Project Title： The Effects of Industrial Robot Adoption on Air Environment: Evidence from Provincial Manufacturing in China

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Abstract

Industrial robots are the key enabling technology of industry 4.0 and the artificial intelligence revolution, which is significant to sustainable development. The existing research mainly focuses on the economic effect of industrial robot adoption, but the research on environmental effects is still insufficient. Based on an environmental Kuznets curve model, this paper empirically examines industrial robot applications' air pollution abatement effects using data on industrial robot applications in China's inter-provincial manufacturing industry from 2006 - 2015. The study presents three key findings. First, the application of industrial robots significantly contributed to reducing air pollution levels. The application of industrial robots brought about productivity improvements, factor structure optimization, and technological innovations in production, improving energy efficiency and reducing air pollution levels. Second, there is a two-dimensional heterogeneity of industrial exhaust emission reduction effects of industrial robot applications by industry and region. Applying industrial robots in labor-intensive and technology-intensive industries is more effective in reducing industrial emissions than in capital-intensive manufacturing industries. Third, the emission reduction effect of industrial robot application in the eastern region is better than that in the central and western regions. This paper finds that there are moderating and mediating mechanisms for the effects of industrial robot applications on industrial exhaust emission reduction. On the one hand, high absorptive capacity brings a better innovation environment, which enhances the effect of industrial waste gas emission reduction; on the other hand, the application of industrial robots promotes industrial waste gas emission reduction by positively influencing the increase of energy intensity. Finally, policy recommendations are made based on the results.

Key Words: Industrial Robot Adoption, Air Pollution, Heterogeneity Characteristics, Influence Mechanism

Contents

1. Introduction

Like climate change, air pollution has become one of the biggest risks to the ecosystem, human health and sustainable development. The air quality database released by the World Health Organization (WHO) (2022) showed that the air quality in most cities has been deteriorating, and more than 99% of the world's people are exposed to fine particulate matter with harmful level. WHO estimated that about 7 million people die prematurely every year due to the impact of environmental and household air pollution. Since the reform and opening up, the rapid development of industrialization has promoted China's economic development, but at the expense of over exploitation of resources and severe air pollution, resulting in environmental deterioration. Slowing down the deterioration of air quality and reducing industrial exhaust emissions are also one of the issues that the Chinese government urgently needs to solve.

Scholars have focused on the factors affecting the air environment, such as economy, policy, population, external impact and technology. Economic factors contain a wide range of variables, such as economic growth, financial development, foreign direct investment (FDI) and trade, energy and infrastructure investment. Nasir et al. (2019) found an important long-term relationship between financial and economic development and environmental degradation. In FDI and trade. There are two competing arguments: both the pollution halo and the pollution haven theories. The first is that FDI harms the environment because the host nation wants to draw FDI by lowering environmental standards. The second is that FDI and trade lead to the development of cutting-edge technology and effective management techniques that lower carbon emissions. Different research findings have been found by experts along these two lines of reasoning. Others found that FDI either produces positive environmental externalities (Tang and Tan, 2015; Paramati et al., 2017; Zhu et al., 2016); or has a nonlinear relationship to pollution emissions (Hanif et al., 2019; Shahbaz et al., 2018; Zhang and Zhou, 2016). Others found that FDI either produces positive environmental externalities (Tang and Tan, 2015; Paramati et al.,2017; Zhu et al.,2016); or has a nonlinear relationship to pollution emissions (Hanif et al., 2019; Shahbaz et al., 2018; Zhang and Zhou, 2016). Although the use of solid fuels has decreased and the energy mix has changed from non-renewable to renewable (Chien et al., 2021; Meng et al., 2019), increasing overall energy consumption increases emissions in a manner comparable to increasing energy intensity (Sadorsky, 2014). Huang et al. (2020) demonstrated the connection between infrastructure spending and elevated air pollution. Rasool's(2019) findings also suggested that transportation infrastructure plays a significant influence.

Environmental taxes and regulations are the key policy factors. Chien et al. (2021), for instance, discovered that environmental taxes aid in the reduction of carbon emissions. According to Neves et al. (2020) and Wu et al. (2021), environmental management can also help to reduce air pollution over time. Urbanization and population density are thought to be the two key demographic factors influencing air pollution (Sadorsky, 2014). The first study on the impact of demographic factors on sulfur dioxide content was proposed by Cole and Neumayer in 2004. While the effects of urbanization and average home area were relatively insignificant, they discovered a U-shaped link between population density and pollution. Recent studies have focused on how external shocks, such as the global financial crisis, affect energy intensity and exhaust emissions. Recent studies have focused on how external shocks, including the financial crisis and the COVID-19 outbreak, affect energy intensity and exhaust emissions (Wang et al., 2021,2022b, 2022c).

Researchers have concentrated on the effect of technology advancements on air pollution since the groundbreaking studies by Ehrlich and Holdren (1971) and Simon (1973), but the argument has never ended. The Environmental Kuznets Curve (EKC) hypothesis, first put forth by Grossman and Krueger in 1991, establishes a theoretical framework connecting environmental impact to technology and contends that technology offers a means of reducing pollution brought on by population expansion. According to Shi and Lai's (2013) research, technological advancements can help reduce environmental pollution. The actual data supporting this influence is complicated, though. Some academics contend that technological expertise is crucial to lowering air pollution (Afonso et al., 2021). Others claim that despite technical advancements, large-scale climate change brought on by greenhouse gas emissions cannot be prevented (Shao et al., 2021). Two key factors account for the contradictory findings: a vague interpretation of the impact mechanism and a disregard for the context that governs the interaction between technological advancement and air pollution.

Artificial intelligence has significantly altered human productivity and daily life in recent years, making it one of the most promising technologies now being explored and used (Acemoglu and Restrepo, 2018). Artificial intelligence has not only directly increased production but also sparked supplementary innovation, much like what happened after the inventions of the steam engine, electric power, internal combustion engine, and the computer. As a result, it qualifies as a broad technology and has a wide range of potential applications. As a result, the world's leading economies are actively creating artificial intelligence. China is no different. China released the New-generation Artificial Intelligence Development Plan in 2017, with the goal of dominating the global artificial intelligence innovation landscape by 2030. Additionally, China sees AI as a new tool for advancing the green economy.

Industrial robots used extensively in manufacturing may be the most economically viable application of artificial intelligence (Cockburn et al., 2018). An industrial robot is a multipurpose automatic control operating machine used for industrial automation and reprogramming, according to the International Federation of Robotics (IFR). A McKinsey Global Institute (MGI) analytical report from 2017 estimates that by 2030, 400 million workers worldwide, or 15% of the total workforce, may be displaced by technology. This demonstrated how industrial robots, the industry 4.0 "symbol of artificial intelligence" (Dantas et al., 2020; Elpidio et al., 2020), have increasingly permeated the manufacturing process. This will have substantial commercial value as well as societal repercussions (Acemoglu and Restrepo, 2019, 2021; Acemoglu and Autor, 2011). More research is being done on the impact of robot adoption on economic growth (Aghion et al., 2019), energy consumption (An et al., 2020; Wang et al., 2022a), productivity (Kromann et al., 2020; Ballestar et al., 2020), innovation (Liu et al., 2020), social influence on equality (Acemoglu and Restrepo, 2018, 2020), and other factors in addition to (Lei, 2021).

