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The Impact of Industrial Robots on Energy Efficiency: Evidence from Chinese Cities

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Abstract

As an important driving force for intelligent transformation, the development and application of industrial robots have promoted the transformation of traditional production modes and the upgrading of energy utilization methods, playing a significant role in improving energy efficiency. Based on the panel data of 283 prefectural-level cities in China from 2008 to 2019, this study used a two-way fixed-effects model to examine the impact of industrial robots on urban energy efficiency. The study found that industrial robots significantly improve energy efficiency, with the mechanisms including scale effects, structural effects, and green technology effects. Heterogeneity analysis shows that this effect is more prominent in innovative cities, central and western regions, and areas with high human capital. The research provides a basis for understanding the pathways through which industrial robots promote the improvement of energy efficiency and offers policy insights for China to advance intelligent manufacturing and green development.

Keywords: industrial robots; energy efficiency; scale economies; structural upgrading; green technology

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1. Introduction

For a long time, energy has served as a crucial foundation for national economic development and social progress, playing a significant role in promoting sustainable economic growth and facilitating the green and low-carbon transformation of cities. The reliable supply of energy in the industry profoundly impacts national energy security and the well-being of the people. As the world's largest energy consumer, China plays a pivotal role in the global energy landscape and climate governance. Data from [1,2] reveal a stark reality: China's energy demand has increased by an astonishing 300.56% over the past 30 years. In 2018, its energy consumption growth contributed to one-third of the global increase, and by 2019, it accounted for more than 75% of the global net energy consumption growth [3]. The industrial sector, as the absolute dominant consumer of energy in China, accounts for 70% of the country's energy mix [4]. Due to the national "13th Five-Year Plan" (2016–2020) [5], which established structural transformation and industrial upgrading strategies through binding energy intensity targets, and ongoing economic expansion, the total energy demand has been growing exponentially, leading to increasingly acute energy supply–demand conflicts and tightening environmental constraints. Against this backdrop, how to significantly improve energy efficiency while controlling total energy consumption and how to break through the bottlenecks of energy dependence and transformation in China's rapid industrialization and urbanization have become core issues for national

development strategies. As the core carrier of intelligent manufacturing, can the large-scale application of industrial robots optimize energy allocation and drive efficiency leaps? In-depth exploration of this question undoubtedly holds significant theoretical and practical implications for understanding the specific pathways of China's transformation in economic growth models.

As a core technology of artificial intelligence, industrial robots are driving the structural transformation of global manufacturing systems. The International Federation of Robotics (IFR) defines them as multi-functional, programmable intelligent manipulators that, through their technical integration with cyber-physical production architectures, have become key drivers of the Industrial 4.0 transformation [6,7]. Global indicators show an exponential growth in the density of manufacturing robots, with China's performance being particularly notable: in 2023, the operational stock of industrial robots reached 1.8 million units, accounting for 51% of the global annual installation volume, more than three times the combined total of Japan, South Korea, and India. Meanwhile, the share of domestic brands has risen by 19 percentage points to 47% over the past decade, upgrading from followers to leaders in the industry and establishing a global leading position in automation infrastructure [8]. Empirical research confirms that the accelerated adoption of industrial robots is not only a response to the long-term pursuit of increasing productivity, reducing costs, and improving resource efficiency [9], but also an empirical demonstration of their catalytic role in the global economic restructuring towards smart manufacturing [10]. China has increasingly emphasized the positive role of industrial robots in production in recent years [11]. As intelligent production emerges as a key force in the future global economic development, it is profoundly influencing changes across various sectors of society.

Theoretically speaking, the large-scale application of industrial robots has a profound impact on the improvement of urban energy efficiency. As the largest energy-consuming sector in China, the level of urban energy efficiency is directly related to the achievement of China's energy conservation and emission reduction goals [12]. Industrial robots are expected to enhance energy efficiency by promoting the advancement and innovation of green technologies. On one hand, the application of industrial robots will force cities to undergo technological transformation and innovative learning, gradually reduce the proportion of high-energy-consuming traditional industries, and optimize the scale of resource allocation in the entire production system to promote the research and development and diffusion of green technologies. On the other hand, through their own high-precision, high-intensity, continuous operation capabilities, they can directly replace traditional production equipment and manual operations with high energy consumption and low efficiency, reducing the energy consumption per unit output from the source of production processes. In addition, the interaction between industrial robot applications and energy consumption may produce an "inverted U-shaped" nonlinear relationship, that is, in the initial promotion stage, energy demand may rise (due to operating energy consumption and production expansion) until a certain technological threshold or penetration rate is reached, at which, the positive effects of energy conservation and consumption reduction gradually become apparent, accompanied by a significant characteristic of diminishing marginal benefits. However, to date, few studies have explored the impact of industrial robots on urban-level energy efficiency [13,14]. Has the application of industrial robots significantly improved urban energy efficiency? If industrial robots have indeed increased energy efficiency, through what channels is this effect transmitted? The academic community is still unclear about this. Moreover, is there heterogeneity in this impact among cities with different characteristics? As a major energy-consuming site, the energy use patterns and efficiency of cities are of great significance to global energy and environmental issues. Therefore, the impact

and mechanisms of industrial robots participating in urban industrial systems on energy efficiency must be further analyzed.

To quantitatively demonstrate the relationship between industrial robots and urban energy efficiency, this study examines the endogenous issues and discusses the impact mechanisms and regional heterogeneity to further determine the impact of industrial robots on energy efficiency. The potential innovations and marginal contributions of this study are as follows. First, unlike the broad discussions on the socio-economic impacts of industrial robots in existing research, this study focuses on an empirical research gap: the impact of industrial robots on urban energy efficiency. Addressing the limitations of traditional single energy efficiency indicators, this study uses Chinese city panel data to construct a comprehensive measurement framework based on total factor productivity, accurately depicting the optimal relationship between energy input and economic output and providing an important empirical benchmark for identifying the net effect of industrial robots on urban energy efficiency. Second, in terms of mechanism validation, this study overcomes the limitation of the existing research, which is often confined to single-path theoretical speculation on scale, structure, and technological effects. By integrating an empirical analysis of city data, this study not only verifies the transmission paths through which industrial robots affect energy efficiency via scale and structural effects but also reveals and emphasizes the key driving role of green technological innovation in this process and its important significance in promoting low-carbon transformation. This finding provides innovative evidence and important policy insights for understanding the role of mechanisms of industrial robots in China's "dual carbon" strategy, contributing to the understanding of key drivers of global energy transformation.

