HOW CHINA'S CARBON EMISSIONS TRADING REDUCES POLLUTION AND CARBON EMISSIONS: THE PERSPECTIVE OF INDUSTRIAL ROBOTS

QIANG, M.

School of Economics and Management, Zhejiang Sci-Tech University, No. 928, No. 2 Street, Qiantang District, Hangzhou City 310018, Zhejiang Province, China
(e-mail: qiangmmdyx@zstu.edu.cn; phone: +86-187-6812-7150)

(Received 15th Oct 2025; accepted 13th Jan 2026)

Abstract. This paper empirically examines a previously unexplored transmission channel of carbon emissions trading (CET) to reduce pollution and carbon emissions: the adoption of industrial robots. Using panel data from 267 cities in China, this paper finds that CET can effectively promote the application of industrial robots, which improves energy efficiency and thereby reduces pollution and carbon emissions. Additionally, it has a positive impact on the economy, fostering growth without harming employment. We further explore strategies to enhance the efficiency of this channel. We find that governmental support for robotics development enhances the effectiveness of CET in accelerating automated production. Industrial robots show greater efficiency in pollution control in areas characterized by strong economic conditions and highly skilled workforces. The value of this study is to provide a new pathway for promoting CET to realize the dual benefits of environmental sustainability and economic prosperity.
Keywords: *co-benefit, CO_2, industrial SO_2, new channel, automated production*

Introduction

The intertwined challenges of atmospheric contamination and greenhouse gas emissions have emerged as critical priorities requiring urgent attention. Because air and climate pollutants are generated similarly, many countries are developing effective environmental policies to manage both issues (Hu, 2023; Zhu et al., 2023). Carbon emissions trading (CET) is one of the most important environmental policies. As of 2024, 36 countries have established systems for CET.

Due to its unique status, the co-benefits of CET have attracted much attention. Although many scholars have criticized the imperfection of the carbon market system, empirical results still show that CET effectively reduces CO_2 emissions (Bai and Ru, 2024; Bayer and Aklin, 2020; Deng et al., 2018). The carbon reduction rate of CET in China and the European Union is approximately 8%-15% (Dechezleprêtre et al., 2023; Shao et al., 2023a). Moreover, CET positively impacts carbon reduction in industries such as the power sector (Cao et al., 2021). Beyond carbon mitigation, the potential ancillary pollution benefits of CET systems are also a focal point in academic circles (Gan et al., 2024). Scholars have verified the reduction effects on distinct pollutants, including industrial SO_2 (Zhang et al., 2024), $PM_{2.5}$ (Dong et al., 2022; Liu et al., 2021; Yang et al., 2022), wastewater, and solid waste (Chen et al., 2024). Some studies synthesize these pollutants into pollution indices for analysis (Min et al., 2022). Overall, empirical analysis indicates that CET has additional effects on pollution reduction.

Despite the apparent effect, a thorough analysis of the underlying mechanism remains incomplete. Regarding the transmission channel, previous studies mainly focused on green innovations and transitions in energy composition (Chen et al., 2024). However, none of these studies touched upon the role of industrial robot applications,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

leaving a significant gap in understanding how automation intersects with market-based environmental regulations.

Automation technology has become quite widespread in enterprise production, with the global number of installed industrial robots reaching 205,000 in 2023. The environmental impact of robots has received widespread attention. While industrial robots consume energy during operation (Zhang et al., 2022a), the prevailing academic view suggests they significantly enhance overall energy efficiency and environmental quality. The reason lies in their ability to shorten production time, promote the number of green jobs, and advance green technologies (Chen et al., 2022b; Liu, 2023). Moreover, industrial robots can enhance productivity and alleviate financing constraints, thereby increasing enterprises' funds for emission reduction (Xu et al., 2025). These findings underscore the environmental protection potential of industrial robots. However, existing literature primarily views robots as a technological factor, failing to examine whether environmental regulations, such as CET, effectively incentivize their adoption. To date, no study has integrated CET, the strategic application of industrial robots, and emission abatement within a unified framework.

This article aims to test a previously unexplored transmission channel of CET for reducing pollution and carbon emissions: the application of industrial robots. We posit that CET could encourage enterprises to install more industrial robots to cope with the pressure of environmental compliance. Industrial robots have the characteristics of automation and precise operation, and can enhance energy conservation and emissions reduction (Li et al., 2025).

On the basis of the empirical evaluation of Chinese cities, this article finds that this new channel is effective. CET has promoted robotic technology, which has reduced the quantity and concentration of CO_2 and air pollutants by lowering energy intensity. Furthermore, this article finds that this transmission channel has beneficial economic consequences, increasing output and not harming employment. We also reveal strategies to enhance the efficiency of this channel, finding that governmental support for robotics, strong regional economies, and abundant human capital enhance the environmental governance effect.

The contribution of this article lies in two aspects. First, we identify a previously unexplored channel for CET to mitigate various pollutants—industrial robotics implementation. Existing research mainly focuses on channels such as energy structure adjustment and technological progress. Our investigation centers on industrial robotics implementation. Identifying this new channel provides a new path for CET to achieve dual dividends in pollution reduction and economic growth. Second, this article further explores strategies to enhance the efficiency of the new channel. This article examines the key regulatory roles of industrial robot support policies, economic development levels, and human capital. The analysis is conducive to exerting the effect of this new channel.

