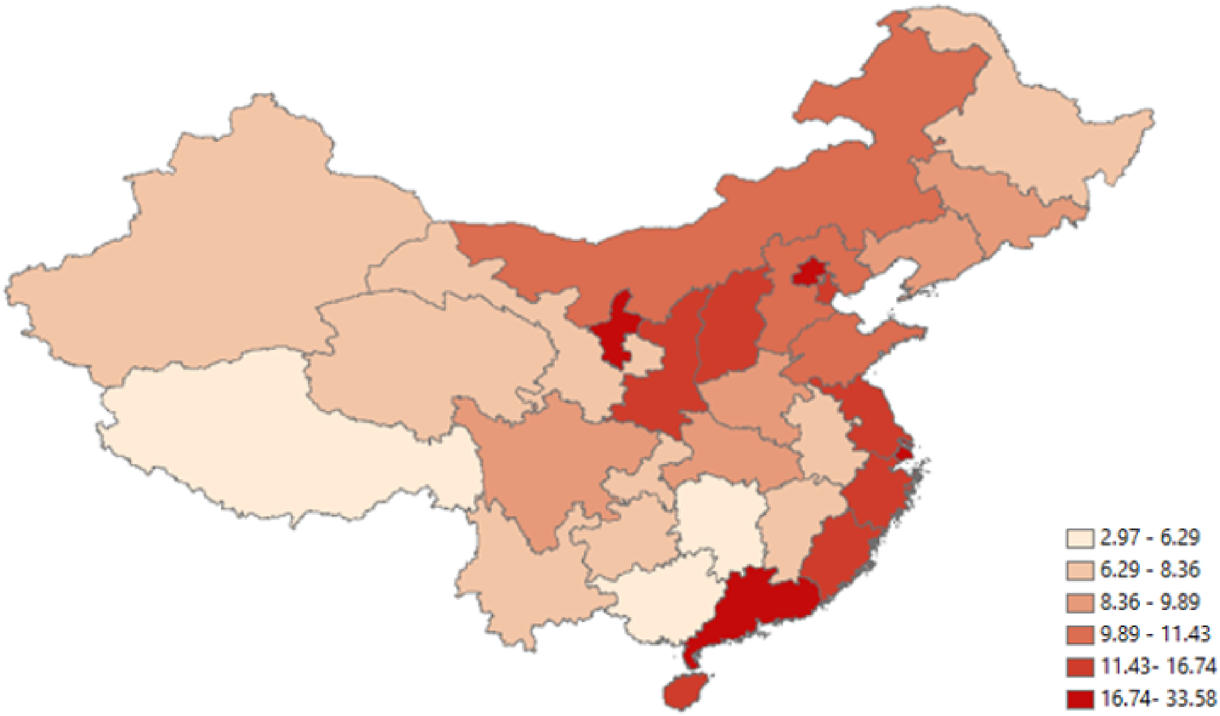
Notes - Data are drawn from the Migrant Population Service Center of China's National Health Commission.

Figure 8: Number of CLB Labor Strikes and Protests, 2011-2016



Notes - Data are drawn from the Strike Map database of China Labor Bulletin (CLB).

Figure 9: Intensity of Labor Strikes and Protests across Provinces, 2011-2016



Notes - Data are drawn from the Strike Map database of China Labor Bulletin (CLB). Intensity of labor strikes and protests in each province is measured as the total number of CLB strike and protest incidents during 2011-2016 per million of 2000 workers.

Table 1: Robot Exposure and Employment, Aggregate Analysis

Outcome: ΔEmployment to population ratio	(1) OLS	(2) First-stage	(3) Reduced form	(4) 2SLS	(5) 2SLS
Panel A: Overall					
ΔExposure to robots	0.055	0.659***	-0.073	-0.110	-0.036
	(0.134)	(0.049)	(0.127)	(0.189)	(0.174)
First-stage F stat		183.6		183.6	210.9
Observations	245	245	245	245	243
Panel B: State-Owned Sector					
ΔExposure to robots	-0.197	0.654***	-0.228*	-0.348*	-0.348**
	(0.157)	(0.049)	(0.132)	(0.200)	(0.168)
First-stage F statistic		176.7		176.7	200.3
Observations	260	260	260	260	258
Panel C: Private Sector					
ΔExposure to robots	0.199	0.659***	0.021	0.032	0.153
	(0.172)	(0.049)	(0.148)	(0.214)	(0.214)
First-stage F stat		183.7		183.7	211.1
Observations	246	246	246	246	244
Region FE	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Broad industry shares	Yes	Yes	Yes	Yes	Yes
Remove highly exposed cities					Yes

