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论文题目：

Automation, Green Investment and the Pollution Abatement: Evidence from Chinese Manufacturing Firms

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Abstract: This paper explores theoretically and empirically the impact of industrial robot adoption on the investment decision of pollution abatement technology (the green investment), and the pollution intensity. A theoretical model predicts that a rising fraction of automation will increase firms' green investment, because the cost-saving advantage of robots over low-skilled labors can reduce the marginal production cost of firms and increase the marginal benefit of investing in pollution abatement technology. The model also predicts that the rising fraction of automatable technology may decrease the level of pollution intensity. Empirical evidence from Chinese manufacturing firms provides support to these theoretical predictions. We find that firms that adopt robots invest more on green facilities and have lower pollution intensity than non-robot firms.

Key Words: Automation; Green Investment; Pollution Abatement

Content

1. Introduction

With rising labor costs in the past two decades, the adoption of industrial robots has been increasing substantially worldwide. The automation technology, such as the robotics and autonomous system, is projected to be deployed by 60% of companies worldwide by 2025 (World Economic Forum, 2020). However, it is also argued that the automation technology has profoundly altered how economy and environment inter-relate (Galaz et al., 2021), and may have created negative environmental impacts such as exacerbating pollution (Guenat et al., 2022).

Could the advancements in productivity, catalyzed by the automation technology such as industrial robots, come at the expense of the environment and ecosystems? There is no systematic examination to this question yet, even though answering this question is so essential. Indeed, the air pollution and the associated global warming have been causing substantial risks to the natural, human and economic systems, in particular in those fast-growing economies like China (Stock, 2020; Wolf et al., 2022; Song et al., 2023) [1]. If automation does induce worse environment, human society may need to be more cautious in pursuing automation.

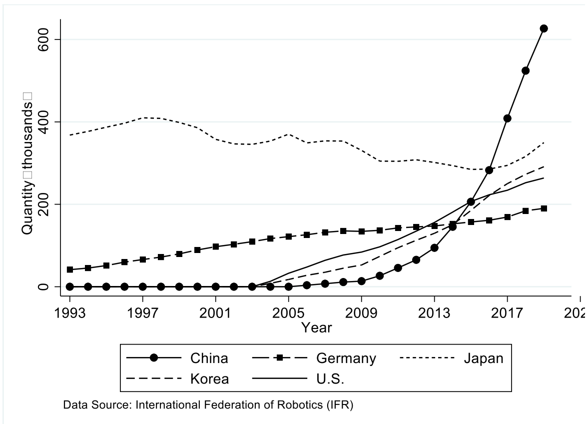
This paper aims to answer this question. Specially, we investigate whether industrial robot adoption encourages firms to invest in pollution abatement technology (henceforth the green investment), and what are the environmental consequences of industrial robot adoption. We first construct a simple model to identify the mechanism through which industrial robots may affect firms' decisions on the investment of pollution abatement technology. The model is featured with automation technology where for tasks capable of automation, firms prefer industrial robots to low-skilled workers as the rental rate of industrial robots is lower than the wage of low-skilled workers (Acemoglu and Restrepo, 2020). Such investments are subject to convex investment costs (Aghion et al., 2018). The negative externality associated with firm production is pollution emissions, which are subject to a costly tax and induce firms to endogenously choose an optimal investment level in pollution abatement technology to avoid the emission tax (Shapiro and Walker, 2018).

[1] Considerable evidence shows that air pollution exposure is detrimental to the cognitive and physical abilities of human (Aguilar-Gomez, et al., 2022), results in over 6 million premature deaths yearly (Health Effects Institute, 2020), and causes climate damages almost seven times of the energy input (Stock, 2020)

We find that in the model, a rising fraction of automatable tasks will encourage firms, and particularly the large and high-productivity firms, to invest more in pollution abatement technology, which may imply a potentially cleaner economy in the process of industrial robotization. The intuition is simple. The marginal benefit of investing green will be amplified by the fraction of tasks capable of automation, as the rental rate of industrial robots is relatively lower than the wage of low-skilled workers (Acemoglu and, 2020). Such a stimulating effect of industrial robots on green investment is particularly strong for high-productivity firms, since for such firms, industrial robotization will deliver them particularly low marginal production costs and result in even large market shares. Thus, the heterogeneity effect of industrial robots on firms' green investment suggests a resource reallocation from low-productivity firms to high-productivity firms during the industrial robotization.

We empirically test these theoretical predictions with Chinese manufacturing firm data. The Chinese setting is especially suitable for addressing the question. China has been a leading country in adopting robots. The stock number of robots in China surpassed that in Japan in 2016, ranking top 1 in terms of the stock of industrial robots since then (Figure 1). According to the "2021 World Robot Report" released by the International Federation of Robotics (IFR) in 2020, China accounted for 43.85% of global robot installations. The robot density in the manufacturing industry amounts to 246 industrial robots for every 10,000 employees, which is twice the world average, and the operational stock of industrial robots in China was 943,223 units by the end of 2020, accounting for 31.4% of the world's total number.[2]

Figure 1. The stock number of robots in major countries



2 https://ifr.org/ifr-press-releases/news/robot-sales-rise-again

Thanks to the Chinese Customs Database (CCD), we obtain firm level information of robotization. This dataset provides firm-level import information on industrial robots, which we use as the measure of the adoption of industrial robots. This is a reliable measure for two reasons. First, the robots deployed by Chinese firms were mainly imported before 2010. Robots made in China emerged only after year 2010 (Fan et al., 2021). Second, robot production is highly monopolistic and concentrated in the six major global manufacturers, none of which resides in China (Bonfiglioli et al., 2020) [3]. Additionally, we obtain firm green investment and pollution data from the Chinese Industrial Firms Pollution Emissions (CIFPE), and firm operation data from the Annual Survey of Industrial Firms (ASIF). We restrict our sample to the years of 2000 to 2009 due to the data availability of the CCD dataset (running from 2000 to 2013), and that the ASIF dataset misses important variables in the year of 2010. During our sample period, the imported robots are the major source of industrial robots for firms.[4]

Table 1 Differences Between Robot Adoptors and Non-robot Adoptors

	(1)	(2)	(3)	(4)	(5)
VARIABLES	Gas Facilities	Coal Consumption	SO2 Emissions	Sales	Output
Robot Adoptors	0.191***	-4.180***	-1.296***	2.257***	2.225***
	(5.63)	(-23.17)	(-14.42)	(70.21)	(66.95)
Constant	0.785***	5.726***	2.454***	9.822***	9.857***
	(327.19)	(460.64)	(394.03)	(6,237.42)	(6,054.19)
Observations	83,926	79,195	87,859	620,520	620,505
F	31.68	536.8	208.0	4930	4482

Notes: (1) Robot Adoptors refer to firms that imported robots from 2000 to 2009, and non-robot firms refer to firms that did not import robots during this period. (2) The coefficients are from the following regression, $y_j = \beta_1 Rob_j + \beta_0 + \varepsilon_j$, where y_j indicates the average value of variable y for firm j over sample years. Rob_j=1 if the firm is robot adoptor, and 0 for a non-robot adoptor. (3) t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 1 reports the raw differences in green investment and pollution emissions between robot adoptors that have ever imported robots from the year 2000 to 2009, and non-robot adoptors that never imported robots during this period. A few points are worth noting. First, robot adoptors are in general larger than non-robot adoptors. They

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[3] The 6 major robot producers are ABB (Switzerland), Omron (USA), Fanuc (Japan), Kawasaki (Japan), KUKA (Germany), Yaskawa (Japan).

[4] Indeed, it is pretty common in the literature to measure firm-level robot usage with imported robots (see Bonfiglioli et al., 2020; Acemoglu et al., 2020; Koch et al., 2021).

have higher sales and output. Second, robot adoptors have significantly larger amount of gas treatment facilities, indicating more green investment than non-robot adoptors. Third, robot adoptors consume less coal resource than non-robot adoptors, and may pollute less in terms of the level of SO2 emissions. We take SO2 emissions as our measure of pollution emission, as it was one of the most important pollutants during the sample period (Vennemo et al., 2009).