2. Theoretical Background and Hypotheses

2.1. Literature Review

The literature related to this paper primarily concerns two aspects. First, the literature on the impact of industrial robot applications on macroeconomic effects. The existing research mainly focused on the impact of robots on the labor market [15], economic growth [16], industrial upgrading [17], and corporate performance [18]. For example, ref. [19] conducted an in-depth study on the substitution and productivity effects of robot applications on employment and wages. Ref. [20] identified the restructuring effects of labor market adjustment caused by robot applications, which promote the contraction of employment in the primary industry and stimulate the elasticity of employment in the tertiary industry. Meanwhile, ref. [21] and others argue that industrial robots are an important component of automation processes, which can improve the productivity of manufacturing enterprises, reduce production and operational costs, and ultimately significantly enhance corporate performance.

With green development becoming a global consensus, the environmental and energy effects of robot applications have gradually attracted attention. In a related study, ref. [22] based on Chinese enterprise data, demonstrated that the adoption of industrial robots improves corporate energy efficiency. Ref. [23] used cross-national panel data and found that deploying robot systems in manufacturing can improve the energy structure by reducing material throughput and stimulating the creation of ecological employment, thereby enhancing ecological performance. Ref. [24] also pointed out that the application of artificial intelligence can reduce pollution while improving energy efficiency, thereby reducing resource waste. These studies collectively confirm that energy efficiency is a key prerequisite for robot applications to reduce pollution emissions. However, the existing literature primarily conducted analyses at the macro or cross-national level or focused on the single dimension of corporate energy efficiency, with insufficient systematic re-

search on the dynamic energy efficiency of industrial robots at the urban scale, the spatial heterogeneity transmission mechanisms, and the comprehensive impact pathways. In particular, robot applications may influence environmental quality through the adoption of advanced emission reduction technologies [25] and green innovation spillovers [26], but such technological effects and their role at the urban level have not been fully revealed and quantified in energy efficiency research.

Second, the literature focuses on factors influencing energy efficiency. A large number of studies have explored the role of technological progress [27,28], industrial structure upgrading, optimization of energy consumption structure, economic agglomeration and scale effects [29], environmental regulation [30,31], foreign investment introduction [32], trade openness [33], and innovation policies, among other factors. Refs. [33,34] particularly emphasized that technological progress represented by productivity improvement is a key channel for enhancing energy efficiency.

2.2. Research Hypothesis

In the field of industrial production, the application of robots itself is a significant form of technological progress. The impact of robot application on energy efficiency is complex. On one hand, it enhances energy efficiency by improving productivity [23,35] and promoting investment in technologies [36]. On the other hand, the expansion of output driven by industrial robots may also lead to an increase in total energy consumption and emissions. The application of industrial robots accelerates the integration of intelligence and energy production processes, thereby improving the intelligent transaction, production, and processing of energy factors through stimulating imitation and learning among enterprises. Based on these findings, this study proposes H1.

H1: *Industrial robots can improve energy efficiency.*

Industrial robot applications can optimize urban energy efficiency through economies of scale. The urban economic scale, measured by capital stock, and the industrial output scale, measured by location entropy of total industrial output value in each region [37], jointly constitute the key economies of scale mechanism. Capital stock reflects the total accumulated physical capital of a city, while total industrial output embodies the output scale of urban industrial activities. Together, they form a solid foundation that provides a "multiplier" basis for industrial robot applications in enhancing urban energy efficiency [38]. Firstly, industrial robots are deployed in production environments with substantial capital investment and output scale, utilizing a sharing economy model to share the costs of purchase, maintenance, and upgrades. This model not only significantly reduces the unit cost of using industrial robots but also increases the density and operational efficiency of equipment deployment, thereby directly improving the efficiency level per unit of output [39]. Secondly, when industrial robots are applied in large-scale economies and industrial clusters, they leverage more easily formed application network synergies to accelerate information sharing, technology exchange, and the spread of best practices among enterprises, achieving optimal allocation of energy factors and effectively reducing energy waste, thus enhancing urban energy efficiency [40]. This scaled ecological expansion promotes the adoption of energy-efficient robots, thereby driving the overall improvement of urban energy efficiency. It is worth noting that industrial robots with high energy efficiency often have high initial costs, and only ultra-large-scale markets can bear their scaled application. By expanding the use of abundant factors and increasing factor productivity, the ultimate goal is to enhance urban energy efficiency and market dominance. Based on this, this study proposes H2a.

H2a: *Industrial robots improve energy efficiency through scale effects, including increasing the size of urban economies and industrial agglomeration, and reducing the intensity of energy consumption per unit.*

Industrial robot applications can optimize urban energy efficiency through structural effects. First, they optimize the energy consumption structure. As highly automated manufacturing equipment, the widespread application of industrial robots accelerates the integration of advanced clean production technologies in manufacturing, significantly reducing the dependence on fossil fuels [19]. This drives the transformation of the energy consumption structure towards low-carbon and clean directions, essentially constituting the core pathway for achieving improved urban energy efficiency. This mechanism significantly enhances the economic output per unit of energy consumption by directly acting on the conversion process of energy input and output, thus effectively improving urban energy efficiency [41]. Second, they promote industrial structure upgrading. The widespread application of industrial robots significantly enhances production automation and intelligence, driving the industry to transform from labor-intensive, resource-consuming, low-end manufacturing to technology-intensive, high-value-added, high-end manufacturing [30]. This transformation not only injects new momentum into the development of high-tech industries but also guides key resources such as capital and talent to concentrate continuously in high-productivity sectors [42]. Compared to traditional industries where technological lag and lack of innovation lead to high energy consumption and emissions, this industrial structure adjustment significantly reduces the energy intensity per unit of industrial added value, thereby directly optimizing urban energy utilization efficiency. These two mechanisms work together to effectively promote the continuous optimization of urban energy efficiency. Based on this, this study proposes H2b.

