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Which firms benefit from robot adoption? Evidence from China

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ABSTRACT

This paper investigates which firms benefit from robot adoption in a developing open economy such as China. First, we construct a unique comprehensive dataset to identify robot adoption in Chinese industrial firms. Second, we adopt difference-in-differences to provide empirical analysis after conducting the common trends tests. Third, we find that adopting robots significantly increases a series of firm performance indicators in robot adoption firms. Compared with adopting firms in the labor-intensive sector, firms in the capital-intensive sector significantly benefit from robot adoption in a series of firm performance indicators, e.g., employment, capital stock, output, total factor productivity, capital returns, and exports. Finally, we check the robustness, investigate the dynamic effects, and find persistent positive effects. Our findings shed some light on the impacts of robot adoption in developing and transition countries.

1. Introduction

As a kind of modern technology, industrial robots have been widely used in modern manufacturing, which is one of the most salient technological changes in recent decades. According to the International Federation of Robotics (IFR), industrial robots are defined as "automatically controlled, reprogrammable, multipurpose manipulators programmable in three or more axes" (ISO 8373).

Recent evidence also shows that robots are increasingly used in developing countries, e.g., China (Graetz and Michaels, 2018). As we can see in Fig. 1, the robot stock in China continued to rise from 2000 to 2019, especially after 2010. After 2016, China is already the world's leading buyer and holder of robots. The Chinese robot stock is nearly 800,000 in 2019, nearly twice that of Japan, the former leading country in the world from 1993 to 2015. Since more and more Chinese firms began to adopt industrial robots, it is natural to raise the question that how robot adoption will affect firm performance in developing countries such as China.

Theoretically, robots can be thought of as a kind of capital. As a special kind of capital, robots can complete routine work usually completed by labor and then crowd out labor to some extent. Moreover, robots can also cause technological progress and other positive impacts, which results in increasing demand for factors such as labor and capital. These positive impacts can also bring increases in other firm performance indicators.

The first strand of literature focuses on the impacts of robot adoption on the labor market (Acemoglu and Restrepo, 2019; Goos et al., 2014; Graetz and Michaels, 2018). In general, in Acemoglu's representative papers about robots (Acemoglu and Restrepo, 2019,

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2020), there are some representative effects at heart which focus on the impacts of robot adoption on the labor market as follows:

The first is the displacement effect. Robots replace workers in tasks in which workers previously performed, and the displacement effect can reduce the demand for labor, wages, and employment. The second is the productivity effect. As the cost of producing automated tasks declines, the economy will expand and increase the demand for labor in nonautomated tasks. It could be an increase in the demand for labor in the same sectors undergoing automation or in non-automated sectors. The third is the capital accumulation effect. It is triggered by increased automation (raising the demand for capital) and will raise the demand for labor. The fourth is the deepening of automation effect. Automation operates not only at the extensive margin – replacing tasks previously performed by labor - but also at the intensive margin, increasing the productivity of machines in tasks that have already been automated. In general, effect 1 can be negative, while effects 2–4 can be positive. For specific countries, the overall effect is ambiguous.

Most of the studies focus on developed countries. Acemoglu and Restrepo (2020) find that industrial robots cause negative shocks to total employment and wages in the US. In contrast, using long-term (1979–2012) industry-level panel data from Japan, Dekle (2020) finds that the introduction of robots increases the demand for labor. When considering occupation heterogeneity, Frey and Osborne (2017) find that approximately 70 % of the total 702 kinds of occupations in the US can be replaced by industrial robots. Humlum (2019) uses the data of imported robots in Sweden and finds that the firms adopting robots have accounted for the fall in the share of production workers and the rise in the share of technology workers since 1990 to some extent.

Fewer but similar findings hold in emerging countries, e.g., Carbonero et al. (2020) find that robots lead to a drop in total employment by 11 % using country-level data in emerging countries, such as Brazil, India, Indonesia, Mexico, Russia, Slovakia, and Turkey. For China, Giuntella and Wang (2019) find significantly negative impacts of robot exposure on the employment and wages of workers in the Chinese labor market using the data of robots at the industry level from IFR, especially for low-skilled workers. However, they make use of the data of robots at the country level or industry level from IFR, not the firm level. Hence, the findings may be different due to different data sources.

The second strand of literature focuses on the impacts of robot adoption on other firm performance. On the one hand, in developed countries, Bonfiglioli et al. (2020) use French data over the 1994–2013 period and find that robot imports increase productivity and the employment share of high-skilled professions but have a weak effect on total sales. Dixon et al. (2021) find that investments in robotics are associated with increases in total firm employment but decreases in the total number of managers in Canada. Robot investments predict improved performance measurement and increased adoption of incentive pay based on individual employee performance. Using data from France between 2010 and 2015, Acemoglu et al. (2020) find that firm-level adoption of robots coincides with declines in labor shares, increases in value added and productivity, and declines in the share of production workers. However, overall employment increases faster in firms adopting robots. Using a rich panel dataset of Spanish manufacturing firms over the 1990–2016 period, Koch et al. (2021) find that robot adoption generates substantial output gains in the vicinity of 20–25 % within four years, reduces the labor cost share by 5–7 %, and leads to net job creation at a rate of 10 %.

On the other hand, there are fewer papers studying the impacts of robot adoption on firm performance in developing countries in addition to employment at the firm level. Using the data of Chinese industrial firms from 2001 to 2012, Huang et al. (2022) identify the causal relationship between robot adoption and firm's energy performance. They find that robot adoption can significantly increase firms' energy efficiency. Mechanism analysis shows that the increase in productivity is a significant factor through which adopting robots can improve a firm's energy efficiency. Moreover, the increase in the firm's energy efficiency is mainly due to the increase in output rather than the decrease in total energy consumption. Gorodnyi and Fedyunina (2022) make use of the data of Russian manufacturing firms from 2011 to 2018. They find that robots contribute to the increase in labor productivity and total factor productivity (TFP) is greater in smaller companies.

Different from their findings, we want to raise more questions as follows: How about the impacts on more comprehensive firm

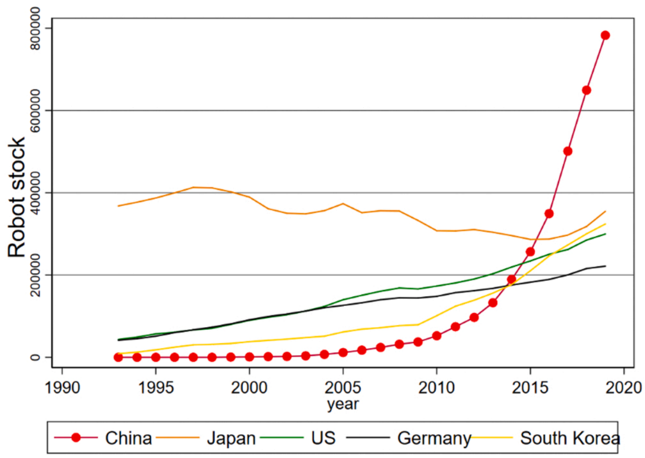

Fig. 1. Industrial Robots stock in main countries:1993–2019. Data Source: The World Robotics Report 2020 released by the IFR.

performance in the open developing countries such as China besides employment, e.g., capital stock, output, TFP, exports, and capital returns? Will these impacts be heterogeneous in different sectors, such as the capital-intensive sector and the labor-intensive sector? Which firms benefit from robot adoption, and which firms lose? In developing and transition countries, which industries should adopt industrial robots first? In this paper, we attempt to answer these important questions using detailed empirical evidence at the firm level.

Specifically, using the Chinese Annual Survey of Industrial Firms (ASIF) database and the Chinese Customs database, we construct a comprehensive unique dataset that covers the detailed information of more than 55,000 firms during the sample period 2000–2013, e.g., the financial information, import-export information, and robot adoption information in these firms. Based on this unique dataset, we adopt difference-in-differences (DID) and propensity score matching difference-in-differences (PSM-DID), conduct parallel trends tests, study the impacts of robot adoption at the extensive margin and investigate the dynamic effects. We conduct multidimensional tests to check the robustness of our findings. In particular, our propensity score matching (PSM) is conducted within the same industry and the same year, which can control some common macroeconomic and industrial shocks within the same industry and year.

Our findings based on the firm-level data show that in China, the largest developing and transition economy in the world, the positive effects brought by robot adoption dominate the negative effects (mainly in the capital-intensive sector) at the extensive margin. Specifically, robot adoption increases a series of firm performance indicators in addition to employment, e.g., capital stock, output, exports, capital returns, and TFP. The findings on employment contradict Giuntella and Wang, (2019) whose results are based on the data of robots at the industry level from IFR, while the other findings are original. Moreover, our empirical findings are found to be very robust after carrying out a multidimensional robustness check. These findings shed some light on the research of industrial robots in developing and transition countries.

Our paper contributes to the literature in the following two respects:

First, we are the first to study the impacts of robot adoption within the framework of the open economy including two sectors (the labor-intensive sector and the capital-intensive sector). Different from most existing studies that focus on the closed economy (Acemoglu & Restrepo, 2020; Bonfiglioli et al., 2020; Dixon et al., 2021; Huang et al., 2022), our research is conducted within the framework of the open economy which is more consistent with the reality in China.

Second, in the realm of developing countries, compared with Huang et al. (2022)'s findings on energy performance in China and Gorodnyi and Fedyunina (2022)'s findings on productivity in Russia, our findings are more comprehensive and necessary for understanding the impacts of robot adoption on firm performance. We also make use of the firm-level data on robot adoption instead of the industry-level data (Giuntella & Wang, 2019). To the best of our knowledge, we are the first to study these comprehensive firm performance indicators that are associated with robot adoption in China.

The rest of this paper proceeds as follows: Section 2 introduces the details of the empirical strategy, including the data, estimation framework, variable description, and stylized facts. Section 3 presents the baseline results. Section 4 discusses the robustness checks. Section 5 investigates the dynamic effects. Section 6 concludes the paper.