Notes - Data are drawn from *China City Statistical Yearbook* (2000 and 2016) published by China's National Bureau of Statistics. The table presents estimates of the impact of exposure to robots on changes in employment to population ratios between 2000 and 2016 across prefectural cities in China. Panel A presents the overall estimates. Panel B presents the estimates for the state-owned sector. Panel C presents the estimates for the private sector. All estimates control for city-level demographic characteristics in 2000 (natural log of population, share of males, share of married, share of population aged 60 and above, share of urban population, shares of population with primary school, secondary school, and college education, share of ethnic minorities, and share of migrants); city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west). Column 5 excludes two outlier cities (Shenzhen and Dongguan) with the highest exposure to robots. Exposure to robots and employment to population ratios are standardized. The estimation sample is weighted using the 2000 population of each city. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 2: Robot Exposure and Unemployment, Aggregate Analysis

Outcome: ΔRegistered urban unemployment rate	(1) OLS	(2) First-stage	(3) Reduced form	(4) 2SLS	(5) 2SLS
ΔExposure to robots	0.372	0.657***	0.575***	0.875***	0.689***
	(0.249)	(0.050)	(0.171)	(0.251)	(0.241)
First-stage F stat		175.8		175.8	202.4
Observations	255	255	255	255	253
Region FE	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Broad industry shares	Yes	Yes	Yes	Yes	Yes
Remove highly exposed cities					Yes

Notes - Data are drawn from *China City Statistical Yearbook* (2000 and 2016) published by China's National Bureau of Statistics. The table presents the estimates of the impact of exposure to robots on changes in the registered urban unemployment rate between 2000 and 2016 across prefectural cities in China. All estimates control for city-level demographic characteristics in 2000 (natural log of population, share of males, share of married, share of population aged 60 and above, share of urban population, shares of population with primary school, secondary school, and college education, share of ethnic minorities, and share of migrants); city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west). Column 5 excludes two outlier cities (Shenzhen and Dongguan) with the highest exposure to robots. Exposure to robots and registered urban unemployment rate are standardized. The estimation sample is weighted using the 2000 population of each city. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 3: Robot Exposure and Wages, Aggregate Analysis

Outcome: ΔLog(average annual wage)	(1) OLS	(2) First-stage	(3) Reduced form	(4) 2SLS	(5) 2SLS
ΔExposure to robots	-0.068***	0.654***	-0.051**	-0.077**	-0.073**
	(0.026)	(0.049)	(0.021)	(0.033)	(0.032)
First-stage F stat		176.7		176.7	200.5
Observations	261	261	261	261	259
Region FE	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Broad industry shares	Yes	Yes	Yes	Yes	Yes
Remove highly exposed cities					Yes

Notes - Data are drawn from *China City Statistical Yearbook* (2000 and 2016) published by China's National Bureau of Statistics. The table presents the estimates of the impact of exposure to robots on changes in the natural log of average annual wage in the state-owned sector between 2000 and 2016 across prefectural cities in China. All estimates control for city-level demographic characteristics in 2000 (natural log of population, share of males, share of married, share of population aged 60 and above, share of urban population, shares of population with primary school, secondary school, and college education, share of ethnic minorities, and share of migrants); city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west). Column 5 excludes two outlier cities (Shenzhen and Dongguan) with the highest exposure to robots. Exposure to robots is standardized. The estimation sample is weighted using the 2000 population of each city. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: By Baseline Share of Manufacturing Employment, Aggregate Analysis

	(1)	(2)	(3)	(4)	(5)	(6)
2SLS	Manufacturing share above median			Manufacturing share below median		
Outcome: Δs in	Employment to Pop ratio	Unemployment rate	Log(annual wage)	Employment to Pop ratio	Unemployment rate	Log(annual wage)
ΔExposure to robots	-0.303*	0.663***	-0.080**	0.108	-0.032	0.120
	(0.167)	(0.238)	(0.031)	(0.204)	(0.985)	(0.093)
Observations	129	126	129	129	127	130
Region FE	Yes	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes	Yes
Broad industry shares	Yes	Yes	Yes	Yes	Yes	Yes

Notes - Data are drawn from *China City Statistical Yearbook* (2000 and 2016) published by China's National Bureau of Statistics. The table presents estimates of the impact of exposure to robots on the 2000-2016 changes in employment to population ratio in the state-owned sector, registered urban unemployment rate and the natural log of average annual wage in the state-owned sector for two types of cities. Column 1-3 present the estimates for the subsample of cities whose employment share in manufacturing was above the median in 2000. Column 4-6 present the estimates for the subsample of cities with below-median employment share in manufacturing in 2000. All estimates control for city-level demographic characteristics in 2000 (natural log of population, share of males, share of married, share of population aged 60 and above, share of urban population, shares of population with primary school, secondary school, and college education, share of ethnic minorities, and share of migrants); city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west). Exposure to robots, employment to population ratio and registered urban unemployment rate are standardized. The estimation sample is weighted using the 2000 population of each city. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Robot Exposure, Employment, and Labor Force Participation, Individual-Level Analysis