H2b: *Industrial robots improve energy efficiency through structural effects, including optimizing the energy mix and promoting industrial upgrading to improve energy efficiency.*

Industrial robot applications enhance urban energy efficiency through the effects of green technology. This study uses the quantity and quality of green innovation as variables to measure the green technology effect and regional innovation vitality. According to resource dependence theory, when the external market environment offers more opportunities and abundant resources, cities are more inclined to adopt innovation-driven business strategies [43]. First, the application of industrial robots reduces the reliance on repetitive manual labor by releasing resources and intellectual capital, allowing human and intellectual capital originally invested in traditional production processes to be reallocated to research and development activities [44]. This resource reallocation model significantly increases green innovation, laying a broader technical foundation for improving energy efficiency. The increase in green innovation means cities have more technical options and a stronger foundation for energy conservation and environmental protection. For example, by developing and applying more energy-saving processes, clean production technologies, and energy efficiency management solutions, cities can more effectively optimize energy use in production processes, directly improving urban energy efficiency [45]. Second, industrial robots leverage their advanced manufacturing and precision control capabilities to drive research and development, utilizing deep technological spillover effects to focus research and development activities on high-value, high-tech, green technology fields. By comprehensively improving the quality of urban green innovation, the overall upgrade of energy efficiency is ultimately achieved [46,47]. High-quality green technology application not only promotes the upgrading of urban energy systems toward intelligence and refinement but also fundamentally optimizes energy allocation methods and usage

processes, achieving a significant improvement in urban energy efficiency. High-quality green innovation inherently has a higher technical complexity and better potential for efficiency enhancement. Through this mechanism, industrial robots can effectively improve urban energy efficiency. Therefore, this study proposes H2c. Figure 1 shows the theoretical mechanism framework of this study.

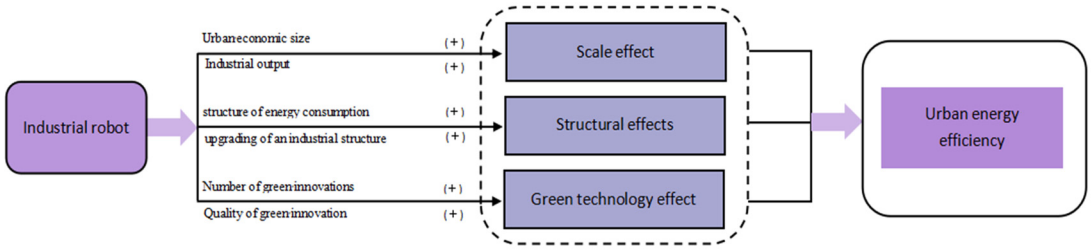


Figure 1. Framework of the mechanism through which industrial robots affect urban energy efficiency.

H2c: *Industrial robots improve energy efficiency through the green technology effect, including increasing the quantity of green innovation, improving the quality of green innovation, and strengthening the radiation effect of technological progress on energy efficiency.*

3. Methodology and Data

3.1. Empirical Modeling

To investigate the impact of industrial robots on urban energy efficiency, this study employed a two-way fixed-effects model for empirical testing. Specifically, we constructed the following econometric model:

$$\text{Ln CCR}_{it} = \alpha_0 + \alpha_1 \text{Robot}_{it} + \sum \beta X_{it} + \mu_i + \nu_t + \varepsilon_{it} \quad (1)$$

where i and t represent cities and years, respectively. Ln CCR_{it} is the total-factor energy efficiency of city i in year t. Robot_{it} is the per capita robot stock in city i during year t. The model incorporates a vector of control variables X that spans socioeconomic dimensions, with city fixed effects (μ_i) and year fixed effects (ν_t) introduced to account for unobserved spatial and temporal heterogeneity.

As both the dependent variable Ln CCR_{it} and the core independent variable Robot_{it} are transformed into natural logarithms, Equation (1) constitutes a log–log model. Consequently, the estimated coefficient β can be interpreted as an elasticity. Specifically, it represents the percentage change in urban energy efficiency in response to a 1% change in the per capita stock of industrial robots while the other factors are held constant.

3.2. Variables

3.2.1. Dependent Variable

Improving energy efficiency is an important component of national energy strategy planning, yet measuring and comparing energy efficiency remains a rather challenging issue. The existing literature typically used energy intensity, which is the ratio of energy consumption to gross domestic product (GDP), to measure energy efficiency. However, this approach gives rise to two problems: First, energy intensity essentially reflects the result of changes in energy efficiency. If energy intensity is treated as a direct measure of energy efficiency, it may lack precision. Second, calculating energy intensity implies an implicit assumption that output is created by solely using energy as the input factor. By ignoring the contributions of other production factors, this can lead to an overestimation of energy efficiency; hence, energy intensity is also referred to as single-factor energy efficiency. Based on this, this study measured urban-level energy efficiency through total-factor energy

efficiency calculations. It employed the Data Envelopment Analysis (DEA) method. This method is based on the following key assumptions: first, the choice of an input-oriented model aligns with the realistic policy orientation of Chinese cities seeking to minimize the input of energy and other factors under established output targets. Second, pollutants were used as inputs, considering environmental pollution as an undesirable output, with the logic that reducing emissions is seen as a consumption of "unfavorable environment" resources. Third, the CCR model based on the constant returns to scale (CRS) assumption was adopted, as it is more rigorous in its assumptions, is suitable for evaluating the overall efficiency frontier of all factors at the macro urban level, and facilitates the absolute ranking and comparison of cross-city efficiency.

The time span of this study is from 2008 to 2019, with the output variables in the model represented as the real GDP calculated at constant prices in 2008. Four input indicators were ultimately established—energy, capital, labor, and environmental impact—as well as an expected output (actual GDP). Based on the above settings, this study applied the MaxDEA 8.0 software to quantitatively measure the total factor energy efficiency of Chinese cities under the input-oriented framework. The definitions of the input–output indicators are as follows:

Energy (E) refers to the amount of energy consumed by the city. Statistically, it involves converting the consumption of the four main primary energy sources—coal, oil, natural gas, and hydropower—into a unified unit (standard coal) according to their respective proportions, and then summing them up for calculation.

Capital (K) refers to the capital stock, which is converted into values calculated using the base year of 2008 and the GDP deflator.

Labor (L) should strictly be measured as the effective labor time of employed personnel. However, due to the lack of statistical data on average working hours, the national employed population was used as a substitute.

The Environmental Effect Indicator (M) consists of sulfur dioxide, industrial dust emissions, and industrial wastewater discharge and was used to characterize the environmental impact of energy utilization.