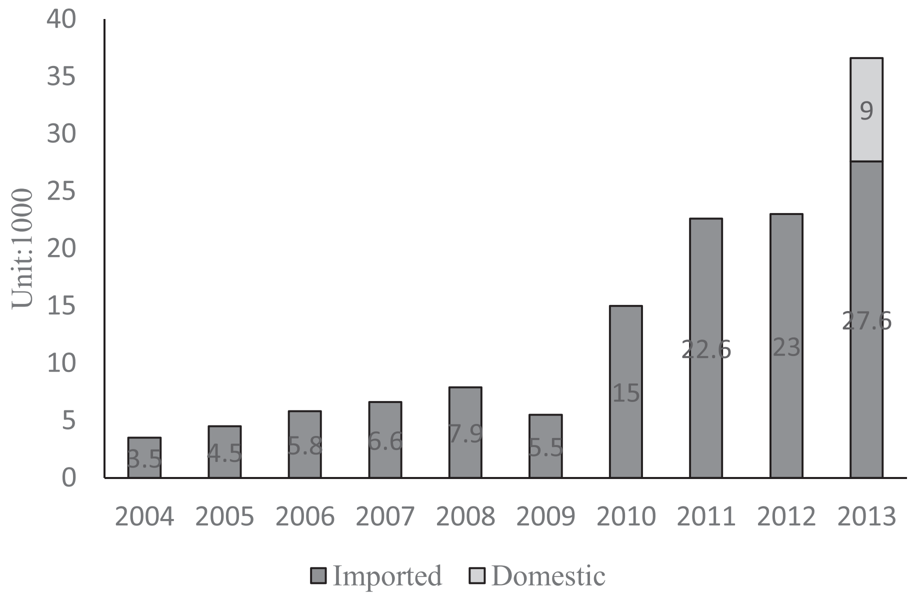

Fig. 2. Estimated annual number of new industrial robots in China. Data
Source: The World Robotics Report 2017 released by the IFR.

2. Estimation strategy

2.1. Data source

Our data sources include two databases:

The first data source is the firm-level data from the ASIF (2000–2013) in China from the National Bureau of Statistics (NBS). The data covered all state-owned enterprises from 2000 to 2007, as well as nonstate-owned enterprises, with annual sales above five million RMB. After 2007, state-owned enterprises with annual sales below five million RMB were excluded from the surveys. After 2011, data include only manufacturing firms with annual sales above 20 million RMB. This dataset contains rich firm-level information, especially corporate financial information.

The second data source is the Chinese Customs database (2000–2013), in which the transaction level monthly trade data for 2000–2013 are obtained from China's General Administration of Customs. Each transaction is described at the HS 8-digit level. For each transaction, the dataset includes three types of information: (1) variables on basic trade information, including value (measured in US current dollar), trade status (export or import), quantity, trade unit, and value per unit; (2) variables on trade mode and pattern, e.g., country of destination for exports, country of origination for imports; and (3) variables on firm information in detail, including firm name, identification number set by customs, telephone number, zip code, and ownership type of firm (foreign affiliate, private, or state-owned).

The third data source is the information on imported industrial robots at the firm level extracted from our second database (i.e., the Chinese Customs database) at the HS 6-digit level following Fan et al. (2021), including the quantities, the value, and the prices of imported industrial robots.

The reason we choose the observation period from 2000 to 2013 is as follows:

During a long period of robot adoption in China, almost all industrial robots were imported from foreign countries and were not homemade. Specifically, as shown in Fig. 2, the annual number of new robots adopted in China increased from 3,500 in 2004–36,600 in 2013. Before 2013, all the new industrial robots in China were imported, while homemade robots started to account for 24.6 % of the annual new supply in 2013. After 2013, an increasing number of industrial robots were made in China. Based on Fig. 2, we employ imported industrial robots as the usage of industrial robots at the firm level from 2000 to 2013. Especially, it is necessary to clarify that the usage of robots in the firms is the robots imported in the last year for the same firm. It is slightly difficult for firms to make use of imported robots in the same year, which is similar to capital investment in macroeconomics as commonly used in the empirical literature.

2.2. Data matching

Following Yu and Tian (2012), we merge the data from the ASIF and the data from the Chinese Customs Database as follows:

First, we merge the two datasets by firm name and year. If a firm has the same Chinese name in both datasets in a given year, it should be the same firm. The year variable is a necessary auxiliary variable for identification. Second, we merge the two datasets by both the zip code and the last seven digits of a firm's phone number year by year. Third, we drop the duplicated firms during the above two matching stages. Then, we drop the firms without identifiable names to ensure that the firms from the above two merging stages are the same. As we found that some firms have the same zip code and the last seven digits of the phone number, but they do not have identifiable names. After comparing the other information (e.g., the names of legal persons, the addresses), they turned out to be different firms. Fourth, we append these yearly datasets to an unbalanced panel.

Moreover, in our study, firms with fewer than five consecutive yearly observations are dropped. Since we employ DID, on the one hand, to conduct the parallel trends tests and choose the PSM variables defined below, the firm should have observations in the two years before its robot adoption. On the other hand, we will study the dynamic effects, i.e., the impacts in the following two years after robot adoption. Hence, the firm should have at least five consecutive yearly observations. We also exclude the firms in abnormal states, e.g., closed down, canceled, in preparation, i.e., our dataset covers the firms in the normal state of operation.

Finally, we obtain an unbalanced panel dataset of 56,141 firms with 423,610 observations for the period 2000–2013. In this panel, each firm has imports or exports each year, which is consistent with our basic setup of the open economy. Among them, 1348 firms have 2555 observations of robot imports.

2.3. Estimation framework

Our goal is to examine the effect of robot adoption on firm performance. However, ordinary least squares (OLS) is susceptible to endogeneity for the following reasons. First, some unobservable characteristics or factors may affect firm performance, i.e., potential missing variables may lead to endogeneity. Second, there may be reverse causality in the effects between robot adoption and firm performance. Thus, we treat robot adoption by firms as a quasi-natural experiment by using the staggered DID method. Firms adopting robots are regarded as the treatment group, while non-adoption firms are regarded as the control group. Moreover, under PSM, the non-adoption firms in the same industry and same year are regarded as the control group since we can control the common factors in the same industry and year faced by the firms.

Based on the discussion above, we implement the specification of the following form:

$$y_{it} = \alpha + \beta D_{it} + \delta x_{it} + \lambda_i + \theta_t + \varepsilon_{it} \tag{1}$$

where y_{it} denotes the related various measures of firm performance at firm i in year t defined below, e.g., total employment, capital stock, gross output, etc. D_{it} is a dummy variable equal to one in the years after robot adoption for firm i. x_{it} denotes the firm-level control variables, including the firm age, the square of firm age, the debt ratio, the average wage, and ownership. λ_i and θ_t denote the firm and year fixed effects, respectively; ε_{it} is an error term. Since our paper evaluates the firm performance brought by robot adoption at the firm level, the standard errors should be clustered at the firm level according to the literature (Bertrand et al., 2004Bertrand, Duflo, & Mullainathan, 2004). Both controlling for the firm fixed effect and clustering at the firm level will capture the time variation within the firm. If it is clustered at the industry (city) level, the standard errors will capture both the time variation within the firm and the variation between robot adoption and non-adoption firms. Moreover, we employ the staggered DID method in this paper since different firms adopt industrial robots in different years and there is no common year for all the firms to adopt robots.

2.4. Summary statistics

Table 1 reports the descriptive statistics of the key variables. For the outcome variables, we include the log of total employment (*Log_L*), the log of capital stock (*Log_K*), the log of gross output (*Log_Output*), and the total export value of the firm in log form (*Log_Export*). Specifically, the total export values are adjusted by the exchange rate in the same year, since their original values are measured in US current dollars. We calculate the real gross output and the real capital stock by deflating these values using the sector-specific price indices provided by Brandt et al. (2012).

We also calculate the real capital return (*Cap_return*) following Shu et al. (2010). The real capital return (*Cap_return*) is defined as the ratio of net revenue of capital to net worth of fixed assets in log form. The net revenue of capital is calculated as the sum of profit, depreciation in the current year, and net taxes (excluding the subsidies). The net worth of fixed assets is calculated as the difference between the value of fixed assets at the original price and the cumulative depreciation.

The average wage (*ave_wage*) is the ratio of total wage to total employment in log form. The total factor productivity (*TFP*) in log form is calculated using the OP method following Olley and Pakes (1996) due to data availability. When using OP, we construct the real investment by adopting the perpetual inventory method to investigate the law of motion for real capital and real investment, using a depreciation rate of 9 %.

We also calculate *TFP_ACF* in log form following Ackerberg et al. (2015) as an alternative measure for a robustness check, and the results are consistent. Since the ASIF data do not have information on either intermediate goods or value added for the years after 2007, we are unable to calculate *TFP* in the LP method (Levinsohn and Petrin, 2003) after 2007.

For the control variables, *robot* is a dummy variable equal to one in the years after robot adoption for the firm, and its mean is 0.023, implying that only a few firms import robots in each industry. The mean of *robot_capital* (0.037) is greater than the mean of *robot_labor* (0.009), meaning that there are much more adoption firms in the capital-intensive sector than the labor-intensive sector. Firm age (*age*) is defined as the difference between the current year and the birth year of the firm in log form, and age^2 is the square of firm age (*age*). Debt ratio (*debtratio*) is the ratio of debt to total assets in log form. The ownership variable (*ownership*) includes six kinds of ownership: state, collective, private, Hong Kong/Macau/Taiwan, foreign, and others.

Moreover, we report the distribution of robot adoption firms in the sample in Table 2. Although the ratio of firms adopting robots is relatively small in our sample (the minimum is 0.388 %, and the maximum is 2.206 %), they account much more for economic performance, e.g., employment share varies from 0.681 % to 6.218 %, fixed assets share varies from 1.566 % to 10.537 %, and gross output share is generally greater than 5 %.

