ASSESSING THE REGIONAL IMPACT OF INDUSTRIAL ROBOT ADOPTION ON GREEN PRODUCTIVITY

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ABSTRACT

This study investigates the spatial effects of industrial robot adoption on green total factor productivity (GTFP) across 30 provinces in mainland China from 2013 to 2019, using a panel spatial Durbin model (PSDM). Drawing on data from national statistical yearbooks and customs databases, the analysis incorporates key control variables including trade openness, R&D intensity, energy structure, human capital, and industrial structure. The results reveal that robot density significantly improves GTFP both within provinces and through spatial spillovers to neighboring regions, underscoring the regional interdependence of technological progress. R&D intensity and clean energy use are found to have positive effects, while trade openness is negatively associated with GTFP, indicating potential environmental trade-offs in export-led growth. The study contributes to the literature on automation, spatial economics, and sustainable development by highlighting how industrial robot deployment can support regional green transformation. Policy implications include the promotion of coordinated robotics adoption, innovation collaboration, and energy restructuring to enhance sustainable productivity across spatially connected economies.

Keywords: Industrial Robots, Green Total Factor Productivity, Spatial Spillover Effects, Panel Spatial Durbin Model, Sustainable Development.

1. INTRODUCTION

Robots are essential for raising living standards and productivity. The majority of robot adoption to date has taken place in manufacturing, where machines are made to carry out a wide range of manual jobs more reliably and efficiently than people. The usage of robots is expanding into numerous other industries, such as logistics, hospitality, and agriculture, thanks to ongoing innovation. As a result, businesses everywhere are implementing robots. The International Federation of Robotics reports that the average number of industrial robots per 10,000 manufacturing workers around the globe increased from 66 in 2015 to 85 in 2017. With 710 robots per 10,000 workers, Korea is the largest adopter in the world; the US comes in seventh with 200 robots. The number of robots per 10,000 workers is displayed in Figure 1. According to the IFR, global robot installations will rise by 27% in 2022, surpassing the 2021 record figure. In 2022, 486,800 units were installed worldwide, setting a new record and a 27% increase over 2021. Demand increased most in Asia/Australia, where installations increased 33% to 354,500 units. Sales in the Americas climbed by 27% to 49,400 units. With 78,000 units deployed, double-digit growth of 15% was observed in Europe.

Automation is based on robotics and control systems. Asia is a global leader in robotics, with 1 million robots in operation in 2018, according to the International Monetary Fund (IMF). Global leaders in robots and automation include the United States, Belgium, Luxembourg, Singapore, South Korea, Japan, Germany, Sweden, Denmark, and Hong Kong. With 918 robots per 10,000 workers in the electronics sector, Singapore has the greatest robot density in 2019, according to the International Federation of Robotics (IFR). Second place went to South Korea (868 units per 10,000 employees), Japan (365 units), and Germany (346 units). In 2018, there were 140 robots per 10,000 workers in China's manufacturing industry.

With 45% of the world's supply, Japan leads the world in robot manufacture. Robots are used in many industries, including manufacturing, processing, food and beverage, healthcare, and agriculture, to easily and conveniently do time-consuming and important jobs. The use of medical robots in the healthcare sector is growing. Benefits of advanced surgical robotics include less pain and discomfort and a shorter recovery period following procedures. For assembly line tasks including welding, painting, assembling, picking and placing, packaging and labeling, and product inspection, the automobile sector uses industrial robots.

A number of trends become apparent when comparing the rankings of anticipated and actual robot adoption rates. The first is that East Asian countries are the world's top adopters of robots on a wage-adjusted basis, holding six of the top seven spots: Korea is at the top, followed by Singapore, China, Thailand, and Taiwan (see figure 2). Only Slovenia and the Czech Republic are adopting at a higher rate than anticipated given wage levels, making Europe a laggard overall. With adoption rates 49% lower than anticipated and a rating of 16th, the US is far behind, especially considering its higher pay levels.

There are many trends that show up when comparing the rankings of projected and actual robot adoption rates. The first is that East Asian countries make up six of the top seven countries in the world in terms of robot adoption on a wage-adjusted basis: Korea is at the top, followed by Singapore, China, Thailand, and Taiwan. (Refer to Figure 2.) With only Slovenia and the Czech Republic adopting at a faster rate than anticipated given pay levels, Europe is generally lagging behind. With adoption rates 49% lower than anticipated, the United States is well behind, ranking 16th, despite having higher pay levels.