Due to worries that machines could outcompete people, a lot of current research focuses on how industrial robots will affect the labor market (Acemoglu and Restrepo, 2021; Acemoglu and Autor, 2011). Some academics believe that the use of industrial robots is a sign of impending unemployment. Robots with lower pay are gradually replacing workers, especially low-skilled workers (Graetz and Michaels, 2018; Acemoglu and Restrepo, 2020). Due to three distinct functioning mechanisms — productivity effects, substitution effects, and reinstatement effects — Acemoglu and Restrepo (2019) reach various conclusions. When more affordable machinery takes the place of more expensive labor, output rises, manufacturing costs decrease, and productivity increases. The need for labor rises as a result of productivity. More duties that the labor force once performed are moved to industrial robots, which results in the replacement effect. It lowers wage growth and labor demand while decreasing employment availability. The workforce's comparative advantage in completing more difficult and creative activities is the cause of the reinstatement effect. Numerous highly skilled employees leave their regular jobs to produce new product content or take on new labor-intensive duties as a result of automation standardizing the manufacturing process. Various labor market effects are caused by how these three factors are balanced. A growing body of literature addresses the impact of robot adoption on economic growth (Aghion et al., 2019), energy consumption (An et al., 2020; Wang et al., 2022a), productivity (Kromann et al., 2020; Ballestar et al., 2020), innovation (Liu et al., 2020), and the social impact on equity in addition to the debate over robot use and employment, wage and income share (Lei, 2021).

In contrast, there is insufficient research on how industrial robots affect the environment. From a theoretical and qualitative standpoint, very few academics have examined how industrial robot technology might affect pollution reduction (Javaid et al., 2021; Liu and De Giovanni, 2019). However, there is currently a dearth of quantitative analysis to empirically investigate how industrial robot adoption may alter the characteristics of heterogeneity, the air environment, and potential mechanisms. Three research issues are thus posed in light of the existing studies:(1) Can air pollution be efficiently reduced by using industrial robots? (2) Do the effects of industrial robot applications on the air environment vary depending on the sectors and geographical locations? (3) What are the potential means through which industrial robots might be used to encourage the reduction of industrial emissions? The answers to these issues have significant and beneficial ramifications for society as a whole as well as for policymakers, academics, and business professionals.

This report uses data on industrial robot usage in manufacturing in 30 Chinese provinces and regions between 2006 and 2015 to undertake a thorough empirical examination of these challenges based on the EKC model. The following three aspects are connected to this paper's contributions. First, this article investigates the connection between industrial robot applications and air pollution, in contrast to the previous literature, which concentrates on the economic impacts of industrial robot applications. The impact of industrial robot applications on the reduction of industrial exhaust gas emissions is being empirically examined for the first time in this subject in our study. This not only closes a gap in the research on how industrial robot applications affect the air environment but also offers a fresh viewpoint on how to advance initiatives for a green economy and sustainable growth. Second, in relation to the research framework, we think that a high capacity for absorption makes industrial robots more likely to flow over and be absorbed. We also investigate how this can enhance the effects of industrial robotics applications on industrial exhaust gas reduction. In this study, we examine the mechanisms by which industrial robot applications affect the air environment using energy intensity as a mediating variable. Finally, in terms of research design, we combine data from various databases to create a regional-industry-level dataset for China that allows us to empirically test the heterogeneity of industrial exhaust emission reduction effects and take into account the heterogeneity of industrial robot applications across different provinces and regions. This broadens the scope of the entire research field.

The remainder of the essay is structured as follows. The research hypotheses are presented in Chapter 2 after a study of the pertinent literature. The methodology and data for the study are described in full in Chapter 3. Results of the empirical tests are presented and discussed in Chapter 4. Chapter 5 concludes with recommendations for associated policies.

2. Theoretical Basis and Assumptions

2.1 Industrial Robot Application and Air Environment

Industrial robots are a key enabler for Industry 4.0, and their use offers numerous economic advantages such as increased manufacturing flexibility, operational cost reductions, labor productivity, and total factor productivity gains (Graetz and Michaels, 2018; Dalenogare et al., 2018). Industrial robots have unintentionally improved the environment by reducing waste, increasing energy efficiency, and attaining cleaner output, despite the fact that their use does not always prioritize environmental sustainability (Javaid et al., 2021; Liu and De Giovanni, 2019). Manufacturers can lower material losses in manufacturing and supply chain operations thanks to industrial robot automation's dependability and the digital production operations monitoring platform created around it (Javaid et al., 2021; Martinelli et al., 2021). Additionally, the employment of industrial robots powered by cognitive evaluation algorithms and optical identification technology enables the transformation of organic or solid waste into high-quality secondary raw materials, advancing the circular economy and sustainability objectives (Wilts et al., 2021). The widespread use of industrial robots in manufacturing operations has also encouraged the reallocation of production resources and elements and optimized the production process, resulting in a decrease in industrial emissions throughout the production chain (Wang et al, 2022a). Industrial robot utilization also boosts labor productivity, grows production while using the same amount of inputs, lowers resource and energy consumption, and minimizes air pollution (Graetz and Michaels, 2018). Industrial robot use, in particular, encourages technological innovation in businesses through knowledge generation, spillover, learning capacity enhancement, R&D, and talent investment (Liu et al., 2020). Studies have also demonstrated that industrial robots streamline green process innovation, while green innovation further lowers industrial waste gas emissions (Liu and De Giovanni, 2019). (Du et al., 2019; Yang et al., 2020). Consequently, based on the findings of the discussion above, we suggest the following hypothesis.

Hypothesis 1. *The application of industrial robots can reduce the emission of industrial waste gas, slow down the degree of air pollution, and improve air quality.*

2.2 Heterogeneity in the Application of Industrial Robots to Reduce Air Pollution

Diverse fields and regions have different industrial robot applications, each with its own characteristics. This raises the question of whether industrial robot applications for reducing industrial exhaust gas are heterogeneously effective. It has been noted that the environmental impacts of AI technologies are industry heterogeneous, with labor-intensive and technology-intensive industries having greater environmental impacts compared to capital-intensive industries (Liu et al., 2022). IFR data indicate that in the manufacturing sector, about 64.8% of industrial robots in China were used in the automotive and electronic and electrical equipment manufacturing industries in 2015, while less than 1% of industrial robots were used in the three manufacturing industries of apparel and textiles, wood products and furniture, and paper and printing (Figure 1). The different application intensities may lead to different characteristics of the impact of industrial robots on industrial emissions in each manufacturing industry.