	(1) OLS	(2) Reduced form	(3) 2SLS	(4) 2SLS
		Panel A: Employed		
Exposure to robots	-0.029***	-0.166***	-0.025***	-0.036**
	(0.007)	(0.051)	(0.008)	(0.009)
Observations	111,339	111,339	111,339	102,217
First-stage F stat			281.2	233.9
Mean of Dep. Var.	0.688	0.688	0.688	0.704
Std.Dev. of Dep. Var.	0.463	0.463	0.463	0.456
		Panel B: Labor Force Participation		
Exposure to robots	-0.025***	-0.125***	-0.019***	-0.034**
	(0.005)	(0.045)	(0.007)	(0.008)
Observations	111,339	111,339	111,339	102,217
Mean of Dep. Var.	0.720	0.720	0.720	0.734
Std.Dev. of Dep. Var.	0.449	0.449	0.449	0.442
First-stage F stat			281.2	225.6
		Panel C: Unemployed		
Exposure to robots	0.007	0.076**	0.012**	0.008
	(0.006)	(0.035)	(0.005)	(0.005)
Observations	80,115	80,115	80,115	70,581
Mean of Dep. Var.	0.0436	0.0436	0.0436	0.0372
Std.Dev. of Dep. Var.	0.204	0.204	0.204	0.189
First-stage F stat			283.2	233.1
Individual controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	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 employment status and labor force participation of individuals aged between 16 and 65 in the 2010-2016 CFPS survey. The outcome variable is an indicator variable equal to 1 if an individual is employed (Panel A), or reported to be in the labor force (Panel B), or unemployed (Panel C) and 0 otherwise. All estimates include individual sociodemographic controls for gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county), city fixed effects and year (survey wave) fixed effects. Column 4 also controls for individual fixed effects. Exposure to robots is standardized. The estimation sample is weighted using individual weights. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Robot Exposure, Income, and Working Hours, Individual-Level Analysis

	(1) OLS	(2) Reduced form	(3) 2SLS	(4) 2SLS
	Panel A: log(hourly hage)			
Exposure to robots	-0.116***	-1.014***	-0.157***	-0.072*
	(0.034)	(0.294)	(0.050)	(0.038)
Observations	14,585	14,585	14,585	5,244
First-stage F stat			31.65	11.83
	Panel B: log(hours worked)			
Exposure to robots	0.026**	0.099	0.015	0.036
	(0.011)	(0.083)	(0.013)	(0.022)
Observations	42,961	42,961	42,961	26,459
First-stage F stat			302	206.3
	Panel C: log(annual earnings)			
Exposure to robots	-0.241***	-1.757***	-0.261***	-0.144**
	(0.086)	(0.478)	(0.076)	(0.055)
Observations	37,834	37,834	37,834	26,838
First-stage F stat			269.3	227.9
Individual controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	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 income and working hours of individuals aged between 16 and 65 in the 2010-2016 CFPS survey. The outcome variable in Panel A is the natural log of hourly wage. The outcome in Panel B is the natural log of weekly working hours. The outcome in Panel C is the natural log of annual earnings. All estimates include individual sociodemographic controls for gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county), city fixed effects and year (survey wave) fixed effects. Column 4 also controls for individual fixed effects. Exposure to robots is standardized. The estimation sample is weighted using individual weights. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Robot Exposure and Internal Migration (2SLS)

	(1)	(2)	(3)
	Share of Migrants in Population		
	Total	Men	Women
Exposure to Robots	-0.128**	-0.104*	-0.161**
	(0.061)	(0.057)	(0.066)
Province controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	62	62	62

Notes - Data are drawn from the Migrant Population Service Center of China's National Health Commission. The table presents the 2SLS estimates of the impact of exposure to robots on the share of migrants in population across China's 31 provinces between 2010 and 2015. Column 1 presents the overall estimate, while Column 2 and 3 present the estimates by gender of migrants. All estimates include control for the share of male population, the share of population aged 65 and above, the share of population with college education, the natural log of GDP of each province, province fixed effects and year fixed effects. Exposure to robots is standardized. Regressions are weighted using the 2000 population of each province. Standard errors, shown in parentheses, are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 8: Robot Exposure and Intensity of Labor Strikes and Protests (2SLS)