Policy background and research hypotheses

Policy background

The Kyoto Protocol first proposed the concept of CET. The EU further matured and promoted the practice of CET. The Paris Agreement established a more complete international framework and policy support for the CET mechanism. Since 2017, many countries worldwide have accelerated the pace of carbon market construction.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

China's CET began in 2013, with pilot projects launched in Beijing, Shanghai, Guangzhou, Shenzhen, and Tianjin. As the operation mechanism gradually improved, Chongqing and Hubei joined the pilot program in 2014. Fujian launched its pilot program in 2016. China began implementing CET at the national level in 2021, covering over 1700 power generation enterprises, whose carbon emissions account for approximately 40% of the total carbon output. Transaction records indicate that 630 million metric tons of carbon allowances had been exchanged through this nationwide platform by 2024. This developmental trajectory renders China's experience particularly valuable for academic investigation.

Research hypotheses

CET assigns economic value to carbon emissions through market mechanisms. When enterprises surpass their allocated emission limits, they are compelled to acquire extra allowances through trading platforms, thereby elevating operational expenditures. On the contrary, enterprises can obtain economic benefits if they can control carbon emissions within the quota (Shi et al., 2022). This economic incentive and cost constraints prompt enterprises to actively explore methods to reduce carbon emissions.

Enterprises usually adopt three main ways to reduce emissions when responding to environmental regulations (Shao et al., 2023b). The first strategy is to control pollution generation at the source by reducing the production scale and adjusting the energy structure. The second approach is to reduce energy intensity through technological upgrading and management innovation. The third method involves implementing end-of-pipe treatment, which addresses CO_2 emissions using technological methods like carbon sequestration. Among these three emission reduction methods, pollution source control and production process optimization have demonstrated superior efficacy in reducing atmospheric pollutants and greenhouse gas emissions (Mao et al., 2014). Hence, we propose:

H1: CET has synergistic benefits of air pollution reduction and carbon mitigation.

The adoption of industrial robotics serves as a critical tool for streamlining manufacturing operations. Enterprises will inevitably seek more sustainable production methods to deal with the increasing production costs. Although production scale reduction and energy optimization offer emission mitigation alternatives, these strategies demonstrate limited economic viability. There is also considerable uncertainty about the effectiveness of green technological innovation (Roper and Tapinos, 2016). With the continuous maturation of industrial robot technology and the gradual reduction of costs, an increasing number of enterprises can afford and widely apply this technology (Dzedzickis et al., 2021). However, robots themselves are merely technical instruments; their adoption depends on the firm's strategic decisions. Under the CET system, enterprises face hard constraints on emission quotas. To minimize compliance costs or profit from selling surplus quotas, management is incentivized to optimize production processes. Consequently, the application of industrial robots becomes a vital strategic choice for enterprises to improve energy efficiency and save carbon quotas. Therefore, under the pressure of CET, enterprises accelerate robotic integration to gain a competitive edge in the carbon market.

Moreover, industrial robots have the potential to improve environmental quality (Han et al., 2024). Industrial robots perform repetitive physical tasks, such as welding and handling, as well as high-precision activities, such as precise assembly and quality inspection. On the one hand, industrial robots possess strong stability and accuracy,

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

which can reduce mismatches in the production process and shorten production time, thereby reducing energy consumption (Chen et al., 2022b; Liu, 2023). On the other hand, industrial robots can increase productivity, which helps alleviate financial constraints and enables enterprises to invest more in emissions reduction funds and green technology (Xu et al., 2025). Collectively, these effects lower energy intensity, thereby achieving the dual goals of reducing pollution and carbon emissions. Therefore, this paper proposes:

H2: Promoting the application of industrial robots is an important mechanism for CET to reduce pollution and carbon emissions.

Several additional factors could influence the operational efficiency of this mechanism. The relationship between CET and industrial robot adoption might be strongly associated with governmental policy backing for automation technologies. Despite marginal cost reductions, substantial capital investments remain necessary for deploying industrial robotics. The government's policy support for industrial robots can effectively reduce the cost for enterprises to adopt industrial robot technology and enhance their willingness to apply it. Therefore, the government's support for industrial robots motivates enterprises to implement these advanced systems.

In addition, the impact of industrial robots on emission reduction will also be affected by the economic level and human capital. In economically developed regions, industrial robots have more application scenarios and better operating conditions, thus more effectively penetrating the production process and having a more obvious effect on improving energy efficiency. Furthermore, human capital is also crucial in this process (Luo and Qiao, 2024). Industrial robots' efficiency and stability require the operation and maintenance of professional talent. Enterprises with highly skilled workforces can have a deeper understanding and application of industrial robot technology, quickly solve various problems that arise during the operation of robots, and ensure the stable operation of robots. Therefore, we propose:

H3: The support policies for industrial robots positively regulate the impact of CET on their application.

H4: Economic development levels and human capital positively moderate industrial robot applications' air pollution reduction and carbon mitigation effects.