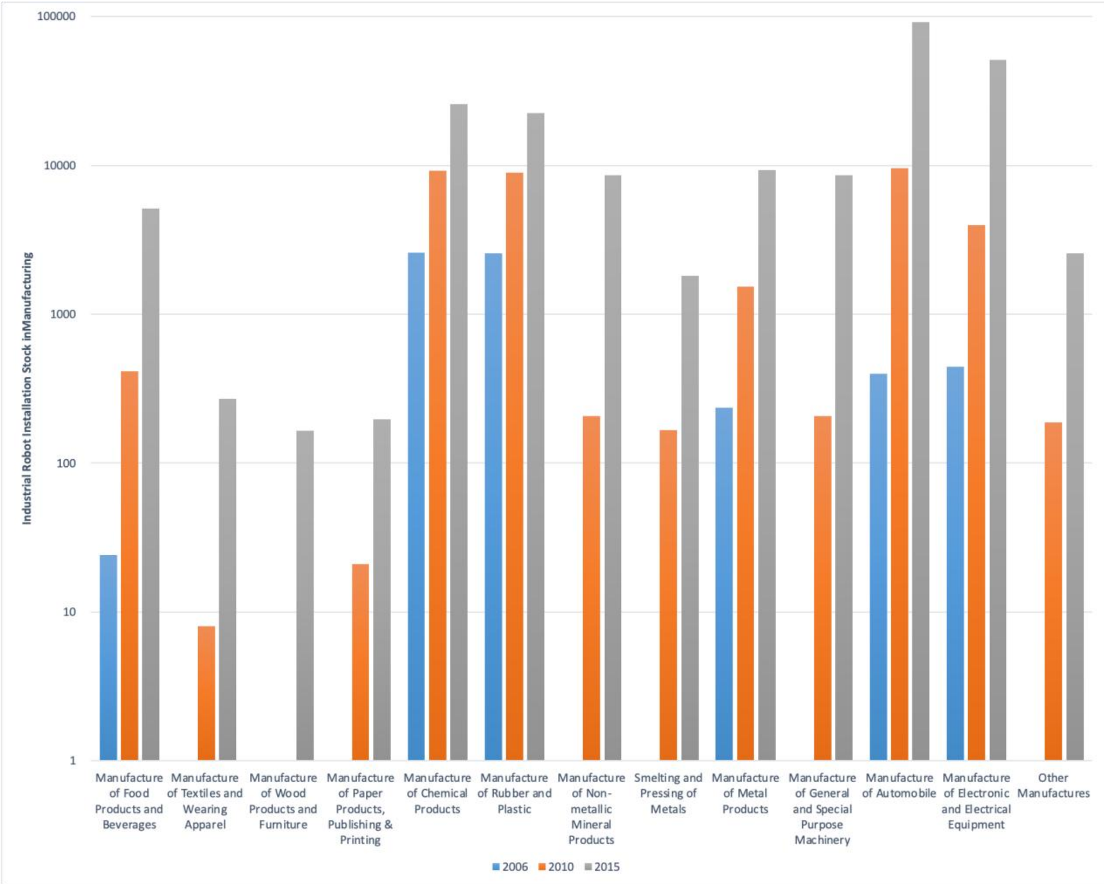

Figure 1. Industrial robot application in China's Manufacturing in 2006,2010 and 2015.

Notes: The vertical axis is a logarithmic scale with base 10.

The 30 provinces studied are further divided into three main geographic sub-regions in this paper: the eastern region, the central area, and the western region[1], according to Han Zhaoan et al. (2021). In 2015, the eastern region accounted for around 62.7% of all industrial robot uses worldwide, whereas the central and western regions only accounted for 24.2% and 13.1%, respectively (Figure 2). On the one hand, the levels of technology and R&D in various countries vary significantly, which affects the spread and uptake rates of industrial robotics. As a result, the reduction in air pollution caused by technical advancement and structural improvement may vary. On the other side, variations in industrial robot applications may result from regional variations in industrial structure, which will exacerbate the impact of reducing industrial exhaust emission levels. Consequently, the following theory is put forth.

[1] The eastern region includes 11 provinces: Beijing, Tianjin, Hebei, Liaoning, Shanghai, Jiangsu, Zhejiang, Fujian, Shandong, Guangdong and Hainan; the central region includes 8 provinces: Shanxi, Henan, Hubei, Hunan, Jilin, Heilongjiang, Anhui and Jiangxi; 11 provinces: Chongqing, Sichuan, Guizhou, Yunnan, Shaanxi, Gansu, Qinghai, Ningxia, Xinjiang, Guangxi and Inner Mongolia.

Hypothesis 2. *Applications of industrial robots have different effects on reducing air pollution in different locations and in factor-intensive manufacturing industries.*

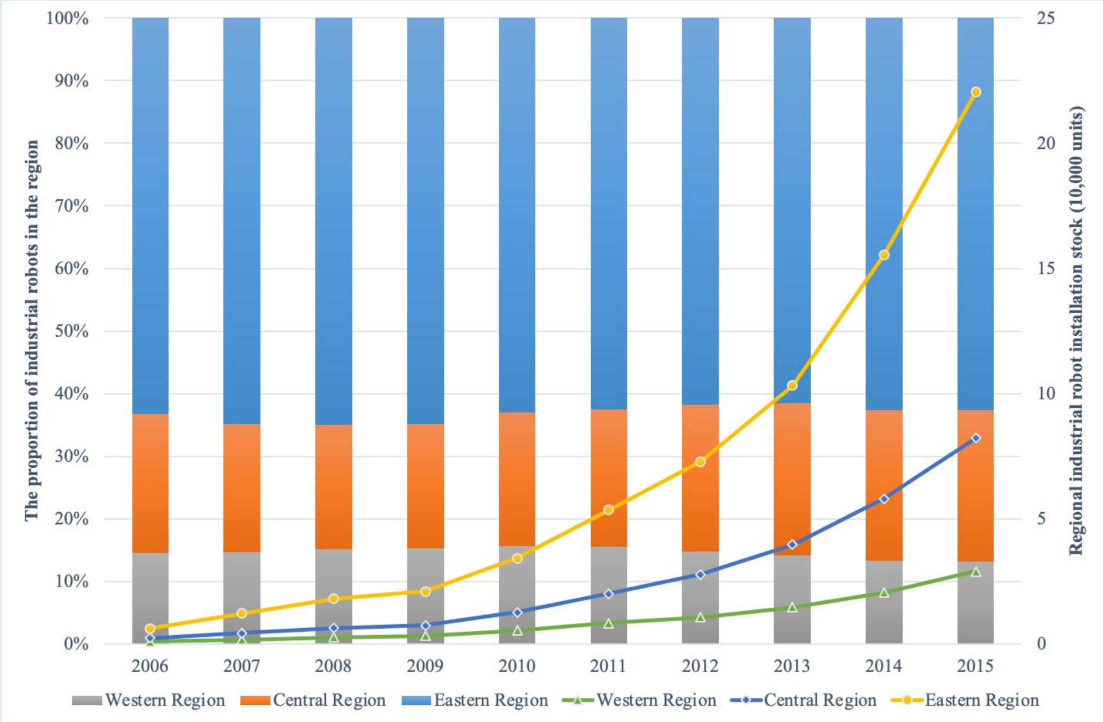

Figure 2. Industrial robot application in three regions of China from 2006 to 2015.