3.2.2. Independent Variable

The per capita stock of urban robots was calculated using the IFR data from the International Federation of Robotics and industrial enterprise data. Since the IFR data only contains the stock of industrial robots at the industry level in China, information at the city level cannot be directly obtained. A common practice in the references [48–50] adopts the Bartik instrumental variables method to calculate the per capita stock of industrial robots in cities (units per 100,000 people) as follows.

Stage 1: Baseline Employment Structure Calibration

Employing cross-sectional empirical data obtained from China's Second National Economic Census (2008) [51], the baseline employment share for sectors in city i is calculated as

$$l_{si}^{2008} = \frac{e^{employ_{si}^{2008}}}{employ_{i}^{2008}} \quad (2)$$

where $e^{employ_{si}^{2008}}$ denotes employment in sector s of city i in 2008, $employ_{i}^{2008}$ represents the total employment in city i, and ℓ_{si}^{2008} captures the pre-automation industrial composition.

Stage 2: Industry-Adjusted Penetration Rate

IFR robot stock data were merged with census data to compute the industry-level adjusted penetration rate (APR) anchored to the 2008 baseline:

$$APR_{st} = \frac{Robot_{st}}{employ_s^{2008}} \quad (3)$$

Here, $Robot_{st}$ is the IFR-reported robot stock in sector s during year t, and $employ_s^{2008}$ represents the national-level benchmark employment in sector s for 2008. This design ensures temporal exogeneity by fixing baseline employment weights.

Stage 3: City-Level Stock Aggregation

City-specific robot stock was synthesized through sectoral summation:

$$Robot_{it} = \sum_{s=1}^{s} l_{si}^{2008} \cdot APR_{st} \quad (4)$$

The final per capita robot stock (In $Robot_{it}$) was derived by normalizing the total stock with the city population and applying logarithmic transformation.

The application level of urban industrial robots in this study depends on two factors: one is the share in the industry employment structure, which is the proportion of the employed population in specific manufacturing industries from the total employed population in the city, and the weight of this indicator is positively correlated with the scale of industry employment; the other is the penetration rate of industry robots, which is represented by the number of robots per unit of employed population, and the higher the penetration rate, the more significant the technology diffusion effect. In terms of indicator construction, this study calculated the "stock density" and "installation density" of industrial robots using the stock of industrial robots and the installed volume of industrial robots, respectively. The density of industrial robots calculated based on the stock was used as the benchmark indicator, while the density of industrial robots calculated based on installed volume was used as the alternative indicator for robustness testing.

3.2.3. Control Variables

In empirical analysis, the following city-level control variables were selected because they may affect a city's energy efficiency. (1) Level of economic development (lnGdp): A city's economic development is often accompanied by a higher energy consumption output [30]; thus, we used per capita GDP to measure this. (2) Actual use of foreign capital amount (lnFdi): The actual use of foreign capital amount often has a positive impact on local economic construction, thereby driving the development of related industries and affecting energy consumption levels. It can be expressed as the actual amount of foreign capital utilized as a percentage of the GDP. (3) Industrial structure (lnIS): The proportion of added value in the secondary industry out of the total industrial added value reflects the industrial structure in the city. Industrial production tends to lead to higher energy consumption [52]. (4) Degree of government intervention (lnGov): This is represented by the ratio of government budget expenditure to budget revenue. Some scholars believe that an increase in government intervention leads to an increase in energy consumption intensity and a decrease in energy efficiency. (5) Educational level (lnEdu): This is represented by the number of university students per 10,000 people. (6) Population size (lnPop). We used the total population of prefecture-level cities at the end of the year to represent population size. Many scholars consider population size to be one of the important variables affecting energy consumption. Population growth promotes economic development and increases energy use, thus intensifying energy consumption.

3.3. Data Sources and Processing

The data on industrial robots came from the official database of the International Federation of Robotics (IFR), which provides annual increases in and stock numbers of industrial robots across 75 countries, covering the agricultural, manufacturing, and some service sectors. City-level energy classification data and city-level industrial data were taken from the "China Energy Statistics Yearbook" and the "China Industrial Statistics Yearbook." The data on the explained variables, control variables, and mechanism variables came from the "China City Statistics Yearbook," "China Energy Statistics Yearbook," "China Environmental Statistics Yearbook," Wind Database, China Customs Database, and national intellectual property patent database. The selected years were 2008 to 2019. Descriptive statistics for variables in the baseline regression are presented in Table 1, and definitions and sources for all variables are provided in Appendix A. The substantial maximum value of the logged robot stock (lnRobot) is indicative of the highly skewed distribution of robot adoption across Chinese cities. This reflects a reality where a small number of advanced industrial hubs or policy pilot cities have achieved exceptionally high robot densities, while the vast majority of cities exhibit significantly lower exposure. The logarithmic transformation mitigates the influence of these extreme values in the regression analysis, but their presence underscores the pronounced spatial disparity in technological diffusion.

Table 1. Descriptive statistics of main variables.

VarName	Obs	Mean	SD	Min	Median	Max
lnCCR	3384	0.436	0.088	0.255	0.428	0.690
lnRobot	3384	0.261	0.809	0.001	0.092	24.162
lnGdp	3384	15.328	1.205	11.805	15.174	19.504
lnEdu	3384	5.809	0.996	0.400	5.909	8.027
lnFdi	3384	11.674	2.035	3.057	11.807	16.835
lnPop	3384	4.660	0.779	2.779	4.587	7.816
lnGov	3384	2.800	0.449	0.704	2.787	5.603
lnIS	3384	0.024	0.027	0.000	0.015	0.261

4. Results

4.1. Baseline Regression Analysis

Column (1) of Table 2 quantifies the impact of industrial robots on energy efficiency. The results show that the coefficient of industrial robots was significantly positive at the 1% statistical level, confirming the direct impact of industrial robot application on urban energy efficiency. This means that industrial robots can not only improve energy efficiency in the production process through their unique features of precise control and efficient operation, but also accelerate the replacement and upgrading of traditional fossil energy with renewable energy, further promoting the low-carbon transformation of the energy structure in manufacturing. In summary, the widespread application of industrial robots at the urban level has a significant and positive promoting effect on improving urban energy efficiency.

