Can Robotization Save Jobs from Slowbalization? [*]

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Abstract

This paper investigates how robot adoption interacts with trade slowdowns to impact local labor markets in China. We highlight the role of industrial robots in mitigating the adverse impact of export slowdown on the local labor market. Employing a Bartik-style instrumental variable approach, we construct a prefecture-level measure of robot adoption and find that an interquartile increase in robot installations leads to a relative increase in the employment of around 0.16 percentage points, holding the Chinese export shock constant at its mean value of 61.42 dollars per worker. Our evidence suggests that firms' adoption of robots helps offset employment losses from trade slowdown by increasing domestic sales. Moreover, this adjustment is accompanied by an increase in local consumption, and coincides with shifts in employment structure that disproportionately benefit highly educated workers, as they are less vulnerable to automation.

JEL Classification: F10, F14, F16, J23, O33

Keyword: trade, technology, robots, employment, export slowdown

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Introduction

Since the Great Recession, world trade has fallen from 61% of global GDP in 2008 to 58% in 2019 due to a set of political and economic factors, including weakened global value chains, trade war, and COVID-19 (Goldberg and Reed, 2023).[1] This deceleration of globalization, also termed "Slowbalization", has generated economic uncertainty and posed new challenges to labor markets (Fajgelbaum et al., 2020, 2022; Waugh, 2019). Empirical studies suggest that trade tension, such as U.S.-China trade war, has reduced employment and job postings (Flaaen and Pierce, 2021; Javorcik et al., 2022; Autor et al., 2023). This raises a critical question for policymakers: how to design policies to mitigate the adverse impact of trade slowdown on the labor market?

A concurrent trend over the past decades has been the rise of robotization. In this paper, we argue that the adoption of robots may either mitigate or exacerbate the negative effects of the export slowdown, as both trade shocks and automation primarily affect the same group of workers—specifically, unskilled workers who engage in routine tasks. So far, there is no clear evidence as to how robotization would impact a local labor market simultaneously experiencing trade slowdowns. On one hand, firms adopting more robots could maintain their competitiveness by improving product quality and expanding production, which may offset the employment and wage losses resulting from the trade slowdown (productivity effect) (DeStefano and Timmis, 2024). On the other hand, to reduce production costs, firms might increase their usage of robots as labor-saving technologies, which could cause more job disruptions in trade-exposed industries (displacement effect).

This paper provides the first empirical evidence examining whether robot adoption mitigates or exacerbates the effects of trade shocks on labor market outcomes. More specifically, we investigate whether greater robot adoption in the local labor market reduces the negative employment and wage impacts of trade slowdowns compared to less robotic local labor markets.

Our context is the Chinese labor market over 2010–2016, when the country experienced a significant export slowdown driven by both external and internal factors

[1] See more via https://www.economist.com/briefing/2019/01/24/globalisation-has-faltered.

(Brandt and Lim, 2024).[2] Although China's manufacturing export growth, on average, exceeded an annual rate of 25% before 2010, it fell from 30% in 2010 to -7% in 2016.[3] Meanwhile, robot installation in China increased more than sixfold during this period, despite growing anxiety about the use of robots from advanced countries.[4] Given the potential critical roles of exports and robotization in the job growth, and the dramatic changes in both two factors in China over the past years, it is important to understand how robot adoption affects local labor market responses to export slowdowns in the manufacturing sector.

To identify the interactive effects of export slowdown and robotization, we introduce two prefecture-level shocks: year-on year export shock and initial robot installation.[5] The underlying rationale of interacting the two variables is that prefectures' exposure to export shocks varies with the initial robot installation. If the productivity effect dominates the job displacement effect by robots, prefectures with more robots may have fewer job losses from export slowdown as automation-driven efficiency gains could partially offset the negative labor market impacts (Koch et al. 2021). Our export shock is measured by the change in manufacturing exports per worker at the prefecture level. Unlike most studies that rely on industry-level robot adoption and local employment composition to approximate local robot installation, our analysis utilizes prefecture-level robot import data, enabling more accurate measurement of actual robot installation (Acemoglu and Restrepo, 2020; Fan et al., 2021). To avoid the correlation between robot adoption and other contemporaneous shocks, we focus on the initial period of robot installation.

Our empirical strategy poses two major identification challenges. First, the export shock variable may be correlated with unobserved shocks that are simultaneously impacting China's labor market. For instance, China's export slowdown after 2010 might be driven by internal factors, including China's rising industrial capacity and its domestic demand expansion strategy. To address this issue, we follow Campante et al. (2023) to construct a Bartik instrumental variable (IV) that combines the initial export

[2] Brandt and Lim (2024) document that China's export slowdown after 2007 is explained by weakened foreign demand and the country's lack of access to improvements in imported inputs.

[3] This figure is from author's calculation. Furthermore, the annual growth rate of exports in manufacturing has declined from 31% in 2010 to -8% in 2016. Source: China's General Administration of Customs export data.

[4] Robot installation in China increased from 14,978 units in 2010 to 96,500 units in 2016 according to the IFR statistics.

[5] Prefectures, by which we define our local labor market, are second-level administrative divisions that encompass all areas in China.

share of each prefecture with export changes from other countries, excluding China. The second challenge is that prefectures adopting more robots might be affected by other confounding factors correlated with local demand. To overcome this challenge, we use industrial robot installation in the rest of the world, excluding China, along with the initial prefecture-by-industry specific share of robot installations to instrument for the endogenous robot exposure variable. It is assumed that industry-level robot installations in other countries are not correlated with unobserved shocks that impact robot-intensive regions; additionally, prefectures with more robots in certain industries are not systematically different from the other prefectures with respect to unobserved shocks.

Applying this empirical strategy, our first set of results shows that robotization mitigates the negative employment effects of China's export slowdown. An interquartile increase in initial robot installations leads to a relative increase in the employment by around 0.16 percentage points when holding the Chinese export shock at its mean value of 61.42 dollars (per worker). This result withstands a comprehensive set of tests on identification concerns as well as robustness checks.

Our wage estimate is statistically insignificant but indicates fewer wage declines in prefectures with more robots. However, when extending the analysis to additional years, we find a significant effect on wages—an interquartile increase in robot installations leads to a relative increase in wages by approximately 0.311 log points. One possible interpretation is that wages are rigid in the short run, and firms may gradually adjust their labor inputs over time.

We then provide insights into potential mechanisms through which robotization mitigates the effects of export slowdown on local labor markets. We first consider whether our results can be attributed to an increase in local demand growth in labor driven by the adoption of robotics. Using comprehensive corporate-level tax survey data, we estimate the interactive effects of robotization and export shocks on sales and costs at the firm level.[6] Our results show a statistically significant increase in sales in more robot-intensive prefectures but no change in costs relative to those in less robot-intensive prefectures, while holding constant the export shock. This finding aligns with prior studies that demonstrate how automation positively impacts firms by increasing

[6] The National Tax Survey Database (NTSD) (NTSD) data records detailed firm-level information, such as total production, administrative expenses, sales, and number of employees.

productivity and sales (Aghion et al. 2020; Stapleton and Webb, 2020; Chung and Lee, 2023; Babina et al., 2024; Bonfiglioli et al., 2024).

Importantly, we find that the increase in total sales by robotization in response to the export slowdown is primarily driven by a rise in domestic rather than export sales. This suggests that the adverse export condition induces a shift in firms' sales from overseas to the domestic market. Finally, we discuss several alternative explanations, including migration, firm's diversification strategy, robot subsidies, and find little supporting evidences from these alternatives to explain our main result.

In additional discussions, we find a larger local household consumption increase in areas with more robots, despite the overall negative effect of China's export slowdown on consumption. This may suggest an overall improvement of household welfare. However, we refrain from making strong claims under our reduced-form framework. Moreover, we find that robotization under export slowdown leads to increased hiring of managerial workers, particularly significant for those with college and above education. This shift of firms' hiring strategy suggests that industrial robots are a skill-biased technology that disproportionately benefits more educated workers because they perform tasks that are difficult to automate (Acemoglu and Restrepo, 2022a, 2022b; Barth, 2020; Graetz and Michaels, 2008; Katz and Murphy, 1992). Moreover, the heterogeneity analysis suggests that the main effect is statistically significant in both the manufacturing and nonmanufacturing sectors. Although the export shock directly pertains to manufacturing sectors, this result is not surprising as it may imply a positive spillover effect of robotization outside the manufacturing sector. In particular, the robot-driven expansion of manufacturing production may have raised local demand for services through sectoral linkages.

This paper relates to various streams of literature in trade and technology. First and foremost, we contribute to an expansive literature on deglobalization and its economic consequences. Most studies use the U.S.-China trade war to quantify its economic impacts and find that retaliation tariffs generate negative employment impacts in the U.S. (Autor et al., 2023; Benguria and Saffie, 2020; Flaaen and Pierce, 2021; Perla et al., 2021; Laverick et al., 2022). More pertinently to our paper, Campante et al. (2023) analyze the political consequences of China's export slowdown and find that contraction in exports leads to substantial rises in labor strikes. Ma et al. (2023) further study the impacts of Chinese export slowdown on crime rates, demonstrating that cities with greater exposure to export slowdown experience sharper increases in local crime rates. We show that robotization could mitigate the negative effects of exports slowdown, which is important for understanding how interactions between trade slowdown and automation impact the local labor market.

More broadly, we connect to an extensive literature on trade shocks and the impacts on the labor market (Topalova, 2010; Autor et al., 2013; Acemoglu et al., 2016; Hakobyan and McLaren, 2016; Dix-Carneiro and Kovak, 2017). Prior studies have suggested that trade shocks generate localized impacts that could persist for more than a decade. Our paper considers the interdependence between trade slowdown and robot shocks in the local labor market by demonstrating that robotization may help distribute the impacts of trade shocks across local labor markets. This finding yields valuable insights for policymakers designing robot policies aimed at areas most impacted by trade slowdowns.

Second, our work adds to a growing body of evidence on how robots affect the labor outcomes in developing countries. Evidence from developed countries presents mixed evidence on whether robotization positively or negatively impacts employment and wages (Dachs et al., 2017; Dauth et al., 2018; Graetz and Michaels, 2018; Pedemont et al., 2018; Artuc et al., 2019; Humlum, 2019; Maloney et al., 2019; Bessen et al., 2020; Acemoglu and Restrepo, 2020; Farber et al., 2020; Eggleston et al., 2021; Koch et al. 2021; Krentz et al., 2021; Adachi et al., 2022; Acemoglu et al., 2023; Chung and Lee, 2023; Javed, 2023; Kugler et al., 2023; Albinowski and Lewandowski, 2024; Bonfiglioli et al., 2024).[7] There is limited evidence from developing countries because of difficulties in obtaining detailed robot data as well as the lower prevalence of automation in the developing world (Carbonero et al., 2020; Giuntella et al., 2025). Prior studies have used the International Federation of Robotics data to measure robot installation at the industry level. The availability of Chinese robot imports data at the firm level enables us to more precisely measure robot installation at the micro-region level. Tang et al. (2021) find a positive effect of Chinese robot adoption on more skilled workers, thus corroborating our own results.[8] Previous work by Dixon et al. (2023)

[7] For example, some studies have shown that automation in developed world increases reshoring but decreases employment and wages in developing countries by replacing workers (Dachs et al., 2017; Pedemont et al., 2018; Artuc et al., 2019; Maloney et al., 2019; Farber et al., 2020; Krentz et al., 2021; Kugler et al., 2023). By contrast, a recent study by Stapleton and Webb (2021) demonstrates that automation might lead to more offshoring by raising labor demand for non-automatable tasks.

[8] Consistently, we show that robots benefit college-above-educated managers more during export slowdown.

suggest that, in Canada, robots lower the demand for managers by reducing the product variance process. By contrast, we find an increase in the labor demand for managers with college-and-above education, indicating a possible shift toward more skill-based occupations in Chinese labor market.

Third, the current growing literature has a focus on the bilateral relation between trade and technology, either discussing how technology induces trade growth by lowering trade barriers, enhancing product quality, and reducing production costs, or claiming trade encourages firm to invest in technology.[9] However, there is less empirical evidence on how technology and trade shocks simultaneously impact labor markets. Autor et al. (2015) study the distinct effects of technology and trade shocks by including these two variables as explanatory variables; their findings indicated that trade and technology shocks generate distinct impacts on U.S. local labor markets, which highlights the importance of distinguishing technology from trade shocks. Another research by Farber et al. (2022) finds that, in China, compared to trade shocks, robot shocks result in more population declines. The most relevant work to ours is by Firooz et al. (2025), who study the interaction between trade uncertainty and automation using a macro model. Their model predicts that trade uncertainty accelerates reshoring, but this process does not increase employment for unskilled workers because of the job-displacing effect of automation. Similar to our study, they also find that robots raise demand for skilled workers because robots complement skilled workers. We complement their work by connecting robotization to trade slowdown and highlighting the productivity effect over the job displacement effect of robots, where domestic demand plays a vital role. Our finding is important for designing effective policies on robot regulation in an integrated world (Aghion et al., 2020).[10]

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[9] On one hand, technology may induce trade growth by lowering trade barriers, enhancing product quality, and reducing production costs-- See, e.g., Arctuc et al. (2023), Freund and Weinhold (2004), Fernandes et al. (2018), Kneller and Timmis (2016) Bloom et al. (2016), DeStefano and Timmis (2024). Fernandes et al. (2018) find that internet access in China increased firm manufacturing exports by reducing trade barriers. Similarly, Kneller and Timmis (2016) find that the broadband use in UK increases trade in business service sector. DeStefano and Timmis (2024) use robot data from 26 developed and 27 developing economies, finding that robotization leads to export quality upgrading. On the other hand, trade encourages firm to invest in technology by increasing overall returns and lowering production costs (Ekholma and Midelfart, 2005; Yeaple, 2005; Lileeva and Trefler, 2010; Bustos, 2011; Boler et al., 2015; Autor et al., 2020; Perla et al., 2021).