	(1)	(2)	(3)
	Panel A: Overall		
	Total	Wage-related	Layoff-related
Exposure to robots	0.288*	0.332**	0.668***
	(0.173)	(0.156)	(0.254)
Observations	186	186	186
	Panel B: Manufacturing Sector		
	Total	Wage-related	Layoff-related
Exposure to robots	0.541***	0.637***	0.852***
	(0.094)	(0.095)	(0.270)
Observations	186	186	186
Province controls	Yes	Yes	Yes
Province FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes - Data are drawn from the Strike Map database of China Labor Bulletin (CLB) for the period of 2011-2016. The table presents the 2SLS estimates of the impact of exposure to robots on labor strike and protest intensity across China's 31 provinces for the period 2011-2016. Labor strike and protest intensity is measured as the number of CLB strike and protest incidents per million of 2000 workers for each province. Panel A presents the overall estimates. Panel B presents the estimates for incidents in the manufacturing sector. Within each panel, Column 1-3 show the estimates for total, wage-related and layoff-related incidents respectively. All estimates include the interaction of year dummies with 2000 baseline province controls (natural log of province population, share of population aged 60 and above, share of males, share of urban population, share of married population, and share of population with college education). Exposure to robots is standardized. Regressions are weighted using the number of workers in each province in 2000. Standard errors, shown in parentheses, are clustered at the province level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 9: Placebo Test (2SLS)

	(1)	(2)	(3)	(4)	(5)
Outcome:	Total employment	State-Owned Sector	Private Sector	Unemployment	Wages
Exposure to robots	0.303	0.097	-0.306	-0.281	0.125
	(0.185)	(0.316)	(0.234)	(0.280)	(0.117)
Observations	247	247	247	247	247
First-stage F stat	279.5	279.5	279.5	279.5	279.5

Notes - Data are drawn from *China City Statistical Yearbook* (1990 and 2000) published by China's National Bureau of Statistics. The table presents the estimates of the impact of exposure to robots between 2000 and 2016 on changes in city-level outcomes between 1990 and 2000. Outcome variables are total employment to population ratio in Column 1, state-owned sector employment to population ratio in Column 2, private sector employment to population ratio in Column 3, registered urban unemployment rate in Column 4 and the natural log of average annual wage in the state-owned sector in Column 5. All estimates control for city-level demographic characteristics in 2000 (natural log of population, share of males, share of married, share of population aged 60 and above, share of urban population, shares of population with primary school, secondary school, and college education, share of ethnic minorities, and share of migrants); city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; and regional fixed effects (northeast, east, central, and west). Exposure to robots, employment to population ratios and unemployment rate are standardized. The estimation sample is weighted using the 2000 population of each city. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix : Supplemental Figures and Tables

Table A.1: Robot Exposure and Labor Market Effects by Education Level (2SLS)

	(1) Middle school or below	(2) High school	(3) 3-Year college or above
	Panel A: Labor Force Participation		
Robot Exposure	-0.037***	-0.026***	-0.021**
	(0.011)	(0.007)	(0.010)
Observations	75,017	13,207	7,321
First-stage F stat	210	211.4	276.8
Mean of Dep. Var.	0.741	0.725	0.880
Std.Dev. of Dep. Var.	0.438	0.446	0.325
	Panel B: Employment		
Robot Exposure	-0.039***	-0.029***	-0.026*
	(0.011)	(0.008)	(0.015)
Observations	75,017	13,207	7,321
First-stage F stat	210	211.4	276.8
Mean of Dep. Var.	0.712	0.690	0.854
Std.Dev. of Dep. Var.	0.453	0.463	0.353
	Panel C: Unemployment		
Robot Exposure	0.006	0.009	0.008
	(0.006)	(0.006)	(0.006)
Observations	52,542	9,030	6,212
First-stage F stat	211.6	203.2	288.8
Mean of Dep. Var.	0.0358	0.0432	0.0274
Std.Dev. of Dep. Var.	0.186	0.203	0.163
	Panel D: Hours Worked		
Robot Exposure	0.068**	-0.014	-0.013
	(0.027)	(0.028)	(0.019)
Observations	16,435	4,599	4,083
First-stage F stat	178.7	142.7	256.8
Mean of Dep. Var.	3.795	3.769	3.735
Std.Dev. of Dep. Var.	0.568	0.448	0.312
	Panel E: Income		
Robot Exposure	-0.226***	-0.038	0.001
	(0.077)	(0.106)	(0.068)
Observations	15,379	5,102	5,050
First-stage F stat	206.8	181.9	284.8
Mean of Dep. Var.	8.787	9.191	9.941
Std.Dev. of Dep. Var.	3.044	2.774	2.246