2.3 Application of Industrial Robots and How It Impacts the Air Environment

Regional absorptive capacity may have an impact on how industrial robot applications affect the decrease of industrial exhaust emissions. The ability of a corporation or region to recognize, assimilate, and apply external knowledge utilizing pertinent knowledge already accessible and transform it into commercial value is referred to as absorptive capacity (Hashai and Almor, 2018). In the literature, absorption capacity is frequently determined by R&D activity (De Jong and Freel, 2010; Mahmoudian et al., 2021). High absorptive regions are better able to locate and use outside knowledge sources (Bertrand and Mol, 2013). Due of the complexity of industrial robotics as a technology, some application organizations or geographical areas may find it difficult to absorb and integrate the new technology. The ability to quickly react to changes in the innovation environment and technology allows businesses to better absorb and use industrial robotics while boosting their competitive advantage. As a result, the interaction between absorptive capacity and industrial robot applications may serve as a catalyst for the decline in air pollution levels, enhancing the impact of industrial robot applications on the reduction of industrial exhaust emissions. Particularly, the greater the favorable influence of industrial robot applications on air pollution level decrease when regional absorptive capacity is large. Contrarily, regions with limited absorptive capacity have trouble absorbing and applying industrial robotics knowledge and technology, which could impede the impact of industrial robotics applications on reducing air pollution levels. As a result, we speculate the following.

Hypothesis 3. *The association between air pollution reduction and industrial robotics applications is positively moderated by absorbtive capacity.*

This study also attempts to investigate whether energy intensity is a mediating mechanism for the impact of air pollution levels caused by industrial robot applications. According to the European Environment Agency (2004) "Air pollution, climate change, water pollution, thermal pollution, and solid waste disposal are some of the environmental issues directly linked to the production and consumption of energy. The primary cause of urban air pollution is the production of air pollutants from the combustion of fossil fuels ". Numerous studies have also demonstrated that air pollution is primarily caused by energy consumption and that there is a positive link between energy intensity and air pollution levels, i.e., a reduction in energy intensity results in a reduction in air pollution intensity (Afonso et al., 2021; Rahman and Kashem, 2017). Additionally, it has been noted that the use of industrial robots helps to lower the energy intensity of manufacturing. On the one hand, using industrial robots in businesses can encourage technical innovation to increase energy efficiency and decrease energy intensity, effectively reducing the level of air pollution (Liu et al., 2020; Wang et al., 2022a). Contrarily, industrial robots boost productivity and replace unskilled labor, lowering energy use and industrial emissions per unit of output (Graetz and Michaels, 2018; Wang et al., 2022a). Due to the technical innovation effect and productivity enhancement effect, the use of industrial robots thereby increases energy efficiency and decreases energy intensity, thereby lowering the amount of air pollution. This study makes the following claim in light of the debate above.

Hypothesis 4. *By adversely influencing energy intensity, the use of industrial robots helps to lower the amount of air pollution.*

Figure 3 depicts the study's theoretical framework.

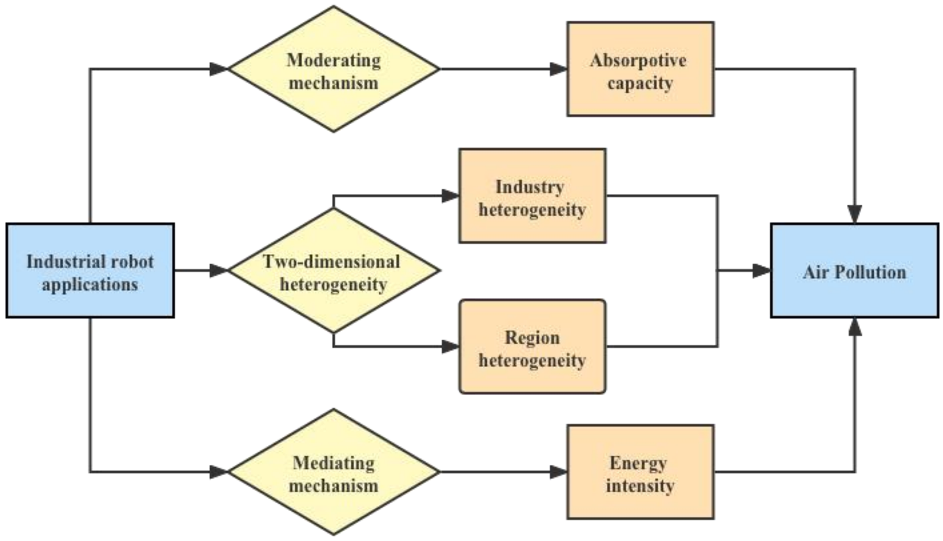

Figure 3. Theoretical model.

3. Data and methods

3.1 Data

In order to analyze the effect of industrial robot adoption on air environment, we combined various data sources to construct a province-industry level data set.

(1) International Federation of Robotics (IFR) data. The IFR data are based on the annual survey of global robot manufacturers, aggregating national-industry-year level data from 2006-2015, and are currently the most authoritative statistics on industrial robots at the macro level. In this paper, the raw data are processed as follows: 1. The 2006-2015 Chinese industry-level data are selected, and the IFR data are matched with the National Industry Code 2011 standard (GB/T 4754-2011) according to the study of Yan Xueling et al. (2020) to obtain industrial robot installation data for 13 manufacturing industries[2]. For consistency, this paper does not

[2] 13 manufacturing industries are [1] food and beverage processing manufacturing; [2] textile and apparel products; [3] wood products and furniture manufacturing; [4] paper and printing products; [5] chemical products; [6] rubber;

calculate the railroad, ship, aerospace, and other transportation equipment manufacturing employment[3]. 2. Following the approach of Lu and Zhu (2021), the percentage of employment in each province of these 13 manufacturing industries to the total employment in the country was collected from inside the Chinese Labor Statistics Yearbook, and then this percentage was multiplied by the number of industrial robots installed in that manufacturing industry to obtain industrial robots for 13 manufacturing industries in 30 provinces of China Installation data[4].

(2) China Industrial Environment Database. This database (2022) includes 31 regions and four pollutants: chemical oxygen demand (COD), sulfur dioxide (SO2), ammonia nitrogen (NH3-N), and nitrogen oxides (NOX). The database is based on micro-enterprise emission data from the China Environmental Statistics Database, connecting industrial exhaust gas emission data at the regional level and industry level from the China Environmental Statistics Yearbook, using top-down and bottom-up methods to constitute the regional-industry level data, and finally using cross-entropy to balance the two-dimensional data. In this paper, the region-industry-level data of this database for the period 2006-2015 are used as proxy variables for air pollution.

(3) China Industrial Statistical Yearbook. This statistical yearbook is a helpful yearly publication that accurately depicts the growth of China's industrial economy. It systematically includes national industrial economic statistics of all economic types, industrial industries and provinces, autonomous regions, and municipalities directly under the central government, as well as the historical data of key indicators from 2006 to 2015. This database is used in this paper to collect indicators related to value added, employment, owner's equity, foreign capital, and R&D investment of industries in each region.

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and plastic products; [7] non-metallic mineral products; [8] metal processing and smelting; [9] metal products; [10] general and special equipment manufacturing; [11] automotive manufacturing; [12] electronic and electrical equipment manufacturing; [13] other branches of manufacturing.

3 Because the manufacturing segment code came in 2002 and 2011 in 2006-2015, rail, shipping, aerospace and other transportation equipment manufacturing did not have in 2002, meaning that relevant data was missing for 2006-2011.

4 Due to the availability of data, Tibet, Hong Kong, Macao and Taiwan were not included in the scope of the study.

(4) China Statistical Yearbook. The National Bureau of Statistics compiles and publishes this statistical yearbook, an educational annual publication that fully portrays China's economic and social progress. This statistics yearbook was used to gather information for this article on GDP, urban population, and the sum of all commodities imported and exported from each region between 2006 and 2015.