Table 2. Baseline regressions, robustness, and endogeneity.

	(1)	(2)	(3)	(4)	(5)
	lnCCR	Installations	Lagging Quantity	Excluding Special Large Cities	Endogeneity Test
lnRobot	0.004 **	0.074 ***	0.006 ***	0.004 **	0.016 **
	(0.002)	(0.021)	(0.002)	(0.002)	(0.007)

Table 2. *Cont.*

	(1)	(2)	(3)	(4)	(5)
	lnCCR	**Installations**	**Lagging Quantity**	**Excluding Special Large Cities**	**Endogeneity Test**
lnGdp	0.045 ***	0.041 ***	0.046 ***	0.045 ***	0.063 ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.013)
lnEdu	−0.011 ***	−0.011 ***	−0.01 **	−0.011 ***	−0.012 ***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
lnFdi	0.000	0.001	0.001	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
lnPop	−0.054 ***	−0.052 ***	−0.056 ***	−0.054 ***	−0.063 ***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)
lnGov	−0.003	−0.001	−0.004	−0.003	−0.004
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
lnIS	0.641 ***	0.676 ***	0.584 ***	0.641 ***	0.662 ***
	(0.119)	(0.121)	(0.133)	(0.119)	(0.115)
constant	0.000	0.001	−0.029	−0.04	−0.244
	(0.154)	(0.105)	(0.109)	(0.100)	(0.154)
Observations	3168	3168	2904	3168	3168
R-squared	0.773	0.777	0.779	0.777	0.773
KP rk LM statistic	/	/	/	/	59.43
p-value	/	/	/	/	0.000
KP rk Wald F stat	/	/	/	/	62.73
Hansen J statistic	/	/	/	/	0.000
city fe	yes	yes	yes	yes	yes
year fe	yes	yes	yes	yes	yes

Note: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.2. Robustness Checks

4.2.1. Replacement of Independent Variable Measures

Per capita robot installation rather than per capita robot stock was used to analyze whether differences in the statistical scope of industrial robots could affect the estimation results. The results shown in column (2) of Table 2 indicate that the coefficient of per capita industrial robot installation remained positive at the 1% significance level. This suggests that under different measurement methods for the application level of industrial robots, the benchmark estimates remain robust, i.e., the application of industrial robots can significantly improve urban energy efficiency.

4.2.2. Lagged One-Period Regression Treatment

Considering that the processes of industrial robot installation, commissioning, and production process optimization require a certain amount of time, leading to a time delay in their energy efficiency effects, this study performed a regression treatment with a lag of one period for the core explanatory variable—the urban industrial robot application indicator. The results shown in column (3) of Table 2 indicate that after regressing with the lagged one-period explanatory variable data, the coefficient of the explanatory variable was significantly positive, confirming the robustness of the benchmark regression results.

4.2.3. Excluding Megacities

Due to the larger economic output and population size of municipal cities, their economic output and population size can even be several times those of ordinary prefecture-level cities. Therefore, after removing the sample data of the four municipal cities, a re-estimation of the remaining 270 cities was conducted, with the results shown in column (4) of Table 2. The regression results show that, when the four major municipal cities—Beijing, Tianjin, Shanghai, and Chongqing—were removed from the sample, the results remained largely consistent with the previously obtained ones. However, the reduction in the sample size of ultra-large cities did not change the regression coefficient signs.

4.3. Endogeneity Test

As the number of cities in China applying industrial robots continues to increase, regions with higher manufacturing energy consumption face greater pressure to improve energy efficiency. This encourages local governments to adopt measures such as optimizing factor allocation to incentivize enterprises to introduce industrial robot equipment, thereby enhancing efficiency in manufacturing production. Consequently, the manufacturing energy efficiency in a city can also influence the impact of industrial robots, potentially creating a reverse causal relationship between industrial robot adoption and manufacturing energy efficiency. If this is the case, then the core variable per capita robot stock (lnRobot) is likely to exhibit endogeneity issues, requiring the use of external instruments to mitigate them.

According to the research by [48–50], the number of robots in the different industrial sectors across Chinese cities, as a primary source of imports and employment, can be combined to measure robot penetration and used as an instrument variable for per capita robot stock (lnRobot). According to the theory of the technological gap and the principle of comparative advantage in international trade, cutting-edge technological innovation and production are highly concentrated in a few advanced economies with capital-intensive R&D. As a technological follower, the accessibility and import scale of China's industrial robots largely depend on the total supply capacity, technological level, and export policy of these source countries (United States, Japan, Germany, Sweden, and South Korea). The use of this variable can also meet the exclusive constraint conditions. We believe that the macroeconomic conditions of these developed economies have no direct correlation with the energy efficiency levels of China's manufacturing cities. Industrial robots affect energy efficiency through their own technological applications rather than through other competitive channels. In addition, instrumental variables belong to macro variables at the national level, far higher than the city level, making the possibility of reverse causality extremely low, thus ensuring the rationality of the exclusive constraint conditions.

Consistent with methodological conventions, the sectoral diffusion intensity of imported robotic technologies was quantified through the APRImports metric (anchoring the analysis to the 2008 baseline period) as per the standardized measurement framework formalized in Equation (5). According to Equation (6), APRImportst is multiplied by ℓ_{si}^{2008}, where ℓ_{si}^{2008} is calculated using Equation (2) to obtain the penetration of robots imported by Chinese city i from the five main source countries in year t.

$$\text{APR_Importst}_{st} = \frac{\text{Robot_Import}_{st}}{\text{employ}_{s}^{2008}} \tag{5}$$

$$\text{Robot_Import}_{it} = \sum_{s=1}^{s} \ell_{si}^{2008} \cdot \text{APR_Import}_{st} \tag{6}$$

The instrumental variable (IV) estimators were constructed through computational aggregation of mean diffusion intensities from the predominant source countries, operationalized via the econometric specification delineated in Equation (7), where the country codes US, JP, GE, SW, and KR correspond to the United States, Japan, Germany, Sweden, and the Republic of Korea, respectively.

$$\text{Robot_IV}_{it} = \frac{1}{5}\begin{pmatrix} \text{Robot_Import_US}_{it} + \text{Robot_Import_JP}_{it} + \\ \text{Robot_Import_GE}_{it} + \text{Robot_Import_S}_{it} + \\ \text{Robot_Import_KR}_{it} \end{pmatrix} \tag{7}$$