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. The outcome variable is an indicator variable equal to 1 if an individual is employed (Panel A), or reported to be in the labor force (Panel B), or unemployed (Panel C) and 0 otherwise. The outcome in Panel D is the natural log of annual earnings. All estimates include individual sociodemographic controls for gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county), city fixed effects, year (survey wave) fixed effects and individual fixed effects. Exposure to robots is standardized. The estimation sample is weighted using individual weights. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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

	(1) 16-24	(2) 25-44	(3) 45-65
	Panel A: Labor Force Participation		
Robot Exposure	0.023**	-0.026***	-0.047***
	(0.010)	(0.007)	(0.010)
Observations	11,947	37,028	46,066
First-stage F stat	192.8	219.8	203.8
Mean of Dep. Var.	0.440	0.842	0.714
Std.Dev. of Dep. Var.	0.496	0.365	0.452
	Panel B: Employment		
Robot Exposure	0.026**	-0.032***	-0.047***
	(0.012)	(0.009)	(0.011)
Observations	11,947	37,028	46,066
First-stage F stat	192.8	219.8	203.8
Mean of Dep. Var.	0.395	0.809	0.693
Std.Dev. of Dep. Var.	0.489	0.393	0.461
	Panel C: Unemployment		
Robot Exposure	-0.006	0.010**	0.003
	(0.027)	(0.005)	(0.005)
Observations	3,806	29,648	30,983
First-stage F stat	181	230.4	199.9
Mean of Dep. Var.	0.0985	0.0363	0.0256
Std.Dev. of Dep. Var.	0.298	0.187	0.158
	Panel D: Hours Worked		
Robot Exposure	0.008	0.027	0.064*
	(0.057)	(0.024)	(0.033)
Observations	1,803	12,955	8,277
First-stage F stat	137	208.8	167.2
Mean of Dep. Var.	3.841	3.808	3.708
Std.Dev. of Dep. Var.	0.476	0.456	0.608
	Panel E: Income		
Robot Exposure	0.051	-0.155***	-0.144**
	(0.335)	(0.057)	(0.073)
Observations	2,138	13,301	7,951
First-stage F stat	186.8	232.7	211.5
Mean of Dep. Var.	7.966	9.332	9.087
Std.Dev. of Dep. Var.	3.686	2.705	2.750

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 age group. The outcome variable is an indicator variable equal to 1 if an individual is employed (Panel A), or reported to be in the labor force (Panel B), or unemployed (Panel C) and 0 otherwise. The outcomes are the natural log of weekly working hours in Panel D and the natural log of annual earnings in Panel E. All estimates include individual sociodemographic controls for gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county), city fixed effects, year (survey wave) fixed effects and individual fixed effects. Exposure to robots is standardized. The estimation sample is weighted using individual weights. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.3: Robot Exposure and Labor Market Effects by Gender (2SLS)

	(1)	(2)	(3)	(4)	(5)
Dep.Var.:	Labor Force	Employment	Unemployment	Hours Worked	Income
			Men		
Robot Exposure	-0.038***	-0.043***	0.011*	0.029	-0.168**
	(0.010)	(0.012)	(0.006)	(0.021)	(0.069)
Observations	50,526	50,526	39,161	16,960	17,084
First-stage F stat	221.4	221.4	221.7	179.8	206.2
Mean of Dep. Var.	0.811	0.777	0.0390	3.806	9.210
Std.Dev. of Dep. Var.	0.392	0.416	0.194	0.489	2.875
			Women		
Robot Exposure	-0.030***	-0.030***	0.004	0.054*	-0.100
	(0.008)	(0.008)	(0.004)	(0.031)	(0.066)
Observations	51,567	51,567	31,325	9,447	9,702
First-stage F stat	229.2	229.2	248.7	234.4	246.4
Mean of Dep. Var.	0.659	0.632	0.0349	3.733	8.819
Std.Dev. of Dep. Var.	0.474	0.482	0.184	0.550	

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. The outcome variables are being in the labor force in Column 1, being employed in Column 2, being unemployed in Column 3, the natural log of weekly working hours in Column 4, and the natural log of annual earnings in Column 5. All estimates include individual sociodemographic controls for gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county), city fixed effects, year (survey wave) fixed effects and individual fixed effects. Exposure to robots is standardized. The estimation sample is weighted using individual weights. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: Controls for Offshoring, Aggregate Analysis (2SLS)

	(1) Total Employment	(2) State-Owned Sector	(3) Private Sector	(4) Unemployment	(5) Wage
Exposure to robots	-0.117	-0.338*	0.009	0.889***	-0.087***
	(0.190)	(0.200)	(0.217)	(0.257)	(0.033)
Observations	236	251	237	246	252
First-stage F stat	185.8	178.1	185.8	177.3	177.9
Offshoring controls	Yes	Yes	Yes	Yes	Yes
Demographics	Yes	Yes	Yes	Yes	Yes
Broad industry shares	Yes	Yes	Yes	Yes	Yes
Region FE	Yes	Yes	Yes	Yes	Yes