Methods

Econometric models

The study employs a set of econometric models to examine the four hypotheses outlined in this research. First, we apply a multi-period difference-in-differences (DID) to assess Hypothesis 1:

$$lny_{it} = \alpha_0 + \alpha_1 DID_{it} + \boldsymbol{X'_{it}}\alpha + \mu_i + \nu_t + \varepsilon_{it} \quad \text{(Eq.1)}$$

where ln represents the logarithmic transformation. y_{it} serves as the outcome variable, capturing emission levels of pollutants in the city i in the year t. It is important to note that although the primary goal of the CET is to reduce carbon dioxide emissions, governments are increasingly recognizing the synergistic benefits that environmental policies can bring in addressing both local pollution and global climate change. Therefore, whether the CET can also achieve additional pollution reduction effects has

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

attracted widespread attention. Verifying the impact on air pollutants highlights the added value of promoting industrial robots under the CET framework and demonstrates its contribution to achieving the dual benefits of environmental sustainability and economic prosperity. For climate pollutants, this paper selects CO_2 emissions ($lnco2_{it}$); for air pollutants, this paper focuses on industrial SO_2 emissions ($lnso2_{it}$). This choice is because CET mainly targets the industrial sector, and industrial SO_2 is highly representative. In addition, we also consider industrial dust emissions ($lndust_{it}$) and $PM_{2.5}$ concentrations ($lnpm2.5_{it}$) as alternative variables for robustness checks. The independent variable is the dummy variable DID_{it}. If the city i implemented CET in year t, its value is 1; otherwise, it is 0. μ_i and ν_t represent city-fixed effects and year-fixed effects, respectively. ε_{it} is the noise.

The vector X_{it} encompasses control variables influencing emission levels. Existing research demonstrates that economic and social indicators significantly impact pollution discharge (Chen et al., 2022a). They include GDP per capita ($lnpgdp_{it}$), demographic scale ($lnpop_{it}$), industrial composition ($struc\_sec_{it}$), international investment (fdi), consumer market volume ($lnrsv_{it}$), joblessness rate ($unem_{it}$), and financial development ($finance_{it}$). In the pollution control process in China, the government plays a crucial role, so we also controlled for the two variables of government intervention (gov_{it}) and emission reduction targets (ert_{it}).

To ensure the reliability, we also employ several robust econometric methodologies. First, we use an event study model to verify the parallel trend assumption. The investigation designated 2006 as the baseline reference period. The model is specified as follows:

$$lny_{it} = \alpha + \sum_{k=1}^{6} \beta_{pre\_k} pre\_k + \sum_{j=0}^{9} \beta_{post\_j} post\_j + \gamma X_{it} + \mu_i + \nu_t + \varepsilon_{it} \qquad \text{(Eq.2)}$$

where the dummy variable pre_k equals one in the *k*th year before the city i implements CET; and $post\_j$ equals one in the *j*th year after the city i implements CET. In other cases, all three variables are equal to zero. If the coefficients β_{pre_k} are statistically insignificant, it indicates that the parallel trend assumption holds.

Second, we conduct a placebo test to ensure that the observed emissions reduction effects are indeed caused by the CET policy rather than unobserved random factors. By randomly assigning pseudo-treatment status to cities and repeating the estimation 500 times, we construct a distribution of "pseudo-policy effects" to rule out the interference of unobserved variables and confirm the robustness of the primary results.

Third, considering the staggered timing of CET implementation across different regions, we apply the Goodman-Bacon decomposition to examine the potential influence of "bad control groups". This method assesses whether the overall DID estimator is biased by inappropriate comparisons between early-treated and late-treated units, ensuring the internal validity of our multi-period DID estimation.

Next, we established models (3) and (4) to verify Hypothesis 2, which posits that using industrial robots is a key channel for achieving co-benefits in CET:

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

$$robot_{it} = \beta_0 + \beta_1 DID_{it} + \boldsymbol{X'_{it}}\beta + \mu_i + \nu_t + \varepsilon_{it} \quad \text{(Eq.3)}$$

$$lny_{it} = \delta_0 + \delta_1 robot_{it} + \boldsymbol{X'_{it}}\delta + \mu_i + \nu_t + \varepsilon_{it} \quad \text{(Eq.4)}$$

where $robot_{it}$ refers to the industrial robot application. Drawing on the methodology outlined by Acemoglu and Restrepo (2020), we employ the density of installed industrial robots as a proxy variable. It refers to the number of industrial robot installations per unit of labor. The calculation for urban robotic installation density follows a Shift-Share (Bartik) approach (with 2002 serving as the base year):

$$robot_{it} = \sum_j \frac{labor_{i,j,t=2002}}{labor_{i,t=2002}} \times \frac{robot_{jt}}{labor_{j,t=2002}} \quad \text{(Eq.5)}$$

Here $labor_{i,j,t=2002}$ is the number of employees in industry j in city i in 2002; $labor_{i,t=2002}$ is the total number of employees in city i in 2002; and $labor_{j,t=2002}$ is the number of employees in industry j in 2002. $robot_{jt}$ is installation volume of industrial robots in industry j in year t. Since the IFR provides robot installation data only at the industry level, not at the city level, this formula allows us to disaggregate industry trends to the city level, using each city's initial industrial employment structure as a weight. If both coefficients β_1 and δ_1 are significantly negative, then Hypothesis 2 is validated.

Finally, we use three interaction term models to test Hypotheses 3 and 4:

$$robot_{it} = \phi_0 + \phi_1 DID_{it} + \phi_2 DID_{it} \times robot\_policy_{it} + \boldsymbol{X'_{it}}\phi + \mu_i + \nu_t + \varepsilon_{it} \quad \text{(Eq.6)}$$

$$lny_{it} = \varphi_0 + \varphi_1 robot_{it} + \varphi_2 robot_{it} \times lnpgdp_{it} + \boldsymbol{X'_{it}}\varphi + \mu_i + \nu_t + \varepsilon_{it} \quad \text{(Eq.7)}$$

$$lny_{it} = \gamma_0 + \gamma_1 robot_{it} + \gamma_2 robot_{it} \times lnhc_{it} + \boldsymbol{X'_{it}}\gamma + \mu_i + \nu_t + \varepsilon_{it} \quad \text{(Eq.8)}$$

where $robot\_policy_{it}$ is the industrial robot policy support intensity. The number of regulations is an important measure of government support. The more policies there are, the more the government emphasizes robotic technology. Therefore, we mainly collect the regulation documents related to industrial robots and use the cumulative quantity to represent the government's support intensity. We assume that a provincial-level policy will also apply to the city. From model (5), the coefficients of ϕ_1 and ϕ_2 collectively determine the enhancement impact of CET on industrial robotics advancement. Stronger governmental prioritization of robotic development correlates with improved CET-driven promotion effectiveness.