(5) China Energy Statistical Yearbook. This statistical yearbook is implemented by the Department of Energy Statistics of the National Bureau of Statistics to collect, organize and provide statistical data of the survey. This statistical yearbook is used in this paper to collect the energy consumption indicators of each industry in each region from 2006 to 2015.

3.2 Variables

3.2.1 Dependent and Independent Variables

To study the influences of industrial robot applications on air pollution, we use the total emissions of four industrial exhaust gases, chemical oxygen demand (COD), sulfur dioxide (SO2), ammonia nitrogen (NH3-N), and nitrogen oxides (NOX), as proxy variables for the dependent variable air pollution; The number of industrial robots installed is aggregated yearly to obtain the operational stock of those robots, which is used as a proxy variable for industrial robot applications. To attenuate the effect of heteroskedasticity in the data, both variables are treated logarithmically.

3.2.2 Covariates

Gross Domestic Product per capita (ln *pgdp*). The EKC model emphasizes the nonlinear relationship between income and environmental pollution. To verify the EKC hypothesis, the paper uses GDP per capita by region to express the income levels.

Average employment (ln *employ*). Labor demand reflects the efficiency of energy utilization and industrial structure, which influences the level of air pollution indirectly. In general, large industrial enterprises which are energy-intensive and have more employees have relatively higher industrial emissions, particularly for heavy industries. While high-tech industries with low labor demand have relatively low air pollution levels. Therefore, we use the logarithm of the average employment in each manufacturing industry in each region as one of the factors.

Foreign Direct Investment ($\ln FDI$). Through investment and technology diffusion to the host country, FDI may bring more environmentally friendly production standards and technologies. Therefore, it will have a positive impact on environmental protection in the host country. However, foreign firms take advantage of the relatively more lenient environmental regulation in developing countries to transfer intensively polluting industries to the host country, which may increase pollution emissions there. We use foreign capital in owner's equity to measure FDI and take logarithm of it.

Urbanization rate (*urban*). The urbanization makes cities the main gathering place for energy expenditure and air pollution. During the urbanization process, manufacturing develops, causing industrial emissions increasing. However, a proper process of urbanization can also improve environment, remarkably increase the energy using rate, and ultimately reduce air pollution. Therefore, urbanization may have different effects on air pollution at different stages. In this study, the ratio of urban population to total population in each region is used as a representative of urbanization rate.

Industrial structure (*indus*). The degree of air pollution is influenced by changes in the industrial structure. Unquestionably, the growth of energy-efficient, environmentally friendly, and high-tech enterprises will further aid in the reduction of industrial exhaust emissions. The industrial structure is expressed in the following paper using the secondary industry's contribution to GDP as a percentage.

Trade openness (*trade*). Trade liberalization lowers resistance and enables additional production growth, which encourages industrial emissions. Additionally, through trade connections, sophisticated technology can be passed from technologically advanced economies to relatively less advanced economies, allowing countries that import technology to minimize industrial emissions by increasing energy use efficiency. In this study, trade openness is expressed as the total of goods exported and imported per unit of GDP.

3.2.3 Moderator

Absorptive capacity (ac). The term "absorptive capacity" describes a region's or an enterprise's capacity to recognize, use, and absorb external knowledge while utilizing locally existing information in order to create commercial value. According to Lu et al. (2021), this study measures absorptive capacity using the ratio of nominal R&D expenditure to nominal GDP, also known as regional R&D intensity.

3.2.4 Mediator

Energy intensity (ln *ei*). In this paper, energy intensity is defined as the amount of energy used per RMB 10,000 of industrial value added (constant purchasing power parity (PPP) in 2011) for each manufacturing sector in each region, where a low rate indicates high energy efficiency. Again, the energy intensity is treated logarithmically.

Table 1 provides statistical descriptions of all variables. The Variance Inflation Factor (VIF) and correlation coefficients for the variables are displayed in Table 2. From this we found that the VIF values much less than 10 and determined that there was no significant covariance between the variables.

Table 1. The variable statistical description.

Variable	Definition	Unit	Obs.	Mean	Std. dev.	Min	Max
ln *WG*	Industrial waste gas emissions	Thousand tons	3900	2.469	1.968	-5.368	8.039
ln *robot*	Industrial robot application	Units	3399	2.563	2.900	-4.605	9.787
ln *pgdp*	Per capita GDP	CNY/person	3900	4.323	0.532	2.8848	5.3452
ln *employ*	Average employment	10,000 people	3900	6.273	0.650	4.158	7.409
ln *FDI*	Foreign capital in owner's equity	100 million CNY	3900	6.744	1.102	3.342	8.694
urban	Urbanization rate	%	3900	49.48	17.60	27.50	87.48
indus	Industrial structure	%	3900	28.83	6.872	17.24	48.53
trade	Trade openness	%	3900	84.85	62.25	15.64	427.3
ac	Absorptive capacity	%	3819	1.575	0.977	0.476	4.553
ln *ei*	Energy intensity	tons of standard coal/ thousands CNY	38975	4.746	0.392	3.773	6.002

Table 2. VIF test and correlation analysis.

	VIF	ln *WG*	ln *robot*	ln *pgdp*	ln *employ*	ln *FDI*	*urban*	*indus*	*trade*	*ac*	ln *ei*
ln *WG*		1									
ln *robot*	1.81	-0.34	1								
ln *pgdp*	1.64	-0.75	0.44	1							
ln *employ*	1.27	0.42	-0.20	-0.56	1						
ln *FDI*	1.31	-0.37	0.48	0.87	1.102	1					
urban	1.01	-0.55	0.35	0.83	17.60	27.50	1				
indus	1.78	0.62	-0.06	-0.63	0.31	-0.43	-0.52	1			
trade	1.78	-0.11	0.26	0.10	-0.52	0.15	0.18	0.10	1		
ac	1.80	-0.62	0.53	0.74	-0.28	0.68	0.62	-0.40	0.01	1	
ln *ei*	1.46	0.75	-0.16	-0.41	0.28	0.05	-0.23	0.44	-0.15	-0.13	1

3.3 Measurement Model Setting

Most researchers utilize the extended Environmental Kuznets Curve (EKC) model to investigate the factors that affect carbon emissions (Lin and Zhou, 2019). The association between income level and environmental pollution was identified via the conventional EKC model. They were discovered to have an inverse U-shaped connection. The researchers then expanded the traditional EKC model by researching how commerce, urbanization, climate change, and other variables affect environmental contamination (Zhang et al., 2017; Wu et al., 2021). This study examines how industrial robot adoption affects the air environment and suggests a new model that builds on the traditional EKC model by include industrial robot adoption and other control factors. The newly proposed model is as follows:

$$\ln WG_{ijt} = \beta_0 + \beta_1 \ln robot_{ijt} + \beta_2 \ln pgdp_{ijt} + \beta_3 (\ln pgdp_{ijt})^2 + \beta_4\, control_{ijt} + \gamma_i + \gamma_j + \gamma_t + \varepsilon_{ijt} \qquad (1)$$

$\mathrm{WG}_{\mathrm{ijt}}$ denotes the total industrial emissions in year t of manufacturing industry j in province i. $\mathrm{robot}_{\mathrm{ijt}}$ represents the industrial robots operating stock. $\mathrm{control}_{\mathrm{ijt}}$ is GDP per capita. $\mathrm{control}_{\mathrm{ijt}}$ represents other control variables, i.e. average employment (ln *employ*), foreign direct investment (ln *FDI*), urbanization rate (urban) industrial structure (*indus)*, trade openness *(trade*). Variables γ_{i}、γ_{j}、γ_{t} express denote province, industry, and year fixed effects respectively. $\varepsilon_{\mathrm{ijt}}$ is the random perturbation term. β is the coefficient of each variable. Variable $i$represents province and j represents industry, t represents year, and ln denotes the logarithmic form that eliminates heteroskedasticity.