[10] There may be a heterogeneous effect of automation on the employment change in response to trade shocks. Aghion et al. (2020) show that the positive relationship between automation and employment is primarily through firms with more exposure to international competition.

2. Background and Data

2.1 A brief overview of China's exports

China's transformation from centrally planned to market-oriented economy has contributed to the country's remarkable economic growth over the past decades. According to the IMF statistics, China has achieved an average annual growth rate of 9% since the late 1970s. The rapid growth in China's exports in manufacturing has been the most important factor contributing to its economic success. Between 1991 and 2010, China's share of world exports in manufacturing grew from 2.3% to 16% (Lemoine and Unal, 2012). One prominent feature of China's export sector is its great comparative advantage in producing industrial goods. Unlike other major emerging economies that are primarily specialized in only one or two commodities, such as Brazil, Indonesia, and Russia, China's product mix is more diversified (Autor et al., 2016). Because of this wide distribution of comparative advantage across industries, China's export growth increased substantially in almost every manufacturing industry.

However, China's rapid growth in exports was halted after the 2008 Great Recession. Due to the global crisis, foreign countries' demand decreased substantially, leading to a slowdown in global trade (Baldwin, 2009; Jing, 2012). Given China's important role in global trade and dominance in global supply chains, the crisis impeded the country's export growth, contributing to a remarkable decline in exports between 2010 and 2016.[11] According to China's National Bureau of Statistics, exports as a share of China's national GDP fell from 26.0% in 2010 to 18.5% in 2016.[12] Thus, our main sample of analysis focuses on the period from 2010 to 2016. Moreover, the export decline varied significantly across manufacturing sectors, with the processing trade sector being hit the hardest due to its greater integration into foreign production. Our identification strategy hinges upon the variation in export decline across manufacturing industries. To construct each prefecture's exposure to export slowdown, we further weight the industry-level export change with prefecture-level export specialization at the initial period.

2.2 Robot adoption

Industrial robots are machines designed to autonomously perform manual tasks

[11] See details via https://voxdev.org/topic/trade/socioeconomic-effects-export-slowdowns-evidence-china.
[12] The Data source is National Bureau of Statistics of China.

without human intervention. Advancement in robot technology in the past decades has prompted a significant global proliferation of robots. Driven by the rapid growth of its high-tech sectors and government policies promoting modernization, China has emerged as one of the largest markets for industrial robots.[13] Although the adoption of robots in China was negligible before 2000, China became the world's largest market for industrial robots in 2013, with the number of installed robots growing by around 66% annually between 2001 and 2010. Since China relied primarily on imported robots to meet the growing demand for automation in its manufacturing sector, we use China's custom data of robot imports to measure robot installation.

Unlike China's broadly diversified trade across industries, the installation of robots is concentrated in high-tech sectors such as electronics, automative, metal, and machinery industries. These robots are extensively used for performing tasks such as handling operations, electronics, welding and automative production.[14] Due to the initial difference in industry specialization, the geographic variation in robot-installation intensity is prominent. For example, about 20% of firms in Huizhou, a prefecture in Guangdong, have adopted robots. By contrast, no firms in Hubei's Qianjiang prefecture use robots. (Cheng et al., 2019)

2.3 Data Sources

Our analysis relies on a comprehensive empirical setting and several data sources, which we introduce in this section. We draw on data including overall exports, the import of industrial robots, local employment, and a variety of other economic indicators. These datasets enable us to examine the intricate relationship between export performance, robot adoption, and employment outcomes. China's prefectures serve as the primary unit of analysis in this paper, being administrative divisions larger than counties but smaller than provinces. Overall, our sample covers 296 prefectures between 2010 and 2016 based on our data availability. We select these years because they mark a documented decline in export activity, which may trigger notable changes in employment patterns (Campante et al., 2023).

Overall Exports and Initial Robot Installation: Our analysis emphasizes manufacturing export performance and robot imports, which we use as primary

[13] Author's calculation using IFR data.
[14] See more via https://www.macquarie.com/au/en/insights/why-china-is-focused-on-a-robotic-future.html

indicators of local economic shocks. To construct these variables, we utilize trade data from China's General Administration of Customs. This dataset comprehensively covers all exporting and importing firms in China, offering detailed information on each firm's location as well as a breakdown of trade volumes by product at the six-digit level of the Harmonized System (HS). Following Campante et al. (2023), we develop a measure of export shock at the prefecture level as below:

$$ExpShock_{it} = \sum_k \sum_{f \in i} \frac{\Delta X_{fikt}}{L_{i,2010}} \qquad (1)$$

where ΔX_{fikt} is the annual change in total manufacturing exports of product k for exporting firm *f* that locates in prefecture *i* in the year *t*. *k* represents the HS six-digit product codes, and our analysis includes all products k classified under the manufacturing sector. The working-age population, denoted as $L_{i,2010}$, refers to individuals aged between 15 and 64 in prefecture *i* in the year 2010. We weight the total manufacturing exports of a prefecture with its working-age population so that this variable measures per-worker exposure to the export shock. This demographic data, sourced from the China Population Census, encompasses residents both with and without formal residency rights (*hukou*). Our study utilizes a panel dataset spanning the years between 2010 and 2016.

To measure prefecture-level robot installation, we extract each firm's imports of industrial robots, $Robots_{fit}$, from the customs records between 2000 and 2010. We then aggregate this data to the prefecture level, utilizing firms' location details. This approach yields the following measure:

$$RobotStock_{2010} = \sum_{f \in i} \frac{Robots_{fit}}{L_{i,2010}} \qquad (2)$$

In the above equation, we do not include the dimension of k (HS code-level information) because we focus on imports of industrial robots.[15] All other notations remain consistent with Equation (1). To avoid correlation between robot adoption and other contemporaneous shocks during our sample period, we use the predetermined level of robot. It is important to note that the robot data represents the stock of robots,

[15] The robot adoption data is extracted based on product import codes (HS), with robots defined as goods beginning with the prefix "84." Specifically, the relevant categories include spray robots (84248920), handling robots (84289040), multifunctional robots (84795010), and automated handling robots for integrated circuit (IC) factories (84864031). Notably, robots with import codes beginning with "85," including resistance welding robots (85152120), arc welding robots (85153120), laser welding robots (85158010), and other robots (84795090), began to appear in the custom data only from 2014 onward.

aggregating the total number of robots imported up until 2010.[16]

Figure 1 displays the geographic variations in our explanatory variables, namely export shocks and robot installation. The graph in Panel A shows the density of prefecture-level robot installations up to 2010, highlighting that cities in central and southeast coastal areas have the highest levels of robot adoption. The graph in Panel B presents the average annual export growth for each city over 2010–2016. It is evident that coastal cities continued to experience relatively robust export growth over the sample period. However, we observe that the export performance of some central and inland cities was moderate or even negative. Table 1 displays the descriptive statistics for these variables. On average, in 2010, China adopted approximately 15 robots per 1,000 workers.

Employment Data: In the main analysis, we obtain employment data from the Chinese City Statistical Yearbooks, covering the period from 2010 to 2016. These yearbooks provide detailed records, including the total population and the number of employed individuals in each prefecture.[17] Using this information, we calculate the change in the employment share for prefecture i in year t, denoted as $\Delta EmployShare_{it}$.

Another set of employment data, used as complementary evidence for the robustness check, is sourced from the Population Census conducted by the National Bureau of Statistics of China, which collects detailed demographic, economic, and social data at the individual level. It is a 1% national population sample survey conducted every five years between the decennial censuses. Using the 2010 and 2015 waves of surveys, we derive a variable similar to $\Delta EmployShare_{it}$, which accounts for the change in employed workers as a percentage of all working-age population between 2010 and 2015.

Other Local Economic Data: We collect a set of socioeconomic variables at the prefecture level, which we use as controls or additional local economic outcomes for analysis. These datasets are sourced from official Chinese publications. Population data and the distribution of residents by migration status (*hukou* vs. non-*hukou*) are gathered from the 2010 Population Census. Other economic indicators, such as the share of the population with a college education and the share of urban households, are derived from

[16] The import data is available starting from the year 2000, offering a comprehensive accumulation of robot adoption over time.

[17] To the best of our knowledge, this is the best public available data that provides updates at the prefecture level on an annual basis.

the China City Statistical Yearbooks.

Firm-level Data: Additionally, we use auxiliary data from the National Tax Survey Database (NTSD), which includes comprehensive records such as annual tax returns, enterprise financial reports, income tax submissions, business accounts, and other relevant information audited by tax authorities. Local fiscal and tax authorities collect these data via direct online reporting, ensuring high-quality data through management and supervision by fiscal and taxation authorities. The NTSD applies a stratified random sampling method each year to select a large number of firms for survey data, covering their basic details, financial metrics, tax payments, and more. For our analysis, we extract firm-level variables from the NTSD, including sales, revenue, costs and net hirings, which serve as additional dependent variables in our mechanism analysis.

Household-level Consumption Data: We also incorporate household-level consumption data from the Urban Household Survey (UHS). Organized by China's National Bureau of Statistics, this survey employs a multi-stage probabilistic sampling method with a stratified design. Data collection occurs throughout the year, with households recording their daily income and expenditures, which surveyors collect quarterly. We further aggregate this quarterly data to an annual level. The UHS is China's official source for essential indicators of urban household living standards. We extract service, product, and total consumption from the UHS, which we use as additional dependent variables in our mechanism analysis. Household consumption panel data is acquired from the China Family Panel Studies (CFPS), a nationally representative longitudinal survey administered by Peking University. The CFPS collects comprehensive information on household income, expenditure, education, and demographics through biennial interviews, using a multi-stage, probability-proportional-to-size sampling strategy. We utilize household-level annual consumption measures from the CFPS to complement the UHS data, enabling us to capture the changes of consumption.

3. Theoretical Framework

In this section, we develop a simple theoretical model to illustrate how the robot adoption would change the elasticity of employment to export shocks. Our model is built on Graetz and Michaels (2018) who proposes a task-based production function and characterizes how the decline in robot price affects production, labor, output, and product price. Different than their work, our model assumes that the robot price is fixed over time and exogenously determined.

Consider an economy consisting of a continuum of industries indexed by $i \in [0,1]$. Within any industry i, there is a representative firm j producing output by employing robots or labor. Firm j uses either industrial robots or labor to produce. Suppose the fraction of tasks performed by robot is $\alpha_{i,j}$ which is between 0 and 1, then the remaining fraction 1- $\alpha_{i,j}$ is performed by labor only. The fraction $\alpha_{i,j}$ is a predetermined variable that firms choose prior to export shocks. That is to say, export shocks affect firm's labor demand but not their robotization choice. This is consistent with the fact that investment in robots involves installation and adjustment costs, and robot adoption may not respond to trade shocks in the short run. The output $Y_{i,j}$ is described by a CES production function and determined by the amounts of tasks performed by robots and labor.[18]

$$Y_{i,j} = [\alpha_{i,j} R_{i,j}^{\frac{\sigma-1}{\sigma}} + (1-\alpha_{i,j}) L_{i,j}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where $R_{i,j}$ is robot input and denotes the bundle of tasks performed by robots. $L_{i,j}$ is labor input and denotes the bundle of tasks performed by labor. σ is the task-substitution elasticity which is greater than one.

The robot price is set to ρ and is assumed constant in the short run. Worker's wages are normalized to 1 so that all prices are expressed in terms of wage units. We assume perfect substitute between robots and labor in tasks can be performed by robots. Then the marginal cost of firm j in industry i is as below. Because $\sigma > 1$, $\rho^{1-\sigma} < 1$, the marginal cost $c_{i,j}$ is strictly decreasing in robot adoption.[19]

$$c_{i,j} = [a_{ij}\rho^{1-\sigma} + (1-a_{ij})]^{\frac{1}{1-\sigma}} \tag{4}$$

Under monopolistic competition market with CES demand by consumers, we could derive the price of firm j in industry i which is equal to a constant markup over marginal cost via Dixit-Stiglitz-type setup:

[18] For simplicity, we do not include the task notation because our paper is not to derive how tasks performed by robots will affect the marginal cost and therefore affects firms' decision to adopt robots as Graetz and Michaels (2018). Instead, we focus on how the elasticity between export shock and labor varies by robot adoption, and the robot intensity is predetermined.