However, Table 1 does not imply any causality from robot adoption to firm performance. To identify such causal effects, we exploit the more rigorous instrumental variable (IV) approach. In particular, we construct two instrumental variables, one built on robot tariffs (the Tariff IV) and the other on robot adoption in the same industry in the U.S. (the US IV). We find that firms that adopt robots will invest more on gas treatment facilities (green investment). This is especially true for the high-productivity firms. We also find that firms adopting industrial robots in general have significantly lower SO2 pollution intensity. Such empirical findings are consistent with our theoretical predictions.

Our paper contributes to the literature that investigates the impact of industrial robot adoption on environmental related issues, such as the energy consumption (Luan et al., 2022), energy efficiency and pollution emissions (Song et al., 2023). Due to the lack of data on robot adoption at the firm-level (Koch et al., 2021), most of the existing studies measure robot adoption at the industry, regional, or country level (Luan et al., 2022). The underlying assumption is the homogeneity of firms' capacity and willingness to use robots while ignoring the potential resource reallocation across heterogeneous firms. Among the very few papers that search for firm-level evidence (Song et al., 2023), none of them offers a theoretical explanation or empirical evidence of the causality from automation to firm green investment. We fill in these gaps.

Our paper is also related to a growing literature that studies the economic impacts of industrial robots. The IFR defines industrial robots as "automatically controlled, multipurpose, and reprogrammable" machines that do not require a human operator (IFR, 2014). Accordingly, industrial robots are argued to change or replace low-skilled labors in a range of tasks (Acemoglu and Restrepo, 2020). However, Acemoglu and Restrepo (2018) also pointed out that the cost savings brought by automation and the new tasks created by productivity improvements may boost demand for labor and increase their income share. Furthermore, existing studies mainly measure robot penetration at the industry or country level (Acemoglu and Restrepo 2018, 2020). With limited firm-level robot survey or import data, a few papers find that the use of robots can significantly improve the labor productivity and total factor productivity of firms, and reduce firms' product prices (Bonfiglioli et al., 2020; Acemoglu et al., 2020; Koch et al., 2021). We contribute to this strand of literature by exploring the impacts of industrial robots in a new field, the environmental sustainability.

Our paper is also related to the literature that studies the determining factors of pollution. Existing studies find that economic growth may be at the cost of environmental deterioration (Shapiro and Walker, 2018). To balance economic growth with environmental sustainability, environmental regulation policies were adopted to tackle environmental issues and climate change.[5] Different from the literature, we emphasize the mechanism that industrial robot adoption reduces firms' marginal cost of production, which on one hand expands firm production, but on the other hand encourages firms to invest green, leading to pollution abatement effect and reducing pollution intensity.

The paper is organized as follows: section 2 develops a theoretical model; section 3 presents the data and variable constructions; section 4 describes the empirical strategy and reports the empirical results; section 5 concludes.

2. Model

We construct a theoretical model to analyze the environmental impacts of industrial robot adoption. We identify the mechanism through which industrial robot adoption may affect a firm's decision on green investment and the corresponding changes in its pollution emission intensity. The model includes three key ingredients, the automation technology where for a certain fraction of tasks, cheaper industrial robots will replace low-skilled workers (Acemoglu and Restrepo, 2020), the costly pollution emission which is associated with firm production and subject to a pollution tax (Shapiro and Walker, 2018), and the green investment which will reduce the level of pollution emission but is subject to convex investment cost (Aghion et al., 2018).

[5] Literature states that the rapid economic growth, the advanced financial development, openness to the world through foreign direct investment (FDI) or trade, population level and rising urbanization may all cause environmental deterioration. Relevant policies include environmental taxes and regulations (Shapiro and Walker, 2018; Fan et al., 2019).

2.1 Market Structure

Final consumption good, Y, is produced by combining intermediate varieties, $\mathrm{y}(\omega)$, with a CES type of aggregator, $Y = \left[\int_{\omega\in\Omega} \mathrm{y}(\omega)^{\frac{\sigma-1}{\sigma}} \mathrm{d}\omega\right]^{\frac{\sigma}{\sigma-1}}$, where $\omega \in \Omega$ denotes a unique variety produced by a specific firm i (hence, $i = \omega$), and $\sigma > 1$ is the substitution elasticity across intermediate inputs. Such a market structure implies that the market demand for each individual variety would be given by: $\mathrm{y}(\omega) = \mathrm{p}(\omega)^{-\sigma}\mathrm{X}$, where $\mathrm{p}(\omega)$ is the price of intermediate good ω, and X captures the aggregate factor, given by $\mathrm{X} \equiv \mathrm{P}^{\sigma} Y$, with $P = \left[\int_{\omega\in\Omega} \mathrm{p}(\omega)^{1-\sigma} \mathrm{d}\omega\right]^{\frac{1}{1-\sigma}}$ representing the aggregate price index. When we consider individual firm's decisions, we treat the aggregate factor as fixed.

2.2. Intermediate Goods Sector

2.2.1 Automation and Production

Following Bonfiglioli et al. (2020) and Acemoglu and Restrepo (2020), each firm i with productivity level (φ_i) produces a unique variety (y_i) with two types of inputs, the worker-robots combined task input, H_i, and natural resource (N_i).[6] Eq. (1) describes the production function of firm i,

$$y_i = \varphi_i \left(\frac{H_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{N_i}{\alpha}\right)^{\alpha} \tag{1}$$

where α denotes the cost share of the natural resource in the production process.

The production of combined tasks, H_i, follows a CES type of aggregation specified in Eq. (2),

$$\widetilde{H}_i = exp\left[\int_0^1 ln[x_i(z)]dz\right], \tag{2}$$

where $x_i(z)$ denotes the input of task $z \epsilon [0,1]$. We assume that tasks ($z \in [0, \vartheta_i)$) are exogenously assigned to the industrial robots (A_i), and the left ones ($[\vartheta_i, 1]$) are given to the low-skilled workers (L_i). The functional forms of the inputs ($x_i(z)$) associated to each task is given in Eq. (3),

[6] The conclusion is similar when introducing physical capital or high-skilled labor into the production function.

$$x_i(z) = \begin{cases} \frac{A_i}{\vartheta_i} & , z \in [0, \vartheta_i) \\ \frac{L_i}{1-\vartheta_i} & , z \in [\vartheta_i, 1] \end{cases} \tag{3}$$

where ϑ_i measures the exogenous fraction of tasks capable of automation. The larger the ϑ_i, the more the tasks that robots can work on. In the extreme case where $\vartheta_i = 1$, we have $x_i(z) = A_i$, which means that all tasks will be completed by industrial robots. In the other extreme where $\vartheta_i = 0$, $x_i(z) = L_i$, all tasks will be done by low-skilled workers. Substituting Eq. (3) into Eq. (2), the task combination can be re-written in Eq.(4),

$$\widetilde{H}_i = \left(\frac{A_i}{\vartheta_i}\right)^{\vartheta_i} \left(\frac{L_i}{1-\vartheta_i}\right)^{(1-\vartheta_i)} \tag{4}$$

Following Shapiro and Walker (2018), we assume pollution emission (E_i) follows production, and pollution is costly, subject to a market price of τ_i. Hence, each firm assigns $\delta_i \in (0,1)$ fraction of labor, L_i, to abate pollution, and the remaining fraction, $(1-\delta_i)$ to produce output. The combined task input of firm i completed by low-skilled workers and industrial robots can be re-written in Eq. (5),

$$H_i = \left(\frac{A_i}{\vartheta_i}\right)^{\vartheta_i} \left(\frac{(1-\delta_i)L_i}{1-\vartheta_i}\right)^{(1-\vartheta_i)} = (1-\delta_i)^{(1-\vartheta_i)} \widetilde{H}_i \tag{5}$$

Correspondingly, the production function of Eq. (1) can be re-written in Eq. (6),

$$y_i = (1-\delta_i)^{(1-\vartheta_i)(1-\alpha)} \varphi_i \left(\frac{\widetilde{H}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{N_i}{\alpha}\right)^{\alpha} = (1-\delta_i)^{(1-\vartheta_i)(1-\alpha)} \tilde{y}_i. \tag{6}$$

where the productive factor ($\tilde{y}_i$) is given by Eq. (7),

$$\tilde{y}_i = \varphi_i \left(\frac{\widetilde{H}_i}{1-\alpha}\right)^{1-\alpha} \left(\frac{N_i}{\alpha}\right)^{\alpha}. \tag{7}$$

2.2.2 Production and Pollution

As in Shapiro and Walker (2018), the amount of pollution emission is assumed to be an increasing function of production. To investigate how robot adoption affects a firm's decision on green investment, we assume the pollution emission is a decreasing function of the level of green investment (I_i), given by Eq. (8),

$$E_i = \lambda(I_i)\gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}} (1-\delta_i)^{\frac{(1-\vartheta_i)(1-\alpha)}{\gamma}} \tilde{y}_i \tag{8}$$

where $\lambda(I_i)$ captures the effect of green investment on pollution abatement, with $\frac{\partial\lambda(I_i)}{\partial I_i}$<0, reflecting that green investment reduces pollution intensity ($\frac{\partial\lambda(I_i)}{\partial I_i}$). The term, $\gamma(1-\gamma)^{\frac{1-\gamma}{\gamma}}$, is a scale factor to have a clean representation of the transformed production function in Eq. (9) below, satisfying $\gamma \in (0,1)$.