Additionally, *lnpgdp* and *lnhc* represent urban economic development and human capital, respectively. Regarding measuring human capital, the literature presents different perspectives, such as expenditure and income (Abraham and Mallatt, 2022). This study adopts an expenditure-based approach through per-capita education funding analysis. Elevated educational spending reflects greater investments in human capital

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

development. Similarly, models (7) and (8) indicate that regional economic advancement and workforce competencies will moderate the effectiveness of industrial robot environmental governance.

Finally, during the auxiliary analysis, we also incorporated three indicators related to the level of urban economic development ($lngdp$), employment ($lnem$), and energy consumption intensity ($lnei$). Given the unavailability of comprehensive municipal-level energy consumption figures, electrical power usage serves as our substitute indicator. The energy intensity is calculated as the proportion of electrical energy consumed relative to regional GDP.

Data

The empirical analysis utilizes panel data from 267 cities in China covering the period from 2006 to 2022. The CO_2 emissions data comes from the Emissions Database for Global Atmospheric Research (EDGAR). The industrial robot data are sourced from the International Federation of Robotics. Employment data by industry for 2002 are taken from the China Labor Statistical Yearbook. The Atmospheric Composition Analysis Group provides $PM_{2.5}$ concentration data. Industrial robot policy documents are collected from the Peking University Legal Database. Other data are sourced from the China City Statistical Yearbook. *Table 1* provides the definition and description of variables.

Table 1. *The definition and description of variables*

Variable	Definition	N	Mean
lnco2	Log of CO_2 emissions	4539	3.106
lnso2	Log of industrial SO_2 emissions	4527	10.104
lndust	Log of industrial dust emissions	3556	9.712
lnpm2.5	Log of $PM_{2.5}$ concentration	4539	3.631
lnpgdp	Log of per capita GDP	4001	1.278
lnpop	Log of the total population	4270	5.938
struc_sec	Ratio of the secondary industry's GDP to urban GDP	4267	0.465
fdi	Ratio of foreign direct investment to urban GDP	4539	0.026
lnrsv	Log of retail sales of social consumer goods	4527	15.446
gov	Ratio of government fiscal expenditure to urban GDP	4269	0.174
finance	Ratio of deposits to GDP	4267	1.390
ert	Energy consumption reduction targets in the 11th, 12th, 13th, and 14th Five-Year Plans	4539	12.671
unem	Ratio of unemployed labor to the total labor	4539	0.071
robot	Installation density of industrial robots	4539	0.762
lnei	Log of the proportion of electrical energy consumed relative to regional GDP	2868	5.970
lngdp	Log of regional GDP	4269	7.966
lnem	Log of regional employment	3611	12.731
robot_policy	Cumulative number of regulations related to industrial robots	4539	0.282
hc	Per capita education expenditure.	4270	0.131

Results

Baseline regression

Given that the CET policy is being administered provincially, standard errors are grouped by province. This approach yields conservative standard errors, ensuring more robust inference. In *Table 2,* the estimates of models (1) and (2) indicate that, relative to

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

non-pilot cities, CET decreases CO_2 emissions by 13.43% (=1-exp(-0.09)) and industrial SO_2 emissions by 22.5% (=1-exp(-0.255)). Hypothesis 1 is validated.

Additionally, the significance level of the control variables is relatively low. A plausible explanation is that air pollutants and climate pollutants have been regulated in China since 2000. Consequently, enhanced administrative measures have diminished the effect of economic factors on emissions, rendering their impact less substantial than theoretically anticipated.

Table 2. *Effects of CET on CO_2 and industrial SO_2 emissions*

Variables	(1)	(2)
	lnco2	**lnso2**
DID	-0.144^{***}	-0.259^{**}
	(0.049)	(0.116)
lnpgdp	0.326^{***}	0.204
	(0.083)	(0.166)
lnpop	0.352	-0.188
	(0.241)	(0.457)
struc_sec	-0.204	0.251
	(0.210)	(0.684)
fdi	0.020	-0.071
	(0.018)	(0.057)
lnrsv	0.032	0.037
	(0.027)	(0.060)
gov	0.171	0.499
	(0.235)	(0.448)
finance	-0.012	0.002
	(0.017)	(0.029)
ert	-0.004^{*}	-0.017^{*}
	(0.002)	(0.008)
unem	0.086	-0.127
	(0.051)	(0.191)
_cons	0.202	11.282^{***}
	(1.625)	(3.343)
City	Yes	Yes
Year	Yes	Yes
N	3985	3973
R^2	0.661	0.797

Standard errors are reported in parentheses; * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The following tables are annotated as in *Table 2*

Robustness check

Parallel trend test

As introduced in the methodology section, the validity of the multi-period DID model relies on the parallel trend assumption. *Table 3* presents the estimation results of

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

the event study model specified in *Equation 2*. It can be observed that the coefficients for the pre-policy periods (*pre_6* to *pre_1*) are all statistically insignificant and close to zero. This confirms that prior to the implementation of the CET policy, there was no systematic difference in the emission trends between the treatment and control groups, satisfying the parallel trend assumption.