To verify Hypothesis 3, this study employs a moderating effect analysis to determine whether regional absorptive capacity influences the pathway by which industrial robot application affects air pollution. The model includes interaction terms for both absorptive capacity and absorptive capacity with industrial robot application. If the interaction term's coefficient is significant, it is demonstrated that the absorptive ability has an exceptional moderating influence. The precise model configuration is as follows:

$$\begin{aligned} \ln WG_{ijt} = {} & \beta_0 + \beta_1 \ln robot_{ijt} + \beta_2 \ln pgdp_{ijt} + \beta_3 (\ln pgdp_{ijt})^2 + \beta_4\, control_{ijt} \\ & + \varphi ac_{it} + \omega \ln robot_{ijt} \times ac_{it} + \gamma_i + \gamma_j + \gamma_t + \varepsilon_{ijt} \qquad (2) \end{aligned}$$

$\mathrm{ac}_{\mathrm{it}}$ is the moderator, i.e., absorptive capacity. Φ represents the coefficient of the moderator. ω expresses the interaction coefficient. If ω is less than 0 and the p value is less than 0.1, it means that the relationship between the use of industrial robots and the decrease of industrial exhaust gases is favorably regulated by the absorptive capacity.

In addition, to test whether energy intensity is a mediating mechanism for industrial robot applications to promote industrial exhaust emission reduction, the following model is constructed in this paper.

$$\ln ei_{ijt} = \beta_0 + \beta_1 \ln robot_{ijt} + \beta_2 \ln pgdp_{ijt} + \beta_3 (\ln pgdp_{ijt})^2 + \beta_4\, control_{ijt} + \gamma_i + \gamma_j + \gamma_t + \varepsilon_{ijt} \quad (3)$$

$$\ln WG_{ijt} = \beta_0 + \beta_1^{'} \ln robot_{ijt} + \lambda \ln ei_{ijt} + \beta_2 \ln pgdp_{ijt} + \beta_3 (\ln pgdp_{ijt})^2 + \beta_4\, control_{ijt} + \gamma_i + \gamma_j + \gamma_t + \varepsilon_{ijt} \quad (4)$$

ei_{ijt} is the mediator, which is energy intensity. If the estimates of β_1 and λ are both significant, it indicates the existence of a mediating effect. At this point, it is necessary to further analyze whether β_1 is significant, and if β_1 is also obvious then it indicates the existence of partial mediation effect, otherwise it is a full mediation effect.

4. Results and Discussions

4.1 Baseline Regression

The optimum statistical approach is determined in this study by applying the F-test, Lagrange Multiplier (LM) test, and Hausman test. The outcomes provide strong evidence that using a fixed effect model as the foundation for our empirical research is the best choice.

Table 3 displays the baseline regression estimates with the corresponding control variables added, as displayed in Columns (1)- (4). Column 5 demonstrates by stepwise regression that the effect of industrial robot adoption on industrial exhaust pollution is negative at a 1% significance level, supporting the research hypothesis. According to the findings, the use of industrial robots has greatly decreased industrial exhaust emissions. Widespread use of industrial robots has encouraged waste reduction, increased energy efficiency, and clean production, all of which have a favorable impact on the environment's air quality.

Table 3. The baseline regression results.

Variables	（1）	（2）	（3）	（4）	（5）
ln *robot*	-0.544***	-0.006	-0.011***	-0.010***	-0.008***
	（-13.26）	（-0.87）	（-3.28）	（-3.31）	（-2.69）

ln *pgdp*		3.23***	0.239***	0.412***	0.379***
		（13.59）	（3.01）	（4.13）	（2.94）
(ln *pgdps*)^2		-0.312***	-0.091***	-0.093***	-0.087***
		（-22.15）	（-12.39）	（-11.63）	（-10.29）
ln *employ*			0.197***	0.207***	0.176***
			（3.19）	（3.41）	（2.81）
ln *FDI*			-0.487***	-0.685***	-0.677***
			（-4.49）	（-7.34）	（-7.15）
urban				-0.039***	-0.036***
				（-2.98）	（-2.75）
indus				0.002***	0.003***
				（2.90）	（3.17）
trade					-0.001***
					（-3.98）
constant	-0.685***	-9.278***	-5.918***	-6.294***	-5.872***
	（-39.18）	（-15.28）	（-12.49）	（-12.31）	（-11.23）
Observation	3319	3319	3236	3236	3236
Adjusted R-square	0.2084	0.6903	0.9190	0.9135	0.9185

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are con- trolled in all columns.

Additionally, the findings of the control variable regression show that, first, the GDP per capita coefficient is positive and the GDP per capita square term coefficient is negative. The variables' respective significance levels of 5% and 1% show that income and air pollution have an inverse U-shaped relationship. It is in line with the EKC theory. Second, the average number of employees and the industrial structure are both significantly positive, indicating that an increase in the average number of employees and the share of the secondary industry will have a detrimental impact on environmental performance and raise the level of industrial exhaust emissions. There is a clear promotion influence on industrial exhaust pollution as a result of the secondary industry's quick development and high energy intensity, like the manufacturing industry. Third, urbanization is negative at a 1% level of significance, which shows that thanks to developments in green urbanization, the ecological benefits of innovation have received greater attention in the process of urbanization, which has led to a decrease in air pollution. Finally, at a 1% level of significance, the regression coefficient of foreign direct investment and trade opening is negative. It shows that there is a technological spillover effect in the process of foreign direct investment and trade ties, which has brought more eco-friendly production standards and technology, increased the energy efficiency of relevant regions and sectors, and decreased industrial exhaust emission.

4.2 Robustness Check

In order to further verify the reliability of the model, robustness check is carried out in this paper. We start by swapping out the independent variable. In order to replace the installed stock of industrial robots measured by employment share, we use the installed stock of industrial robots measured by value-added share. The installed stock of industrial robots in the industry is multiplied by the value-added share that each industry in each region contributes to the country as a whole. This value-added share is used to measure the installed stock of industrial robots in the industry.The regression results are displayed in Table 4's Column 1. Each coefficient's sign and significance are in line with the findings of the initial regression. This demonstrates the model's robustness. The number of articles on industrial robots in various Chinese industries (including machine learning, deep learning, and computer vision, among others) is then used to gauge the acceptance level of industrial robots for robustness testing, according to Liu et al. (2020). The volume of articles may, in part, indicate the technological sophistication of the sector. The China National Knowledge Internet provides the information for related papers on industrial robots. And then they are divided into regions according to the unit of the first author or the corresponding author, thus the related paper data of regional industry level are obtained. The second column of Table 4 shows that the estimated effect of papers related to the industrial robots is the same as the baseline result. They are negatively related to air pollution.