Column (5) of Table 2 presents the IV estimation results. In the first-stage estimation, the coefficient of the instrument variable was significantly positive at the 1% level, which is

consistent with theoretical expectations and similar to the empirical results based on U.S. data [48–50]. Compared to the fixed-effects estimation results in Table 2, the IV estimation yielded a higher absolute value for the coefficient of industrial robots, suggesting that the fixed-effects method may underestimate the inhibitory effect of industrial robots on urban energy efficiency in the presence of endogeneity issues. This also highlights the importance of using instrumental variables for estimation. However, it must be emphasized that even when considering endogeneity issues, and with the core findings of the study being robust, the promotion effect of industrial robots on urban energy efficiency remained significantly negative. In addition, to ensure the validity of the instrumental variable (IV) estimation results, this paper systematically reports the relevant diagnostic test statistics. As shown in column (5) of Table 2, the Kleibergen–Paap rk Wald F statistic was 62.73, far exceeding the critical value at the 10% bias level, indicating the absence of weak instrument problems and a strong statistical correlation between the instrumental variables and the endogenous variables. At the same time, the Kleibergen–Paap rk LM statistic was significant at the 1% level, further rejecting the null hypothesis of insufficient instrument identification. Additionally, the Hansen J statistic was 0.000, indicating that the selected instrumental variables satisfied the exogeneity condition. These diagnostic results collectively confirm the rationality of the instrumental variable setting in this study, ensuring the credibility of the subsequent estimation results.

4.4. Heterogeneity Analysis

4.4.1. Innovative Cities

Technological innovation is the fundamental driving force for high-quality development of the industrial economy. For example, the national innovative city pilot policy, which began in 2008, promotes the enhancement of urban innovation levels by increasing innovation investment, encouraging technology research and development and facilitating industrialization transformation. Theoretically, innovative cities possess abundant endowments of innovative elements, an active innovative atmosphere, and higher regulatory levels, which may provide favorable conditions for industrial robots to improve energy efficiency. However, the empirical results reported in columns (1) and (2) of Table 3 show that the role of industrial robots in improving energy efficiency was more significant in non-innovative cities. This counterintuitive finding suggests that the interaction between the application of industrial robots and the level of urban innovation may be more complex than a simple linear relationship. The reason may lie in the fact that innovative cities themselves have a higher technological foundation, and the improvement of their energy efficiency faces diminishing marginal benefits; conversely, in non-innovative cities, robots produce a more significant transformation effect by directly replacing outdated and high-energy-consuming manual processes.

Table 3. Heterogeneity regression results.

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative City = 0	**Innovative City = 1**	**Midwest**	**East**	**Student Enrolment in Colleges = 0**	**Student Enrolment in Colleges = 1**
lnRobot	0.005 ***	−0.068 ***	0.006 ***	−0.001	0.005 **	0.001
	(0.002)	(0.017)	(0.002)	(0.013)	(0.002)	(0.008)
lnGdp	0.048 ***	0.078 ***	0.052 ***	0.024	0.049 ***	0.045 ***
	(0.009)	(0.021)	(0.009)	(0.015)	(0.01)	(0.012)
lnEdu	−0.006	−0.079 ***	−0.008 *	−0.012	0.001	−0.036 ***
	(0.004)	(0.022)	(0.005)	(0.009)	(0.005)	(0.010)

Table 3. *Cont.*

Variable	(1)	(2)	(3)	(4)	(5)	(6)
	Innovative City = 0	**Innovative City = 1**	**Midwest**	**East**	**Student Enrolment in Colleges = 0**	**Student Enrolment in Colleges = 1**
lnFdi	0.000	0.001	−0.002	0.011 ***	−0.001	0.005 **
	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.002)
lnPop	−0.051 ***	−0.133 ***	−0.06 ***	−0.044 ***	−0.055 ***	−0.077 ***
	(0.008)	(0.028)	(0.009)	(0.015)	(0.011)	(0.013)
lnGov	−0.001	0.01	−0.001	−0.011 *	0.006	−0.013 ***
	(0.004)	(0.009)	(0.004)	(0.006)	(0.005)	(0.005)
lnIS	0.107	−0.386 **	1.101 ***	−0.017	0.672	0.463 ***
	(0.241)	(0.163)	(0.170)	(0.167)	(0.483)	(0.133)
constant	−0.102	0.213	−0.1	0.204	−0.143	0.46 **
	(0.110)	(0.396)	(0.122)	(0.200)	(0.132)	(0.183)
Observations	2731	437	2256	912	1584	1584
R-squared	0.774	0.890	0.779	0.760	0.768	0.818
city fe	yes	yes	yes	yes	yes	yes
year fe	yes	yes	yes	yes	yes	yes

Note: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.4.2. Geographically Differentiated Development

This study divided the samples from the eastern region and the central and western regions and then conducted regression analysis. The results are shown in columns (3) and (4) of Table 3. The results indicate that the promotion effect of industrial robot application on urban energy efficiency was significant in the central and western regions, but not significant in the eastern region. The possible reason is that the central and western regions themselves have a higher level of energy consumption compared to the eastern region, and they do not have advantages in terms of economic development level, industrial structure rationalization, and industrial foundation. Meanwhile, the spatial agglomeration generated by production scaling in the central and western regions has accelerated the consumption of fossil energy such as coal and oil, while the improvement in production efficiency has led to more energy use in heavily polluting industries. The popularization of industrial robots can drive local industrial upgrading of production technology and optimization of production capacity, thereby enhancing the energy efficiency optimization capability of the central and western regions. Therefore, the impact of industrial robots on energy efficiency in the central and western regions was greater.

4.4.3. Level of Human Capital

This study divided the sample into two groups based on the median number of on-campus students in colleges and universities, which represented high human capital and low human capital levels, and then conducted the regression analysis separately. The regression results are shown in columns (5) and (6) of Table 4. It can be observed that in cities with a high human capital level, the promotion effect of industrial robot application on urban energy efficiency was significantly stronger than in cities with a low human capital level. This indicates that a high level of human capital strongly supports the application of industrial robots in cities, greatly enhancing urban energy efficiency. This result is not difficult to understand. Labor with a higher level of education or highly skilled labor can quickly master modern information technology and skillfully apply it in practice. Therefore, in a city with a high human capital level, it is easier to carry out the corresponding construction work, and the effects on energy efficiency transformation and improvements in the city are also more pronounced.