For the division of the labor-intensive sector and the capital-intensive sector, we first calculate the ratio of the book value of fixed assets to total employment for each firm each year. However, this ratio can be time varying for the same firm. Thus, we take the mean of the ratios within the firm to obtain a constant capital-labor ratio for each firm in log form. Then, we take the mean of the ratios of all the firms as the benchmark ratio. If the ratios of firms are below this benchmark one, we treat them as labor-intensive firms; if the ratios are above this benchmark one, we treat them as capital-intensive firms. After the division, we have 27,898 firms in the labor-intensive sector and 28,243 firms in the capital-intensive sector. If we choose the median of the ratios of the book value of fixed assets to total employment to divide the labor-intensive sector and the capital-intensive sector instead of the mean, our main results are generally robust.

In principle, we should adopt the capital-labor ratio before the policy when employing the DID method. However, the time of robot adoption varies for different firms, and it is difficult to set a common time for all robot adoption firms. Thus, we define the labor-intensive sector and the capital-intensive sector above alternatively.

3. Baseline results

3.1. Parallel trends test

Following Beck et al. (2010), we consider a 7-year window, spanning from 3 years before robot adoption until 3 years after robot adoption. The dashed lines represent 95 % confidence intervals adjusted for firm-level clustering. We report the estimated coefficients from the following regression:

$$y_{it} = \alpha + \beta_1 D_{it}^{-3} + \beta_2 D_{it}^{-2} + \beta_3 D_{it}^{0} + \beta_4 D_{it}^{+1} + \beta_5 D_{it}^{+2} + \beta_6 D_{it}^{+3} + \delta x_{it} + \lambda_i + \theta_t + \varepsilon_{it} \tag{2}$$

D's equal zero, except as follows: D^{-j} equals one for the firms in the *j*th year before adopting robots for the first time, while D^{+j} equals

Table 1
Summary statistics of main variables.

Variable	Definition	Observations	Mean	Std. Dev.	Min	Max
robot	Robot Adoption Dummy	423,610	0.023	0.151	0	1
robot_labor	Robot Adoption Dummy in the Labor-intensive Sector	205,897	0.009	0.093	0	1
robot_capital	Robot Adoption Dummy in the Capital-intensive Sector	217,713	0.037	0.189	0	1
Log_L	Log of Total Employment	422,451	5.539	1.063	3.401	7.914
Log_K	Log of Capital Stock	421,398	9.452	1.624	6.227	13.020
Log_Output	Log of Gross Output	423,196	11.086	1.314	8.830	14.268
Log_Export	Log of Total Export Value	379,438	16.417	1.910	11.548	20.003
age	Log of Firm Age	423,567	2.169	0.594	0.693	3.466
age^2	The Square of Firm Age	423,567	5.058	2.512	0.480	12.011
debtratio	Log of the Ratio of Debt to Total Assets	422,666	-0.792	0.649	-2.789	-0.001
ave_wage	Log of Average Wage	334,047	2.868	0.721	1.442	4.575
Cap_return	Capital Return	378,720	-0.934	1.250	-3.812	1.711
ownership	Ownership	423,600	3.027	1.642	1	6
TFP	Total Factor Productivity (OP)	420,112	4.501	0.817	2.888	6.357

Data Source: The ASIF Database and the Chinese Customs Database.

Table 2
The fraction of firms adopting robots in the sample.

Year	Adoption firms	Non-adoption firms	Share of adoption firms in sample	Employment share of adoption firms	Fixed assets share of adoption firms	Gross output share of adoption firms
2000	0	11,169	0	0	0	0
2001	58	14,948	0.388 %	0.681 %	1.566 %	1.417 %
2002	154	18,134	0.849 %	1.659 %	3.121 %	3.251 %
2003	239	22,024	1.085 %	2.484 %	5.306 %	6.177 %
2004	301	35,677	0.844 %	2.439 %	5.108 %	5.443 %
2005	428	37,818	1.132 %	3.461 %	5.146 %	6.710 %
2006	531	40,055	1.326 %	4.942 %	8.728 %	8.424 %
2007	530	39,721	1.334 %	4.366 %	9.717 %	8.562 %
2008	586	46,331	1.265 %	4.824 %	9.571 %	7.797 %
2009	552	39,675	1.391 %	5.132 %	9.949 %	7.907 %
2011	635	35,460	1.791 %	5.392 %	8.646 %	8.596 %
2012	739	37,368	1.978 %	6.218 %	9.142 %	10.443 %
2013	780	35,361	2.206 %	6.133 %	10.537 %	11.896 %

Data Source: The ASIF database and the Chinese Customs Database.

one for the firms in the *j*th year after robot adoption. We exclude the previous year of robot adoption and estimate the dynamic effect of robot adoption on the outcome variables relative to the previous year of robot adoption, which means that we treat the previous year of robot adoption as the base period.

In Figs. 3–8, we plot the estimates of β_s in Eq. (2) for the outcome variables. We find that all the outcome variables satisfy the parallel trends tests in general, the pretrends are not distinguishable from zero, i.e., there are no obvious pretrends for these variables, which lays a solid foundation for the DID.

3.2. Baseline results

The baseline results in the unmatched cases are reported in Tables 3–5. In Table 3, we can find significantly positive impacts brought by robot adoption in adoption firms in the full sample. For instance, total employment in adoption firms increases by 13.883 %,[1] capital stock increases by 10.407 %, gross output increases by 13.542 %, TFP increases by 6.184 %, total exports increase by 21.774 %, and capital returns increase by 13.202 %.

Similarly, we can also find positive impacts of robot adoption on firm performance in the capital-intensive sector in Table 4, which implies that the positive impacts brought by robot adoption dominate the negative impacts in the capital-intensive sector. For the labor-intensive sector in Table 5, we find that most of the estimates are insignificant; specifically, only the impacts of robot adoption on total employment and gross output are significantly positive.

Moreover, it is unnecessary to directly compare the estimates in Tables 3–5 since the samples are in different sectors with differing firm characteristics. We need to compare the average economic effect of the sector, i.e., from the perspective of the representative firm in a sector, usually represented by the mean. As we can see in Table 1, the means of robot adoption dummy are 0.023 (the full sample), 0.009 (the labor-intensive sector), and 0.037 (the capital-intensive sector), respectively. Based on these means together with our above

[1] The change rate is calculated as (exp(a) - 1) × 100 %, e.g., for 0.130, the change rate is (exp(0.130) - 1)× 100 % = 13.883 %.

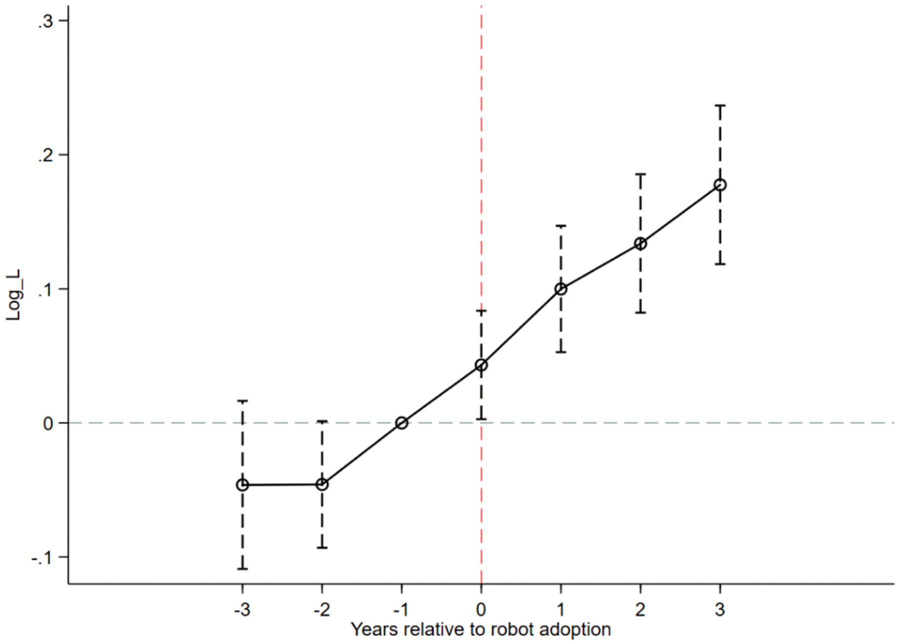

Fig. 3. The dynamic impact of robot adoption on labor. Notes: Following Beck et al. (2010), we consider a 7-year window, spanning from 3 years before robot adoption until 3 years after robot adoption. The dashed lines represent 95 % confidence intervals adjusted for firm-level clustering.

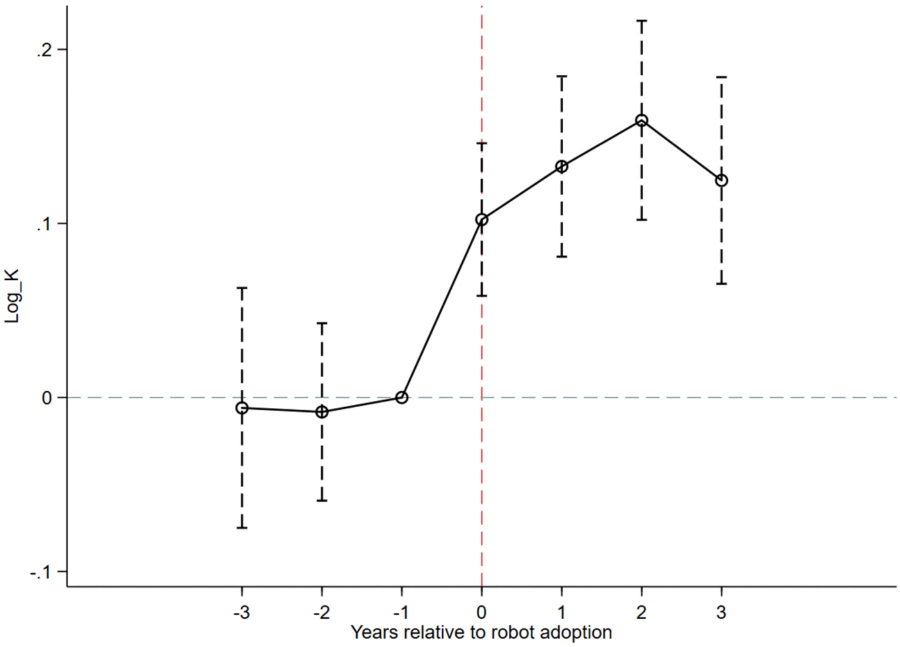

Fig. 4. The dynamic impact of robot adoption on capital. Notes: See notes to Fig. 3.

estimates, we try to explain the average economic effects in different samples. For instance, for the total employment, the average economic effects are 0.319 %[2] in the full sample, 0.365 % in the capital-intensive sector, and 0.101 % in the labor-intensive sector, respectively. Although the estimate of total employment in the full sample (0.130) is greater than the estimates in the subsamples (0.094 and 0.106), the average economic effect in the capital-intensive sector (0.365 %) is greater than these in the full sample (0.319

[2] The average effect is calculated as (exp(0.130) - 1)$\times$ 0.023 $\times$ 100 % = 0.319 %.