Table 3. *Parallel trend tests*

Variables	(1)	(2)
	lnco2	**lnso2**
pre_6	0.014 (0.021)	0.146 (0.121)
pre_5	0.020 (0.033)	0.073 (0.159)
pre_4	0.017 (0.035)	0.094 (0.164)
pre_3	-0.005 (0.041)	0.125 (0.174)
pre_2	-0.033 (0.043)	0.011 (0.136)
pre_1	-0.050 (0.043)	0.028 (0.164)
Post	Yes	Yes
Controls	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	3985	3973
R^2	0.668	0.798

Placebo test

We also conducted placebo tests, as illustrated in *Figure 1*. Specifically, we randomly selected eight provincial regions from the sample without repetition and randomly assigned the corresponding policy pilot years. We use this method to generate false DID variables for estimation. We repeated the entire process 500 times to generate 500 false policy effects. The simulated policy analysis yields mean coefficients clustering near the zero value, and the actual policy effect falls in the left tail, indicating that the placebo tests pass successfully.

Goodman-Bacon decomposition

In estimating multi-period DID models, bad control groups may arise. Specifically, when early-treated samples are used as the control group for late-treated samples, the outcome variables of the control group already reflect treatment effects, leading to potential bias (Goodman-Bacon, 2021). Consequently, the larger the weight of such control groups, the greater the bias in the estimates.

We employ the Goodman-Bacon decomposition methodology to examine how the bad control groups affect estimated results. *Table 4* indicates that when industrial SO_2

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

emissions are the dependent variable, the percentage of bad control groups is 1.2%. When CO_2 emissions are the dependent variable, this proportion is merely 0.9%. The proportions are minimal and do not substantially influence the outcomes.

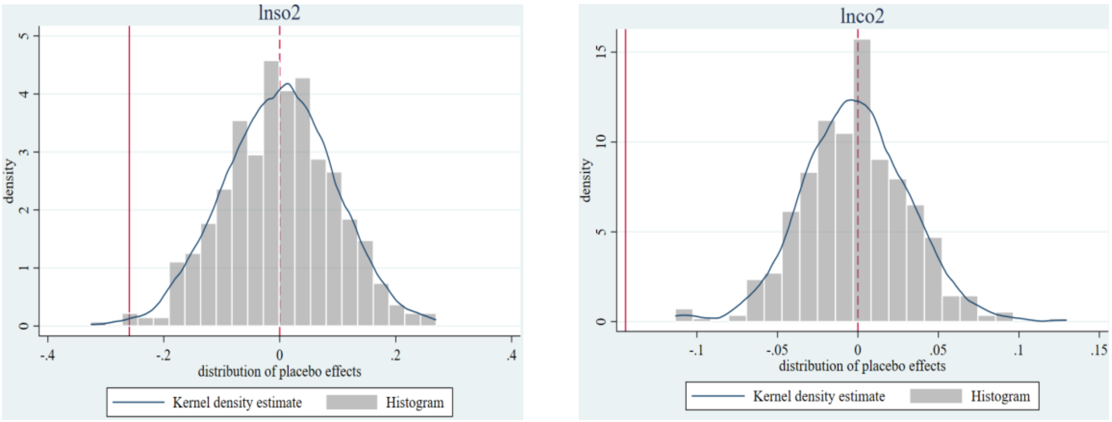

Figure 1. *Placebo tests*

Table 4. *Goodman-Bacon decomposition*

Group	lnso2		lnco2	
	Coefficient	**Weight**	**Coefficient**	**Weight**
Early-treated group vs. late-treated group	-0.048	0.009	-0.107	0.012
Late-treated group vs. early-treated group	0.596	0.009	-0.001	0.012
Treated group vs. Untreated group	-0.240	0.982	-0.087	0.976

Other robustness checks

This paper also performed additional robustness checks. (1) Utilizing various air contaminants. *Table 5* indicates that when industrial dust emissions and $PM_{2.5}$ concentration are proxy factors for air pollution, CET yields co-benefits. (2) Controlling for concurrent policy interventions. The SO_2 emissions trading and low-carbon city pilot policies may influence CO_2 and industrial SO_2 emissions, complicating the estimation results. *Table 6* illustrates that even accounting for the impacts of these two policies, CET continues to exhibit substantial co-benefits. (3) Excluding exceptional samples. The four municipalities in China possess elevated political significance, potentially affecting the estimation results. The CET in Fujian province was adopted later, perhaps influencing the outcomes. *Table 7* indicates that the results remain significant when eliminating these atypical samples.

Channel test: the perspective of industrial robot application

Building upon the established co-benefits of CET outlined earlier, this analysis investigates whether industrial robotics implementation serves as a critical pathway for realizing these synergistic advantages. Model (1) in *Table 8* indicates that implementing CET exhibits a favorable effect on industrial robot adoption. Models (2) and (3) indicate that industrial robots have inhibitory effects on the total emissions of both pollutants.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

Models (4) and (5) indicate that industrial robots also reduce the concentrations of the two pollutants. Hypothesis 2 is validated.