[19] One could infer $c'_{i,j}(\alpha_{ij}) < 0$.

$$P_{i,j}(a_{ij}) = \frac{\eta}{\eta - 1} c_{i,j} \tag{5}$$

where $\eta > 1$ is the elasticity of substitution within industries. Since the marginal cost is strictly decreasing with robot adoption, the price $P_{i,j}(a_{ij})$ is also strictly decreasing with robot adoption by firms. This is consistent with Graetz and Michael (2018) who find that firms adopting robots tend to have lower prices. Similarly, the industry-level price, P_i, would be derived following the CES price index where ε is the elasticity of substitution across industries.

$$P_i = (\int_0^1 P_{i,j}(a_{ij})^{1-\eta} d_j)^{\frac{1}{1-\eta}} \tag{6}$$

Now we introduce export shocks into our model framework by adding an industry-specific demand shifter A_i to model the export shock. Under CES monopolistic competition, each firm faces the demand curve as below:

$$Y_{ij} = A_i \left(\frac{P_{i,j}(a_{ij})}{P_i}\right)^{-\varepsilon} \tag{7}$$

For a firm j in industry i that uses a fraction α_{ij} of tasks performed by robots, under the impact of export shocks, its demand for labor would be as the following equation[20]:

$$\frac{\partial L_{ij}}{\partial A_i} = (1 - a_{ij}) \left(\frac{P_{i,j}(a_{ij})}{P_i}\right)^{-\varepsilon} \tag{8}$$

The equation (8) shows that the sensitivity of labor by firm j in an industry indexed i to an industry-level export shock A_i is determined by three components: first, the share of tasks performed by robots, a_{ij}; second, firm j's product price relative to the overall price in the industry I; third, the elasticity of substitution across industries. To see clearly how a_{ij} changes the sensitivity between labor demand and export shock ($\frac{\partial L_{ij}}{\partial A_i}$), let $E_{ij} = \partial L_{ij} / \partial A_i$, then we could rewrite down the equation by taking derivative of equation (8) with respect to a_{ij}. For simplicity, we take the log transformation, which does not change our implication.[21]

In the new equation (9), one could see that robots might change the sensitivity of

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[20] This is implied from our setting that $L_{ij} = (1 - a_{ij}) Y_{ij}$.

[21] In principle, the CES industry price index P_i depends on the prices of all firms in industry i. However, in a standard Dixit–Stiglitz monopolistic competition setting, each firm is infinitesimal and takes P_i as given. We therefore treat the industry price index as an environmental variable that is not influenced by any single firm's automation level α_{ij}

firm j's labor to the export shock via two opposite channels. The first channel is the labor displacement effect, which measures how many workers are directly substituted by robots. This displacement effect will result in lower employment in firms that increase their usage of robots. The second channel is the productivity effect. As robotization reduces the share of tasks that require labor, it lowers marginal costs and ultimately lowers prices. This cost-saving effect improves firms' price competitiveness and sales, thereby mitigates the employment losses from adverse export shocks.

$$\frac{\partial \ln E_{ij}}{\partial a_{ij}} = \underbrace{-\frac{1}{1-a_{ij}}}_{displacement\ effect} + \underbrace{(-\varepsilon \frac{\partial \ln P_{ij}}{\partial a_{ij}})}_{productivity\ effect} \quad (9)$$

Our empirical analysis compares the differential effects of export slowdown on the local employment across prefectures with different robot installations, which capture both the productivity differences and differential displacement effects by robots. Our estimates therefore measure the relative importance of productivity effect to the displacement effect. If there are fewer employment declines by export slowdown in areas with more robots than in areas with fewer robots, then this would imply that the productivity channel dominates the displacement channel, and robots act as a buffer against negative export shocks.

4. Empirical Specification

Now we elaborate on the identification strategy we employ to isolate the effect of robots in mitigating the labor impacts of export slowdowns. Although export slowdowns reduce local employment and wages, the impact may differ across local labor markets, depending on the varying robot intensities across regions. This is because the adoption of robots could enhance firm productivity, thereby increasing local labor demand and potentially offsetting the negative effects of export shocks. To capture this differential effect generated by robots, we introduce an interaction term between our export shocks and robot installation at the prefecture level. We first describe our simple regression specification and then we introduce our instruments for both export shocks and robot installation variables.

OLS Specification: Our analysis begins with ordinary least squares (OLS) estimate that takes the following form:

$\Delta EmployShare_{it} = \beta_1 ExpShock_{it} \times RobotStock_{i,2010} + \beta_2 ExpShock_{it} +$

$\beta_3 RobotStock_{i,2010} + \beta_x \Delta X_{it} + \delta_{pt} + \varepsilon_{it}$ (10)

where $\Delta EmployShare_{it}$ is the dependent variable measuring the change in the employment rate in prefecture *i* between year *t-1* and *t*. $ExpShock_{it}$ is the change in manufacturing exports per worker defined in Equation (1), and $RobotStock_{i,2010}$ is the installation of industrial robot as of 2010 in a given prefecture *i*. The interaction between $ExpShock_{it}$ and $RobotStock_{i,2010}$ is our main independent variable that captures the differential effects of export shocks on the local labor market with varying levels of robotization at the initial period. The coefficient of primary interest, β_1, quantifies the heterogeneous effect of robot installation on the relationship between export shocks and changes in employment rates.

Now we continue our discussion on the control variables and fixed effects. ΔX_{it} represents the year-on-year change of a handful of socioeconomic indicators, including *ΔCollegeShare* (the change in the share of college students), *ΔPopulation* (the change in total population), *ΔUrbanShare* (the change in the share of people with urban *hukou*), and *ΔHukouShare* (the change in the share of people with local *hukou*). It should be noted that $\Delta EmployShare_{it}$, $ExpShock_{it}$, and all variables in X_{it} are constructed as changes between year $t-1$ and *t*. δ_{pt} are the province-by-year fixed effects, capturing the time-varying economic shocks at the regional level. To account for unobserved correlated shocks across prefectures within the same province that may affect the statistical significance of our estimations, we cluster standard errors at the provincial level.[22] In the baseline regression, we exclude prefecture-level fixed effects so that we could observe the impact of robot installation (a time-invariant variable) per se on employment outcomes. Our robustness check reveals that the main results are not affected, neither in terms of statistical significance nor economic magnitude, by the inclusion of prefecture fixed effects.

Instrumental Variables: An immediate concern arising with OLS estimates in Equation (10) is the issue of endogeneities with our export shock and robot installation variables. China's export performance might be correlated with unobserved industry demand shocks in China, which also impact labor market outcomes. Although we use the adoption of robots at the prefecture level in the pre-sample year

[22] In unreported robustness checks, we demonstrate that our findings remain consistent under various alternative clustering approaches, including clustering at the city and province-year levels.

($RobotStock_{2010}$) to address the endogeneity concern, it remains possible that initial robot intensity might reflect ongoing downward trends in manufacturing.

To establish a clearer causal link between the impact of export slowdowns and robot adoption on employment outcomes, we construct a shift-share or Bartik IV for both export shocks and initial robot adoption variables. First, we follow Campante et al. (2023) to construct the IV for the export shock, combining data on the initial export composition of Chinese prefectures with product-level changes in global trade flows excluding China (hereinafter referred to as the "rest of the world" or ROW). Specifically, we formulate the following IV for $ExpShock_{it}$:

$$ExpShockROW_{it} = \sum_k \frac{X_{ik,2010}}{\sum_i X_{ik,2010}} \times \frac{\Delta X_{kt}^{ROW}}{L_{i,2000}} \qquad (11)$$

where $\Delta X_{kt}^{ROW} = X_{kt}^{ROW} - X_{kt-1}^{ROW}$ represents the annual change in the value of trade flows for product *k* within the ROW, derived from HS 6-digit product-level data in the UN Comtrade database. These shifts for each product *k* are then apportioned across Chinese prefectures using weights $X_{ik,2010}/\sum_i X_{ik,2010}$, which reflects the significance of prefecture *i* in China's total exports of product *k* in a pre-sample year (2010). Finally, the IV is expressed as an export shock in units of 1,000 USD per worker by normalizing it with the working-age population of prefecture *i* from the 2000 Census, $L_{i,2000}$.[23]

Second, to construct a Bartik IV for robot adoption, we use prefecture-level robot imports and the industry-level robot installation from other countries excluding China. As specified in the equation below, the instrumental variable, $RobotROW_{it}$, exploits variations in the industry-level adoption of robots in other countries and the concentration of robots across prefectures.

$$RobotRow_{it} = \sum_j \frac{I_{ij,2010}}{\sum_i I_{ij,2010}} \times \frac{Robot_{j,2010}^{Row}}{L_{i,2000}} \qquad (12)$$

In the above, $Robot_{j,2010}^{Row}$ is the robot installation in industry *j* in other countries excluding China in the year 2010. We further apportion industry-level robot installation to each prefecture using the concentration of robots in each prefecture as weights. The concentration of robots, $\frac{I_{ij,2010}}{\sum_i I_{ij,2010}}$, is constructed using the number of imported robots in industry *j* in prefecture *i* as a share of the total number of imported robots in industry

[23] The 2000 Census data is used to avoid inflating the first-stage correlation between the IV and $ExpShock_{it}$ because they use the same denominator.

j in 2010. Different than Acemoglu et al. (2020), we use observed robot installation at the prefecture level rather than a proxy local robot intensity based on the industry-level robot installation and local employment composition. Our IV measure of predicted robot installation is based on the actual robot concentration, rather than on employment shares. Using employment shares risks overestimating the significance of robot intensity in prefectures with lower demand for automation and less reliance on robots. To mitigate the concern that the robot adoption in 2010 might be correlated with temporary changes in the labor market in the 2010s, we also substitute the robot concentration with the year 2005 to construct an alternative IV. The robustness check shows that our result remains unchanged.

Our identification strategy relies on two assumptions that the Bartik IV usually relies on. The first assumption is that the foreign export growth at the national level is not correlated with any downward trend in labor demand. For instance, a fall in global demand leads to declining foreign exports. Then, using the export growth in other countries may still capture unobserved demand shocks within China. Second, the recent work by Goldsmith-Pinkham et al. (2020) emphasizes the importance of testing the exogeneity of the initial industry shares when using Bartik IV. In our setting, the initial export structure and robot concentration in the instruments may directly predict local labor outcomes if they are correlated with other demand shocks. To address these concerns, we (1) run a series of robustness tests that include balance tests suggested by Borusyak et al. (2022), (2) add the prefecture-level fixed effects to our regressions, (3) examine the pre-period results, (4) use alternative constructions of IV via a gravity approach, and (5) conduct the statistical test of Rotemberg weights suggested by Goldsmith-Pinkham et al. (2020). We discuss these in more detail in Section 5.2.

5. Results

We now present our core findings on the effect of export performance, robot adoption and employment. Following the discussion on the baseline results, we then include a discussion of robustness checks and validation exercises for the Bartik IV.

5.1 Baseline Results

In this study, we are particularly interested in whether robot adoption mitigates the relationship between export slowdowns and employment outcomes. To examine this effect, we estimate the main specification in Equation (10) and present the results in Panel A of Table 2. Column (1) reports the findings from the OLS estimation. The result in the second row shows that the export shock is positively, albeit insignificantly, correlated with the change in employment rate, suggesting that a slowdown in exports leads to a declining employment rate.[24] The key coefficient of interest, β_1, in the first row captures the effect of robot adoption on how export shocks impact employment rate. The negative sign of the coefficient suggests that the adverse impact of export slowdowns on employment outcomes is mitigated in cities with higher levels of initial robot adoption. However, the OLS estimates suffer from large standard errors, thereby weakening the statistical significance of the results. Moreover, OLS estimates might be downward biased because robot installations are likely to be correlated with other determinants of labor market outcomes[25].

To provide insights into causal inferences, we proceed to two-stage least squares (2SLS) estimates. In Column (1) of Panel B of Table 2, we examine the first-stage condition for $ExpShockROW_{it}$. In particular, we conduct a regression where $ExpShock_{it}$ serves as the dependent variable and $ExpShockROW_{it}$ is the independent variable. The result demonstrates a significant and positive relationship between the export shock variable ($ExpShock_{it}$) and its corresponding IV ($ExpShockROW_{it}$). The F-statistic is as high as 1682.88, exceeding the commonly accepted threshold of 10, which suggests a strong predictive power of our instrument. We also report the first stage result of $Robot_{2010}$ in Column (2) of Panel B. The correlation between $Robot_{2010}$ and $RobotROW_{2010}$, coupled with an F-statistic of 589.13. Finally, in Column (3), where the dependent variable is the interaction term between $ExpShockROW_{it}$ and $RobotROW_{2010}$, we document a strong positive coefficient for $ExpShock_{it} * Robot_{2010}$. All above results confirm the relevance and the strength of the instruments.