Notes - Data are drawn from *China City Statistical Yearbook* (2000 and 2016) published by China's National Bureau of Statistics. The table presents the estimates of the impact of exposure to robots on changes in city labor market outcomes while controlling for offshoring away from China at the city level. Outcome variables are total employment to population ratio in Column 1, state-owned sector employment to population ratio in Column 2, private sector employment to population ratio in Column 3, registered urban unemployment rate in Column 4 and the natural log of average annual wage in the state-owned sector in Column 5. All estimates control for city-level demographic characteristics in 2000 (natural log of population, share of males, share of married, share of population aged 60 and above, share of urban population, shares of population with primary school, secondary school, and college education, share of ethnic minorities, and share of migrants); city-level broad industry shares that include the 2000 shares of employment in agriculture, manufacturing, durable manufacturing, construction, and the share of female employment in manufacturing; regional fixed effects (northeast, east, central, and west); and offshoring of industries away from China (changes in the natural log of city-level foreign direct investment (FDI) amount and changes in the natural log of city-level value of output by foreign firms, including Hong Kong, Macau and Taiwan firms, between 2000 and 2016). Exposure to robots, employment to population ratios and unemployment rate are standardized. The estimation sample is weighted using the 2000 population of each city. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5: Controls for Offshoring, Individual Analysis (2SLS)

	(1) Employment	(2) Labor Force Participation	(3) Unemployment	(4) Hourly Wage	(5) Hours Worked	(6) Income
Exposure to robots	-0.034***	-0.029***	0.012*	-0.080	0.042*	-0.186***
	(0.010)	(0.009)	(0.006)	(0.051)	(0.024)	(0.058)
Observations	86,652	86,652	59,370	4,806	23,485	24,201
Mean of Dep. Var.	0.698	0.730	0.0393	2.442	3.775	9.076
Std.Dev. of Dep. Var.	0.459	0.444	0.194	0.765	0.515	2.928
First-stage F stat	232.5	232.5	237.2	9.928	227	240
Offshoring controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE and Year FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010-2016). The table presents the estimates of the labor market impact of exposure to robots on individuals while controlling for offshoring away from China at the city level. The outcome variable is an indicator variable equal to 1 if an individual is employed (Column 1), or reported to be in the labor force (Column 2), or unemployed (Column 3) and 0 otherwise. The outcomes are the natural log of weekly working hours in Column 4 and the natural log of annual earnings in Column 5. All estimates include individual sociodemographic controls for gender, age and its quadratic term, marital status, education level (no formal education, elementary school, middle school, high school or vocational school, 3-year college, and 4-year college or above), school attendance, ethnicity (Han or minority Chinese), living in urban or rural area, current *hukou* type (agricultural or non-agricultural) and location (whether *hukou* is registered in the current county), city fixed effects, year (survey wave) fixed effects, individual fixed effects and controls for foreign production and investment at the city level (the natural log of city-level foreign direct investment (FDI) amount and the natural log of city-level value of output by foreign firms, including Hong Kong, Macau and Taiwan firms). Exposure to robots is standardized. The estimation sample is weighted using individual weights. Standard errors, shown in parentheses, are clustered at the city level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.6: Robot Exposure, Employment, and Labor Force Participation, Individual-Level Analysis (IV-1982)

	(1) OLS	(2) Reduced form	(3) 2SLS	(4) 2SLS
	Panel A: Employed			
Exposure to robots	-0.029***	-0.204***	-0.037***	-0.050***
	(0.007)	(0.053)	(0.009)	(0.009)
Observations	111,339	111,339	111,339	102,217
First-stage F stat			128.4	26.44
Mean of Dep. Var.	0.688	0.688	0.688	0.704
Std.Dev. of Dep. Var.	0.463	0.463	0.463	0.456
	Panel B: Labor Force Participation			
Exposure to robots	-0.025***	-0.199***	-0.036***	-0.051***
	(0.005)	(0.044)	(0.011)	(0.010)
Observations	111,339	111,339	111,339	102,217
First-stage F stat			128.4	26.44
Mean of Dep. Var.	0.720	0.720	0.720	0.734
Std.Dev. of Dep. Var.	0.449	0.449	0.449	0.442
	Panel C: Unemployed			
Exposure to robots	0.007	0.028	0.005	0.007
	(0.006)	(0.044)	(0.009)	(0.009)
Observations	80,115	80,115	80,115	70,581
Mean of Dep. Var.	0.0436	0.0436	0.0436	0.0372
Std.Dev. of Dep. Var.	0.204	0.204	0.204	0.189
First-stage F stat			134.4	24.16
Individual characteristics	Yes	Yes	Yes	Yes
City population	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE				Yes