Table 5. *Using different air pollutants*

Variables	(1)	(2)
	lndust	**$lnPM_{2.5}$**
DID	-0.138**	-0.051***
	(0.059)	(0.006)
Controls	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	3306	3985
R^2	0.285	0.521

Table 6. *Eliminating interference from other environmental policies*

Variables	Eliminating the interference of SO_2 emissions trading		Eliminating the interference of low-carbon city pilots	
	(1)	**(2)**	**(3)**	**(4)**
	lnso2	**lnco2**	**lnso2**	**lnco2**
DID	-0.260**	-0.144***	-0.281**	-0.149***
	(0.116)	(0.049)	(0.126)	(0.051)
DID_et	Yes	Yes		
DID_lc			Yes	Yes
Controls	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	3973	3985	3973.000	3985.000
R^2	0.797	0.661	0.797	0.661

Table 7. *Excluding special samples*

Variables	Excluding the four municipalities		Excluding the Fujian province	
	(1)	**(2)**	**(3)**	**(4)**
	lnco2	**lnso2**	**lnco2**	**lnso2**
DID	-0.131***	-0.196*	-0.146***	-0.275**
	(0.046)	(0.100)	(0.049)	(0.118)
Controls	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes
N	3926	3914	3850	3838
R^2	0.672	0.796	0.654	0.799

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

Table 8. *Channel test: industrial robot applications*

Variables	(1)	(2)	(3)	(4)	(5)
	robot	**lnso2**	**lnco2**	**ln(so2/gdp)**	**ln(co2/gdp)**
DID	0.154^{***} (0.053)				
robot		-0.539^{*} (0.267)	-0.265^{**} (0.104)	-0.539^{*} (0.267)	-0.264^{**} (0.104)
Controls	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	3985	3973	3985	3973	3985
R^2	0.907	0.798	0.664	0.876	0.884

Further discussion

How industrial robots affect environmental pollution

Theoretically, we believe that the key mechanism by which industrial robots reduce pollution lies in improving energy efficiency. This section aims to validate this mechanism. *Table 9* shows that adopting industrial robots creates co-benefits via lowering energy intensity. Model (1) indicates that the utilization of industrial robots markedly decreases energy intensity. Models (2) to (5) suggest that energy intensity significantly boosts the overall emissions and concentrations of CO_2 and industrial SO_2.

Table 9. *Industrial robots, energy intensity, and pollution emissions*

Variables	(1)	(2)	(3)	(4)	(5)
	lnei	**lnco2**	**lnso2**	**ln(co2/gdp)**	**ln(so2/gdp)**
robot	-0.704^{***} (0.244)				
lnei		0.034^{**} (0.013)	0.199^{***} (0.050)	0.034^{**} (0.013)	0.199^{***} (0.050)
Controls	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	2855	2855	2855	2855	2855
R^2	0.420	0.675	0.710	0.908	0.790

Economic consequences of the channel

Table 10 further explores the economic consequences of industrial robot applications, focusing primarily on economic growth and employment. The employment examination is particularly relevant, given academic concerns that industrial robots could exacerbate unemployment (Adachi et al., 2024).

Table 10 shows that industrial robots boost GDP. Model (2) indicates that industrial robots do not hurt employment. Although industrial robots could reduce jobs due to substitution effects, they also foster employment growth through increased economic activity, creating two opposing effects. During the study period, these effects appear to balance out, resulting in a slight positive impact on employment rather than any detrimental effect.

Table 10. *Industrial robots, economic growth, and employment*

Variables	(1)	(2)
	lngdp	lnem
robot	0.256**	-0.124
	(0.096)	(0.135)
Controls	Yes	Yes
City	Yes	Yes
Year	Yes	Yes
N	3985	3342
R^2	0.960	0.619

Moderating effects

The above results confirm the existence of the industrial robots channel. To enhance its efficiency, we investigated the moderating effects of three key variables: government support, regional economic development level, and human capital.

Model (1) in *Table 11* investigates the moderating role of policy assistance in industrial robot adoption. The coefficient of *DID×robot_policy* indicates that stronger policy support amplifies the promoting effect of CET on implementing robot technology. In models (2) and (3), the estimation of the interaction term *robot×lnpgdp* implies that robots demonstrate greater effectiveness in curbing air pollutants and carbon emissions in economically developed regions. Models (4) and (5) indicate that the improvement of environmental quality by industrial robots also depends on human capital. These findings confirm Hypotheses 3 and 4.

Table 11. *Moderating effects*

Variables	(1)	(2)	(3)	(4)	(5)
	robot	lnco2	lnso2	lnco2	lnso2
DID	0.096*				
	(0.048)				
DID×robot_policy	0.063**				
	(0.028)				
robot		0.073	0.246	-0.100	-0.141
		(0.162)	(0.294)	(0.115)	(0.265)
robot×lnpgdp		-0.128***	-0.298***		
		(0.046)	(0.094)		
robot×hc				-0.446***	-1.083***
				(0.146)	(0.236)
Controls	Yes	Yes	Yes	Yes	Yes
City	Yes	Yes	Yes	Yes	Yes
Year	Yes	Yes	Yes	Yes	Yes
N	3985	3985	3973	3985	3973
R^2	0.908	0.680	0.801	0.684	0.802

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

Discussion

Our study confirms the co-benefits of CET, aligning with previous findings that CET reduces both carbon and air pollutants (Min et al., 2022; Dong et al., 2022). However, regarding the transmission channel, our findings offer a novel perspective. While prior literature primarily attributed these benefits to energy structure adjustments and green technological innovation (Chen et al., 2024; Liu et al., 2022), our study identifies industrial robot adoption as a tangible micro-level pathway. Unlike general technological progress, industrial robots represent a specific, implementable solution for process optimization. This finding fills the gap in understanding how enterprises specifically adjust their production factors under compliance pressure.