We proceed to report the reduced-form results on the employment outcome. Figure 2 plots the reduced form regression of the change in employment on our instruments. The downward slope in the top graph of Figure 2 suggests that robot adoption mitigates

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[24] We multiply our export shock variable with -1 so that our results are interpreted as the unit change of the export slowdown.

[25] The robot intensity tends to be higher in regions with higher economic growth and a higher concentration of skilled workers, which leads to more economic opportunities.

the employment loss caused by the export shock.[26] Formal estimates of the reduced-form relationship are reported in Column (2) of Panel A of Table 2. The coefficient in the first row suggests that one unit increase in predicted robot adoption is associated with a 0.0284 percentage point increase in the employment rate when holding the export shock constant.

Now we proceed to the 2SLS estimation. As presented in Column (3) of Panel A, although export slowdown adversely impacts the employment, prefectures with higher levels of industrial robot installations experience fewer employment losses. To gauge the magnitude of the mitigating effect, we calculate the economic significance by examining the impact of an interquartile change in robot installations. Specifically, an interquartile increase in robot installations leads to a relative increase in the employment by approximately 0.16 percentage points, assuming that the Chinese export shock remains at its mean value of 61.42 dollars per worker.[27] Moreover, we observe a positive and significant relationship between robot adoption and changes in employment shares. Our documented correlation aligns with the stream of literature indicating that robots promote employment growth (Humlum, 2019; Bonfiglioli et al., 2020; Koch et al., 2021; Adachi, 2021; Albinowski and Lewandowski, 2024).

In Column (4) of Panel A, we report the 2SLS estimates for wage rates. Overall, export slowdowns generate a negative yet insignificant impact on wage rates. Consistent with the employment effect, we find a weak but mitigating wage effect of robot adoption on wage rates. One potential explanation for the weak wage effect is the upward selection of workers. Specifically, those who remain employed in the manufacturing sector during export slowdowns are likely to be high skilled workers. Wage rigidity is another possible explanation for the weak wage effect. In many manufacturing sectors, wages may be less responsive in the short run due to institutional factors, such as labor contracts, minimum wage laws, or long-term wage agreements.

To assess the long-run impact of robot adoption, we extend the sample period beyond the baseline years to cover 2010-2019. The results confirm that the employment effect remains robust over the extended timeframe (Column (1)-(2), Table 3). Notably,

[26] In the middle panel of Figure 2, we show that export performance is positively correlated with employment rate. However, the relationship between robot adoption and employment outcome is mixed, as demonstrated by the unclear trend of the line in the bottom panel.

[27] The 25^{th} and 75^{th} percentiles of our robot installations are 0 and 0.0017 per worker, respectively. The average export shock is 61.42 dollars. Thus, $0.0017 \times 61.42 \times 1.484 = 0.1550$ percentage points.

Columns (3)-(4) show a statistically significant wage effect of robotization in the long-run. An interquartile increase in robot installations leads to a relative increase in wages by approximately 0.311 log points.[28] Finding wage effect only in a long-run might be because firms slowly adjust their labor inputs. However, to avoid the potentially confounding effects of the U.S.-China trade war after 2018, in subsequent analyses, we focus on the baseline years—2010 to 2016— when China experienced a significant export slowdown.

5.2 Validity of Instrumental Variables

In this section, we conduct a series of exercises to address several identification concerns related to our empirical strategy.

Randomness of the product-level shocks. The first threat to the identification assumption of the Bartik IV is that export shocks at the product level might not be randomly assigned. Then prefectures specializing in products more vulnerable to export shocks may be correlated with other unobserved shocks. To address this issue, we follow Borusyak et al. (2022) and conduct a balance test that examine the correlation between our product-level export shocks across an exposure-weighted average of initial prefecture characteristics.[29] The results of this balance test, as presented in Appendix Table A1, provide reassurance that the product-level export shock is not systematically correlated with the initial prefecture characteristics, thus supporting the validity of the instrument. Moreover, we follow Campante et al. (2023) and implement a gravity-equation approach to isolate the variation in foreign export flows that are driven only by product-demand changes in foreign markets rather than China's domestic shocks. Column (1) of Table 4 indicates that our results are robust to this alternative specification. Furthermore, as suggested by Borusyak et al. (2022), we include an interaction term between the initial export exposure tercile dummies and year trend to address the "incomplete share" concern. As shown in Column (2) in Table 4, the main effect remains robust after accounting for trends in the exporting sector.

Local shares and other shocks. Our second concern stems from the prefecture-level

[28] The 25th and 75th percentiles of our robot installations are 0 and 0.0017 per worker, respectively. The average export shock is 61.42 dollars. Thus, $0.0017 \times 61.42 \times 2.977 = 0.311$ log points.

[29] These characteristics considered include the share of workers with a college education (*CollegeShare*), the share of manufacturing employment (*ManufacShare*), the export-to-GDP ratio (Exp/GDP_{2010}), the proportion of the population with *hukou* status ($HukouShare_{2010}$), robot adoption (*Robot*), log GDP per capita (GDP/Pop_{2010}) and log fiscal revenue per capita (*Fiscal Rev*).

export shares and robot concentration at the initial period. Our Bartik IVs rely on geographic variations in the initial export structure and robot concentration that may be correlated with other local shocks and contaminate our results. For instance, if prefectures specializing in industries that house more robots were following a downward trend in labor outcomes, our estimates would capture the effect of the ongoing trend on the local labor market. To alleviate this concern, Appendix Table A2 regresses the change in employment share between 2006 and 2010 on future export shocks between 2010 and 2016 and its interaction with robot installation. No apparent pre-trend effects are detected before the treatment period. Overall, the estimated coefficients are smaller in magnitude compared to our baseline estimates and are not statistically significant. Moreover, we include prefecture dummies in our stacked-differences analysis to check whether prefecture trends alternatively interpret our estimates. We report this result in Column (3) of Panel A of Table 4, suggesting that our estimates remain unchanged after including these prefecture fixed effects.

Sensitivity to misspecification. We examine whether our estimates are sensitive to misspecifications following the methodology proposed by Goldsmith-Pinkham et al. (2020). To assess the distribution of sensitivity across products, we calculate each product's Rotemberg weight, which reflects the relative contribution of each product of the Bartik-IV to the overall estimation. Despite employing a large number of instruments—reflecting shocks across 4,485 HS products—the distribution of sensitivity may be skewed, with a small number of products accounting for a disproportionate share of the weight. As shown in Panel A of Appendix Table A3, the top five instruments collectively account for only 4% of the total absolute weight in the estimator. These instruments include jewelry, telephones, motor cars, machines for reception, and diamonds. Unlike low-skill, technologically stagnant industries where trade is often the primary shock, these industries represent higher-skill, technologically innovative sectors where advancements in technology may play a more significant role than trade dynamics. Alternatively, we repeat this exercise at the SIC industrial level and find similar results regarding the Rotemberg weight (see Panel B of Appendix Table A3).[30] These results suggest that our main effects are not driven by a narrow subset of products but instead reflect broader patterns.

[30] A similar robustness test is performed excluding one industry at a time, and the (unreported) results are consistent.

Dropping each HS section. To determine whether our estimates were driven by a particular product sector, we also reconstruct the export shock variable and the Bartik IV by systematically excluding products from the 4,485 HS codes, one at a time. We assess the robustness of our findings by plotting the distribution of regression coefficients that are obtained by excluding products from each HS code at a time. As shown in Figure 3, the coefficients remain consistently negative across all exclusions, with no significant deviation from the baseline estimate of -1.484. This rules out the possibility that a single HS product disproportionately drives our results.

Past robot shocks and labor market. We also address the concern about the endogeneity of our robot stock variable. One the one hand, it is possible that the robot adoption in 2010 as a pre-sample exposure is serially correlated and captures the effects of past robot shocks on future employment outcomes. To mitigate this concern, we follow Jaeger et al. (2018) and conduct an additional robustness check by adding the robot adoption level from earlier years (i.e., 2005). Adding robot exposure in the earlier period helps to control for the impact of past robot shocks on the local labor market. Again, the instrument for robot installation in 2005 is constructed using the 2005 robot installations in foreign countries and the robot concentration in 2010. Column (4) in Table 4 reports the results and indicates no change of our results after controlling for the past robot shocks. Moreover, in Column (5), we use an alternative IV that is constructed based on robot concentration in earlier years (i.e., 2005). On the other hand, prefectures with higher levels of initial robot installation may have had lower initial labor force participation. That is, the extent of robot adoption may partly reflect local labor market fundamentals. As a result, when the export slowdown occurred, these areas may have experienced smaller declines in employment simply because there was less room for employment to fall. To address this concern, we include interactions between initial robot tercile dummies and year fixed effects in our regressions. We report the result in Column (6). Across all Columns (4)-(6), our results are robust and consistent.

Robot adoption and other technology shocks. Another potential concern is that other technology shocks correlated with robot adoption might confound our estimates. We investigate this issue by controlling for local exposure to innovations and industry value added.[31] These variables are constructed in Bartik style based on the initial prefecture-level employment shares and industry-level innovation growth and value added. Columns (7) and (8) show that our result remains unchanged after controlling for exposure to other technology shocks and industry value added. To rule out the possibility that industry structure changes might confound our results, we include two prefecture-level covariates: the share of service sector value-added in total output and a weighted sum of value added across the agriculture, manufacturing, and service sectors. Column (9) suggests that our result is robust to controlling for the local industry structure changes.

Multiple endogenous variables. Finally, we consider the issue of weak instruments when there are multiple endogenous variables involved. In our main specification, there are three endogenous variables including export shocks, robot stocks, and the interaction of the two. While our previous results suggest strong statistical power of first-stage F-statistics, our identification might be weak when more than one endogenous variable are involved because the reduced form parameters are not local to zero. To address this concern, we follow the approach developed by Sandersona and Windmeijer (2016) and calculate the conditional F-statistics of the first stage. By computing F-statistics conditional on other endogenous variable, this method isolates the strength of one instrument for its corresponding endogenous variable from other endogenous variables.[32]

The first-stage conditional F-statistics for *ExpShock*RobotStock*$_{,2010}$, *ExpShock*, and *RobotStock* are 430.57, 130.37, and 20234.86, respectively, indicating strong statistical power of our instruments in the first-stage.[33] We also conduct an exercise by estimating the alternative specification where we only instrument for export shock or robot stock at each time in Table A4. Overall, the results remain robust to these alternative specifications, alleviating the concern about identification issues arising from the use of multiple endogenous variables in our specification.

[31] We measure the innovation and industry value-added exposure based on the initial employment share at the prefecture level and the change in number of innovations and log industry value-added at the industry level between 2010 and 2016.

[32] For instance, if the instruments strongly affect export shocks (*ExpShock*) but not (*RobotStock*), our conditional F-statistics for *RobotStock* will suggest weakness in the first stage.

[33] According to Sandersona and Windmeijer (2016), we first obtain residuals from regressing endogenous variables X_j on those endogenous regressors X_{-j} with X_j excluded. Then we regress the obtained residuals on those exogeneous regressors and calculate the conditional F-statistics. See more in their Appendix A.3

5.3 Additional Robustness Checks

In this subsection, we conduct a series of additional robustness checks to ensure the validity of our findings. These checks involve exploring alternative variables, dropping extreme values, alternative sampling, and using other data sources.

Alternative Variables. We use the alternative dependent outcome variable—the change in natural logarithm of employment—which allows us to interpret the results as percentage changes in employment and reduce the influence of large employment numbers in certain prefectures. In Column (1) of Panel A of Table A5, the coefficient of -4.3357 indicates that an interquartile increase in robot installations leads to a relative increase in employment by approximately 0.005 log points (about 0.5%).[34]

Extreme Values. We address the potential impact of outliers by systematically dropping extreme observations where the change in employment shares falls below the 5th percentile or exceeds the 95th percentile. In Column (2) of Table A5, we show that the results are not significantly changed by the exclusion of outliers. However, the magnitude of the main coefficient decreases. One possible reason is that the main effect may be stronger in cities with particularly high employment losses, which are excluded from this regression.

Using Census Data. We validate our findings using Population Census survey data, which is collected every five years. For this analysis, we use two waves of the survey, from 2010 and 2015. Although the sample size is reduced to 322 observations, the results in Column (3) of Table A5 are remarkably consistent with our baseline findings.[35] This robustness check underscores the reliability of our conclusions, even when using a distinct dataset with fewer observations.

Accounting for depreciation of robots. To account for the possibility that robots may depreciate over time, we further examine our main results using more recent robot installation statistics. Rather than using the cumulative robot installations up to 2010, we instead use installed robots between 2005 and 2010 in each prefecture to construct our measures of robot shocks and its instrumental variable. The results based on more recent robot installations are reported in Column (4) of Table A5, confirming that depreciation does not affect our findings.

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[34] The 25th and 75th percentiles of our robot installations are 0 and 0.0017 per worker, respectively. The average export shock is 61.42 dollars. Thus, $0.0017 \times 61.42 \times 0.043357 = 0.0045$ log points.