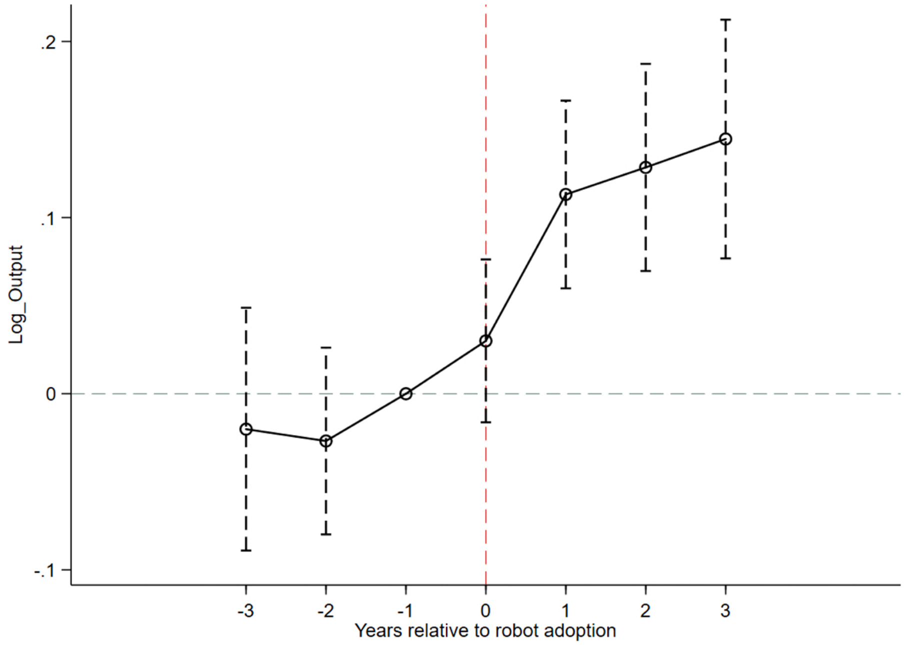

Fig. 5. The dynamic impact of robot adoption on the output. Notes: See notes to Fig. 3.

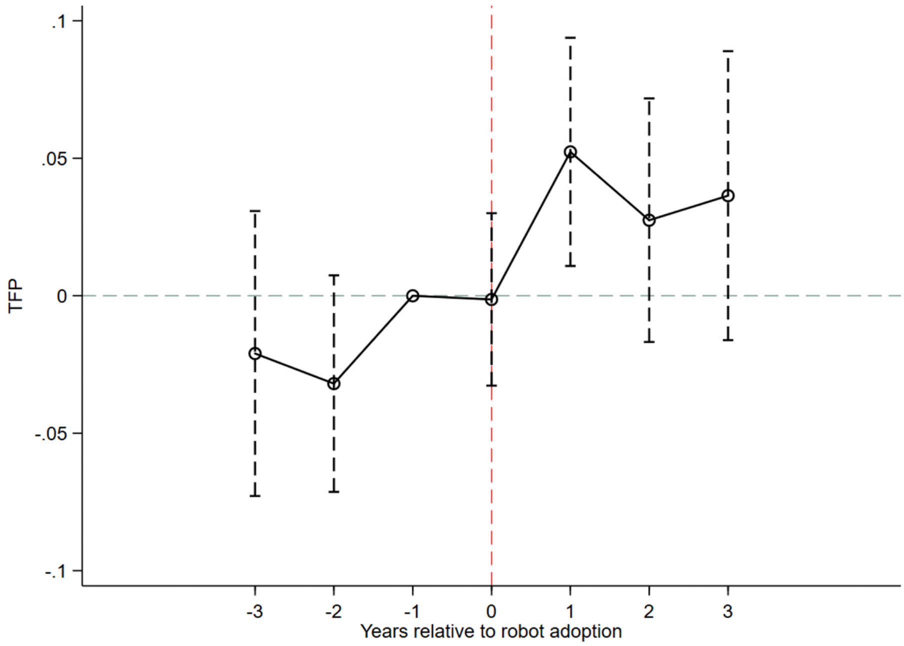

Fig. 6. The dynamic impact of robot adoption on TFP Notes: See notes to Fig. 3.

%) and the labor-intensive sector (0.101 %).

In general, the results in Tables 3–5 imply that robot adoption significantly increases the outcome variables of firm performance, mainly in the capital-intensive sector.

3.3. Mechanism

Based on the recent research on the impacts brought by robot adoption, first, there exists the capital accumulation effect, i.e., increased automation (robot adoption) can trigger the capital accumulation (Acemoglu and Restrepo, 2019). Automation corresponds

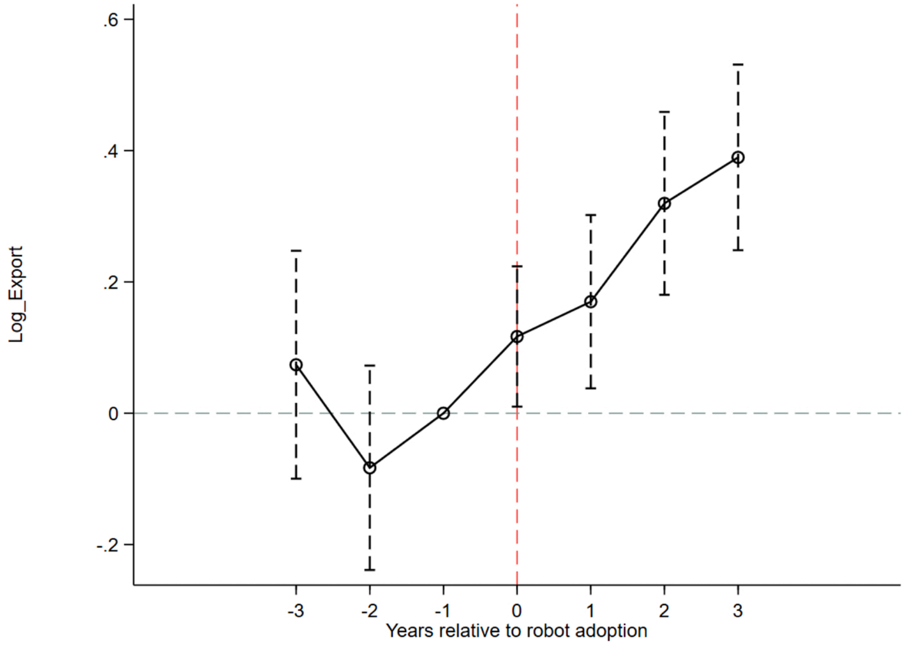

Fig. 7. The dynamic impact of robot adoption on exports. Notes: See notes to Fig. 3.

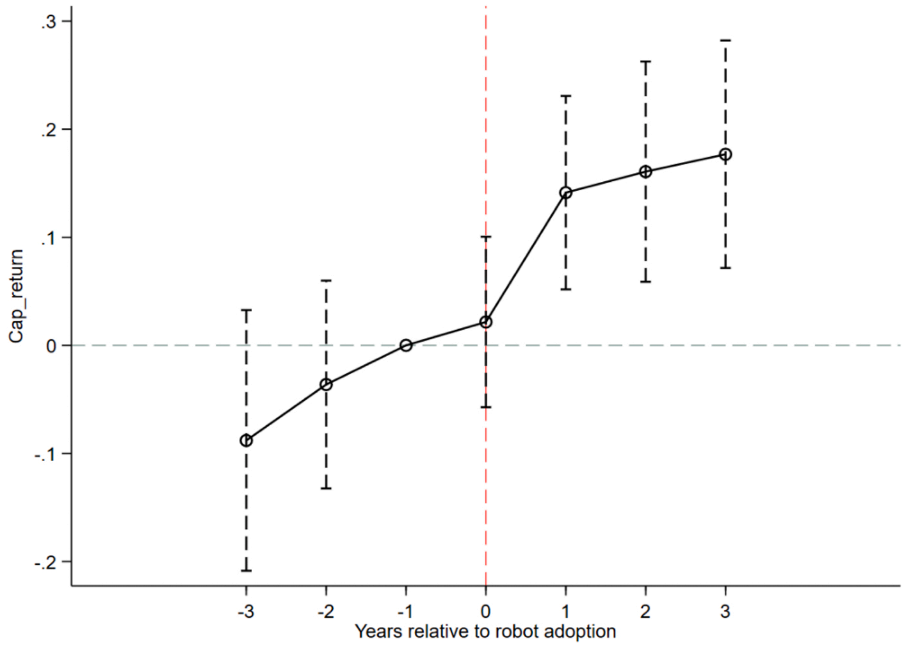

Fig. 8. The dynamic impact of robot adoption on capital returns. Notes: See notes to Fig. 3.

to an increase in the capital intensity of production. The high demand for capital triggers the further accumulation of capital (e.g., by increasing the rental rate of capital), which can further raise total employment.

Second, there exists the productivity effect, i.e., robot adoption can cause productivity growth (Acemoglu and Restrepo, 2018, 2019; Huang et al., 2022), then raise the demand for labor (Acemoglu & Restrepo, 2018, 2019; Li et al., 2021) and output (Koch et al., 2021).