Solving for $(1-\delta_i)$ in Eq. (8) and substituting it into Eq. (6), we show that the production function can be effectively transformed to a Cobb-Douglas function of the pollution emission and the productive factors ($\tilde{y}_i$),

$$y_i = \left(\frac{E_i}{\lambda(I_i)\gamma}\right)^{\gamma}\left(\frac{\tilde{y}_i}{1-\gamma}\right)^{1-\gamma}. \tag{9}$$

Here, it can be seen that, γ captures the fraction of pollution cost in the production process.

The marginal cost of production ($MC(\vartheta_i)$) can then be solved as in Eq. (10),

$$MC(\vartheta_i) = (\lambda(I_i)\tau_i)^{\gamma}\left(\frac{MC_p(\vartheta_i)}{1-\gamma}\right)^{1-\gamma} \tag{10}$$

where $MC_p(\vartheta_i)$ captures the marginal cost on the productive factor ($\tilde{y}_i$), given by Eq. (11),

$$MC_p(\vartheta_i) = \frac{[\varepsilon(\vartheta_i)]^{\alpha}R^{1-\alpha}}{\varphi_i} \tag{11}$$

R is the market price of natural resource, and $\varepsilon(\vartheta_i)$ is the marginal cost associated with the combined tasks ($\widetilde{H}_i$) given by Eq. (12),

$$\varepsilon(\vartheta_i) = r^{\vartheta_i}W^{1-\vartheta_i} \quad , \tag{12}$$

where r is the market price of industrial robots, and W is the wage paid to low-skilled workers. We see that the marginal cost of production ($MC(\vartheta_i)$) is a function of the level of green investment (I_i) and the fraction of tasks capable of automation (ϑ_i). When green investment is high and such that pollution emission intensity is low (falling $\frac{E_i}{\tilde{y}_i}$), the cost due to emission abatement is low. Then, firms have lower marginal costs of production. Similarly, when the fraction of tasks capable of automation is high, with the assumption that $r < W$, firms will also have lower marginal costs of production.

Given the CES type of market structure described in Eq. (1), the market price of good i and the output of firm i would be given in Eqs. (13)-(14):

$$p_i = \frac{\sigma}{\sigma-1} MC_i, \tag{13}$$

$$y_i = \left(\frac{\sigma}{\sigma-1} MC_i\right)^{-\sigma} \text{X}. \tag{14}$$

Here, $\frac{\sigma}{\sigma-1}$ is the price markup, and MC_i the marginal cost of production which captures the cost induced by penalty on pollution emission and the cost on productive factors, as defined in Eqs. (10-11).

2.2.3 Automation and Green Investment

Following Aghion et al. (2018), we introduce firm decision on green investment. On one hand, green investment is beneficial in reducing firm marginal production costs (see Eq. (10)). The intuition is that, green investment will reduce the pollution emission intensity (falling $\frac{E_i}{\tilde{y}_i}$ as $\frac{\partial \lambda(I_i)}{\partial I_i}$<0). This implies that, holding production ($\tilde{y}_i$) fixed, a firm that invests green will decrease its pollution emission level, suffering less from the pollution tax penalty, and thus reduce its total production costs for given amount of outputs.

On the other hand, the investment cost ($g(I_i)$) is a convex function of the investment level (I_i), with $\frac{\partial g(I_i)}{\partial I_i}$ >0 and $\frac{\partial^2 g(I_i)}{(\partial I_i)^2}$ >0. We do not specify the exact functional forms of g_i, as the qualitative discussion is sufficient to illustrate the insights in the relationship between automation and investment.

Firm i chooses optimal amount of robots, low-skilled workers, and green investment to maximize its profit, which yields the following first-order condition on green investment in Eq. (15):

$$-\frac{\partial MC_i}{\partial I_i} y_i = \frac{\partial g(I_i)}{\partial I_i}. \tag{15}$$

The left-hand side of Eq. (15) defines the marginal benefit from investing green (MB_i),

$$MB_i = -\frac{\partial MC_i}{\partial I_i} y_i. \tag{16}$$

Mathematically, we can show that rising green investment would reduce firm marginal production cost,

$$\frac{\partial MC_i}{\partial I_i} = \frac{\gamma MC_i}{\lambda_i} \frac{\partial \lambda(I_i)}{\partial I_i} < 0 \tag{17}$$

as $\frac{\partial \lambda(I_i)}{\partial I_i} < 0$.

We next explore how automation affects a firm's green investment decision. Combining Eqs. (16)-(17), we re-write the marginal benefit of green investment in Eq. (18),

$$MB_i = -y_i \frac{\gamma MC(\vartheta_i)}{\lambda_i} \frac{\partial \lambda(I_i)}{\partial I_i} = -\frac{\gamma}{\lambda_i}\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} \left(MC(\vartheta_i)\right)^{1-\sigma} \mathrm{X} \frac{\partial \lambda(I_i)}{\partial I_i}. \tag{18}$$

We then show that, for a given change of green investment, a higher fraction of tasks capable of automation (rising ϑ_i) would raise the marginal benefit of green investment as shown in Eq. (19),

$$\frac{\partial MB_i}{\partial \vartheta_i} = \left[\frac{\gamma}{\lambda_i}\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma} (\sigma-1)\left(MC(\vartheta_i)\right)^{-\sigma}\mathrm{X}\right]\left[\frac{\partial \lambda(I_i)}{\partial I_i}\right]\left[\frac{\partial MC(\vartheta_i)}{\partial \vartheta_i}\right] > 0, \tag{19}$$

since $\frac{\partial \lambda(I_i)}{\partial I_i} < 0$ and

$$\frac{\partial MC(\vartheta_i)}{\partial \vartheta_i} = (1-\gamma)(1-\alpha)\vartheta_i MC(\vartheta_i)(lnr - lnW) < 0. \tag{20}$$

Note, $\frac{\partial MC(\vartheta_i)}{\partial \vartheta_i} < 0$ because the unit cost of using robots is assumed to be lower than that of low-skilled workers ($r < W$), following Acemoglu and Restrepo (2018) and Bonfiglioli et al. (2020). Eq. (17) suggests that, holding factor prices and aggregate demand constant, as green investment would reduce a firm's pollution emission intensity ($\frac{\partial \lambda(I_i)}{\partial I_i} < 0$), it will reduce the marginal production cost ($\frac{\partial MC_i}{\partial I_i} < 0$). Eq. (20) further shows that, pollution abatement choices depend on the fraction of tasks capable of automation. Ceteris paribus, a larger fraction of tasks capable of automation will reduce a firm's marginal cost of production. This amplifies marginal benefit of doing green investment, and encourages the firm to invest more in pollution abatement technology. We have Proposition 1 below.

Proposition 1: Holding factor prices and aggregate demand constant, when the unit cost of industrial robots is lower than that of low-skilled workers ($r < W$), a rising fraction of tasks capable of automation will reduce the marginal cost of production and increase the marginal benefit of green investment, thereby encouraging a firm's investment on pollution abatement facilities.