[35] The point estimates in Column (3) of Table A5 represent a five-year average effect of robots and export slowdown on employment. Therefore, the coefficient is larger than that in the baseline.

6. Potential Mechanisms

In this section, we delve into the possible mechanism by which robot adoption mitigates the impact of export slowdowns on employment outcomes. We consider several possible explanations for the mitigating effect, including local demand growth, migration effect, diversification strategies of firms, and government subsidies. Overall, we find that robot adoption stimulates local demand growth, as we show evidence that firms in areas with more robots exhibit greater increases in domestic sales than firms in other areas, conditional on the same level of export shock exposure. To further complement this analysis, we also show that local consumption increases more in areas with more robots.

6.1 Domestic Sales

It is possible that robot adoption enhances firms' competitiveness by improving production efficiency and operational flexibility, and therefore enables a local demand growth (Artuc et al., 2023). For instance, more roboticized firms might adjust their output to meet changing demand patterns, minimize labor costs, and avoid significant production disruptions.

To test this hypothesis, we examine the effects of robots on sales and costs of firms. The analysis is conducted at the firm-level so that we could further control for firms' unobservable characteristics by adding firm fixed effects into the baseline specification. As shown in Panel A of Table 5, there is a statistically significant increase in firms' main income (see Columns (4) and (5)). Moreover, we highlight a key finding that although the change in foreign sales remains statistically unaffected by robot adoption (see Column (2)), the change in domestic sales is significantly increased, as indicated by the negative and statistically significant coefficient in Column (1). This effect is observed in terms of both absolute dollar value as well as percentage change (Column (3)), indicating that robots enable firms to pivot their strategies toward domestic markets. Such a reallocation likely reflects the enhanced flexibility and efficiency that robots provide, allowing firms to adapt to declining export opportunities by strengthening their presence in domestic markets. Furthermore, we use this firm-level data to analyze the impact on net hiring. Consistent with our baseline results, as shown in Column (6), the adoption of robots mitigates the decline in net hiring during periods of adverse export shocks.

We also investigate whether firms' ability to retain employment under the impact of adverse export shocks relates to the reduction in operational costs. As shown in Panel B of Table 5, our findings indicate that robot adoption leads to an increase in core expenses such as main business costs (*ΔMain Biz Cost*), but no statistically significant change in overall business costs (*ΔBiz Cost*), salaries (*ΔSalary*), management fees (*ΔMngt Fee*), or R&D expenditures (*ΔR&D Fee*). These results suggest that, at least in the short term, robots do not directly disrupt the major business structures of cost. However, robot adoption may mitigate the effects of export slowdown in other financial and operational dimensions. Specifically, firms in sectors with more robots report in accommodation expenses (Δ*Accommodation Fee*). These fees are related to sales and marketing efforts aimed at compensating for the slowdown in export demand. The rise in accommodation expenses could be directly linked to efforts at expanding domestic market outreach. These adjustments are consistent with the pattern observed in Panel A of Table 5, suggesting that firms are reallocating sales resources in response to changing market conditions.

Overall, our results in Table 5 highlight the strategic role of robot adoption as a mediator for firms during periods of export slowdown. By reallocating resources and prioritizing domestic sales, robot-adopting firms are able to cushion the negative impacts of trade disruptions, showcasing the adaptability fostered by technological investments.

6.2 Alternative Mechanisms

In this section, we aim to examine alternative mechanisms that may explain the observed main effects of robot adoption in mitigating the adverse employment effects of export slowdowns. Specifically, we focus on four possible channels: the initial displacement effect, population migration, firms' diversification strategies, and government subsidies.

Initial displacement effect. As discussed in Section 3, firms with high initial robot adoption may have already undergone substantial labor displacements before the onset of the export slowdown, so that their labor costs would already be relatively low compared to other firms using fewer robots in our sample period. If so, our results show smaller employment losses in areas with more initial robot adoption is simply because a substantial share of the adjustment had already occurred prior to our sample period—

rather than from that robots could buffer the negative labor market effects of the export slowdown.

To assess this possibility, we first examine whether robot adoption prior to our sample period is associated with lower labor intensity at the firm level. Using data from 2010—the year immediately preceding our analysis window—we regress firm-level labor intensity, measured as the number of employees divided by total assets, on cumulative robot adoption up to 2010. If firms with higher robot adoption had already displaced labor, we would expect a negative and significant relationship between robot adoption and labor intensity. However, as shown in Column (1) of Table A6, we find no statistically significant effect, and the estimated coefficient is economically small. This result suggests that, at least along this dimension, higher robot adoption before 2010 did not translate into systematically lower labor intensity.

To further test whether earlier labor displacements are concentrated among firms more exposed to the export slowdown during 2010-2016, we augment the specification by adding an interaction between the firm-level robot adoption as of 2010 and subsequent export shocks, defined as the average prefecture-level export exposure over 2010-2016. By doing so, we could compare the pre-period labor intensity across firms with different levels of robot adoption while holding future export exposure constant. Our results shown in Column (2), however, show that this interaction term is statistically insignificant and small in magnitude. Taken together, these findings provide little support for the hypothesis that our main results are driven by pre-sample labor displacement.

Migration. Export slowdown may dampen local economic performance, leading to outmigration as individuals seek better opportunities elsewhere (Campaniello, 2014). Similarly, the adoption of robots could shift the labor market composition by displacing low-skilled workers, potentially encouraging them to leave the local market (Faber, 2020; Javed, 2023). If either of these scenarios holds true, our findings may be driven by migration effects because the out-migration of workers could reduce local labor market competitiveness and lessen the impacts of export slowdown. By adjusting the local labor supply, the localized impacts may be diffused from areas more exposed to export slowdown toward less exposed areas.

To test this possibility, we use Census data and examine the effects of export slowdowns and robot adoption on population changes, as presented in Appendix Table

A7. Columns (1) and (2) show that neither export shocks nor robot adoption alone significantly influence population changes. In Column (3), the coefficient of the interaction between export shocks and robot adoption remains statistically insignificant. Together, these results suggest that migration is unlikely to be a primary driver of our main findings.

It is important to note that internal migration does not appear to be a major channel through which the effects of trade shocks and robot adoption operate. This raises the question of whether the main effect we estimate reflects any general equilibrium adjustment at all. In a context where migration is limited, we argue that the main findings are best interpreted within a partial equilibrium framework, in which local labor markets adjust independently. The limited role of migration is likely due to internal mobility frictions in China, such as the household registration (hukou) system, which restricts labor movement across regions.

Firm's Diversification Strategy. Another potential channel is firms' diversification strategies. The adoption of robots could enable firms to diversify their operations, either geographically or across industries, which serves as a strategy against export slowdowns. For example, firms might reduce their dependence on a single market or product by expanding into new regions or sectors, thereby preserving employment levels through more effective risk distribution.

To explore this possibility, we analyze data on publicly listed Chinese firms and their subsidiaries, constructing a Herfindahl–Hirschman index (HHI) at both the domestic regional and industry levels to measure diversification. Specifically, we let $s_{i,j,t}$ represent the percentage share of investment of firm i in industry j in year t. The industry-level HHI for firm i in year t is given by $HHI\_Industry_{i,t} = \sum_{j=1}^{N} s_{i,j,t}{}^2$, where N represents for the number of industries of the firm. Likewise, we construct regional-level HHI for firm i in year t, the equation is given by $HHI\_Area_{i,t} = \sum_{k=1}^{M} \alpha_{i,k,t}{}^2$, where M represents for the number of prefectures of the firm and $\alpha_{i,k,t}$ is the percentage share of investment of firm i in prefecture k in year t. Higher values of HHI indicate higher concentration, implying that the firm's activities concentrate on a few industries or geographic regions. Conversely, lower HHI values indicate greater diversification, suggesting the firm's activities are spread across a wider range of industries or regions.

The results, presented in Appendix Table A8, reveal that robot adoption under export slowdowns slightly reduces diversification, although the effect is statistically insignificant. These findings suggest that diversification strategies are not a major contributor to the observed effects.

Robot Subsidy. A third possible alternative mechanism relates to government subsidies. In China, firms adopting robots may benefit from place-based policies or financial incentives that could influence employment outcomes during periods of export slowdowns. To investigate this mechanism, we identify prefectures that received robot-related subsidies during our sample period and conduct a series of analyses to assess the impact of robot subsidies on the employment.[36]

First, we rerun our baseline regressions after excluding prefectures that are identified as major recipients of robot-related subsidies. This helps us to isolate the employment effect of robot adoption from the effect driven by robot subsidies. Second, we create a subsidy dummy variable to indicate whether a prefecture benefits from such policies; we include this dummy, along with its interaction with year trends, as additional control variables in our regressions. This approach allows us to account for time-varying effects of subsidies on employment outcomes. The results, presented in Columns (1) and (2) of Appendix Table A9, show that the main effect remains consistent and robust across these specifications. Then, we construct an interaction term between the subsidy dummy and export shocks, incorporating it into the 2SLS regressions to test whether subsidies contaminate our estimated effects of robot adoption on the employment. The results of this analysis are presented in Column (3), suggesting that robot-related subsidies have a limited impact on the employment change. Therefore, government subsidies are unlikely to drive the observed employment effect, further reinforcing the role of robot adoption as a mitigating factor during export slowdowns.

6.4 Additional Analyses

Consumption Level. We now turn to the consumer side to examine the potential welfare implications of robot adoption. Consumption is widely regarded as a direct and observable measure of household welfare—when individuals consume more, it often

[36] The identification of prefectures with robot subsidies is mainly from web sources, such as http://www.xzlrobot.com/c3531.html. In total, we identified six cities with the heaviest robot subsidies over the sample period: Shanghai, Nanjing, Shunde, Guangzhou, Shenzhen, and Dongguan.

reflects improved income prospects or greater job security. Therefore, we conjecture that, while robots may help households cushion the adverse employment impacts of the export slowdown, they may also contribute to improved welfare by stabilizing or even boosting household consumption. In Table 6, we regress household-level consumption (UHS) and prefecture-level consumption change (CFPS) on the interaction of robot IV and export shock IV. We find that robotization might lead to increased local consumption when the export shock is held constant. The effect is more pronounced for goods than for services, consistent with the fact that the export shock primarily affects the trade of goods. As suggested, one possible reason for the observed increase in local consumption is that greater robot adoption enables an increase in local demand growth, which in turn mitigates employment losses during export slowdown.

It is important to note that the observed consumption patterns may not directly reveal consumers' true preferences for locally produced goods, as many of the items consumed may be imported from outside the region. Due to the lack of detailed data on transportation of goods, we interpret the above consumption analysis only as a potential indicator of local welfare improvement. Nevertheless, we refrain from drawing strong statements regarding welfare changes under our reduced-form framework.

Robot Adoption after 2010. To strengthen evidence that robot installations mitigate the negative effects of export shocks, we examine whether firms adjust their subsequent robot installations in response to export shocks. Our prediction is that these firms may ramp up their robot installations even further in response to adverse export shocks, because these firms possess complementary technological know-how and streamlined processes that enable rapid scaling of automation. In this sense, an export slowdown might act as a catalyst, prompting them to intensify automation efforts to maintain or enhance their competitiveness and efficiently address evolving market demands.

The positive coefficient in Column (1) of Table A10 shows that firms with higher initial robot adoption increase their robot installations when exports slow down. While the coefficient is statistically insignificant when using the absolute level of robot installations as dependent variables, we find significant effects when accounting for the initial differences in robot adoptions across regions. The point estimate in Column (2) suggests that one unit increase in robot exposure per worker in 2010 leads to an approximately 0.52 log point increase in robot installations between 2010-2016, holding the export shock to be constant. A back-of-envelope calculation suggests that an interquartile increase in initial robot exposure will lead to a later increase in robot installations by around 0.054 log points.[37] This result remains robust when we use the logarithm and inverse hyperbolic sine transformation of robot changes as the outcome variable, as shown in Columns (3)-(6). These findings indicate that the deployment of automation is path-dependent, with early adopters exhibiting a higher level of sensitivity. To avoid the reverse causality, our analyses of the robotization and labor market effects rely on the initial-stage installation level of robots.

Hiring Strategy. We further present evidence on how firms adjust their hiring strategies in response to export slowdowns. In response to changes in sales strategy, firms may need to adjust their hiring strategies accordingly, particularly in terms of new employees' skill levels and educational qualifications. For example, to promote domestic sales, firms may demand more strategic planners and experienced sales managers to guide their efforts and promote revenue growth. Then one may expect to find that firms in more robot-intensive areas hire more educated and skilled workers when export slows down.

To test this prediction, we use data from the population census, which provides detailed information on occupation and educational backgrounds. We aggregate this data to the prefecture level and compute the changes in the share of managerial employees (*ΔManagerShare*) and the share of managers with a college degree as a percentage of the working-age population (*ΔCollegeManagerShare*). Our results, as presented in Table 7, reveal that the adoption of robots is associated with a relative increase in the share of managerial employees, as well as in the share of managers with a college degree. This suggests that firms in these regions are more likely to hire highly skilled managers to promote domestic sales in response to export shocks. Columns (3)-(4) additionally show that the mitigating effect of robots is concentrated among more educated workers.