Third, there exists the output effect. The output growth brought by robot adoption can also raise the demand for labor and other firm performance (Huang et al., 2022; Koch et al., 2021; Li et al., 2021). For instance, the increased output can bring growth in total exports. The productivity effect and the output effect can also explain the capital return growth brought by robot adoption to some

Table 3
The impact of robot adoption on firm performance in the full sample.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	*Log_L*	*Log_K*	*Log_Output*	*TFP*	*Log_Export*	*Cap_return*
robot	0.130***	0.099***	0.127***	0.060***	0.197***	0.124***
	(0.023)	(0.024)	(0.024)	(0.017)	(0.051)	(0.036)
age	0.530***	0.820***	1.128***	0.416***	1.353***	1.203***
	(0.020)	(0.020)	(0.018)	(0.015)	(0.035)	(0.027)
age²	-0.080***	-0.183***	-0.239***	-0.096***	-0.303***	-0.263***
	(0.005)	(0.005)	(0.005)	(0.004)	(0.010)	(0.007)
debtratio	0.035***	-0.011**	0.049***	0.040***	0.096***	-0.120***
	(0.003)	(0.005)	(0.004)	(0.003)	(0.007)	(0.006)
ave_wage	-0.166***	0.134***	0.200***	0.288***	0.140***	0.283***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.006)	(0.005)
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	267,824	328,008	329,628	327,806	291,783	299,803
R^2	0.871	0.900	0.880	0.764	0.789	0.650

Notes: Estimation using OLS. Robust standard errors in parenthesis are clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. As mentioned above, the TFP in log form is calculated using the OP method following Olley and Pakes (1996) due to data availability. In column 1, we adopt the log of the average wage in the last year since the log of the average wage in the current year is correlated with the total employment in the same period based on the above definition.

Table 4
The impact of robot adoption on firm performance in the capital-intensive sector.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	*Log_L*	*Log_K*	*Log_Output*	*TFP*	*Log_Export*	*Cap_return*
robot_capital	0. 094***	0.112***	0.107***	0.055***	0.158***	0.106***
	(0.027)	(0.026)	(0.027)	(0.019)	(0.058)	(0.039)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	135,816	168,656	169,304	168,555	144,089	155,106
R^2	0.879	0.866	0.885	0.775	0.786	0.640

Notes: See notes to Table 3.

Table 5
The impact of robot adoption on firm performance in the labor-intensive sector.

	(1)	(2)	(3)	(4)	(5)	(6)
Dep. var.:	*Log_L*	*Log_K*	*Log_Output*	*TFP*	*Log_Export*	*Cap_return*
robot_labor	0.106***	-0.007	0.083*	0.026	0.042	0.059
	(0.039)	(0.060)	(0.050)	(0.034)	(0.102)	(0.081)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,008	159,352	160,324	159,251	147,694	144,697
R^2	0.864	0.833	0.841	0.752	0.795	0.634

Notes: See notes to Table 3.

extent (Acemoglu and Restrepo, 2019). Since we have shown the corresponding empirical evidence for the above three effects in Table 3, we omit them here for simplicity.

4. Robustness

In this section, first, to eliminate selection bias, i.e., firms with better performance indicators are more likely to adopt robots, we employ the PSM-DID as the main specification to check robustness. When adopting PSM, we try to find the most similar control group for the treatment group in the same industry and same year to eliminate some common industrial and macroeconomic factors. In general, although the sample size becomes much smaller under PSM, our main findings are still robust. Furthermore, we employ the instrumental variable (IV) estimation to check endogeneity.

Our matching variables include the following four variables in the trend: firm age (*age*), the square of firm age (age^2), the ratio of debt to total assets (*debtratio*), and the average wage (*ave_wage*). Specifically, for instance, age_{t-1} means the firm age in the year before firm robot adoption, age_{t-2} means the firm age in the two years before firm robot adoption, and Δage_{t-1} measures the difference between age_{t-1} and age_{t-2} (i.e., the trend). We mainly adopt the trend of the above four variables as the matching variables during the PSM process.

4.1. PSM-DID: baseline results

In Table 6, we can find significantly positive impacts brought by robot adoption in adoption firms in the full sample after matching. For instance, the total employment in adoption firms increases by 19.842 %, the capital stock increases by 11.405 %, the gross output increases by 19.125 %, TFP increases by 10.628 %, total exports increase by 29.563 %, and capital returns increase by 22.630 %. These results are highly consistent with the findings in Table 3.

In the left panel of Fig. 9, we find similar significantly positive impacts of robot adoption on firm performance in the capital-intensive sector, consistent with the results in Table 4. While in the right panel of Fig. 9, the results in the labor-intensive sector are insignificant, similar to the findings in Table 5. In general, the main findings reported in Table 6 and Fig. 9 under PSM are consistent with the findings in the above unmatched cases.

Notes: We compile coefficients from different sectors. On the left we show the estimated coefficients in the capital-intensive sector including 95 % confidence intervals. On the right we show the estimated coefficients in the labor-intensive sector including 95 % confidence intervals.

4.2. Heterogeneity of treatment effects

Since we employ the staggered DID in our paper, it is necessary to deal with the heterogeneity of treatment effects considering the variation in treatment timing. Recently, there are several pieces of representative research on this topic, e.g., Borusyak et al. (2022) and De Chaisemartin and D'Haultfoeuille (2020). To deal with the above concern in DID, they construct the alternative DID estimators robust to treatment effects heterogeneity across time and treated units which are adopted more and more often in recent researches in empirical economics, respectively.

Following Braghieri et al. (2022), we adopt the methods in Borusyak et al. (2022) and De Chaisemartin and D'Haultfoeuille (2020) to provide alternative DID estimators considering heterogeneous treatment effects, respectively. The results in the full sample before matching are reported in Table 7. Specifically, we report the Borusyak-Jaravel-Spiess estimators in Panel A and the De Chaisemartin and D'Haultfeuille estimators in Panel B, respectively.

We find that most of the estimates obtained using the robust estimators in Table 7 are positive and significant, implying that robot adoption brings positive impacts to the outcome variables, i.e., the firm performance, highly consistent with our baseline results. We further report the results in the full sample after matching in Table 8 and find similar results, making our results more convincing. Hence, we can infer that heterogeneity of treatment effect is not a serious concern in our paper.

4.3. Excluding possible distributors of industrial robots: PSM

An important concern for our paper is that some firms in the ASIF data may be distributors of industrial robots, i.e., they imported the robots as trade intermediaries and then sold these robots to other firms. This could result in misestimating the robot adoption behavior. To address this concern, we try to identify the possible distributors in the matched dataset and then alleviate the possible disturbance. Following Ahn et al. (2011), Fan et al. (2021), and Yu (2015) we identify the possible intermediary firms based on the Chinese characters meaning "importer", "exporter", "trading", and "robot" in the firm's Chinese name. In our sample, we find very few firms of this kind, only 74 firms with 453 observations. After excluding these firms, we re-estimate the regressions to check the

Table 6
The impact of robot adoption in the full sample after matching.

Dep. var.:	(1) *Log_L*	(2) *Log_K*	(3) *Log_Output*	(4) *TFP*	(5) *Log_Export*	(6) *Cap_return*
robot	0.181***	0.108***	0.175***	0.101***	0.259***	0.204***
	(0.031)	(0.030)	(0.032)	(0.024)	(0.061)	(0.046)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,550	142,633	143,506	142,538	125,569	130,236
R^2	0.881	0.915	0.894	0.788	0.813	0.682

Notes: Estimation using OLS. Robust standard errors in parenthesis are clustered at the firm level. PSM employs kernel matching. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. As mentioned above, the TFP in log form is calculated using the OP method following Olley and Pakes (1996) due to data availability. In column 1, we adopt the log of the average wage in the last year since the log of the average wage in the current year is correlated with the total employment in the same period based on the above definition.

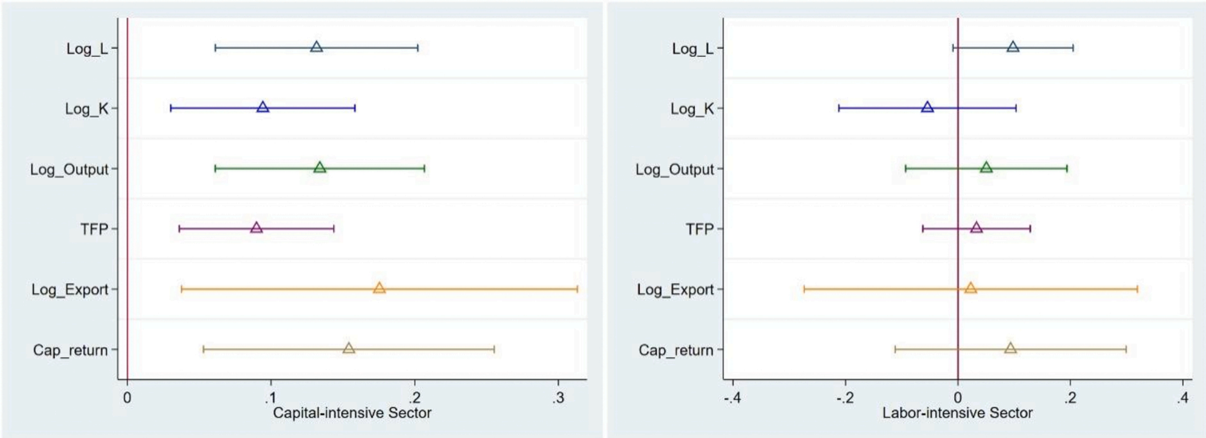

Fig. 9. The impact of robot adoption after matching.

Table 7
The impact of robot adoption in the full sample: alternative DID estimators.