Additionally, Eq. (21) shows that, the positive impact of robot adoption on the marginal benefit of investing green ($\frac{\partial MB(\vartheta_i)}{\partial \vartheta_i} > 0$) will be even larger for firms with higher productivity, as these firms have even lower marginal costs than their peers with lower productivity, as shown in Eq. (21) below,

$$\frac{\partial\left(\frac{\partial MB(\vartheta_i)}{\partial \vartheta_i}\right)}{\partial \varphi_i} = \left[\frac{\sigma\gamma}{\lambda_i}\left(\frac{\sigma}{\sigma-1}\right)^{-\sigma}(\sigma-1)\mathrm{X}(1-\gamma)(1-\alpha)\vartheta_i(lnr - lnW)\right]\left[\frac{\partial\lambda(I_i)}{\partial I_i}\right](1-\sigma)\left(MC(\vartheta_i)\right)^{-\sigma}\left[\frac{\partial MC(\vartheta_i)}{\partial \varphi_i}\right] > 0 \quad (21)$$

as $lnr - lnW < 0, \frac{\partial\lambda(I_i)}{\partial I_i} < 0, 1-\sigma < 0,$ and $\frac{\partial MC(\vartheta_i)}{\partial \varphi_i} < 0$. Eq. (21) implies that firms with larger productivity have stronger incentive to invest green. We then have Proposition 2 below.

Proposition 2: The effect of robot adoption on firm green investment will be stronger for firms with larger productivity than their peers with lower productivity.

Finally, we can work out the impacts of automation on firm's pollution intensity, defined as the ratio of pollution emission to output ($\frac{E_i}{\tilde{y}_i}$). From Eqs. (6) and (8), we have

$$\frac{E_i}{y_i} = \frac{MC_i}{\tau_i}\gamma,$$

which implies that

$$\frac{d(\frac{E_i}{y_i})}{d\vartheta_i} = \frac{\gamma}{\tau_i}\frac{d(MC_i)}{d\vartheta_i} < 0. \quad (22)$$

Intuitively, as automation increases pollution abatement investment and reduces $\lambda(I)$, this will decrease the ratio of emission E_i to a firm's output. We thus have the testable Proposition 3 below.

Proposition 3: Ceteris paribus, when the unit cost of industrial robots is lower than that of low-skilled workers ($r < W$), a rising fraction of tasks capable of automation will reduce the firm's pollution intensity.

We will test these theoretical predictions in the next section.

3. Data and Variables

3.1 Data

We use three firm-level datasets in this study: the environmental data (China Industrial Environmental Statistics Database, CIED), the survey data on Chinese manufacturing firms (Chinese Annual Survey of Industrial Firms, ASIF) and the customs data on trade transactions (China Customs Dataset, CCD).

The CIED dataset includes a variety of information such as firm identity, pollution emissions, and environmental protection facilities. The ASIF dataset provides extensive information on Chinese manufacturing firms with annual sales above 5 million RMB (around US$720,000), including firm employment, assets, ownership type (e.g., state-owned enterprise, foreign invested firm, or private firm), sales, R&D expenditure and industry. The CCD dataset provides detailed information on the universe of China's international trade transactions. Most importantly, the CCD dataset provides firm-level import information on industrial robots (multi-functional industrial robots, robot end control devices, and other industrial robots) under the two HS8-digit codes (84795010 and 84795090) as in Fan et al. (2021). Although the three datasets use different firm identifiers, all include extensive firm contact information (e.g., company name, telephone number, contact person, zip code) which allows us to generate firm-level observations that encompass the trade, environmental and operational activities of the Chinese firms.[7]

Two further datasets used in the paper are: 1) the IFR dataset, which provides the increment and stock of robots at the country-industry-year level, and 2) the tariff data from the WTO which provides information on China's import tariffs. We construct firm-level instrumental variables based on robot stocks in the United States and the import tariffs on industrial robots to deal with the endogeneity problem associated with firm adoption of robots. We also match the IFR data with the firm-level trade, environmental and operational activities of the Chinese firms via the concordance table

[7] The data construction process is as follows. We first clean the ASIF and the CIED dataset following Brandt et al. (2012), and then match the two datasets based on the common identity information, such as firm name, firm id, legal person, zip code, address and phone number. We do the similar matching for the ASIF and the CCD datasets. Finally, we match the three datasets together.

between China's National Industry Classification Standard (CIC) and the International Standard Industrial Classification Standard (ISIC) provided by Brandt et al. (2012).[8]

Due to data availability, our sample runs from 2000 to 2009. Following Yu (2015), we drop observations that do not comply with accounting standards, including that: (1) owner's equity is greater than total assets; (2) fixed assets are greater than total assets; (3) net fixed assets are greater than total assets; (4) any variables such as fixed assets, intangible assets, total assets, and sales are negative; (5) the number of employees is less than eight. We also drop companies that do not comply with accounting standards.

3.2 Variable Construction

3.2.1 Green Investment, Pollution Intensity, and Robot Adoption

We measure a firm’s green investment with the amount of the exhaust gas treatment facilities, which are devices for reducing harmful exhaust emissions from production. We measure pollution emission with SO2 emissions as they were one of the most important pollutants during the sample period (Vennemo et al., 2009). These SO2 emissions are also examined in Shi and Xu (2018), and Chen et al.(2018). We measure the pollution intensity with the ratio of the SO2 emissions to a firm’s output.

To measure firm-level adoption of industrial robots, we use the data of imported robots in the CCD dataset.[9] In the empirical analysis below, we consider two measures of robot adoption, the robot stock value (Rob_{jt}) which is constructed as the cumulative imported robot value from the beginning of the sample period to the current year, and the robot stock dummy (D_Rob_{jt}) in year t.

3.2.2 Instrumental Variables

It is highly possible that, large and profitable firms are more capable of using robots to produce large amount of production, create more pollution, and invest more on green

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[8] The official documents of IFR (such as "WR_Industrial_Robots_2020_Chapter_1") shows that the IFR dataset basically divides the industry according to the ISIC code.

[9] Though the IFR dataset is a widely used source of robot data (see Acemoglu and Restrepo, 2020), the industry-level data in the IFR is not useful to capture the firm-level heterogeneity of robot adoption. Firm-level robot data is preferred in order to explore the micro-influences of robot adoption (Seamans and Raj, 2018).

facilities. In order to deal with such endogeneity problem, we use the instrumental variable approach.

We first follow Acemoglu and Restrepo (2020) to construct the instrumental variable of firm-level robot adoption using the industrial robot stock value in the United States provided by the IFR dataset, as in Eq. (22):

$$IVforRob_{jcht} = \ln\left(L.noRobcap_{jht} * forRob_{usht} + 1\right) \tag{22}$$

where $L.noRobcap_{jht}$ is the lagged import value of non-robot capital goods of Chinese firm j in industry h in year t, and $forRob_{usht}$ is the industry-level total stock value of robots in the U.S.. According to Acemoglu and Restrepo (2020), there are similar characteristics of industry evolution across countries, and hence the development of robot application in China may be similar to that in the United States at the industry level. However, the industry-level data provided by the IFR may not capture the heterogeneity of robot adoptions across firms in the same industry, we thus multiply the industry-level of U.S. robot stock with the lagged import value of other capital goods of a firm. We use the non-robot capital import to measure the exposure of a firm to robot, because according to Koch et al. (2021), robots cannot be placed in a firm independently, but instead need to work with other capital goods, and firms that import more non-robot capital goods are more likely to import robots in subsequent years.

We also construct an alternative instrumental variable with China's import tariff on the industrial robots as in Eq. (23):

$$Ivtariff_{jht} = ln\left(L.noRobcap_{jht} * tariff_t + 1\right) \tag{23}$$

where $tariff_t$ is the robot import tariff of China in year t. Similar to Equation (22), to capture the firm-level heterogeneity in the same industry, the lagged import value of non-robot capital goods is taken into the calculation.[10]

Both instrumental variables are valid. First, it can be seen that the adoption of robots in other countries is relatively independent of the development of Chinese economy, and the import tariffs are often viewed as exogenous policy shocks. Second, it has also been argued that there is a positive correlation between the adoption of robots

[10] Note, the import tariff rate on the HS6-digit good (847950) was 14% from 2000 to 2001, reduced to 3.5% in 2002, and zero tariff since in 2003.

in other countries and in China, while the import tariffs on robots are negatively correlated with the use of robots since in our sample period China's robots mainly come from imports, which means that the reduction of tariffs will directly impact the cost of Chinese firms purchasing robots.