These findings indicate that the employment outcomes observed in our baseline analysis may reflect not only the overall changes in employment but also shifts in the employment structure, with firms adapting to new technologies by hiring workers with the skills required to help firms switch their sales strategy or to more effectively leverage those technologies. In other words, the changes in employment observed in

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[37] The mean value of export exposure is around 61.42 dollars. The 25^{th} and 75^{th} percentiles of our robot installations are 0 and 0.0017 per worker, respectively. Thus $0.0017 \times 61.42 \times 0.52 = 0.054$ log points.

the baseline may, to some extent, be driven by the firms' strategic decisions to enhance their workforce in line with technological adoption, particularly in response to export-related disruptions.

Manufacturing vs Nonmanufacturing Employment. Previous research on trade and the local labor market suggests that trade shocks primarily impact manufacturing industries. However, shocks to manufacturing industry may also impact other sectors through changes in the competitive wage rate, worker migration across sectors, or output linkages between upstream and downstream industries. In Table A11, we further explore the employment effects separately for workers in the manufacturing and nonmanufacturing sectors. We find that robot adoption mitigates the negative employment effects of export slowdown in both the manufacturing and nonmanufacturing sector as the coefficients of the mitigating effects are statistically indistinguishable (-0.7095 and -0.7745 percentage points, respectively). Finding a mitigating effect outside the manufacturing sector is plausible because local demand growth induced by robot adoption may boost the overall economy. For instance, manufacturing firms with robots expand their production, which in turn raises demand for services in the nonmanufacturing sector through sectoral linkages, thereby increasing employment opportunities outside the manufacturing sector.

7. Conclusion

This study examined the role of robotization in mediating the relationship between export slowdown and labor market outcomes in China from 2010 to 2016. By exploiting prefecture-level variations in export shock and robot installations, our analysis reveals that robotization significantly mitigates the adverse impacts of export slowdowns on employment. Specifically, regions with higher initial levels of robot adoption experienced relatively smaller declines in employment during this period.

We further investigate the underlying mechanism, finding that robotics may increase local demand for goods. Prefectures with more robot adoption are associated with higher domestic sales and household consumption, indicating that robotization enables firms to adjust to adverse export conditions by shifting to the domestic market. Additionally, we find that the mitigating effects are concentrated among high-skilled workers, particularly those in managerial roles, whose jobs are less susceptible to automation.

This study adds to the growing research on how deglobalization and robotization impact economies, especially in developing countries. It highlights how automation cushions the negative effects of external trade shocks. The findings also have important policy implications. Although automation creates challenges for labor markets, it also offers opportunities to strengthen resilience during economic disruptions. By showing the close connection between trade and technology, we emphasize the importance of considering how both factors interact when shaping policies for automation and trade in today's interconnected world. Policymakers should focus on strategies that combine the benefits of automation and trade while addressing the unequal distribution of gains across different skill levels.

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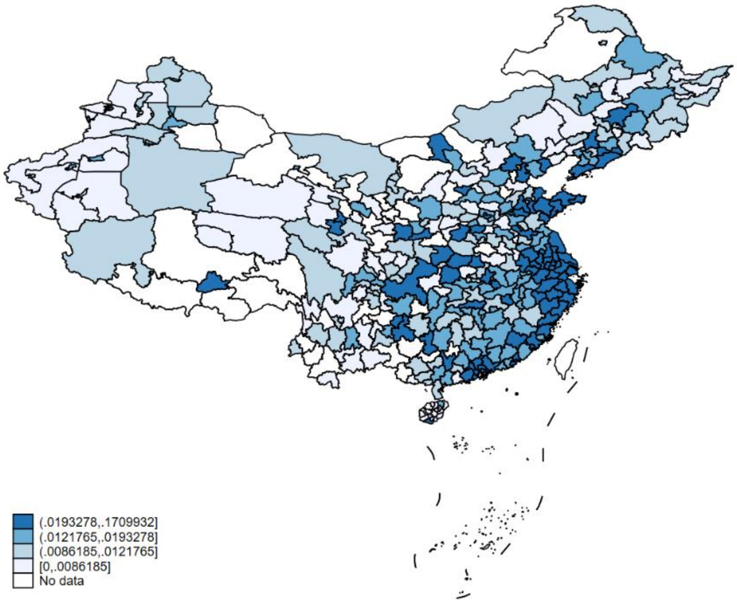
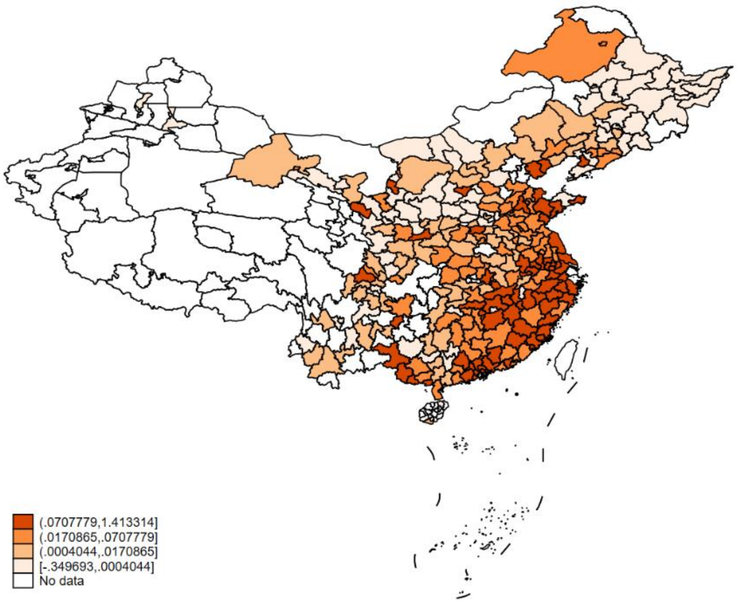


Panel A. Robot Adoption



Panel B. Annual Export Change

Figure 1. Heat Maps on Export Change and Robot Adoption

Notes: This figure displays a heat map of robot adoption and annual export changes. In Panel A, city-level robot adoption intensity in 2010 is divided into quartiles, with darker blue indicating higher intensity. In Panel B, the mean annual change in exports is also divided into quartiles, with darker orange indicating greater growth.

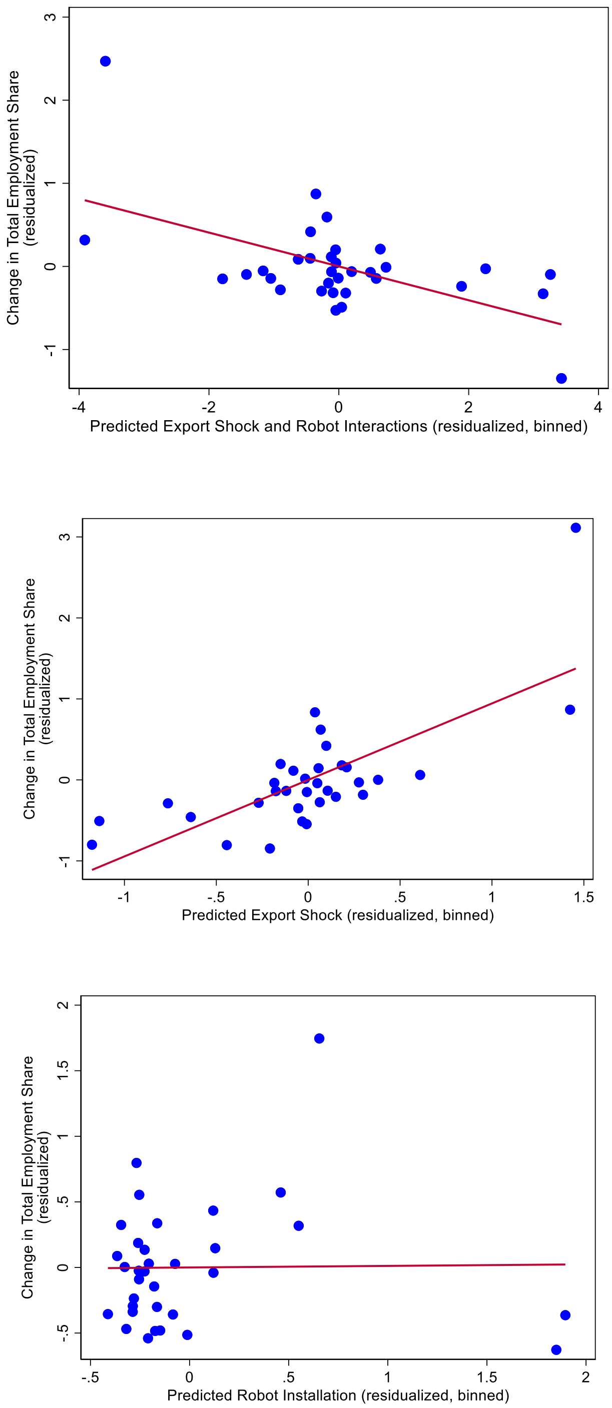


Figure 2. Reduced-form Estimates on Employment Changes

Note: This figure shows the binned scatter plots of our reduced form estimates obtained by regressing the employment change on the predicted export shock ($ExpShockROW_{it}$), predicted robot installation ($RobotROW_{2010}$), and their interactions.

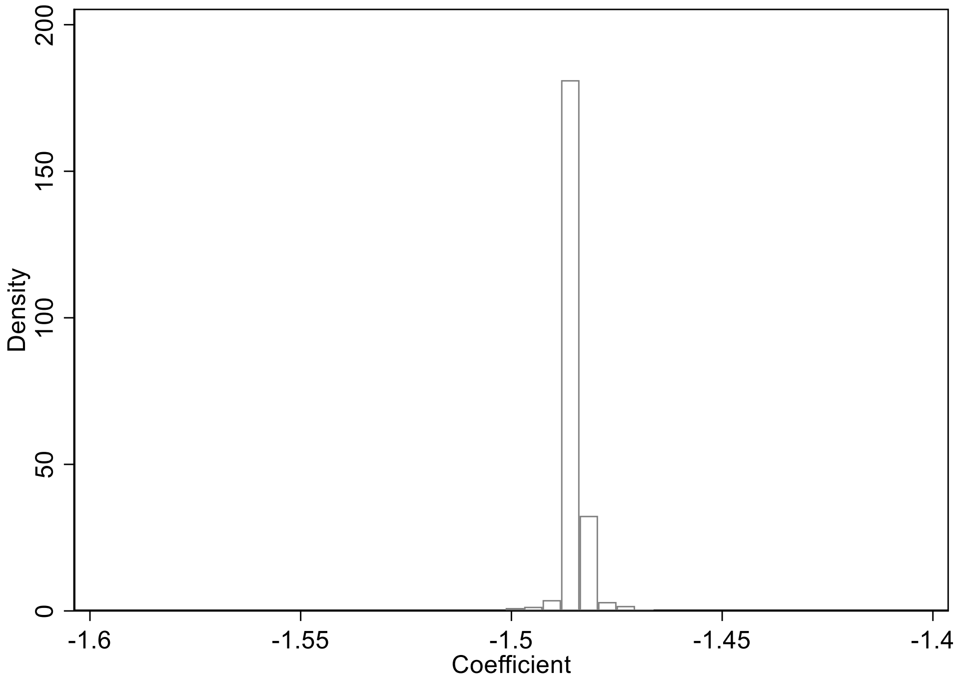


Figure 3. Main Coefficients' Distribution Excluding Each Product

Notes: This figure plots the distribution of the baseline coefficients. For each time, we exclude one product (HS) from the sample and reconstruct an export shock IV. And then, we re-estimate Column (3) of Table 2. The x-axis represents for the coefficient, and y-axis represents for the density of the distribution.

Table 1. Summary Statistics

Note: This table presents unweighted statistics for variables used in this paper.