Dep. var.:	(1) *Log L*	(2) *Log K*	(3) *Log Output*	(4) *TFP*	(5) *Log Export*	(6) *Cap return*
	Pannel A: Borusyak-Jaravel-Spiess					
Point Estimate	0.247***	0.150***	0.262***	0.140***	0.345***	0.213***
Standard Error	0.023	0.025	0.029	0.019	0.057	0.038
Lower Bound 95 % Confidence Interval	0.203	0.101	0.205	0.102	0.234	0.138
Upper Bound 95 % Confidence Interval	0.291	0.198	0.319	0.177	0.456	0.287
	Pannel B: De Chaisemartin and D'Haultfeuille					
Point Estimate	0.084***	0.101***	0.082***	0.017	0.125***	0.019
Standard Error	0.015	0.012	0.015	0.018	0.033	0.029
Lower Bound 95 % Confidence Interval	0.055	0.077	0.052	-0.018	0.060	-0.037
Upper Bound 95 % Confidence Interval	0.113	0.125	0.111	0.052	0.190	0.076

Notes: Following Braghieri et al. (2022), this table presents robustness of our baseline estimate to using the alternative DID estimators introduced in Borusyak et al. (2022) and De Chaisemartin and D'Haultfeuille (2020). The regressions underlying the table do not include controls. See Borusyak et al. (2022) and De Chaisemartin and D'Haultfeuille (2020) for a detailed description of how the estimators are constructed and why they are robust to treatment effects heterogeneity across time and treated units. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 8
The impact of robot adoption in the full sample after matching: alternative DID estimators.

Dep. var.:	(1) *Log L*	(2) *Log K*	(3) *Log Output*	(4) *TFP*	(5) *Log Export*	(6) *Cap return*
	Pannel A: Borusyak-Jaravel-Spiess					
Point Estimate	0.268***	0.154***	0.298***	0.168***	0.415***	0.269***
Standard Error	0.026	0.029	0.033	0.023	0.064	0.045
Lower Bound 95 % Confidence Interval	0.217	0.098	0.233	0.123	0.290	0.181
Upper Bound 95 % Confidence Interval	0.319	0.210	0.364	0.213	0.541	0.358
	Pannel B: De Chaisemartin and D'Haultfeuille					
Point Estimate	0.092***	0.114***	0.109***	0.036**	0.147***	0.037
Standard Error	0.015	0.018	0.016	0.014	0.042	0.034
Lower Bound 95 % Confidence Interval	0.062	0.079	0.078	0.009	0.065	-0.029
Upper Bound 95 % Confidence Interval	0.122	0.149	0.139	0.063	0.230	0.104

Notes: See notes to Table 7.

robustness and report the results in Table 9 and Fig. 10.

As we can see, the estimates in Table 9 and Fig. 10 are highly consistent with the baseline results in Table 6 and Fig. 9. Robot adoption increases a series of firm performance indicators in the adoption firms, mainly in the capital-intensive sector, implying that the existence of possible robot distributors is not a serious concern in this paper.

Table 9
The impact of robot adoption in the full sample after matching: excluding distributors.

Dep. var.:	(1) *Log L*	(2) *Log K*	(3) *Log Output*	(4) *TFP*	(5) *Log Export*	(6) *Cap_return*
robot	0.173***	0.225***	0.212***	0.042*	0.178***	0.283***
	(0.027)	(0.026)	(0.029)	(0.024)	(0.062)	(0.045)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	112,035	134,833	135,438	134,751	118,968	123,184
R^2	0.882	0.907	0.888	0.776	0.801	0.663

Notes: See notes to Table 6.

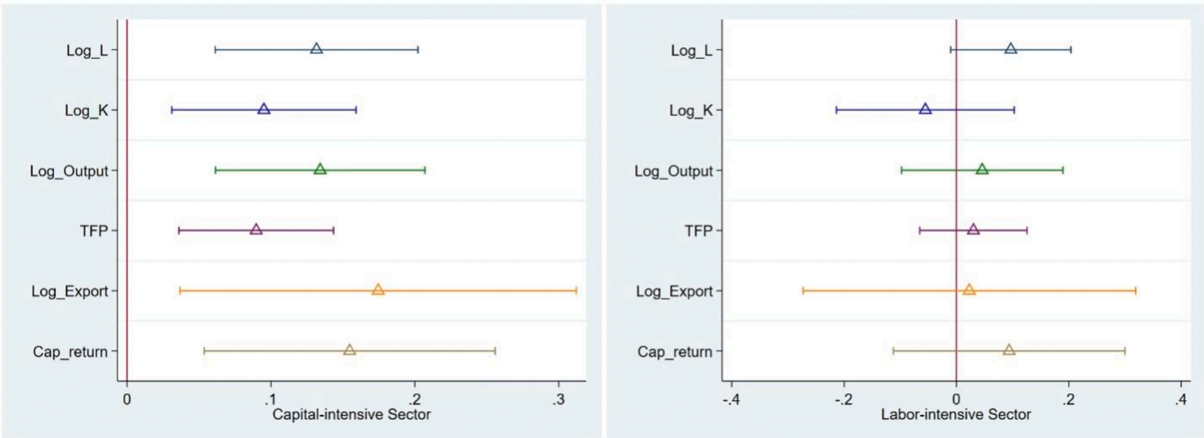

Fig. 10. The impact of robot adoption after matching: excluding distributors. Notes: See notes to Fig. 9.

4.4. Market-level spillovers

Another concern is that there may be great differences between enterprises in the same industry. There may be knowledge spillover, e.g., the neighbors of one firm adopted robots and then increased the sales or price within the same industry, which also affected the firm itself. We can treat it as knowledge spillover at the market level. To alleviate this concern, following Acemoglu et al. (2020), we construct the following index to measure market-level spillovers:

$$Adoptionbycompetitors_f = \sum_i m_{fi} \cdot \sum_{f' \neq f} s_{if'} \cdot robot_{f'} \tag{3}$$

where the first sum is over all four-digit industries, and$m_{fi}$is the share of the sales of firm f that are in industry i, while the second is over all firms other than f, and $s_{if'}$ is the share of industry i's total sales accounted for by firmf'. *robot* is the above defined dummy variable equal to one in the years after robot adoption for the firm.

Table 10
The impact of robot adoption in the full sample after matching including market-level spillovers.

Dep. var.:	(1) *Log L*	(2) *Log K*	(3) *Log Output*	(4) *TFP*	(5) *Log Export*	(6) *Cap_return*
robot	0.158***	0.108***	0.167***	0.078***	0.256***	0.167***
	(0.033)	(0.031)	(0.035)	(0.026)	(0.062)	(0.047)
Adoption by competitors$_f$	0.787***	0.016	0.303	0.930**	0.098	1.402**
	(0.228)	(0.293)	(0.383)	(0.460)	(0.853)	(0.678)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
Ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	114,550	142,633	143,506	142,538	125,569	130,236
R^2	0.881	0.915	0.894	0.788	0.813	0.682

Notes: See notes to Table 6.

In line with Acemoglu et al. (2020), we report the re-estimated results after controlling for market-level spillovers (measured by *Adoption by competitors$_f$*). As can be seen in Table 10 and Fig. 11, the estimates are highly consistent with our baseline results, implying that it is not a serious concern in our paper.

4.5. Alternative control variables

For the selection of control variables in the above baseline results, following Li et al. (2021), we select the firm age (*age*), the square of firm age (*age*^{2}), and the average wage (*ave_wage*) as control variables. Their research about the impact of robot adoption on employment in China is instructive for us. We also select the ratio of debt to total assets (*debtratio*) to measure the firm's financial conditions, since it is costly for the firm to import robots, which depends on the firm's financial conditions to great extent. In addition, following Koch et al. (2021) and Li et al. (2021), we also control the ownership of firms.

To check the robustness and alleviate potential selection bias, we select different controls for different outcome variables and report the results in Table 11 and Fig. 11, respectively. Besides the above control variables (firm age, the square of firm age, the average wage, and ownership), for all the outcome variables except TFP, first, we include labor productivity which is calculated by the ratio of a firm's output to the number of employees (Huang et al., 2022; Koch et al., 2021). Second, following Koch et al. (2021), we also include capital intensity (the ratio of fixed assets to total employment in log form), exporter status (a dummy variable equal to one in the years if the firm has exports), importer status (a dummy variable equal to one in the years if the firm has imports). Third, we replace the average wage with the capital return for the capital stock and omit the exporter and importer status for total exports to avoid potential collinearity. Fourth, we include total employment, capital stock, exporter status, and importer status as additional control variables for TFP (Huang et al., 2022).

As can be seen in Table 11 and Fig. 12, the estimated results are generally consistent with the above baseline results. Moreover, we report the robust results after matching in Table 12 and Fig. 13, implying the potential selection bias of control variables is not a serious concern in our paper.

4.6. Endogeneity: IV estimation

To check robustness, motivated by Acemoglu and Restrepo (2020), adopting the robot stock in Europe as the instrumental variable for the robot stock in the US at the industry level, we try to define an instrumental variable for the robot adoption dummy at the firm level as follows: the interaction term between the robot stock data in Japan on industrial robots and the first value of the ratio of capital to labor in log form in each firm during the observation period.

Since the robot stock in Japan is the data at the industry level, we interact it with the first value of the ratio of capital to labor in each firm to obtain an instrumental variable at the firm level, which is more exclusive and satisfactory in our paper. Thus, our instrumental variable is an extension of that in Acemoglu and Restrepo (2020). First, it is exogenous as we defined above. Second, it is highly correlated with the robot adoption dummy. Because Japan was an important source country for China to import industrial robots during the observation period.

As we can see in the first stage for the robot adoption in Table 13, the coefficients of the instrumental variable are all significantly positive, and all the Kleibergen–Paap F-statistics are greater than 20, satisfying our requirement for the instrumental variable. All the outcome variables increase significantly after robot adoption. Similar results hold in the capital-intensive sector in Table 14, while most results are insignificant in the labor-intensive sector in Table 15. Generally, these findings are consistent with the above results, making our baseline results more convincing.