3.2.3 Control Variables

To identify the impact of robot adoption on pollution, we need to control factors that affect firms' robot adoption decisions and firm performance. Following Koch et al. (2021), we first select factors that affect a firm's decision on whether to adopt robots, using the regression model of Eq. (24), and then control for these relevant factors when examining the impact of automation on firm pollution and green investment:

$$D\_Rob_j = \Phi_1 F_{j,T0} + \delta_h + \varepsilon_{jhT0}. \tag{24}$$

In Eq. (24), if a firm j in industry h ever uses robots in , the indicator variable, D_Rob_j, would be given a value of 1, and 0 otherwise. F_{j,T_0} are the relevant factors in base year T_0 that affect a firm's decision on robot adoption, including: (1) firm size, given by the logarithm of firm total asset (denoted by *logtotasset*) (Bonfiglioli, 2020); (2) trade status, measured by the ratio of the sum of imports and exports to a firm's sales (denoted by *traderat*), and the logarithm of imports of other type of physical capital (denoted by *logcapnoR*) (Koch et al., 2021); (3) firm financial status, such as the leverage ratio measured by the ratio of total debt to total asset (denoted by *lever*) (Bas and Berthou, 2012), and the profitability measured by the return on equity (denoted by *ROA,* calculated as the pre-tax profit to firm owner's equity) and the total cost to total sales ratio (denoted by *cost_rat*) (Ding et al., 2018); (4) firm's labor intensity measured by the ratio of employment to total physical capital. δ_h captures the industry fixed effect. ε_{jhT0} is the residual term. The sample is winsorized at the level of 1% on both sides based on relevant variables including the cost-sales ratio, leverage ratio, and etc..

The regression results are shown in Table 2. In Column (1) the base year is 2000, and hence only firms that show up in 2000 are included in the regression. In Column (2) the base year is the year of the first observation of each firm, and hence all firms are included. It can be seen that, a firm that is large (more total asset and other types of physical capital), more involved in international trade (high trade involvement), highly relying on labor input (high labor-capital ratio), and better financial status (lower leverage and cost-sales ratios) will be more likely to adopt robots. This is because the adoption of robots would incur a substantial amount of fixed costs, and robots need to be imported abroad (especially before 2010). Henceforth, only those large, financially healthy and low cost-ratio firms are more likely to cover these extra costs and import them. Additionally, it has been argued that robots are substitutes of low-skilled labor, and hence firms with higher labor to capital ratios would be more likely to use them.

Table 2 Factors that drive a firm to adopt robots

	(1)	(2)
VARIABLES	Robot Adoptors	Robot Adoptors
Total Asset (log)	0.0016***	0.0013***
	(7.55)	(16.34)
Employment-Capital Ratio	0.0633***	0.0427***
	(4.41)	(8.37)
Debt-Asset Ratio	-0.0022***	-0.0012***
	(-3.10)	(-5.78)
ROA	0.0017***	0.0008***
	(3.72)	(6.60)
Cost-Sales Ratio	-0.0059***	-0.0003
	(-2.87)	(-0.47)
Trade-Sales Ratio	0.0000	-0.0000
	(1.23)	(-0.02)
Non-robot Capital Imports (log)	0.0036***	0.0034***
	(15.41)	(30.44)
Constant	-0.0099***	-0.0120***
	(-3.59)	(-10.97)
Observations	94,155	559,914
F	42.25	155.2

Note: (1) These regressions are cross-sectional. (2) The base year is defined differently in the two columns. Column (1) works with the data of year 2000, and hence only firms that show up in 2000 are included in the regression. Column (2) works with the data of the first observation of each firm, and hence all firms are included. (3) Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

3.2.4 Summary Statistics

Table 3 reports the summary statistics of variables. Both pollution variables and robot adoptions have a wide variation across firms. This suggests that firms' capacity and willingness to use robots and create pollution emissions are heterogeneous. Thus firm-level study on the environmental impacts of industrial robots is highly demanded.

Table 3 Summary Statistics

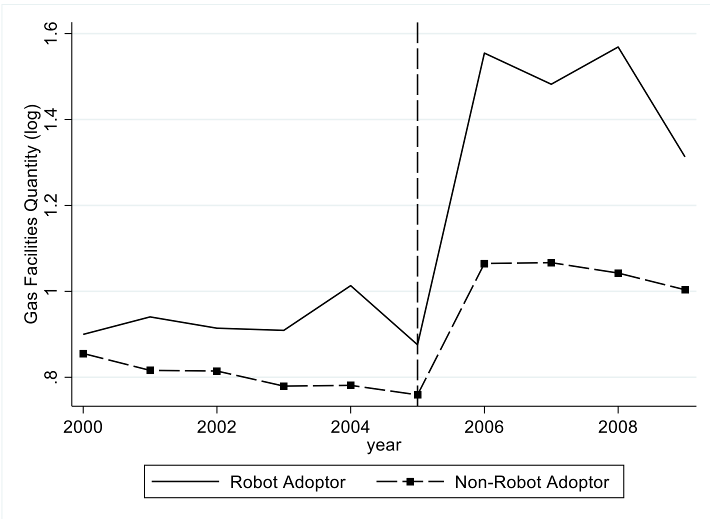
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	N	mean	sd	min	max	p10	p50	p90
Pollution Variables								
Gas Facilities (log)	83,926	0.786	0.693	0	6.235	6.235	6.235	6.235
Coal Consumption (log)	79,195	5.706	3.502	0	16.29	16.29	16.29	16.29
SO2 Emissions (log)	87,859	2.447	1.844	0	11.49	11.49	11.49	11.49
SO2 Emission Intensity	87,801	0.00362	0.207	0	55.57	55.57	55.57	55.57
Robot Adoption								
Robot Adoptors (Cum)	620,520	0.00204	0.0422	0	1	1	1	1
Robot Adoption Value (Cum, log)	620,520	0.0232	0.487	0	17.01	17.01	17.01	17.01
Firm Controls								
Total Asset (log)	620,520	9.480	1.306	4.710	18.33	18.33	18.33	18.33
Debt-Asset Ratio	612,683	0.555	0.249	0.0122	1.238	1.238	1.238	1.238
ROA	615,255	0.224	0.332	-0.832	2.628	2.628	2.628	2.628
Cost-Sales Ratio	614,038	0.853	0.0947	0.424	1.042	1.042	1.042	1.042
Employment-Capital Ratio	613,162	0.0104	0.00979	0.000446	0.0636	0.0636	0.0636	0.0636
Non-robot Capital Imports (log)	620,520	0.580	2.284	0	21.34	21.34	21.34	21.34
Trade-Sales Ratio	618,009	9.910	29.51	0	190.7	190.7	190.7	190.7
Industry Controls								
Industry Output Tariff	595,625	11.12	6.458	0	63	63	63	63
Industry Input Tariff	595,627	8.563	3.332	2.323	35.82	35.82	35.82	35.82
Industry Concentration Level, HHI	620,520	0.0161	0.0262	0.000791	0.905	0.905	0.905	0.905
Industry Trade-Output Ratio	620,520	21.29	19.77	0	197.9	197.9	197.9	197.9
Instrumental Variables								
IV Tariff	456,648	0.0873	0.714	0	19.69	19.69	19.69	19.69
IV U.S.	456,648	0.712	3.217	0	30.75	30.75	30.75	30.75

3.3 Simple Stylized Facts

Before we report our regression results, we first show some raw performance differences of robot adopters and non-adoptors. To provide some causal implications, we divide the sample into two equal periods, 2001 to 2005, and 2005 to 2009, and examine how robot adoptors, if they adopt robots before year 2005, would be different compared to non-robot adoptors, those that never imported robots during 2000-2009. We then calculate the average performance of each group of firms in each year.