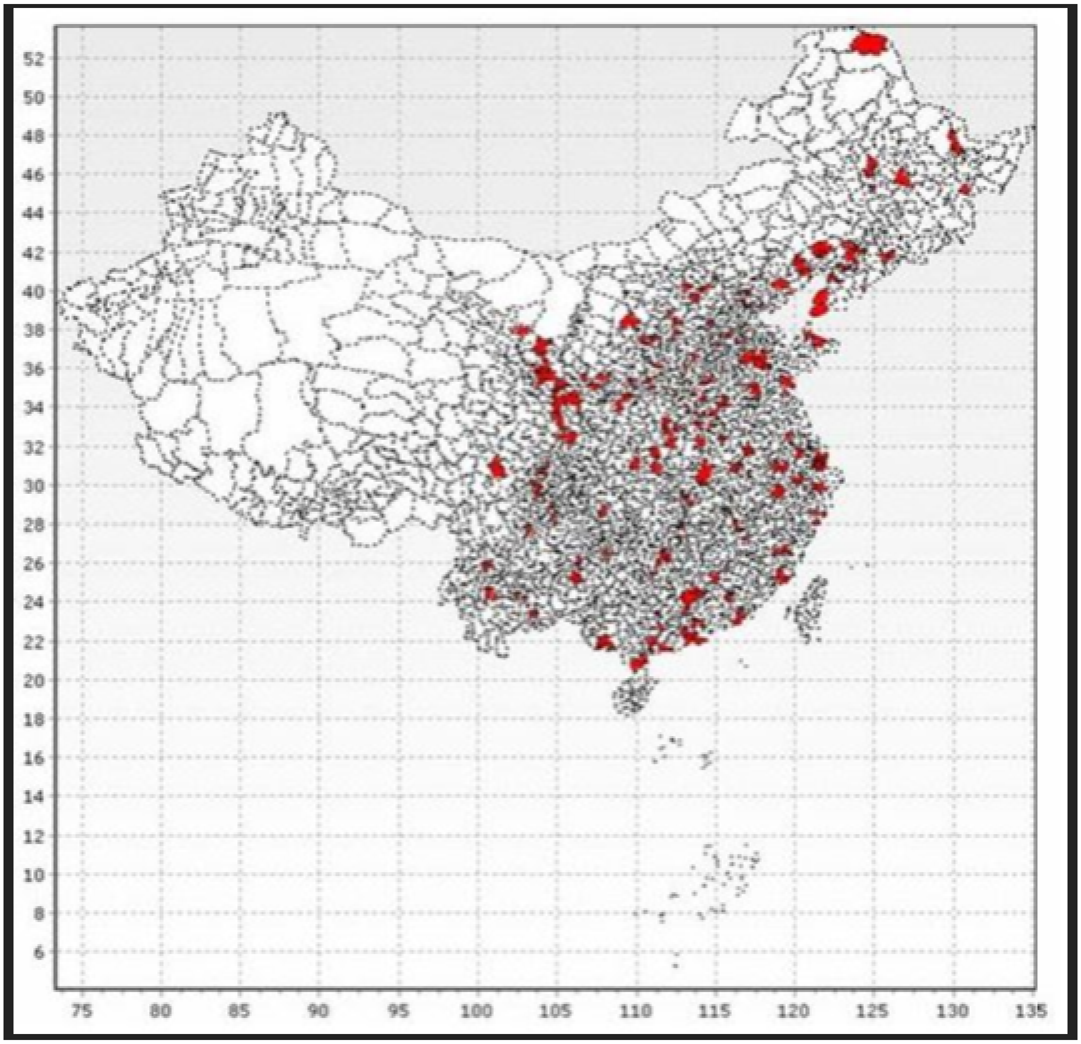
Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010-2016). The table reproduces Table 5 when using 1982 (instead of 2000) as the base year to construct the instrument for robot exposure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.7: Robot Exposure, Income, and Working Hours, Individual-Level Analysis (IV-1982)