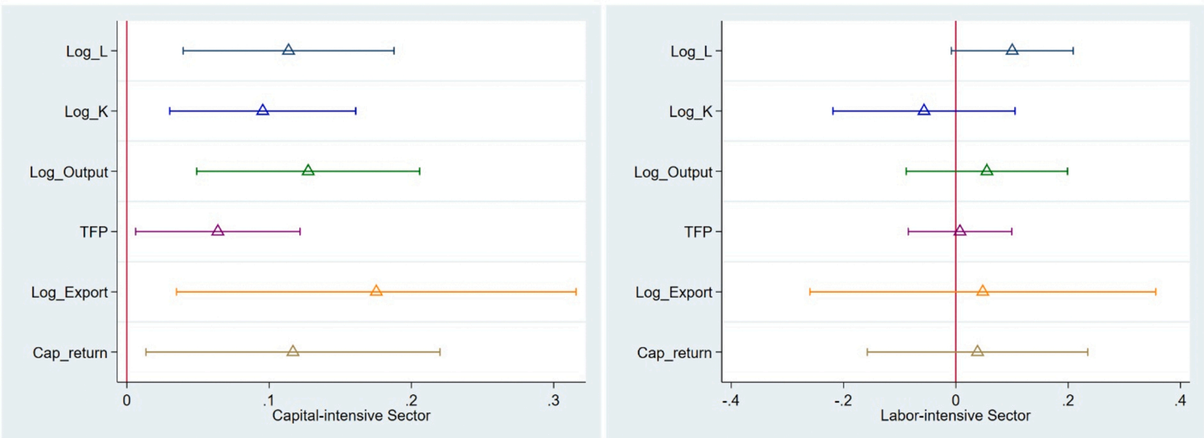

Fig. 11. The impact of robot adoption after matching: market-level spillovers. Notes: See notes to Fig. 9.

Table 11
The impact of robot adoption on firm performance in the full sample with alternative controls.

Dep. var.:	(1) *Log_L*	(2) *Log_K*	(3) *Log_Output*	(4) *TFP*	(5) *Log_Export*	(6) *Cap_return*
robot	0.118***	0.089***	0.147***	0.124***	0.197***	0.158***
	(0.021)	(0.016)	(0.020)	(0.017)	(0.050)	(0.033)
age	0.627***	0.545***	0.829***	0.680***	1.261***	1.003***
	(0.018)	(0.011)	(0.014)	(0.014)	(0.035)	(0.025)
age^2	-0.119***	-0.104***	-0.159***	-0.160***	-0.280***	-0.205***
	(0.004)	(0.003)	(0.004)	(0.004)	(0.010)	(0.007)
capitalintensity	-0.239***	0.770***	-0.204***		-0.120***	-0.036***
	(0.003)	(0.002)	(0.003)		(0.005)	(0.004)
laborproductivity	-0.292***	-0.412***	0.742***		0.285***	0.532***
	(0.003)	(0.003)	(0.004)		(0.007)	(0.006)
ave_wage	-0.032***		-0.134***		0.032***	-0.012**
	(0.003)		(0.003)		(0.007)	(0.005)
Cap_return		0.212***				
		(0.001)				
Log_L				-0.043***		
				(0.003)		
Log_K				-0.215***		
				(0.002)		
exporter	0.099***	0.093***	0.133***	0.080***		0.067***
	(0.007)	(0.005)	(0.006)	(0.006)		(0.011)
importer	0.094***	0.082***	0.122***	0.074***		0.106***
	(0.004)	(0.003)	(0.004)	(0.003)		(0.007)
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	266,505	371,729	328,459	415,746	290,479	298,689
R^2	0.913	0.964	0.929	0.750	0.792	0.679

Notes: See notes to Table 3.

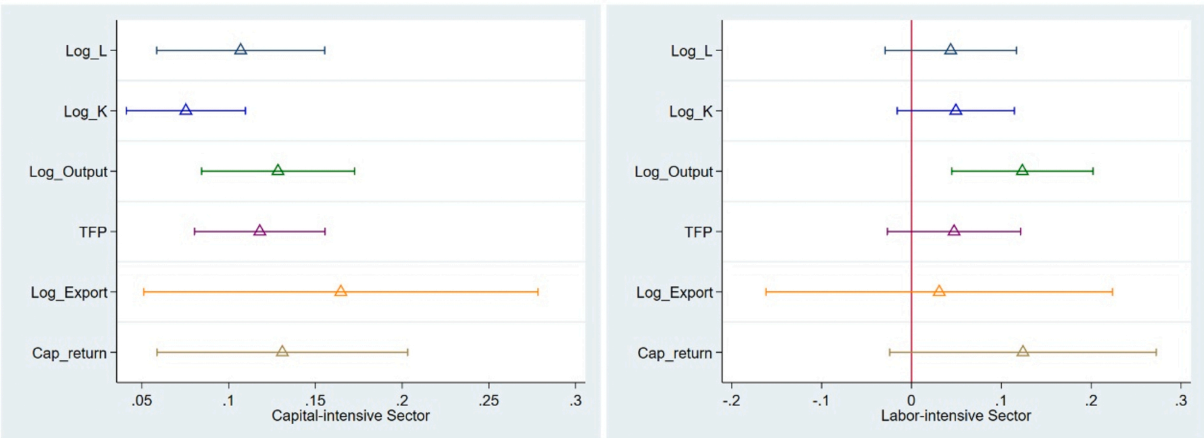

Fig. 12. The impact of robot adoption: alternative controls. Notes: See notes to Fig. 9.

5. Dynamic effects

In this section, we continue to investigate the dynamic effects of robot adoption on firm performance. Following Brucal et al. (2019), we set the regression model as follows:

$$y_{it} = \alpha + \beta R_{it} + \delta x_{it} + \lambda_i + \theta_t + \varepsilon_{it} \tag{4}$$

The key differences between Eqs. (4) and (1) are as follows:

First, we divide time t into two parts: $t = T\text{-}1$ and $t = T + S$. T is the first year when the firm adopted robots, $S = 0,1,2$. Second, similar to the above definition of D_{it}, R_{it} is a dummy variable equal to one in the years after robot adoption for firm i. To highlight the differences between Eqs. (4) and (1), we replace D_{it} with R_{it}. We run Eq. (4) year by year and obtain the dynamic results in the following two years after robot adoption based on the one year before robot adoption. We report the dynamic effects under the unmatched case

Table 12
The impact of robot adoption on firm performance after matching in the full sample with alternative controls.

Dep. var.:	(1) *Log_L*	(2) *Log_K*	(3) *Log_Output*	(4) *TFP*	(5) *Log_Export*	(6) *Cap_return*
robot	0.175***	0.116***	0.168***	0.165***	0.252***	0.204***
	(0.029)	(0.021)	(0.026)	(0.024)	(0.060)	(0.043)
age	0.553***	0.567***	0.781***	0.644***	1.223***	0.853***
	(0.037)	(0.022)	(0.029)	(0.026)	(0.072)	(0.051)
age^2	-0.108***	-0.111***	-0.151***	-0.155***	-0.266***	-0.172***
	(0.009)	(0.006)	(0.008)	(0.007)	(0.021)	(0.013)
capitalintensity	-0.257***	0.764***	-0.205***		-0.120***	-0.050***
	(0.006)	(0.004)	(0.006)		(0.011)	(0.009)
laborproductivity	-0.296***	-0.407***	0.739***		0.309***	0.521***
	(0.007)	(0.005)	(0.007)		(0.015)	(0.011)
ave_wage	-0.024***		-0.141***		0.023***	-0.010
	(0.006)		(0.006)		(0.014)	(0.011)
Cap_return		0.211***				
		(0.003)				
Log_L				-0.037***		
				(0.006)		
Log_K				-0.216***		
				(0.005)		
exporter	0.091***	0.087***	0.115***	0.065***		0.068***
	(0.013)	(0.009)	(0.011)	(0.011)		(0.020)
importer	0.096***	0.084***	0.119***	0.071***		0.107***
	(0.007)	(0.005)	(0.007)	(0.007)		(0.013)
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	113,876	164,283	142,812	184,569	124,814	129,621
R^2	0.921	0.966	0.937	0.760	0.817	0.707

Notes: See notes to Table 6.

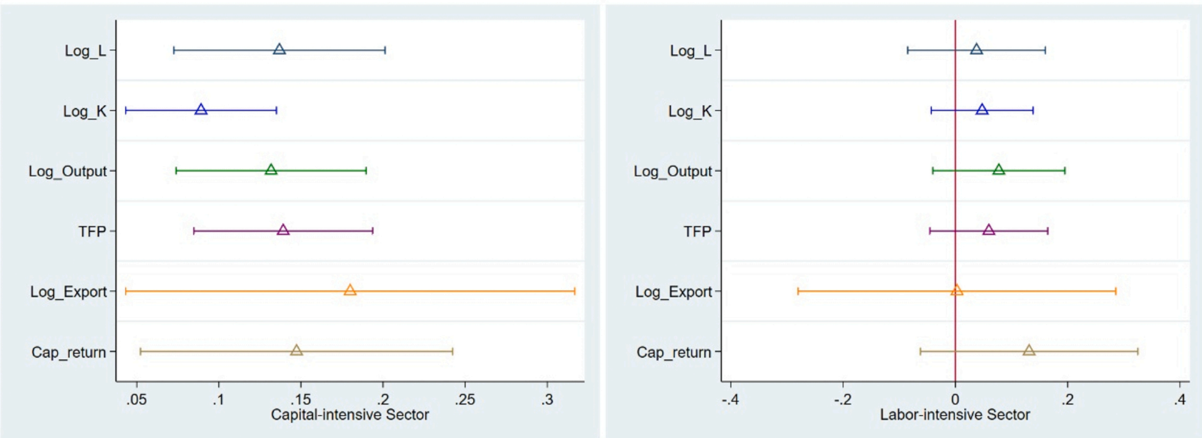

Fig. 13. The impact of robot adoption after matching: alternative controls. Notes: See notes to Fig. 9.

and the PSM case in Tables 16–17, respectively. We only report the results of the robot adoption dummy (*robot*) for simplicity.

In Table 16, we find that in the full sample and the capital-intensive sector, robot adoption significantly increases total employment, capital stock, gross output, TFP, total exports, and capital returns in the three periods we considered. In most cases, these impacts are persistent. In the labor-intensive factor, the impacts are very limited. Only the impacts on labor, output, and exports are significant in some cases, implying that firms in the labor-intensive sector do not benefit much from robot adoption. In Table 17, the results under PSM are highly consistent with those in Table 16. The dynamic results are generally consistent with our previous results, i.e., within the framework of the open economy, the impacts brought by robot adoption are positively significant in the full sample and the capital-intensive sector but not in the labor-intensive sector.

6. Conclusion

As a representative form of artificial intelligence, industrial robots have been increasingly widely used in Chinese manufacturing

Table 13
IV: Limited information maximum likelihood estimation in the full sample.