Table 4. Mechanistic analysis.

	Scale Effects		Structural Effects		Green Technology Effects	
Variable	**(1)** **lnCapsto**	**(2)** **lnIov**	**(3)** **lnEcs**	**(4)** **lnAis**	**(5)** **lnGrepap**	**(6)** **lnGrepau**
lnRobot	0.012 *	0.052 ***	0.009 *	0.041 **	0.182 ***	0.17 ***
	(0.007)	(0.014)	(0.005)	(0.018)	(0.045)	(0.044)
lnGdp	0.256 ***	0.865 ***	−0.008	−0.624 ***	0.537 ***	0.519 ***
	(0.028)	(0.071)	(0.016)	(0.047)	(0.069)	(0.069)
lnEdu	0.018	0.047	−0.015 **	−0.064 ***	0.282 ***	0.143 ***
	(0.017)	(0.029)	(0.008)	(0.018)	(0.052)	(0.051)
lnFdi	0.043 ***	0.063 ***	0.004	−0.002	0.037 ***	0.034 **
	(0.004)	(0.009)	(0.002)	(0.005)	(0.014)	(0.014)
lnPop	−0.153 ***	−0.389 ***	0.036 **	0.195 ***	0.256 ***	0.033
	(0.030)	(0.062)	(0.017)	(0.042)	(0.082)	(0.081)
lnGov	−0.004	0.139 ***	0.003	−0.020	0.132 ***	0.114 ***
	(0.012)	(0.027)	(0.008)	(0.016)	(0.036)	(0.037)
lnIS	−1.395 ***	1.325	−0.262	−3.806 ***	5.009 ***	3.886 ***
	(0.361)	(0.894)	(0.267)	(0.397)	(0.869)	(0.795)
constant	11.378 ***	2.516 ***	0.080	7.703 ***	−9.673 ***	−7.506 ***
	(0.352)	(0.880)	(0.205)	(0.565)	(0.923)	(0.887)
Observations	3163	2348	3108	3166	2112	2112
R-squared	0.981	0.976	0.572	0.889	0.954	0.958
city fe	yes	yes	yes	yes	yes	yes
Year fe	yes	yes	yes	yes	yes	yes

Note: Standard errors are in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

4.5. Analysis of Mechanisms

4.5.1. Scale Effect Test

The theoretical analysis in the preceding text indicates that the expansion of a city's economic scale and industrial scale helps the city apply more industrial robots, and through investment in these intelligent devices, industrial robots enhance energy efficiency, thereby creating a favorable external environment for urban efficiency optimization. This study employed regression analysis using capital stock (lnCapsto) to measure the urban economic scale and location entropy of the total industrial output value in each region (lnIov) to measure the industrial scale. The results, shown in columns (1) and (2) of Table 4, show that the estimated regression coefficients were significantly positive at the 1% level. This means that industrial robots significantly promoted the growth of a city's economic volume and the expansion of its industrial scale, further driving more rapid expansion of the comprehensive scale, thereby accelerating the positive promotion of urban energy efficiency.

4.5.2. Structural Effects

Considering that the energy consumption of industrial robots primarily stems from the consumption of pollution-intensive energy, this study represented the energy consumption structure using the proportion of clean energy consumption out of the total energy consumption (lnEcs) and represented the quality structure as the upgrading of the industrial structure (lnAis). Based on the data in columns (5) and (6) of Table 4, the application of industrial robots significantly optimized the urban energy structure. This specifically manifested in the strengthening of the reliance on clean energy and enhancing the industrial structure. By optimizing the energy supply structure and improving the quality of economic output, industrial robots can consume less energy under the same energy supply demand and under the same economic output conditions through adjustments in the energy supply structure, thereby achieving the goal of improving urban energy efficiency.

4.5.3. Green Technology Effect

The increase in investment in technological innovation and the continuous emergence of outcomes accelerate the progress of production technology, thereby optimizing the performance and precision of industrial robots. This study used the volume of green patent applications (lnGrepap) and the volume of green patents granted (lnGrepau) to characterize the technological effect of cities. The regression results are shown in columns (3) and (4) of Table 4. The estimated coefficients of industrial robots for both types of green patent indicators were significantly positive at the 1% level. It can be seen that green technology often has a higher energy efficiency ratio and environmental friendliness. Industrial robots can accelerate the breakthrough and application iteration upgrade of technological research and development through the accumulation and transformation of green technology outcomes, effectively improving urban energy efficiency.

5. Discussion

5.1. Conclusions

Against the backdrop of the ever-increasing energy demand and increasingly stringent environmental constraints, in-depth research on the role and mechanism of industrial robots in enhancing urban energy efficiency is of great theoretical and practical significance for China in promoting intelligent manufacturing and achieving green and low-carbon transformation. Inspired by the studies by [53,54] on the enhancement of energy efficiency through market-type environmental regulation and [55–57] on the research of environmental regulation and green total factor energy efficiency, and based on the discussions of [58–60] on artificial intelligence and industrial development, this study used panel data from 283 prefecture-level cities in China from 2008 to 2019, adopting a two-way fixed-effects model and the instrumental variable method to systematically evaluate the impact of industrial robot applications on urban energy efficiency. The empirical results show that the promotion of industrial robots significantly improved urban energy efficiency, and this conclusion remained valid after a series of robustness tests including variable replacement, sample adjustment, and endogeneity treatment. This finding indicates that in the context of the global shift towards intelligent transformation, industrial robots, with their own technical empowerment attributes, have become a key force in promoting energy conservation and efficiency improvement in urban economic systems, injecting new vitality into the urban kinetic transformation [61,62].

The mechanism analysis shows that industrial robots had a positive impact on urban energy efficiency through scale effects, structural effects, and green technology effects, with the contribution of the technological effect being relatively larger and the contribution of the structural effect being relatively smaller. A large number of studies have shown that the integrated applications brought by industrial robots have a positive impact on the productivity of the manufacturing industry [63]. Inspired by these studies, we confirmed the scale effect of industrial robot applications. In addition, consistent with the research of [64–66], we found that industrial robots have structural effects. This study also found that the popularization of industrial robots will force the city to adjust the industrial structure and optimize the industrial energy consumption structure, and thus achieve a low-carbon transformation of the manufacturing industry. Furthermore, industrial robots were shown to have green technology effects based on the findings of [67–71], which showed that technological progress is fundamental to efficiency improvement. This study further indicates that industrial robots can directly promote the innovation and adoption of green production processes through technological innovation and act on the entire production process, thereby effectively enhancing the level of innovation and environmental efficiency, and have become an important channel for promoting energy efficiency.