The results in Figure 2 show that robot adoptors on average have more exhaust gas treatment facilities than non-robot adoptors. This difference is particularly large after year 2005. As robot adoptors import robots in the period of 2000-2005, this enlarged difference in exhaust gas treatment facilities suggests a potential role of robot adoption.

Figure 2 Differences between Robot Adoptors and Non-robot Adoptors



We then present the kernel distributions of robot and non-robot adoptors in 2005 and 2009 respectively, for the exhaust gas facilities investment (Figure 3). The left column reports the kernel distributions for the non-robot adoptors, and the right column for the robot adoptors. Clearly, there is a rightward shift of the kernel densities for the robot adoptors, indicating that the robot adoptors invest more on exhaust gas treatment facilities from 2005 to 2009. However, the pattern is less obvious for the non-robot adoptors.

Figure 3 Kernel Density of Gas Facilities Quantity for Robot Adoptors and Non-robot Adoptors (2005 v.s. 2009)

Fig. 3a Non-Robot Adoptors

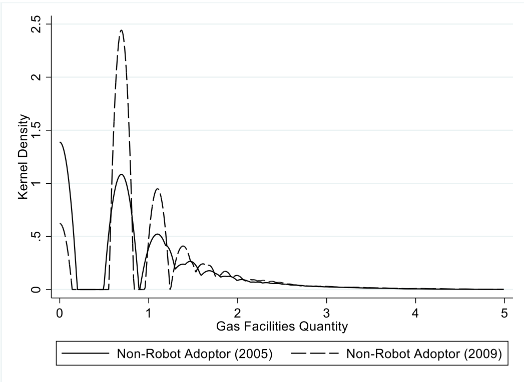
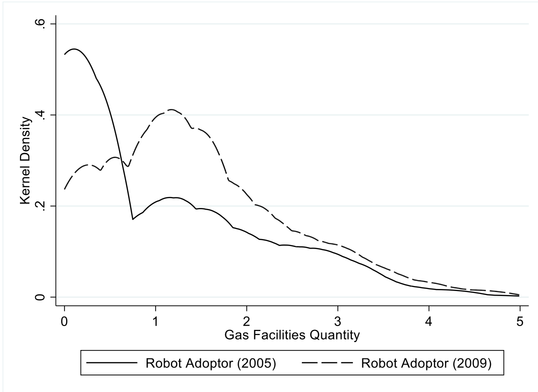


Fig. 3b Robot Adoptors



4. Empirical Results

4.1 Automation Firms Invest More on Green Facilities

4.1.1 Empirical Framework

The model predicts that, holding all else constant, a rising fraction of tasks capable of automation will encourage a firm to invest more on pollution treatment facilities. We test this hypothesis with the following regression,

$$PTFacilities_{jht} = \beta_1 Rob_{jht} + \Gamma\Phi_{jh(t-1)} + \Gamma_h \Psi_{ht} + \delta_j + \delta_t + \varepsilon_{jht} \qquad (25)$$

where $PTFacilities_{jht}$ is the logarithm of the quantity of the exhaust gas treatment facilities of firm *j* in industry *h* in year *t* (log_gas_facilities_qty). Rob_{jht} is the firm's adoption of robots, measured by the stock of robots that indicates a firm's holding of robots (logcumRob), or a dummy that indicates whether a firm adopts robots (dumRocum). We expect a firm that increases robot holdings or adopts robots would spend more on exhaust gas treatment facilities on average, hence $\beta_1 > 0$. $\Phi_{jh(t-1)}$ are the lagged firm-level controls selected from Table 2, whose effects on green investment are captured by the coefficients Γ. Ψ_{ht} are the industry-level controls, including the tariff on the industry output (denoted by *outputtariff*) to capture the competition effect from the rest of the world on domestic industry, the tariff on the industry input (denoted by *inputtariff*) to capture the imported input effect, the industry concentration level (denoted by *hhi_sales*) to capture the overall competition effect in the industry, and the industry exposure to the world market (denoted by *indutraderat*) to capture the involvement into the world market. δ_j controls the firm features that affect firms' green investment decision but do not vary over time, and δ_t controls the business cycle factors or country-level environmental polies that are time varying but common to all firms.

4.1.2 Fixed Effect Estimation Results

Table 4 reports the baseline results of firm robot adoption on their investment in exhaust gas treatment facilities. A firm's usage of robots is measured with the stock of robots in Columns (1)-(3), and a dummy indicating whether or not to adopt robots in Columns (4)-(6). Firm-level controls are added in Columns (2) and (5), and additional industry-level controls are added in Columns (3) and (6). All columns control firm and year fixed effects.

As expected, a firm that adopts robots would invest more on exhaust gas treatment facilities. The estimated coefficients in all columns are positive and significant at 1% significance level. According to Columns (1) – (3), on average when a firm raises its stock of industrial robots by 10%, its holdings of exhaust gas treatment facilities will rise, ranging from 0.121% to 0.137%. For those firms ever choosing to deploy robots as shown in Columns (4) – (6), their investment in exhaust gas treatment facilities is higher by 1.232% to 1.446%, than those firms never adopting robots. Additionally, a firm will invest more on exhaust gas treatment facilities, when the firm has larger size (total asset), better performance (ROA), higher exposure to labor (employment to capital ratio), or from an industry that faces higher input tariff.

4.1.3 IV Estimation Results

As stated earlier, there is a concern of the endogeneity of robot adoption in the fixed effect estimations. Both omitted variables and reverse causality may exist, causing estimates on robot usage to be biased. Although we include selected control variables and firm fixed effects to alleviate such concern in the baseline estimations, there may still be other unobservable but time-varying factors that simultaneously affect firms' adoption of industrial robots, green investment decisions and the pollution consequences.

Table 4 Gas Treatment Facilities (Fixed Effect Estimations)

VARIABLES	(1) Gas Facilities (log)	(2) Gas Facilities (log)	(3) Gas Facilities (log)	(4) Gas Facilities (log)	(5) Gas Facilities (log)	(6) Gas Facilities (log)
Robot Adoption Value (Cum, log)	0.0116***	0.0121**	0.0122**			
	(2.85)	(2.50)	(2.51)			
Robot Adoption Dummy (Cum)				0.1173**	0.1267**	0.1271**
				(2.52)	(2.31)	(2.32)
logtotasset_tm1		0.1135***	0.1136***		0.1136***	0.1137***
		(25.26)	(25.31)		(25.28)	(25.33)
logem_rat_tm1		0.0572***	0.0576***		0.0573***	0.0577***
		(15.33)	(15.44)		(15.34)	(15.46)
lever_tm1		-0.0028	-0.0022		-0.0028	-0.0022
		(-0.37)	(-0.29)		(-0.36)	(-0.28)
ROA_tm1		0.0039	0.0037		0.0039	0.0037
		(1.58)	(1.50)		(1.58)	(1.50)
logcamnoR_tm1		-0.0001	-0.0002		-0.0001	-0.0002
		(-0.27)	(-0.38)		(-0.25)	(-0.36)
Industry Output Tariff			0.0006			0.0006
			(1.01)			(1.00)
Industry Trade-Output Ratio			-0.0001			-0.0001
			(-0.47)			(-0.46)
Industry Input Tariff			0.0053***			0.0053***
			(3.87)			(3.87)
Industry Concentration Level, HHI			-0.0702			-0.0707
			(-1.08)			(-1.09)
Constant	0.9122***	0.0086	-0.0412	0.9124***	0.0080	-0.0418
	(1,121.12)	(0.22)	(-1.00)	(1,126.26)	(0.20)	(-1.02)
Observations	238,375	182,245	182,245	238,375	182,245	182,245
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
F	8.105	108.4	68.48	6.335	108.3	68.43

Note: (1) Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

In this section, we introduce instrumental variables to deal with such endogeneity. The first-stage model is constructed as follows,

$$Rob_{jht} = \beta_1 IV_{jht} + \Gamma_1 \Phi_{jh(t-1)} + \Gamma_{1h}\Phi_{ht} + \delta_\mathrm{j} + \delta_\mathrm{t} + \mu_\mathrm{jht} \tag{26}$$

where IV_{jht} are measured with two variables, the one built on robot tariffs (IVtariff) and the one on robot adoption in the same industry in the U.S. (IVus). The control variables are the same as in the baseline regressions, including firm-level, industry-level controls, firm and year fixed effects.