A critical debate in environmental economics is the trade-off between protection and growth. Conventional views suggest that CET increases operational costs (Shi et al., 2022). However, our results show that the robot-mediated channel boosts GDP without harming employment. Theoretically, CET can generate beneficial economic effects by promoting green technological innovation. However, the academic consensus regarding CET's influence on green technological advancements remains elusive. Some scholars argue that CET effectively drives green innovation processes (Liu et al., 2022), while alternative perspectives suggest potential suppression of R&D expenditures through market mechanisms (Zhang et al., 2022b) or propose that the policy fails to produce a statistically meaningful effect (Zhang et al., 2020). Our research indicates that when enterprises are under regulatory pressure, they may adopt the more reliable approach of installing more industrial robots to achieve a win-win situation for both the environment and the economy.

We also found that this channel is not uniform across all regions. The positive moderating effects of government support, economic level, and human capital highlight a threshold effect in robot adoption. Automation requires high initial capital investment and skilled maintenance (Luo and Qiao, 2024). In underdeveloped regions, the lack of financial resources and talent may hinder firms from using robots to cope with CET pressure, potentially trapping them in a low-efficiency cycle. This interpretation underscores that market-based environmental policies must be coupled with industrial support policies to be effective.

Conclusion

This study provides empirical evidence on the co-benefits of CET and identifies a novel micro-mechanism mediated by industrial robots. Based on the analysis of 267 Chinese cities from 2006 to 2022, we draw the following conclusions. First, CET yields significant synergistic effects, simultaneously reducing CO_2 and industrial SO_2 emissions. Second, the application of industrial robots serves as a vital transmission channel. Driven by compliance costs, enterprises increase robot adoption, which subsequently lowers energy intensity and emissions. This pathway contributes to the dual goals of environmental sustainability and economic prosperity. Third, the efficacy of this channel is contingent upon regional conditions; it is more pronounced in areas with strong government support, advanced economic development, and high human capital.

Based on these findings, we propose three policy implications. First, the government should further improve the CET system by optimizing quota allocation and market transparency to amplify its synergistic governance effects. Second, policy coordination

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

between environmental regulation and industrial upgrading should be strengthened. Governments can offer targeted financial subsidies or technical guidance to encourage regulated enterprises to adopt robotic technologies. Third, differential support strategies are necessary. For less developed regions, policymakers should focus on improving infrastructure and workforce training to lower the threshold for robot adoption and prevent a green divide.

Finally, this study has some limitations. We did not distinguish between different types of industrial robots, nor did we examine other environmental regulations beyond CET. Future studies could explore the heterogeneous effects of specific robot categories and extend the analysis to a cross-national context to validate the channel's global applicability.

Funding. This work is supported by the Social Science Foundation of Zhejiang Province: [Grant Number: 25NDJC054YBMS].

REFERENCES

[1] Abraham, K. G., Mallatt, J. (2022): Measuring human capital. – Journal of Economic Perspectives 36(3): 103-130.

[2] Acemoglu, D., Restrepo, P. (2020): Robots and jobs: evidence from US labor markets. – Journal of Political Economy 128(6): 2188-2244.

[3] Adachi, D., Kawaguchi, D., Saito, Y. U. (2024): Robots and employment: evidence from Japan, 1978–2017. – Journal of Labor Economics 42(2): 591-634.

[4] Bai, J., Ru, H. (2024): Carbon emissions trading and environmental protection: international evidence. – Management Science. https://doi.org/10.1287/mnsc.2023.03143.

[5] Bayer, P., Aklin, M. (2020): The European Union Emissions Trading System reduced CO_2 emissions despite low prices. – Proceedings of the National Academy of Sciences 117(16): 8804-8812. https://doi.org/doi:10.1073/pnas.1918128117.

[6] Cao, J., Ho, S., Ma, R., Teng, F. (2021): When carbon emission trading meets a regulated industry: evidence from the electricity sector of China. – Journal of Public Economics 200: 104470. https://doi.org/https://doi.org/10.1016/j.jpubeco.2021.104470.

[7] Chen, L., Wang, D., Shi, R. (2022a): Can China's carbon emissions trading system achieve the synergistic effect of carbon reduction and pollution control? – International Journal of Environmental Research and Public Health 19(15): 8932.

[8] Chen, Y., Cheng, L., Lee, C.-C. (2022b): How does the use of industrial robots affect the ecological footprint? International evidence. – Ecological Economics 198: 107483. https://doi.org/https://doi.org/10.1016/j.ecolecon.2022.107483.

[9] Chen, Z., He, Y., Liao, N. (2024): Can carbon emission trading policy enhance the synergistic emission reduction of carbon dioxide and air pollutants? A comparative study considering different pollutants. – Energy 305: 132364.

[10] Dechezleprêtre, A., Nachtigall, D., Venmans, F. (2023): The joint impact of the European Union emissions trading system on carbon emissions and economic performance. – Journal of Environmental Economics and Management 118: 102758. https://doi.org/https://doi.org/10.1016/j.jeem.2022.102758.

[11] Deng, Z., Li, D., Pang, T., Duan, M. (2018): Effectiveness of pilot carbon emissions trading systems in China. – Climate Policy 18(8): 992-1011.

[12] Dong, Z., Xia, C., Fang, K., Zhang, W. (2022): Effect of the carbon emissions trading policy on the co-benefits of carbon emissions reduction and air pollution control. – Energy Policy 165: 112998.