The outliers are also disregarded in the way that follows. All explanatory variables in this study were tested at significance levels of 1% and 99%. For regression findings, please refer to Column 3 of Table 4. We discovered that the deployment of industrial robots continues to have a significant negative impact on industrial exhaust pollution, and other variables' significance and coefficient sign are unaffected. As a result, the model is thought to be reliable.

Table 4. Robustness checks of the baseline regression

Variable	（1）	（2）	（3）
	ln *WG*	ln *WG*	Winsorisd
ln *robot*	-0.006*** （-2.57）		-0.021*** （-5.42）
ln *paper*		-0.059*** （-3.19）	
Control Variables	YES	YES	YES
Observation	3236	3718	3324
Adjusted R-square	0.9127	0.9029	0.9192

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are con- trolled in all columns.

4.3 Endogenous Problem

Since there is bi-directional causality between the dependent and the independent variable, deviation may exist on the regression results of the fixed effect model. Based on this, the lagged item of industrial robot adoption is used as instrumental variable (IV) to alleviate the potential endogenous problem.

We use 2SLS (two stage least square) to estimate the parameters. The regression results are given in Table 5. The following findings can be attained based on the first stage empirical results of the 2SLS approach in Column (1) of Table 5:

First, the null hypothesis of unidentified IV is rejected since the Anderson Canon. corr. LM statistic is 72.48, which is substantially higher than the threshold value of 1% significance level. Second, the Cragg-Donald Wald F statistic's p value is considerably lower than 1%, rejecting the weak IV null hypothesis. Third, the null hypothesis that the sum of endogenous regression coefficients equals 0 is rejected at the 1% level based on the Anderson-Rubin Wald test, further confirming the association between IV and the use of industrial robots.

According to the coefficient of IV, which is 0.6764 and significant at the 1% level, there is a strong linear association between IV and the adoption of industrial robots, and the adoption of industrial robots during the lag period has a positive impact on the base period. Column (2) of Table 6 lists the empirical results from the 2SLS method's second stage. The industrial robots' coefficient is -0.0591, which is significant at the 1% level and in line with the initial finding. The robustness of the finding is confirmed once more.

Table 5. Regression results of the 2SLS model

Variable	（1）	（2）
L ln *robot*	0.676***	
	（11.43）	
ln *robot*		-0.059***
		（3.76）
ln *pgdp*	-0.275**	0.379***
	（-2.05）	（2.94）
(ln *pgdps*)^2	0.012*	-0.016***
	（1.78）	（-3.75）
ln *employ*	0.068***	-0.087***
	（3.85）	（-3.21）
ln *FDI*	0.714***	-0.697***
	（5.39）	（-6.15）
urban	0.027***	-0.031***
	（3.18）	（-2.73）
indus	-0.004***	0.002***
	（-2.98）	（2.45）
trade	0.002	-0.003**
	（1.58）	（-1.98）
constant	-18.0069***	-18.0069***
	（-39.18）	（-39.18）
Anderson canon. corr. LM statistic	72.48***	
Cragg-Donald Wald F statistic	130.51***	
Anderson-Rubin Wald test	12.15***	
Observation	2916	
Adjusted R-square	0.6084	

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are con- trolled in all columns.

4.4 Heterogeneity Analysis

4.4.1 Industrial Heterogeneity

There are obvious differences in the exhaust emission of different industries in China, and there are also great differences in the adoption and distribution of industrial robots in various industries. Therefore, the significant negative effect of industrial robot adoption on air pollution in the baseline model may also have industrial heterogeneity. We categorize the sample industries into three groups in accordance with the reliance of various production factors in order to explore this industrial heterogeneity: labor-intensive, capital intensive and technology intensive[5], and consider the effect of the industrial robot adoption in different types of industries on air environment. Table 6 contains the results from the sub-sample. According to the empirical findings, the use of industrial robots in labor- and technology-intensive industries has resulted in a 1% significance level reduction in air pollution, while the use of industrial robots in capital-intensive industries has resulted in a 5% significance level reduction in industrial exhaust emission. The results in Table 6 also show that the effect of industrial robots on air environment is robust in industrial heterogeneity.

Table 6. The results of industrial heterogeneity analysis

Variable	（1）	（2）	（3）
	labor-intensive	capital-intensive	technology-intensive
ln *robot*	-0.019*** （-3.79）	-0.004** （-1.78）	-0.014*** （-3.12）
Control Variables	YES	YES	YES
Observation	1126	1493	617
Adjusted R-square	0.7239	0.6892	0.7932

[5] Labor-intensive manufacturing industries include food and beverage processing, textile and garment products, wood and furniture manufacturing and paper and printing products; Capital-intensive manufacturing industries include chemical products, rubber and plastic products, non-metallic mineral products, metal processing and smelting, metal products and other branches of manufacturing; Technology-intensive manufacturing industries include general and special equipment manufacturing, automotive manufacturing, electronics and electrical equipment manufacturing.

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are con- trolled in all columns.

Industrial robots are proven to have a stronger impact on the reduction of industrial exhaust emission in labor-intensive and technology-intensive sectors when compared to capital-intensive businesses. The findings of Graetz and Michaels (2018), who discovered that robots have decreased the employment of less skilled workers, are consistent with the industrial heterogeneity of industrial robots. We do believe that there are differences in how industrial robots affect labor-intensive and technology-intensive industries. On the one hand, labor-intensive businesses with a high proportion of low and medium skilled workers—particularly those that need formal manual labor and blue collar work—are most affected by the substitution effect of industrial robots. Therefore, industrial robots have a greater impact on air pollution in industries that require a lot of labor. The results support the conclusions of a study by Pieri et al. (2018), who hypothesized that low-tech businesses benefit more from technological progress. On the other hand, technology-intensive businesses have enhanced their capacity to absorb industrial robots thanks to more advanced ICT infrastructure and significant investments in the digital economy. IFR data show that the three industries with the highest application rates of robots are also the most technologically advanced. Therefore, compared to capital-intensive businesses, the impact of industrial robots on air pollution is greater in those sectors.

4.4.2 Regional Heterogeneity

The level of economic growth and industrial structure vary significantly between different regions of China, which may also affect how industrial robots are used. The degrees of technology and R&D in various countries also range significantly, which affects the spread and absorption rates of industrial robot technologies. Therefore, the effect of industrial waste gas reduction from industrial robot applications in the base model may vary regionally. According to the degree of economic development and geographic location, this paper divides the sample regions into three regions: the eastern region, the central region, and the western region. It then examines the effects of industrial robots used in each region on the level of air pollution in order to demonstrate the regional heterogeneity. In Table 7, which displays the empirical findings for the sub-sample, it can be seen that the explanatory variable in column (1) has a coefficient of -0.021, which is significant at the 1% level, and that the coefficient of industrial robot application in column (2) is -0.003, which is significant at the 5% level. Surprisingly, column (3)'s results contradict those of columns 1 and 2, and its coefficient is positive, albeit neither are significant at the 10% level. This suggests that while the decrease of industrial exhaust gas in the western region is not particularly significant, the use of industrial robots in the eastern and central regions can greatly reduce the amount of air pollution. Additionally, the eastern region's use of industrial robots has a better impact on reducing industrial exhaust emissions than the central region. One explanation could be that the eastern region, in comparison to other regions, has a superior climate for innovation and a greater potential to absorb new technology. As a result, the eastern region can more effectively utilize how these technologies affect the air environment. As a result, Hypothesis 2 has been confirmed. Regional and industry heterogeneity are both present in the air pollution level reduction effect of industrial robotics applications. This study explores the causes of regional variations in terms of impact mechanisms in Section 4.5.