Table 5 and the following tables will only present the IV estimation results. Given that our IVs are constructed based on continuous variables which are not suitable for the robot dummy variable, we report the results for the stock of industrial robots only. The results based on the Tariff IV are reported in Table 5 Panel A Columns (1)-(3), and the results based on the US IV are reported in Table 5 Panel A Columns (4)-(6).

The estimates are ten times bigger than those in Table 4 Columns (1)-(3), ranging from 1.435% to 1.565% in the case of tariff IV, and 1.336% to 1.424% in the case of US IV, when a firm increases its robot stock by 10%. Again, all estimated coefficients are positive and significant at the 1% significance level. The results suggest that, after correcting the downward bias in the fixed effect estimations, a firm's holding of exhaust gas treatment facilities will rise significantly when the firm raises its stock holding of industrial robots, a finding that is consistent with the theoretical prediction.

Table 5 Panel B presents the first-stage estimation results, where the control variables are the same as in the fixed effect regressions. As expected, rising import tariff on industrial robots will significantly reduce firms' usage of robots as shown in columns (1) to (3), suggesting that the reduction of robot import tariff will promote the usage of industrial robots. The estimated coefficients in columns (4) to (6) are significantly positive, indicating that there is a positive relationship between U.S. robot adoption and the Chinese robot adoption. As the first stage results are similar for all the regressions below, we will not report them anymore.

The IV-related statistics in Panel B reject the null hypothesis of weak instrumental variables (Kleibergen-Paap rk Wald F statistic) and under-identification (Kleibergen-Paap rk LM statistic and the P-value of KP statistic), suggesting the validity of these instrumental variables.

Table 5 Exhaust Gas Treatment Facilities (IV Estimations)

	(1)	(2)	(3)	(4)	(5)	(6)
		IV Tariff			**IV US**	
VARIABLES	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)
Panel A: Second-stage Estimation Results						
Robot Adoption Value (Cum, log)	0.1487***	0.1223***	0.1340***	0.1421***	0.1282***	0.1357***
	(3.44)	(3.23)	(3.48)	(4.35)	(3.73)	(3.90)
Observations	193,999	182,245	182,245	193,999	182,245	182,245
R-squared	-0.015	-0.004	-0.006	-0.014	-0.005	-0.006
Firm Controls	NO	YES	YES	NO	YES	YES
Industry Controls	NO	NO	YES	NO	NO	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
N	193999	182245	182245	193999	182245	182245
F	11.84	106.6	67.34	18.92	106.7	67.43
	.	.	.	.	.	.
Panel B: First-stage Estimation Results						
	logcumRob	logcumRob	logcumRob	logcumRob	logcumRob	logcumRob
IVtariff	-0.017***	-0.020***	-0.020***			
	(-9.52)	(-10.29)	(-10.23)			
IVus				0.014***	0.015***	0.015***
				(11.56)	(10.93)	(10.92)
weakKP_stat	90.556	104.441	103.319	133.741	117.846	117.445
UnderKP	118.683	136.408	135.044	174.415	154.345	153.917
UnderKP_p	0.000	0.000	0.000	0.000	0.000	0.000

Note: (1) Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.1.4 Robustness

This section will consider a series of robustness checks, such as whether the application of domestic robots and the environmental regulation changes in 2006 may invalidate the findings in the baseline regressions.

(1) Domestic Robots

In the baseline regressions, we measure a firm's usage of industrial robots with its imports of robots. However, with the development of China's robot industry, the application of domestic robots is gradually expanded. Although Chinese domestically produced robots are mainly made after the year 2010, we want our findings to be clean enough. According to Fan et al. (2021) and the annual report of IFR (2014), robots made in China are mainly used in plastic, rubber, electronics, and other manufacturing industries, we hence exclude the observations in these industries to ensure that the results are not violated by the presence of domestically produced robots.[11] The results are shown in Table 6 Columns (1)-(2). All estimates are positive and significant, as in the baseline regressions.

(2) Before Year 2007

In August 2006, China's central government issued a much stricter environmental regulation, *the 11th Five-Year Plan for the Control of Total Emissions of Major Pollutants in China*, to meet the environmental targets of the 11th Five-Year Plan. The central government specified exact emission reduction targets for local governments, and linked government officials' promotion to the implementation of pollution reductions. The stricter environmental policies of the 11th Five-Year Plan reduced the country's overall SO2 emissions substantially by about 14% from 25.5 million tons in 2005 to 21.9 million tons in 2010,[12] which may be consequences of the increased investment in pollution treatment facilities.

Associated with the stricter environmental policies is the rapid economic growth, which creates a potential for the quick increase in firms' robot adoptions. To ensure our findings are not driven by the stricter environmental policies, we investigate the period before 2007. The results are shown in Table 6 Columns (3)-(4). All estimates are again positive and significant, consistent with the baseline results.

(3) Alternative IVs

In the baseline regressions, we construct US IV based on the robot adoption in the same industry in the U.S.. Here, we use the industry-level robot adoption data in five European countries to construct another instrumental variable, the IVEUR5.

[11] Domestically produced robots are mainly used in industries with CIC codes and names of: 29-Rubber products industry; 30-Plastic products industry; 366-Manufacturing of special equipment for electronic and electrical machinery; 391-Manufacturing of electrical machinery; 404-Manufacturing of electronic computers; 405-Manufacturing of electronic devices; 406-Manufacturing of electronic components; 409-Manufacturing of other electronic equipment.

[12] https://www.ndrc.gov.cn/fggz/fzzlgh/gjjzxgh/200806/P020191104623848907871.pdf.

Considering that as a developing country, China's industry development may be even closer to that of other emerging developing countries, we also construct an instrumental variable, the IVgold, based on the industry robot adoption in the BRICs countries. Considering the geographical and cultural similarities, we also construct an instrumental variable, the IVAsia4, based on the industry adoption of robots in developed Asian regions adjacent to China. [13] All these IVs are firm-level, computed using Eq. (25). Table 6 Columns (5)-(7) report the results. All estimates of robot adoptions are positive and significant, consistent with the baseline results, except for the IV of IVEUR5 whose estimate is positive, though insignificant.

Table 6. Robustness Checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	IVtariff Excluding Domestic Robots	**IVus** Excluding Domestic Robots	**IVtariff** Pre-2007	**IVus** Pre-2007	**IVEUR5** IVEUR5	**IVAsia4** IVAsia4	**IVgold** IVgold	**IVtariff** Expanded Robots	**IVus** Expanded Robots
VARIABLES	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)	Gas Facilities (log)
Robot Adoption Value (Cum, log)	0.0946**	0.1148***	0.0871**	0.0704**	0.4250	0.1105***	0.0776***	0.1269***	0.1130***
	(2.30)	(2.98)	(2.18)	(2.04)	(1.35)	(3.21)	(2.66)	(2.93)	(3.12)
Observations	175,300	175,300	122,988	122,988	182,245	182,245	182,245	171,812	171,812
R-squared	0.002	-0.001	-0.001	0.001	-0.147	-0.001	0.004	-0.004	-0.002
Firm Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
F	65.75	65.75	33.27	33.31	54.79	67.66	67.93	64.75	65.05

Note: (1) Robust t-statistics in parentheses.*** p<0.01, ** p<0.05, * p<0.1

[13] The Asian regions includes: South Korea; Singapore; Taiwan, China; Hong Kong, China. The BRICS countries include: Brazil, South Africa, India, Russia. The European countries include: Germany, France, Portugal, Poland, Switzerland.

(4) Expanded Measures of Robots

In the baseline regressions, we measure robots with two HS8 products following Fan et al. (2021) and Acemoglu and Restrepo (2018). However, some papers also measure robot usage with an expanded measure which includes seven HS6 codes (Song et al., 2023). Table 6 Columns (8)-(9) report the results for this expanded robot measure.[14] Again, all estimates are positive and significant, consistent with the baseline results.