	(1) OLS	(2) Reduced form	(3) 2SLS	(4) 2SLS
		Panel A: log(hourly hage)		
Exposure to robots	-0.116***	-1.072***	-0.157***	-0.055*
	(0.034)	(0.272)	(0.040)	(0.032)
Observations	14,585	14,585	14,585	5,244
First-stage F stat			135.7	17.85
		Panel B: log(hours worked)		
Exposure to robots	0.026**	0.047	0.008	0.019
	(0.011)	(0.083)	(0.018)	(0.028)
Observations	42,961	42,961	42,961	26,459
First-stage F stat			173.9	39.12
		Panel C: log(annual earnings)		
Exposure to robots	-0.241***	-1.840***	-0.328***	-0.145*
	(0.086)	(0.455)	(0.525)	(0.100)
Observations	37,834	37,834	37,834	26,838
First-stage F stat			152.3	29.16
Individual controls	Yes	Yes	Yes	Yes
City population	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Individual FE				Yes

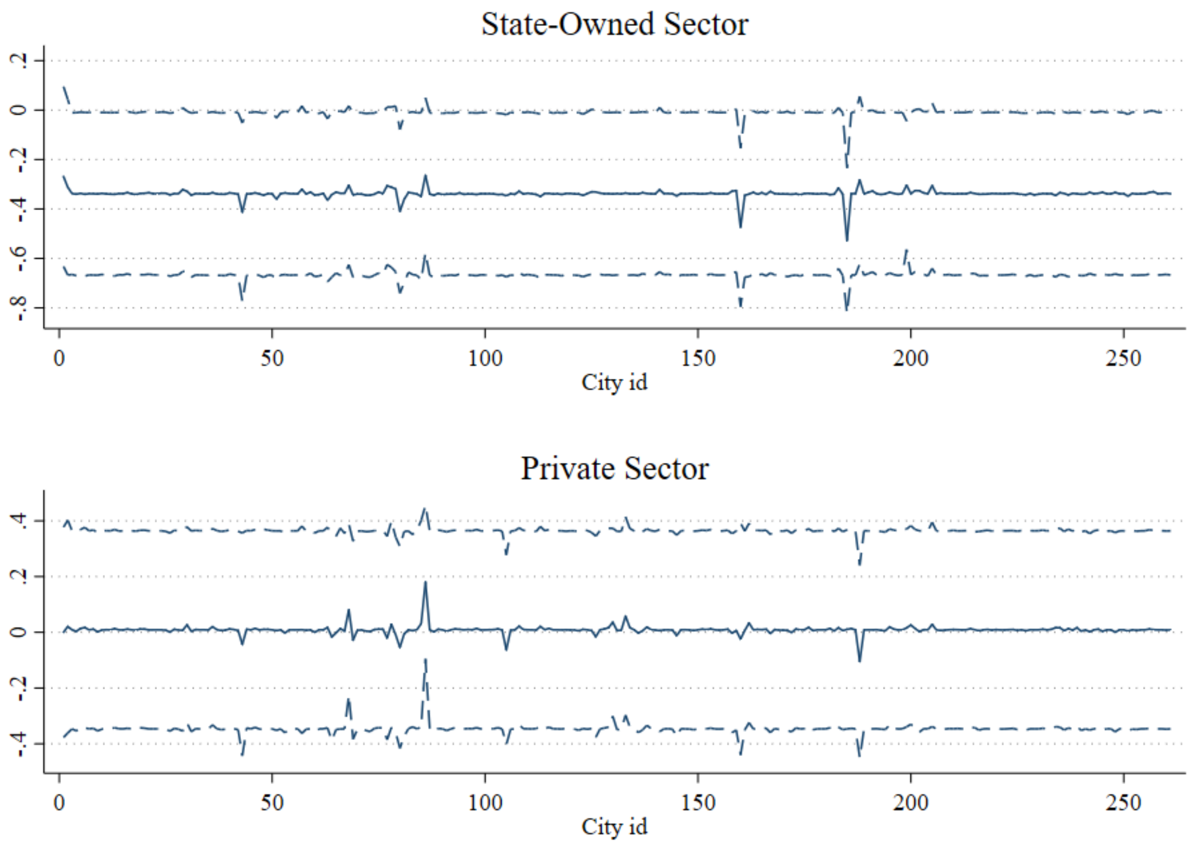
Notes - Data are drawn from the China Family Panel Studies (CFPS, 2010-2016). The table reproduces Table 6 when using 1982 (instead of 2000) as the base year to construct the instrument for robot exposure. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A.1: Counties in the CFPS Sample



Notes - Source: China Family Panel Studies (CFPS)

Figure A.2: Remove One City at a Time: Effects on Employment to Population Ratios



Notes - This graph plots the regression coefficients on the exposure to robots (with their 90% confidence intervals) when one city is removed from the sample at a time.

Figure A.3: Remove One City at a Time: Effects on Unemployment Rate and Wage

Notes - This graph plots the regression coefficients on the exposure to robots (with their 90% confidence intervals) when one city is removed from the sample at a time.