[13] Dzedzickis, A., Subačiūtė-Žemaitienė, J., Šutinys, E., Samukaitė-Bubnienė, U., Bučinskas, V. (2021): Advanced applications of industrial robotics: new trends and possibilities. – Applied Sciences 12(1): 135.
[14] Gan, T., Zhou, Z., Li, S., Tu, Z. (2024): Carbon emission trading, technological progress, synergetic control of environmental pollution and carbon emissions in China. – Journal of Cleaner Production 442: 141059.
[15] Goodman-Bacon, A. (2021): Difference-in-differences with variation in treatment timing. – Journal of Econometrics 225(2): 254-277.
[16] Han, D., Wu, H., Zhu, Y., Diao, Y. (2024): The road to carbon win, the wise first: evidence of robot impact enabling the synergistic effects of pollution reduction and carbon emissions. – Air Quality, Atmosphere & Health 17(8): 1739-1751. https://doi.org/10.1007/s11869-024-01542-1.
[17] Hu, J. (2023): Synergistic effect of pollution reduction and carbon emission mitigation in the digital economy. – Journal of Environmental Management 337: 117755.
[18] Li, H., Li, X., Hu, Z., Li, Y. (2025): Does industrial robot adoption inhibit environmental pollution in China? An empirical study on energy consumption and green technology innovation. – Journal of Environmental Management 373: 123392. https://doi.org/https://doi.org/10.1016/j.jenvman.2024.123392.
[19] Liu, J.-Y., Woodward, T., Zhang, Y.-J. (2021): Has carbon emissions trading reduced $PM_{2.5}$ in China? – Environmental Science & Technology 55(10): 6631-6643.
[20] Liu, W., Qiu, Y., Jia, L., Zhou, H. (2022): Carbon emissions trading and green technology innovation—a quasi-natural experiment based on a carbon trading market pilot. – International Journal of Environmental Research and Public Health 19(24): 16700.
[21] Liu, Y. (2023): Impact of industrial robots on environmental pollution: evidence from China. – Scientific Reports 13(1): 20769. https://doi.org/10.1038/s41598-023-47380-6.
[22] Luo, H., Qiao, H. (2024): Exploring the impact of industrial robots on firm innovation under circular economy umbrella: a human capital perspective. – Management Decision 62(9): 2763-2790.
[23] Mao, X., Zhou, J., Corsetti, G. (2014): How well have China's recent five-year plans been implemented for energy conservation and air pollution control? – Environmental Science & Technology 48(17): 10036-10044.
[24] Min, L., Hao, X., Fuxing, C. (2022): Pollution and carbon reduction effects of the carbon emissions trading mechanism in the context of the 'dual carbon' goals. – China Population Resources & Environment 32(11).
[25] Roper, S., Tapinos, E. (2016): Taking risks in the face of uncertainty: an exploratory analysis of green innovation. – Technological Forecasting and Social Change 112: 357-363.
[26] Shao, S., Cheng, S., Jia, R. (2023a): Can low carbon policies achieve collaborative governance of air pollution? Evidence from China's carbon emissions trading scheme pilot policy. – Environmental Impact Assessment Review 103: 107286.
[27] Shao, S., Wang, C., Guo, Y., Xie, B.-C., Tian, Z., Chen, S. (2023b): Heterogeneous performances and consequences of China's industrial environmental governance: clean production vs. end-of-pipe treatment. – Journal of Environmental Planning and Management 66(1): 143-168.
[28] Shi, B., Li, N., Gao, Q., Li, G. (2022): Market incentives, carbon quota allocation and carbon emission reduction: evidence from China's carbon trading pilot policy. – Journal of Environmental Management 319: 115650.
[29] Xu, R., Zhang, H., Han, M., Yang, L. Y. (2025): Robot adoption and corporate pollution emissions: evidence from China. – Pacific-Basin Finance Journal 90: 102647. https://doi.org/https://doi.org/10.1016/j.pacfin.2024.102647.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551

[30] Yang, H., Gan, T., Liang, W., Liao, X. (2022): Can policies aimed at reducing carbon dioxide emissions help mitigate haze pollution? An empirical analysis of the emissions trading system. – Environment, Development and Sustainability 24(2): 1959-1980.

[31] Zhang, Q., Zhang, F., Mai, Q. (2022a): Robot adoption and green productivity: curse or boon. – Sustainable Production and Consumption 34: 1-11. https://doi.org/https://doi.org/10.1016/j.spc.2022.08.025.

[32] Zhang, W., Li, G., Guo, F. (2022b): Does carbon emissions trading promote green technology innovation in China? – Applied Energy 315: 119012. https://doi.org/https://doi.org/10.1016/j.apenergy.2022.119012.

[33] Zhang, X., Liu, X., Zhang, Z., Tang, R., Zhang, T., Yao, J. (2024): The synergistic effect of the carbon emission trading scheme on pollution and carbon reduction in China's power industry. – Sustainability 16(19): 8681.

[34] Zhang, Y.-J., Shi, W., Jiang, L. (2020): Does China's carbon emissions trading policy improve the technology innovation of relevant enterprises? – Business Strategy and the Environment 29(3): 872-885. https://doi.org/https://doi.org/10.1002/bse.2404.

[35] Zhu, J., Wu, S., Xu, J. (2023): Synergy between pollution control and carbon reduction: China's evidence. – Energy Economics 119: 106541.

http://www.aloki.hu ● ISSN 1589 1623 (Print) ● ISSN 1785 0037 (Online)
DOI: http://dx.doi.org/10.15666/aeer/2402_25352551