Table 7. The results of regional heterogeneity analysis

Variable	（1）	（2）	（3）
	Eastern region	Central region	Western region
ln *robot*	-0.021***	-0.003**	0.001
	（-4.13）	（-2.17）	（1.08）
Control Variables	YES	YES	YES
Observation	1391	920	925
Adjusted R-square	0.7239	0.6892	0.7932

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are controlled in all columns.

4.5 Mechanism Analysis

4.5.1 Regulation Mechanism Test

We confirmed the moderating effect of absorptive capacity using a moderating effect model to understand better the causes of regional variation in the decreased impact of the air pollution level of industrial robots. The interaction terms of absorptive capacity and industrial robot application with absorptive capacity were gradually included following the test path in Eq. (2). Column (3) of Table 8 shows the regression results. It shows that the regression coefficients of the independent variables and the interaction term are negative at the 1% significance level, which indicates a moderating mechanism. According to this theory, high absorptive capacity is thought to positively increase the effect of industrial robot application on air pollution levels. As a result, we proved Hypothesis 3.

Table 8. The results of the moderating mechanism test

Variable	（1）	（2）	（3）
ln *robot*	-0.008*** （-2.69）	-0.007** （-2.28）	-0.019*** （-3.96）
ac		-0.010 （-1.14）	0.019* （1.66）
ln *robot* × *ac*			-0.011*** （-3.12）
Control Variables	YES	YES	YES
Observation	3263	3263	3263
Adjusted R-square	0.9185	0.9073	0.9212

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are controlled in all columns

This mechanism explains why the application of industrial robots in the East has better air pollution reduction effects. The eastern region has a higher share of R&D investment, so it has a stronger absorptive capacity and is able to adapt faster to changes brought about by the environment of innovation and technological progress. Industrial robots can therefore absorb more technology and have a greater capacity to do so in the eastern region, where they can significantly contribute to the reduction of industrial exhaust emissions. Contrarily, the R&D environment in the central and western regions is worse, and enterprises find it challenging to absorb and implement the knowledge and technology of industrial robotics. The abatement impact is further constrained by this, making it relatively moderate in the central and western regions. Therefore, the impact of industrial robot applications on the decline in air pollution levels is positively moderated by absorptive capacity.

4.5.2 Intermediary Mechanism Test

Because of this, industrial robots are better able to absorb technology in the eastern part of the world, where they can dramatically reduce industrial exhaust emissions. In contrast, the R&D environment is worse in the central and western areas, and businesses find it difficult to understand and use the knowledge and technology of industrial robotics. This further limits the abatement impact, making it rather mild in the central and western regions. Absorbent capacity thus serves to positively attenuate the effect of industrial robot applications on the reduction of air pollution levels. The findings of the baseline regression are shown in column (1), and those of the mediating mechanism model are shown in columns (2) and (3). First, at the 1% level of significance, the estimation findings in column (1) show a negative value, i.e., industrial robots reduce air pollution. Second, it is negative at the 1% significance level in column (2) while being positive at the same level in column (3), suggesting a mediating mechanism. Additionally, the one in column (3) is unsignificant at the 1% level of significance, demonstrating the relevance and partial mediation of the mediating effect of energy intensity. The use of industrial robots thus indirectly lowers the level of air pollution by reducing energy intensity, which acts as a mediator and exhibits a partial intermediary impact. As a result, Hypothesis 4 is supported, proving that the use of industrial robots dramatically lowers air pollution by reducing energy intensity.

Table 9. The results of the mediating mechanism test

Variable	（1）	（2）	（3）
	ln *WG*	ln *ei*	ln *WG*
ln *robot*	-0.008***	-0.013***	-0.007***
	（-2.69）	（-4.83）	（-3.12）
ln *ei*			0.495***
			（3.74）
Control Variables	YES	YES	YES

Observation	3263	3128	3128
Adjusted R-square	0.9185	0.9783	0.9201

Notes：Robust t-statistics are shown in parentheses. *, ** and *** denotes the significance at the 10%, 5% and 1% level, respectively. Region fixed effects, industry fixed effect and year fixed effects are controlled in all columns.

5. Conclusion and Policy Recommendations

The economic effects of industrial robot applications have received more attention in previous studies, while the environmental effects have received less attention. Using data on industrial robot applications in manufacturing industries from 2006 to 2015 and based on the EKC model, this paper empirically examines the effects of industrial exhaust emission reduction and the resulting heterogeneity characteristics of industrial robot applications in 30 Chinese provinces and regions. In addition, investigations on the moderation and mediation of air pollution mechanisms provide insight into how industrial robot applications effect air pollution levels.

First, this study discovers that the use of industrial robots significantly lowers air pollution levels. The use of industrial robots increases production output, optimizes factor structures, and introduces technical innovation, which boosts energy efficiency and lowers air pollution levels. Therefore, in order to achieve a green economy and sustainable development, China should make efforts to promote the application of industrial robots in various industries and regions, improve the coverage of industrial robots, and fully recognize the important role of industrial robots in the reduction of industrial exhaust emission.

The effects of industrial robot applications on the decrease of industrial waste gas emissions are two-dimensionally heterogeneous in terms of industry and geography. Industrial robot use in labor-intensive and technology-intensive industries has a more notable impact on reducing industrial waste gas emissions than in capital-intensive manufacturing businesses. Additionally, while the effect of reducing industrial exhaust emissions in the western region is very limited, the application of industrial robots in the eastern and central regions can dramatically lower air pollution levels. The use of industrial robots in the eastern region has a better impact on reducing industrial emissions than it does in the central region. The use of industrial robots in technology-intensive production should be encouraged as a priority, followed by expansion to labor-intensive and capital-intensive manufacturing industries, taking into account the two-dimensional heterogeneity of industries and locations. Industrial robot application varies significantly from region to region. To continually increase the application intensity of industrial robots and more effectively encourage the decrease of air pollution levels, the central and western areas should use the eastern region as a benchmark.

Finally, this study discovers that the influence of industrial robot application on industrial exhaust emission reduction is subject to moderating and mediating factors. High absorptive capacity improves the environment for innovation, which increases the effect of reducing industrial waste gas emissions. On the other hand, the use of industrial robots encourages reducing industrial waste gas emissions by favorably influencing the rise in energy intensity. The effect of applying industrial robots to reduce industrial exhaust emissions is partially mediated by improvements in energy intensity. China should encourage increased R&D spending across the board, strengthen its capacity for independent innovation, and support the thorough fusion of manufacturing industries with digital technologies like artificial intelligence, big data, and fifth-generation mobile communication (5G), using industrial robots as a conduit. In addition to actively developing new sectors with low energy consumption, high added value, and minimal harm to the environment while sustaining economic growth, the government should restructure traditional, high energy-consuming industries.

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