Table 7 Productivity Heterogeneity Effect on Exhaust Gas Treatment Facilities (IV Estimations)

VARIABLES	(1) high_iv3 Gas Facilities (log)	(2) high_iv6 Gas Facilities (log)	(3) low_iv3 Gas Facilities (log)	(4) low_iv6 Gas Facilities (log)
Robot Adoption Value (Cum, log)	0.1144***	0.0912***	0.0801	0.7877
	(2.86)	(2.63)	(0.13)	(0.87)
Observations	91,637	91,637	70,339	70,339
R-squared	-0.008	-0.002	0.004	-0.059
Firm Controls	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES
Year FE	YES	YES	YES	YES
F	31.28	31.39	15.12	14.73

Note: (1) Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

4.1.5 Productivity Heterogeneity

The theoretical model predicts that, the stimulating effect of robot adoption on firm green investment is stronger for firms with larger productivity than their peers with lower productivity. To examine such heterogeneity productivity effect, we divide firms into two groups, the high-productivity firms whose TFPs are greater than the median

[14] The two original HS8 codes are 84795010 and 84795090, which include three types of robots, the multi-functional industrial robots, the robot terminal manipulation devices, and other industrial robots. In the expanded exercises, we include seven HS6 codes, which are 851531 (arc including plasma arc welding robots), 847950 (multi-purpose robots, other multi-purpose robots and robot-end manipulator), 851521 (other electric resistance welding robots, automobile production line resistance welding robots), 851580 (other laser welding robots, automobile production line laser welding robots), 842489 (spraying robots), 842890 (handling robots), and 848640 (IC factory dedicated automatic handling robots).

of the industry where the firms are from, and the low-productivity firms whose TFPs are lower than the industry median. We compute a firm's TFP with the Levinsohn-Petrin TFP estimation (Levinsohn and Petrin, 2003).

Table 7 presents the IV estimation results. Columns (1)-(2) are for firms in the high-productivity group, where rising usage of industrial robots significantly increases their investment of gas treatment facilities, which is consistent with the theoretical prediction. Columns (3)-(4) are for the low-productivity group, where rising usage of robot does not have significant effect on the firms' green investment, but the coefficients are positive.

4.1.6 Whether to Invest Green (IV Estimations)

We next examine whether firms increasing industrial robot adoption are more willing to invest in gas treatment facilities. The dependent variable is now defined as a dummy variable, with 1 representing that the firm has a positive amount of exhaust gas treatment facilities, and 0 representing that the firm has no gas treatment facilities.

Table 8 Effect of Robots on the Probability of Investing Green (IV Estimations)

VARIABLES	(1) **FE** Probability of Investing Green	(2) **FE** Probability of Investing Green	(3) **FE** Probability of Investing Green	(4) **IVtariff** Probability of Investing Green	(5) **IVus** Probability of Investing Green
Robot Adoption Value (Cum, log)	0.0021***	0.0040***	0.0040***	0.0454***	0.0889***
	(3.30)	(4.62)	(4.62)	(4.66)	(9.26)
Constant	0.9666***	1.0731***	1.0651***		
	(9,018.26)	(279.30)	(252.29)		
Observations	1,972,658	1,404,835	1,404,828	1,404,828	1,404,828
R-squared	0.481	0.497	0.497	-0.005	-0.024
Firm Controls	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES
F	10.91	146.4	92.02	90.78	95.03

					.	.

Note: (1) Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 8 reports the results. Columns (1) –(3) are the fixed effect estimation results, and Columns (4)-(5) are the IV estimation results. All estimated coefficients are significant at 1% significance level, indicating that increased robot stock will significantly raise the probability a firm invests in exhaust gas treatment facilities. In particular, on average when a firm raises its stock of industrial robots by 10%, its probability of investing green will rise by 0.021% to 0.038%.

4.2 Automation Firms May Not Pollute More

The theoretical model predicts that, a rising fraction of tasks capable of automation may reduce the firm's pollution intensity. We examine this prediction in Table 9.

Table 9 The Impact of Robots Adoption on SO2 Emission Intensity

VARIABLES	(1) **IVtariff** SO2 Emission Intensity (log)	(2) **IVus** SO2 Emission Intensity (log)	(3) **IVtariff** SO2 Emission Intensity (log)	(4) **IVus** SO2 Emission Intensity (log)	(5) **IVtariff** SO2 Emission Intensity (log)	(6) **IVus** SO2 Emission Intensity (log)
Robot Adoption Value (Cum, log)	-0.5216***	-0.2930**	-0.3400**	-0.2703**	3.5265	2.7406
	(-3.35)	(-2.30)	(-2.18)	(-1.99)	(0.37)	(0.67)
Observations	169,618	169,618	80,583	80,583	70,364	70,364
R-squared	-0.017	-0.001	-0.012	-0.006	-0.109	-0.065
Firm Controls	YES	YES	YES	YES	YES	YES
Industry Controls	YES	YES	YES	YES	YES	YES
Firm FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Ajusted R2	-0.633	-0.633	-0.633	-0.633	-0.633	-0.633
N	169618	169618	80583	80583	70364	70364
F	52.13	52.64	13.29	13.36	16.17	16.34
r2_within	.	.	.	.	.	.

Note: (1) Robust t-statistics in parentheses. *** p<0.01, ** p<0.05, * p<0.1

We measure pollution intensity with the logarithm of the SO2 emission to firm output. As expected, a firm that adopts robots would have lower SO2 emission intensities. In the full sample reported in Columns (1)-(2), a 10% rise in robot stocks will reduce SO2 emission intensity from 3.277% to 5.054%. However, such pollution depressing effect only occurs in the full and the high-productivity samples. In particular, when a firm increases its robot stock by 10%, its SO2 emission intensity will reduce by 2.277% to 5.054% in the full sample, and 2.812% to 3.055% in the high-productivity firm sample. Instead, there is no significant change in the SO2 emission intensity in the low-productivity sample.

5. Conclusion

This paper explores the impact of industrial robot adoption on the green investment of manufacturing firms theoretically and empirically. A theoretical model featuring automation, pollution, and green investment predicts that, when the unit cost of industrial robots is lower than that of low-skilled workers, rising fraction of tasks capable of automation will reduce the marginal cost of production and increase the marginal benefit of green investment, thereby encouraging a firm's green investment. Such falling marginal cost and investment stimulating effect is stronger for high-productivity firms, suggesting a potential resource reallocation from low-productivity firms to high-productivity firms.

We empirically test the theoretical predictions with the firm-level trade, environmental and operation data of Chinese manufacturing firms for the years 2000 to 2009. We identify causal effects of robot adoptions on firm green investment and environmental performance. In particular, we find that firms that adopt robots invest more on green facilities, and do not necessarily create more pollution in the sense that they have lower SO2 emission intensity. We find high-productivity firms are more willing to invest more in green, suggesting resource reallocation from low-productivity firms to high-productivity firms.

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In school I took a project-oriented program named “INNO”. Within the program, we were asked to build on a project related to the environment and economy. We chose to investigate in the sand-mining and its impacts on the society. During the period we work on this project, I encountered some discussions on the relationship between economic growth and the cost of environment. These discussions led me to think about the most fast developing technologies concurrently, i.e. industrial robots and AIs, and their impacts on the ecosystem. Could it be true that the development of AIs and industrial robots are at the expense of the ecosystem?

With this question in mind, I contacted Professor Chen. He supported me to dig further into this question. As a first step, he offered me a paper list and suggested me to read through these papers and write a literature review. Then, Professor Chen provided me a dataset that has information of firm robotization, firm green investment and pollution data, and firm operation data. He directed and sometime taught me to explore my questions by working with the dataset. In particular, he taught me the idea of regression and instrumental variables, asked me to read a Stata book, and guided me to do fixed effect and instrumental variable estimations in Stata.

After I had preliminary results that robot adoption increases firms’ green investment and reduces firms’ pollution intensity, which Professor Chen viewed as interesting, he suggested me to develop a model to have a frame to think about the question. As I have very limited knowledge in economic modeling even though I have taken calculus related courses, Professor Chen patiently helped me build the theoretical framework but asked me to do all detailed derivations. With this theoretical framework, we realize that the encouraging effect of robot adoption on green investment comes from that robot usage magnifies the marginal benefit of investing green, allowing firms to reduce marginal production costs as tax burden on pollution falls, and hence gaining larger market sales.

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