	Variable Definition	Obs	Mean	SD
DEPENDENT VAR.				
ΔEmploymentShare	Change in employment as a percentage of total population.	1,666	0.4300	2.1102
Δlog(wage)	Change in log wage	1,666	14.4854	15.9778
Log(Employment Change)	Change in log employment	1,666	4.4893	13.5449
ΔManufacturingEmploymentShare	Change in manufacturing employment as a percentage of total population	1,666	0.1007	1.0603
ΔNonManufacturingEmploymentShare	Change in nonmanufacturing employment as a percentage of total population	1,666	0.3293	1.5193
EXPLANATORY VAR.				
$ExpShock*RobotStock_{,2010}$	The interaction term between export shock and robot adoption.	1,666	-0.0039	0.3100
ExpShock	Export decrease rate between 2010-2016.	1,666	-0.0632	0.8244
$RobotStock_{,2010}$	Robot per capita in 2010.	1,666	0.0145	0.0609
CONTROL VAR.				
ΔCollegeShare	Change in college enrollment rate	1,666	-0.2722	1.9823
ΔPopulation	Change in log population	1,666	0.3976	5.0139
ΔUrbanShare	Change in urban population share	1,666	1.3869	2.2503
ΔHukouShare	Change in log population with hukou	1,666	0.4920	3.8227

Table 2. Export Shock, Robot and Employment Outcomes

Notes: This table reports the baseline results. Panel A presents the role of robot adoption and export shock on employment outcomes. In Column (1), the *ExpShock*—the change in export rate—is interacted with *RobotStock*—the robot adoption level, serving as the main independent variable. In Column (2), the interaction of instrumental variables for *ExpShock* and *RobotStock* is the main independent variable. Both columns take the change in employment rate—ΔEmploymentShare—as the dependent variable. In Column (3), IV 2SLS regression specification is adopted. In Column (4), we report the IV regression using the change in log wages as the dependent variable. Panel B reports the first-stage results of the IV regressions, using the instrumental variables for *ExpShock* and *RobotStock*, as well as their interaction term as the dependent variables. For all specifications, control variables include the change of share of college students (*ΔCollegeShare*), the change in total population (*ΔPopulation*), the change of share of urban residences (*ΔUrbanShare*) and with-Hukou residences (*ΔHukouShare*). We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Panel A. Change of Employment Shares and Wages

	(1)	(2)	(3)	(4)
	OLS	OLS Reduce Form	IV-2SLS	IV-2SLS
VARIABLES	ΔEmploymentShare	ΔEmploymentShare	ΔEmploymentShare	Δlog(wage)
*ExpShock*RobotStock,₂₀₁₀*	0.8769		1.4840***	1.0501
	(0.7448)		(0.2839)	(1.6372)
ExpShock	-0.4972		-1.3690***	-1.0749
	(0.4172)		(0.1761)	(1.1209)
RobotStock,₂₀₁₀	2.4754**		2.1024***	6.4753***
	(1.0142)		(0.1957)	(2.1789)
*ExportShock(IV)*RobotStock(IV)*		-0.0284***		
		(0.0070)		
ExportShock(IV)		0.2796***		
		(0.0555)		
RobotStock(IV)		0.3094***		
		(0.0719)		
ΔCollegeShare	0.0341	0.0283	0.0063	0.4747
	(0.0325)	(0.0299)	(0.0348)	(0.2921)
ΔPopulation	-0.1337***	-0.1223***	-0.1110***	-0.9389***
	(0.0355)	(0.0213)	(0.0062)	(0.0478)

ΔUrbanShare	0.0404*	-0.0329	-0.0137	0.0744
	(0.0216)	(0.0417)	(0.0272)	(0.2093)
ΔHukouShare	0.0609**	0.0450*	0.0499**	0.1780*
	(0.0262)	(0.0223)	(0.0194)	(0.0877)
Province*Year FE	√	√	√	√
Observations	1,696	1,684	1,666	1,666
R-squared	0.2163	0.5181		0.1143

Panel B. First-stage Results

VARIABLES	(1) IV-1st Stage *ExpShock*(IV)	(2) IV-1st Stage *RobotStock,2010*(IV)	(3) IV-1st Stage *ExportShock(IV)*RobotStock,2010(IV)*
*ExpShock*RobotStock,2010*	0.0178***	0.0001	0.0354***
	(0.0051)	(0.0002)	(0.0005)
ExpShock	0.2016***	0.0004	-0.0030
	(0.0260)	(0.0007)	(0.0048)
RobotStock,2010	-0.0989	0.1160***	-0.0472***
	(0.0606)	(0.0123)	(0.0083)
ΔCollegeShare	0.0195**	0.0005*	0.0032
	(0.0077)	(0.0003)	(0.0021)
ΔPopulation	-0.0110	0.0000	-0.0026
	(0.0162)	(0.0002)	(0.0033)
ΔUrbanShare	-0.0078	-0.0023	0.0023
	(0.0184)	(0.0021)	(0.0065)
ΔHukouShare	-0.0018	-0.0000	0.0018
	(0.0133)	(0.0003)	(0.0021)
Province*Year FE	√	√	√
Observations	1,714	1,696	1,696
R-squared	0.4900	0.8661	0.2767

Table 3. Extending to the Year 2019

Notes: This table reports the results extending the sample to the year 2019. In Columns (1)-(2), the dependent variables are the change in employment rate—ΔEmploymentShare. In Columns (3)-(4), the dependent variables are the change in log wages. For all specifications, we employ the same set of control variables as in Table 2. We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

VARIABLES	(1)	(2)	(3)	(4)
	OLS	IV-2SLS	OLS	IV-2SLS
	ΔEmploymentShare	ΔEmploymentShare	Δlog(wage)	Δlog(wage)
*ExpShock*RobotStock,$_{2010}$*	0.1276**	1.1014***	0.6883	2.9770***
	(0.0590)	(0.1614)	(0.6421)	(1.0190)
ExpShock	-0.0651	-0.8161***	-0.4997	-1.6889**
	(0.0659)	(0.1101)	(0.3976)	(0.7101)
RobotStock,$_{2010}$	1.9698***	1.8837***	8.0170*	8.1501***
	(0.6889)	(0.2127)	(4.2735)	(2.7303)
Baseline Controls	√	√	√	√
Province*Year FE	√	√	√	√
Observations	2,498	2,498	2,493	2,493

Table 4. Robustness Checks

Notes: This table reports the main estimated effect on the employment share. In Panel A, we use alternative specifications to check the robustness of our main results. In Column (1), we report the results from a gravity specification following Campante, et al., (2023). In Column (2), we add export tercile variable with year trend. In Column (3), we add city-level fixed effects. In Column (4), we include the robot installation level in 2005. In Column (5), we reconstruct the robot shock IV using the robot concentration at the prefecture level in the year 2005. In Column (6), we add initial robot tercile variable with year trend. In Column (7), we add the Bartik-style exposure to innovation change. In Column (8), we add the Bartik exposure to industry value added. In Column (9), we additionally include the share of service sector value-added in total output and a weighted sum of value added across the agriculture, manufacturing, and service sectors. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Gravity Specification	Incomplete Share	Add City FE	Add *RobotStock,*$_{2005}$	Alternative Robot IV	Initial Robot Time Trend	Technology Shocks	Industry Value Added	Industry Structure
VARIABLES									Change
*ExpShock*RobotStock,*$_{2010}$	5.2335***	1.2723***	1.5020**	1.5457***	1.5120***	1.2709***	1.1269***	1.4816***	1.6961***
	(0.8379)	(0.3043)	(0.2872)	(0.3169)	(0.4004)	(0.2616)	(0.2232)	(0.2838)	(0.4682)
ExpShock	-2.7753***	-1.2283***	-1.3744**	-1.4226***	-1.3774***	-1.2158***	-1.1580***	-1.3675***	-1.5777***
	(0.3349)	(0.2203)	(0.1754)	(0.2012)	(0.2216)	(0.1697)	(0.1409)	(0.1764)	(0.3546)
RobotStock,$_{2010}$	2.2159**	2.0005***		-8.6014	1.9958***	1.8011***	3.2097***	2.0997***	1.6104***
	(0.4141)	(0.2274)		(6.5025)	(0.2617)	(0.0930)	(0.9577)	(0. 1939)	(0.4921)
Baseline Controls	√	√	√	√	√		√	√	√
Province*Year FE	√	√	√	√	√		√	√	√
City FE			√						
Export Tercile*Year		√							
Initial Robot Tercile*Year						√			
Industry Structure Change									√
Observations	1,666	1,666	1,666	1,666	1,666		1,666	1,666	1,656

Table 5. Firm Income and Expenditures

Notes: This table presents the results for the relation between export shock, robot adoption and firm financial and hiring outcomes. The data used for this analysis is NTSD. Firms with missing information in domestic and export sales are excluded from the sample. The data is winsorized at the top and bottom 1%. The dependent variables in Panel A are the change in firm's domestic sales, export sales, share of domestic shares, main-business income, total sales (in 1000 RMB), respectively. The dependent variables in Panel B are the change in firm's main-business cost, business cost, salary, management fees, R&D fees, accommodation fees (in 1000 RMB), respectively. For all specifications, we use 2SLS specification and employ the same set of control variables as in Table 2. We include province-year and firm fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

Panel A. Firm Income

	(1)	(2)	(3)	(4)	(5)
	ΔDomestic Sales	ΔExport Sales	ΔDomestic Sales %	ΔMain Biz Income	ΔTotal Sales
*ExpShock*RobotStock*, $_{2010}$	25.036***	7.035	0.146***	335.578***	29.488**
	(7.662)	(15.512)	(0.029)	(48.175)	(13.766)
ExpShock	-12.255**	-5.197	-0.038**	-149.939***	-15.238*
	(5.291)	(11.561)	(0.019)	(35.745)	(8.873)
Constant	√	√	√	√	√
Baseline controls	√	√	√	√	√
Province*Year FE	√	√	√	√	√
Firm FE	√	√	√	√	√
Observations	918176	832361	592674	891324	918176

Panel B. Firm Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)
	ΔMain Biz Cost	ΔBiz Cost	ΔSalary	ΔMngt Fee	ΔR&D Fee	ΔAccommodation Fee
*ExpShock*RobotStock,* $_{2010}$	152.113***	103.638	0.492	1.329	-2.292	2.549***
	(41.240)	(302.220)	(0.607)	(1.585)	(6.154)	(0.769)
ExpShock	-51.134*	-69.244	-0.336	-0.952	0.054	-1.660**
	(28.658)	(195.691)	(0.410)	(0.951)	(4.636)	(0.642)
Constant	√	√	√	√	√	√
Baseline controls	√	√	√	√	√	√
Province*Year FE	√	√	√	√	√	√
Firm FE	√	√	√	√	√	√
Observations	884182	915902	813072	887277	423482	519460

Table 6. Consumption Level

Notes: This table presents the results for the relation between export shock, robot adoption and consumption outcomes. The data used for analyses across Columns (1)-(3) is UHS, and the data used for analyses across Columns (4)-(5) is CFPS. In Column (1), the dependent variable is *Consumption*, the total consumption in a household in a given year. In Column (2), the dependent variable is *Service Consumption*, the service consumption in a household in a given year. In Column (3), the dependent variable is *Product Consumption*, the product consumption in a household in a given year. In Column (4), the dependent variable is *Consumption Growth*, the changes in consumption in a household in a given year. In Column (5), the dependent variable is *Consumption Growth Rate*, the percentage changes in consumption in a household in a given year. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)
	UHS			CFPS	
VARIABLES	Total Consumption	Service Consumption	Product Consumption	Consumption Growth	Consumption Growth Rate
*ExpShock*RobotStock,₂₀₁₀*	24,786	12,072	12,714*	14,061*	1.0578*
	(11,832)	(7,174)	(4,683)	(7,577)	(0.6042)
ExpShock	-4,617*	-2,326*	-2,291**	-4893**	-0.2120
	(1,553)	(958.0)	(640.2)	(2036)	(0.1392)
RobotStock,₂₀₁₀	31,206	14,561	16,645	43,441**	0.8292
	(25,828)	(13,970)	(11,860)	(17658)	(1.1656)
Constant	√	√	√	√	√
Controls	√	√	√	√	√
Province*Year FE	√	√	√	√	√
Observations	524,298	524,298	524,298	27,061	21,571

Table 7. Employment Structure

Notes: This table presents the results for the relation between export shock, robot adoption and employment structure by occupation and skills. Data is from Census five year data from 2010 to 2015. In Column (1), the dependent variable is *ΔManagerShare*, annual change of the share of management employees in a prefecture. In Column (2), the dependent variable is *ΔCollegeManagerShare*, annual change of the share of management employees with a college degree in a prefecture. Columns (3) and (4) use the share of employment among working-age population by education background. In Column (3), the dependent variable is the college and above employment-to-population ratio. In Column (4), the dependent variable is noncollege employment-to-population ratio. For all specifications, we use 2SLS specification and employ the same set of control variables as in Table 2. We include province-year effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

VARIABLES	(1) ΔManager Share	(2) ΔCollegeManager Share	(3) ΔNoCollegeEmp Share	(4) ΔCollegeEmp Share
*ExpShock*RobotStock,$_{2010}$*	1.8297	3.4427***	3.9343	33.8509*
	(2.7016)	(1.2264)	(6.3616)	(18.4432)
ExpShock	-0.4512	-0.2568	-2.4407**	3.0166
	(0.4512)	(0.2446)	(1.0689)	(3.1923)
RobotStock,$_{2010}$	-7.9819	17.9300	-32.9229	300.6037***
	(15.1318)	(11.2503)	(29.0820)	(97.0021)
RobotStock,$_{2005}$	0.0004*	0.0001	0.0009	-0.0015
	(0.0002)	(0.0001)	(0.0009)	(0.0015)
Constant	√	√	√	√
Baseline controls	√	√	√	√
Province*Year FE	√	√	√	√
Observations	322	322	326	325

Appendix Tables

Table A1. Balance Test

Notes: This table presents the results for the balance test. The independent variable is product-level export shocks, and the independent variables are an array of exposure-weighted average of initial prefecture characteristics, including the share of population with college education (*CollegeShare*), the share of manufacturing employment (*ManufacShare*), the export-to-GDP ratio(Exp/GDP_{2010}), the proportion of the population with hukou status ($HukouShare_{2010}$), robot adoption (*Robot*), log GDP per capita (GDP/Pop_{2010}) and log fiscal revenue per capita (*Fiscal Rev*). We include year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	CollegeShare	ManufacShare	Exp/GDP_{2010}	$HukouShare_{2010}$	Robots	GDP/Pop_{2010}	Fiscal Rev
ExpShock	-0.0000	-0.0000	-0.0001	-0.0000	-0.1637	-0.0000	-0.0000
	(0.0000)	(0.0000)	(0.0003)	(0.0002)	(1.3414)	(0.0000)	(0.0000)
Year FE	√	√	√	√	√	√	√
Observations	26,394	26,394	26,394	26,394	26,394	26,394	26,394
R-squared	0.6297	0.6174	0.5497	0.5959	0.4337	0.6696	0.6478

Table A2. Pretrend Test

Notes: This table presents the result for the pretrend test. The dependent variable is the change in employment rate over 2006-2010. IV 2SLS regression specification is adopted. We employ a same set of control variables as in Table 2. We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)
VARIABLES	ΔEmploymentShare
$ExpShock*RobotStock_{,2010}$	-0.2342
	(0.1857)
ExpShock	-0.0957
	(0.0977)
$RobotStock_{,2010}$	-0.1191
	(0.6293)
Province*Year FE	√
Observations	1,656
R-squared	-0.0166

Table A3. IV Externality Test: Top 5 Rotemberg Weight

Notes: This table presents the statistics about the Rotemberg weights for top 5 products (industries), following Goldsmith-Pinkham et al. (2020). In Panel A, we estimate the parameters including the weights ($\hat{\alpha}_k$), the national component of growth (g_k), the just-identified coefficient estimates ($\hat{\beta}_k$) at the product (HS) level. In Panel B, we repeat this process at the industrial (SIC) level.