Consistent with the conclusion by [72] that the application of technology exhibits regional heterogeneity, the heterogeneity analysis of this study further showed that the energy efficiency improvement effect of industrial robots was more significant in innovative pilot cities, cities with high levels of human capital, and the central and western regions, while in the technologically saturated eastern coastal areas, there was a trend of diminishing marginal returns. This finding also resonates with the research by [73,74] on the efficiency boundary of robot applications.

This study not only provides empirical evidence for the enhancement of China's industrial dynamism from the perspective of industrial robot applications, but also offers references for the formulation of relevant policies.

5.2. Policy Recommendations

Based on data at the city level in China, this study examined the importance of industrial robots for urban energy efficiency and provides reference experiences for other countries in similar stages of industrial transformation. To better promote the construction of low-consumption, green cities and enhance the positive role of industrial robots in energy consumption, the following policy recommendations are proposed.

(1) Promote the use of industrial robots to enhance urban energy efficiency. The application of industrial robots has a reinforcing effect on improving cities' energy efficiency and the development of green competitiveness. Cities should attach importance to the investment and application of industrial robots to help them achieve efficiency improvements and energy-saving goals.

(2) Focus on promoting the application of industrial robots in the central and western regions and traditional industries. This study found that there was a huge "latecomer advantage" and "transformation dividend" in the optimization of energy efficiency in the central and western regions. Therefore, policy resources should be primarily allocated to the central and western regions, encouraging local enterprises, especially traditional manufacturing industries with high energy consumption and low automation levels, to prioritize the introduction and deployment of industrial robots. At the same time, the developed eastern coastal regions should be encouraged to utilize their advanced experience, build cross-regional technology collaboration and transfer platforms, and export mature robot application solutions, energy management experiences, and talent training systems to the central and western regions.

(3) Encourage the deep integration of robot technology with energy-saving and efficiency-improving technologies. Policies should establish special research and development funds to encourage cooperation between robot manufacturers, universities, and research institutions. They should focus on breaking through the key links of energy-saving and consumption reduction, improving energy utilization efficiency and production efficiency, enhancing the role of industrial robots in reducing the energy consumption per unit of output and promoting the green development of the robot industry itself.

(4) Cultivate a high-skilled workforce that matches the application of robots. Highly skilled labor is the "catalyst" for releasing the energy-saving potential of robots. On one hand, through educational reform, vocational colleges and universities should be encouraged to offer interdisciplinary majors such as intelligent manufacturing to cultivate talents with both operational skills and energy-saving awareness. On the other hand, subsidies should be provided for skills training for intelligent equipment for workers in traditional manufacturing industries; reducing the human cost of urban transformation; and preventing structural unemployment during the process of technological upgrading.

This study still has some limitations. Firstly, this study only assumed a linear relationship between industrial robots and urban energy efficiency. Theoretically, the application of

industrial robots is accompanied by high initial investment and learning costs. In the initial stage of application, their energy consumption may precede efficiency improvements. Only after the scale of application crosses a certain threshold will the scale effect and technological spillover effect of efficiency improvement and energy reduction dominate. Therefore, future research can test the possible nonlinear dynamic processes. Secondly, the time scope of this study ended in 2019, and it did not cover the latest development trends in industrial robots and their potential impact on energy efficiency. Subsequent research can further explore whether and how more intelligent robot technology brings additional intelligent dividends by extending the observation window.

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Appendix A

Table A1. Variable definition and data source.

Index Code	Variable	Definition	Data Source	Reference
Dependent variable				
lnCCR	Total factor energy efficiency	The measurement was performed using the ultra-efficient CCR-DEA model	China Urban Statistical Yearbook, China Industrial Statistical Yearbook, China Environmental Statistical Yearbook, China Energy Statistical Yearbook	[29]
Independent variable				
lnRobot	Industrial robot penetration rate	Municipal per capita robot stock (per 100 people)	China Customs Database, Official Database of International Federation of Robotics (IFR)	[24]
Control variable				
lnGdp	Level of economic development	Per capita GDP	China Urban Statistical Yearbook	[67]
lnEdu	Educational status, education, or training received	The number of college students per 10,000 people	China Urban Statistical Yearbook	[56]
lnFdi	Actual use of foreign capital	The proportion of foreign capital actually used in GPT	China Urban Statistical Yearbook	[43]
lnPop	Population size	Total population of prefecture-level cities at the end of the year	China Urban Statistical Yearbook	[43]
lnGov	Extent of Government Intervention	Ratio of government budget expenditure to budget revenue	China Urban Statistical Yearbook	[45]
lnIS	Industrial structure	The proportion of added value of the secondary industry out of the total industrial added value	China Urban Statistical Yearbook, China Industrial Statistical Yearbook, Wind Database	[24]

Table A1. *Cont.*

Index Code	Variable	Definition	Data Source	Reference
Mechanism variable				
lnCapsto	Economies of scale	Stock of capital	China Urban Statistical Yearbook	[42]
lnIov	Industrial scale	Location entropy of total industrial output value in each region	China Urban Statistical Yearbook, China Industrial Statistical Yearbook	[33]
lnEcs	Energy structure	The proportion of clean energy consumption out of the total energy consumption	China Energy Statistical Yearbook, China Environmental Statistical Yearbook	[45,51]
lnAis	Quality structure	Upgrading of industrial structure	China Industrial Statistical Yearbook, China Urban Statistical Yearbook, Wind Database	[55]
lnGrepap	Number of green innovations	Green patent applications	China Urban Statistical Yearbook, National Intellectual Property Patent Database	[56]
lnGrepau	Quality of green innovation	Green patent authorization	China Urban Statistical Yearbook, National Intellectual Property Patent Database	[56]
Instrumental variable				
Five countries import	Five countries' import of industrial robots	Computational aggregation of mean diffusion intensities from the predominant source countries	China Customs Database	[58]

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