Dep. var.:	*Log_L*	*Log_K*	*Log_Output*	*TFP*	*Log_Export*	*Cap_return*
robot	3.543***	1.438**	4.533***	2.075***	12.004***	4.569***
	(1.047)	(0.666)	(0.924)	(0.681)	(3.499)	(1.200)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	270,362	331,088	332,727	330,890	294,620	302,566
	First stage for *robot*					
IV	0.172***	0.191***	0.196***	0.190***	0.161***	0.192***
	(0.037)	(0.033)	(0.034)	(0.033)	(0.035)	(0.035)
F test of instruments	21.56	33.39	34.14	32.98	21.03	30.58

Notes: The test for endogeneity uses the Durbin–Wu–Hausman test, which tests the null hypothesis that the robot variable is exogenous. The F-test of instruments uses the Kleibergen–Paap F statistic. The definition of the IV is provided above. Robust standard errors are clustered at the firm level. Firm controls are similar to those in Table 3. In column 1, we adopt the log of the average wage in the last year since the log of the average wage in the current year is correlated with the total employment in the same period based on the above definition. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14
IV: Limited information maximum likelihood estimation in the capital-intensive sector.

Dep. var.:	*Log_L*	*Log_K*	*Log_Output*	*TFP*	*Log_Export*	*Cap_return*
robot_capital	3.139***	1.525***	4.197***	1.890**	11.980***	4.597***
	(1.064)	(0.726)	(0.962)	(0.721)	(3.838)	(1.307)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	137,977	171,290	171,955	171,192	146,493	157,483
	First stage for *robot_capital*					
IV	0.164***	0.177***	0.182***	0.175***	0.149***	0.178***
	(0.037)	(0.033)	(0.033)	(0.033)	(0.035)	(0.034)
F test of instruments	19.47	28.89	29.65	28.51	17.89	26.59

Notes: See notes to Table 9.

Table 15
IV: Limited information maximum likelihood estimation in the labor-intensive sector.

Dep. var.:	*Log_L*	*Log_K*	*Log_Output*	*TFP*	*Log_Export*	*Cap_return*
robot_labor	30.093	0.942	24.513*	15.815*	16.828	10.980
	(34.561)	(5.767)	(13.219)	(9.305)	(14.372)	(9.917)
Firm Controls	Yes	Yes	Yes	Yes	Yes	Yes
ownership	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,385	159,798	160,772	159,698	148,127	145,083
	First stage for *robot_labor*					
IV	0.097	0.211*	0.109*	0.216	0.179***	0.220**
	(0.075)	(0.114)	(0.066)	(0.117)	(0.068)	(0.111)
F test of instruments	1.68	3.42	3.47	3.39	2.59	3.92

Notes: See notes to Table 9.

firms. What impacts will robots have on adoption firms relative to non-adoption firms? Based on the setup of the open economy, we merge the ASIF database and the Chinese Customs database to identify the firms that imported industrial robots from 2000 to 2013 and then adopt DID to provide empirical analysis.

We find that robot adoption in China significantly increases a series of firm performance indicators in robot-adoption firms (mainly in the capital-intensive sector), which is different from existing findings (Giuntella & Wang, 2019), e.g., total employment, capital stock, gross output, TFP, total exports, and capital returns at the extensive margin. We conduct a multidimensional robustness check, and investigate the dynamic effects, finding robust and persistent positive impacts.

Our paper presents the original findings on the impacts of robot adoption in open developing and transition countries such as China and finds that robot adoption brings significant positive impacts on firm performance for adoption firms. These impacts are heterogeneous in different sectors. Specifically, firms in the capital-intensive sector significantly benefit from robot adoption instead of the labor-intensive sector. The conclusions in our paper shed some light on the introduction of industrial robots in open developing and

Table 16
Dynamic effects (Raw).

Var.	Full sample			Capital-intensive Sector			Labor-intensive Sector		
	t	*t + 1*	*t + 2*	*t*	*t + 1*	*t + 2*	*t*	*t + 1*	*t + 2*
Log_L	0.143***	0.178***	0.162***	0.152***	0.178***	0.164***	0.078**	0.124**	0.100*
	(0.022)	(0.028)	(0.036)	(0.025)	(0.032)	(0.043)	(0.039)	(0.048)	(0.054)
Observations	141,036	141,030	140,988	68,778	68,774	68,745	72,258	72,256	72,243
R^2	0.937	0.937	0.937	0.944	0.944	0.943	0.930	0.930	0.930
Log_K	0.154***	0.190***	0.185***	0.164***	0.194***	0.194***	0.090	0.131*	0.087
	(0.025)	(0.032)	(0.031)	(0.027)	(0.035)	(0.036)	(0.064)	(0.077)	(0.061)
Observations	138,895	138,816	138,756	67,956	67,898	67,855	70,939	70,918	70,901
R^2	0.941	0.941	0.941	0.923	0.923	0.923	0.899	0.899	0.899
Log_Output	0.174***	0.258***	0.232***	0.165***	0.256***	0.230***	0.148***	0.166***	0.112
	(0.024)	(0.031)	(0.037)	(0.028)	(0.036)	(0.043)	(0.048)	(0.056)	(0.070)
Observations	139,205	139,128	139,074	68,072	68,014	67,979	71,133	71,114	71,095
R^2	0.929	0.928	0.928	0.934	0.934	0.934	0.902	0.902	0.902
TFP	0.054***	0.113***	0.092***	0.042*	0.118***	0.093**	0.059	0.024	0.013
	(0.020)	(0.027)	(0.030)	(0.023)	(0.031)	(0.035)	(0.042)	(0.050)	(0.051)
Observations	138,850	138,771	138,711	67,923	67,865	67,822	70,927	70,906	70,889
R^2	0.838	0.837	0.837	0.848	0.847	0.847	0.829	0.828	0.828
Log_Export	0.226***	0.130*	0.306***	0.160**	0.068	0.249***	0.312***	0.119	0.205*
	(0.052)	(0.076)	(0.069)	(0.062)	(0.087)	(0.081)	(0.089)	(0.159)	(0.116)
Observations	128,621	128,559	128,516	60,301	60,252	60,230	68,320	68,307	68,286
R^2	0.863	0.862	0.863	0.857	0.856	0.856	0.872	0.872	0.872
Cap_return	0.125***	0.235***	0.243***	0.125***	0.218***	0.277***	0.050	0.199	-0.037
	(0.038)	(0.051)	(0.061)	(0.040)	(0.056)	(0.066)	(0.098)	(0.126)	(0.149)
Observations	126,821	126,750	126,712	62,764	62,712	62,683	64,057	64,038	64,028
R^2	0.708	0.707	0.707	0.702	0.701	0.700	0.693	0.693	0.692

Notes: See notes to Table 3.

Table 17
Dynamic effects after matching.

Var.	Full sample			Capital-intensive Sector			Labor-intensive Sector		
	t	*t + 1*	*t + 2*	*t*	*t + 1*	*t + 2*	*t*	*t + 1*	*t + 2*
Log_L	0.152***	0.200***	0.230***	0.172***	0.200***	0.236***	0.058	0.161***	0.195***
	(0.023)	(0.030)	(0.035)	(0.028)	(0.035)	(0.043)	(0.040)	(0.055)	(0.059)
Observations	23,389	21,739	29,071	11,581	10,414	13,586	12,708	12,653	12,932
R^2	0.972	0.954	0.922	0.975	0.959	0.933	0.962	0.937	0.910
Log_K	0.139***	0.169***	0.175***	0.122***	0.152***	0.163***	0.106***	0.099	0.090
	(0.023)	(0.028)	(0.030)	(0.028)	(0.033)	(0.035)	(0.046)	(0.061)	(0.059)
Observations	32,346	38,829	36,325	15,832	18,841	18,118	17,497	17,145	15,777
R^2	0.971	0.960	0.952	0.958	0.942	0.930	0.934	0.916	0.903
Log_Output	0.119***	0.213***	0.219***	0.108***	0.195***	0.184***	0.095**	0.161***	0.119*
	(0.024)	(0.032)	(0.037)	(0.029)	(0.039)	(0.044)	(0.043)	(0.053)	(0.070)
Observations	32,439	39,113	36,781	15,864	18,939	18,261	17,562	17,271	15,927
R^2	0.958	0.946	0.931	0.960	0.946	0.930	0.930	0.918	0.900
TFP	0.018	0.088***	0.079***	0.014	0.085**	0.058*	0.023	0.032	0.011
	(0.021)	(0.028)	(0.029)	(0.025)	(0.033)	(0.035)	(0.037)	(0.048)	(0.051)
Observations	32,327	38,790	36,286	15,819	18,820	18,097	17,487	17,137	15,761
R^2	0.895	0.879	0.856	0.898	0.878	0.854	0.879	0.863	0.844
Log_Export	0.122**	0.052	0.239***	0.028	-0.032	0.147*	0.317***	0.028	0.120
	(0.056)	(0.079)	(0.073)	(0.064)	(0.091)	(0.088)	(0.105)	(0.182)	(0.127)
Observations	27,498	33,647	31,586	12,642	15,407	14,902	15,714	15,357	14,117
R^2	0.908	0.886	0.871	0.908	0.884	0.866	0.893	0.875	0.867
Cap_return	0.120***	0.233***	0.237***	0.079*	0.165***	0.186***	0.147	0.293***	0.163
	(0.039)	(0.048)	(0.058)	(0.043)	(0.056)	(0.065)	(0.095)	(0.100)	(0.147)
Observations	28,334	33,946	31,593	13,974	16,581	15,946	15,313	14,901	13,657
R^2	0.828	0.807	0.795	0.817	0.787	0.770	0.792	0.774	0.763

Notes: See notes to Table 6.

transition countries. Since the positive impacts brought by robot adoption dominate the negative impacts, the government can promote and subsidize firms to adopt industrial robots. Moreover, when formulating industrial policy associated with robot adoption, the government can encourage companies in the capital-intensive sector to adopt robots first because the impacts can be greater and exemplary. Then the government can formulate some industrial policies targeted at the labor-intensive sector to promote robot adoption.

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The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data Availability

The data that has been used is confidential.

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