Panel A. By Product

HS Code	HS Name	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$
711319	Jewelry And Parts Thereof, of Precious Metal Other Than Silver	0.0131333	4.488256	0.5987197
851712	Telephones For Cellular Networks or For Other Wireless Networks	0.0094613	4.246681	0.4776216
870332	Motor cars and other motor vehicles that are primarily designed to transport people	0.0078822	6.80144	2.771605
851762	Machines For Reception, Conversion and Transmission or Regeneration of Voice, Images or Other Data	0.0052067	2.368066	0.2605908
710239	Diamonds, non-industrial, sorted, worked, not mounted or set diamonds	0.0043963	10.65061	3.616197

Panel B. By Industry

Industry Code	Industry Name	$\hat{\alpha}_k$	g_k	$\hat{\beta}_k$
3911	Jewelry, Precious Metal	0.0395493	3.772014	0.5473242
2821	Plastics Materials, Synthetic Resins, and Nonvulcanizable Elastomers	0.0377709	17.86498	1.431779
3523	Farm Machinery and Equipment	0.034524	37.46374	1.907975
3312	Steel Works, Blast Furnaces (Including Coke Ovens), and Rolling Mills	0.0341703	24.2241	2.284018
3661	Telephone and Telegraph Apparatus	0.0328248	1.229385	0.1500471

Table A4. Using Only Export Shock or Robot Stock Instrument at each time

Note: This table presents the 2SLS estimates from regressions where only one instrumental variable is used. Column (1) reports the results from regression where export shock (*ExpShock*) is instrumented with its IV and robot stock is not instrumented. Column (2) reports the results from regression where robot stock ($RobotStock_{,2010}$) is instrumented with its IV and export shock is not instrumented. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

VARIABLES	(1)	(2)
	IV-2SLS	IV-2SLS
	ΔEmploymentShare	ΔEmploymentShare
$ExpShock*RobotStock_{,2010}$	1.4994***	0.3285***
	(0.4608)	(0.0400)
ExpShock	-1.4987***	-0.2404***
	(0.3385)	(0.0388)
$RobotStock_{,2010}$	1.6758***	2.1484***
	(0.1819)	(0.2690)
Baseline Controls	√	√
Province*Year FE	√	√
ExportShock(IV)	√	
RobotStock(IV)		√
Observations	1666	1666

Table A5. Additional Robustness Checks

Note: In this table, we utilize alternative specifications. In Column (1), we change the dependent variable to be the logarithm of employment changes. In Column (2), we remove extreme observations where the change in employment shares fall below the 5th percentile or exceed the 95th percentile. In Column (3), we replace the data with Census data in 2010 and 2015 and use the change in the employment rate as the dependent variable. In Column (4), we use the robot installations between 2005 and 2010 to construct robot shocks and its instrumental variable. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

VARIABLES	(1) ΔLog Employment	(2) Drop Outliers	(3) Census Data	(4) Robots between 2005-2010
*ExpShock*RobotStock,$_{2010}$*	4.3357**	0.7572**	9.5107**	1.4832***
	(1.7043)	(0.3344)	(4.0113)	(0.2850)
ExpShock	-2.7532***	-0.5326**	-1.3449*	-1.3677***
	(0.8327)	(0.2476)	(0.6950)	(0.1764)
RobotStock,$_{2010}$	9.0074**	-1.1505**	29.5529	3.1971***
	(4.1760)	(0.5056)	(20.3262)	(0.2855)
Baseline Controls	√	√	√	√
Province*Year FE	√	√	√	√
Observations	1,666	1,516	322	1,666

Table A6. Robot, Export Shock, and Initial Displacement Effect

Notes: This table presents the results for the relation between robot adoption, future export shock, and the initial labor intensity. The data used for this analysis is from NSTD. The dependent variable is firm-level labor intensity in 2010. $RobotStock_{,2010}$ is the robot adoption at the prefecture level in 2010, which is the same as the one in our baseline specification in equation (10). *Avg ExpShock* is the average prefecture-level export exposure over 2010–2016. In Column (1), robot adoption in 2010 is the independent variable. Then in Column (3), the interaction between the mean of future export shock and robot adoption in 2010 servs as the explanatory variable. We include industry fixed effects in all specifications. The standard errors in parentheses are clustered at the industry level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)
	OLS	OLS
VARIABLES	Labor Intensity$_{,2010}$	Labor Intensity$_{,2010}$
$RobotStock_{,2010}$	-0.003	0.003
	(0.011)	(0.016)
Avg ExpShock		0.001**
		(0.000)
*Avg ExpShock**$RobotStock_{,2010}$		-0.004
		(0.004)
Constant	√	√
Industry FE	√	√
Observations	205,304	205,304

Table A7. Export Shock, Robot and Population

Notes: This table presents the results for the relation between export shock, robot adoption and prefecture population. The data used for this analysis is from city yearbook. The dependent variable is the change in population. In Column (1), export shock is the independent variable, and in Column (3), robot adoption is the independent variable. Then in Column (3), the interaction between these two variables serves as the independent variable. IV 2SLS regression specification is adopted for all specifications. We include province-year fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)
	IV-2SLS	IV-2SLS	IV-2SLS
VARIABLES	ΔPopulation	ΔPopulation	ΔPopulation
*ExpShock*RobotStock,2010*			-1.2001
			(3.0196)
ExpShock	1.0890		1.4401
	(1.2302)		(2.0560)
RobotStock,2010		4.5878	5.1820
		(4.9208)	(5.9171)
Constant	√	√	√
Province*Year FE	√	√	√
Observations	1,684	1,666	1,666

Table A8. Export Shock, Robot and Diversification

Notes: This table presents the results for the relation between export shock, robot adoption and firm diversification. The data used for this analysis is listed firms. In Column (1), the dependent variable is *ΔHHI_industry*, the measure of diversification of a listed firm across industries. In Column (2), the dependent variable is *ΔHHI_area*, the measure of diversification of a listed firm across domestic cities. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year and firm fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)
	IV-2SLS	IV-2SLS
VARIABLES	ΔHHI_industry	ΔHHI_area
*ExpShock*RobotStock*$_{,2010}$	1.9539	0.8292
	(2.3502)	(0.7062)
ExpShock	-1.4203	-0.4817
	(1.9111)	(0.5843)
RobotStock$_{,2010}$	0.0000	0.0000
	(0.0000)	(0.0000)
Baseline Controls	√	√
Constant	√	√
Firm FE	√	√
Province*Year FE	√	√
Observations	11,749	11,749

Table A9. Export Shock, Robot and Employment Rate: the Role of Robot Subsidy

Notes: This table presents the results for the relation between export shock, robot adoption and employment rate. The data used for this analysis is from city yearbook. The dependent variable is the change in employment rate. In Column (1), cities with robot subsidies are excluded from the sample. In Column (2), we add an additional control variable that interacts the year trend with *Subsidy*, a dummy variable indicating a firm has robot subsidies. In Column (3), we add an additional control variable that interacts export shock with *Subsidy*. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year and firm fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)
	IV-2SLS	IV-2SLS	IV-2SLS
VARIABLES	ΔEmploymentShare	ΔEmploymentShare	ΔEmploymentShare
*ExpShock*RobotStock,2010*	1.3800***	1.4971***	1.2944***
	(0.4425)	(0.2934)	(0.4014)
*ExpShock*Subsidy*			-0.2225
			(0.1879)
ExpShock	-1.3466***	-1.3727***	-1.2037***
	(0.3578)	(0.1761)	(0.2719)
RobotStock,2010	1.8534***	1.9831***	1.9963***
	(0.3047)	(0.2158)	(0.2006)
Subsidy			0.3194***
			(0.1028)
Baseline controls	√	√	√
Constant	√	√	√
Subsidy*Year			√
Province*Year FE	√	√	√
Observations	1,642	1,666	1,666

Table A10. Export Shock, Initial Robot Adoption and Robot Installations between 2010-2016

Notes: This table reports the estimated impact on the annual robot installations in manufacturing using IV 2SLS regression specification. In Columns (1) and (2), we report the IV regression using the level of robot installations as the dependent variable. In Columns (3) and (4), we use the logarithm of robot installations as the dependent variables. In Columns (5) and (6), dependent variables are inverse hyperbolic sine transformation of robot installations. For specifications in even columns, we only control for province-year fixed effects. For specifications in odd columns, control variables include the change of share of college students (*ΔCollegeShare*), the change in total population (*ΔPopulation*), the change of share of urban residences (*ΔUrbanShare*) and with-Hukou residences (*ΔHukouShare*), and province-year fixed effects. All regressions are weighted by the prefecture's working-age population. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS	IV-2SLS
VARIABLES	Robot Installations	Robot Installations	log (Robot Installations)	log (Robot Installations)	IHS(Robot Installations)	IHS(Robot Installations)
*ExpShock*RobotStock*$_{,2010}$	138.0754	130.3481	0.5194**	0.9189***	0.9648*	1.0273**
	(163.2757)	(155.4016)	(0.1973)	(0.2664)	(0.5555)	(0.4327)
ExpShock	-91.9228	-91.1865	-0.1879*	-0.5736***	-0.9374**	-1.0209***
	(77.9684)	(73.3802)	(0.1058)	(0.1759)	(0.3691)	(0.2632)
RobotStock$_{,2010}$	1,826.4241***	1,832.0443***	7.0325***	5.5159***	10.1669**	9.8587**
	(233.9422)	(218.4068)	(1.9360)	(0.7406)	(4.0650)	(3.7149)
Constant	√	√	√	√	√	√
Baseline Controls		√		√		√
Province*Year FE	√	√	√	√	√	√
Observations	1,693	1,666	279	278	1,693	1,666
R-squared	0.0228	0.0261	0.2200	0.2720	0.1257	0.1303

Table A11. Manufacturing and Nonmanufacturing Employment

Notes: This table presents the results for the relation between export shock, robot adoption and employment rate in the manufacturing and nonmanufacturing sectors. The data used for this analysis is from city yearbook. The dependent variable is the change in manufacturing and nonmanufacturing employment as a percentage of total population. In Column (1), we report the estimated total employment effect, which is the same as the baseline estimate in Table 2. In Columns (2)-(3), we estimate the effects for manufacturing and nonmanufacturing employment respectively. For all specifications, we use 2SLS specification and employ a same set of control variables as in Table 2. We include province-year and firm fixed effects. All regressions are weighted by the prefecture's working-age. The standard errors in parentheses are clustered at the provincial level. The significance levels of 1%, 5%, and 10% are denoted by ***, **, and *, respectively.

	(1)	(2)	(3)
VARIABLES	ΔTotal Employment	ΔManufacturing EmploymentShare	ΔNonmanufacturing ΔEmploymentShare
*ExpShock*RobotStock,2010*	1.4840***	0.7095***	0.7745***
	(0.2839)	(0.2320)	(0.1900)
ExpShock	-1.3690***	-0.8352***	-0.5339***
	(0.1761)	(0.1506)	(0.1074)
RobotStock,2010	2.1023***	1.6270***	0.4754
	(0.1957)	(0.4291)	(0.5956)
Baseline controls	√	√	√
Province*Year FE	√	√	√
Observations	1,666	1,666	1,666