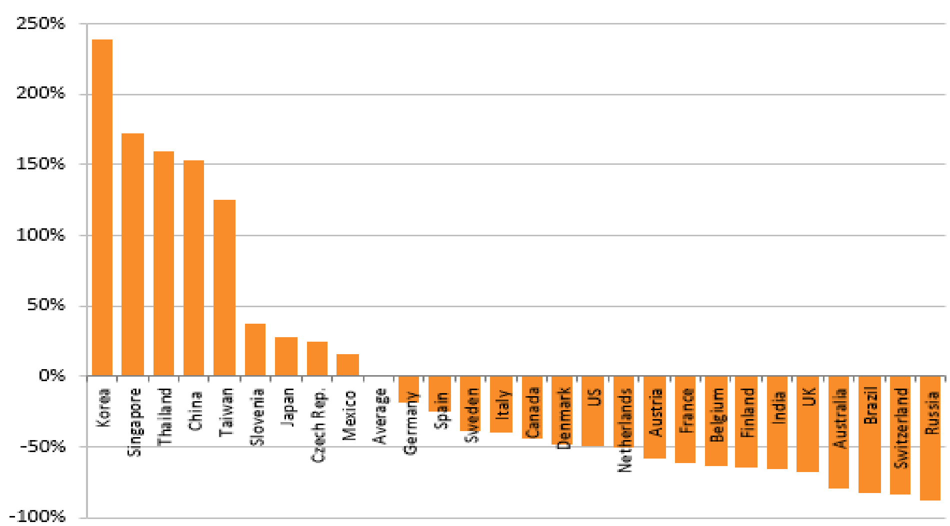

FIGURE 1
ROBOTS PER 10,000 WORKERS

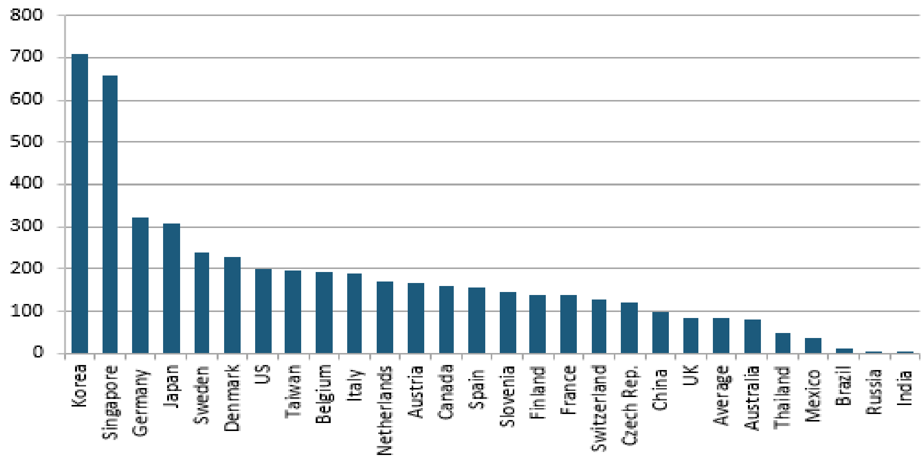

FIGURE 2
ACTUAL ROBOT ADOPTION RATE AS A SHARE OF EXPECTED ROBOT ADOPTION RATE

In 2021, China imported $2204 million worth of industrial robots, while exports were about US$593 million. This represents just about 27% of the whole sum of the amounts of these eight types' import value, according to Chinese customs records. Strong domestic demand, especially for high-end industrial robots, is indicated by this significant import value proportion. Robot is measured using the number of imported industrial robots from the China Customs database (HS8 code).

The main factors influencing imports are handling and multipurpose robots; the other six categories make up a lesser portion and do not show any clear trends of change. Rtotalt shows a varying increase tendency overall, increasing from 40,914 units in 2012 to 145,106 units in 2021. With 182,767 units, the biggest peak was recorded in 2017. The rapid development of industrial intelligence and modernization in China in recent years has been closely connected to the rise in imported robots (Acemoglu et al., 2020; Fan et al., 2021). At the federal level, the quantity of imports from each province varies significantly. With over 20,000 units in 2012 and close to 80,000 units in 2021, Shanghai keeps its dominant position and accounts for half of all imports into the country. Second, the map's color gradient shows a significant geographical disparity as it progressively moves from light to dark and from west to east. Imports of industrial robots are primarily concentrated in the eastern provinces, including Beijing, Guangdong, and Shanghai, whereas the central and western regions import less overall.

More capital-, knowledge-, and technology-intensive items are produced in the eastern coastal provinces due to their advanced industrial structures and comparatively high levels of economic and manufacturing development. Because of this, there is a bigger need for industrial robots, they are more affordable to buy, and as a result, there are more imports. Even though they began at a lower point, the central and western areas are also continuously developing, with Hubei Province showing particularly strong growth. The remainder of this paper is organized as follows. Section 2 reviews literature on robot adoption and its economic impacts, with emphasis on productivity, employment, and technological diffusion. Section 3 presents a detailed analysis of the methodology. Section 4 explores the results. Finally, Section 5 offers conclusions and recommendations with implications for future research in robotics and automation.

2. LITERATURE

The importance of industrial robots in increasing worker productivity and total factor productivity (TFP) has been generally supported by prior research (Acemoglu et al., 2020; Acemoglu and Restrepo, 2019; Graetz and Michaels, 2018; Kromann et al., 2011). The use of industrial robots boosts labor productivity by facilitating more effective material utilizations with less worker input by expediting setup, production, and inspection procedures and extending productive time (Tilley, 2017). For instance, industrial robots increase labor productivity and earnings while reducing employment possibilities for low-skilled individuals across many industries and nations, according to Graetz and Michaels (2018). Kromann et al. (2020) projected that a one-standard-deviation increase in robot intensity was associated with a TFP increase of more than 6% based on industry-level data from nine different nations. Similarly, Koch et al. (2021) used data from Spanish manufacturing companies from 1990 to 2016 and discovered that robots increase productivity. They also observed that exports and robots work in tandem to increase production.

According to Du and Lin (2022), there is a "U-shaped" link between the density of industrial robot installations and TFP, with complimentary effects and labor replacement appearing as robot density rises. TFP growth can be facilitated by labor cost savings and better alignment between technical expertise and industrial robots. Nonetheless, some academics, such as Gordon (2014), contend that emerging technology, including robotics, have little potential to boost productivity across the economy. A large amount of research has been done recently on how industrial robots affect green total factor productivity. Economic growth based on resource conservation and environmental preservation is reflected in GTFP, which integrates unwanted outputs like carbon dioxide emissions into industrial technology (Zhang et al., 2021). By taking into account both desired (like products and services) and undesirable (like environmental pollution) outputs, GTFP expands on the idea of TFP. In particular, GTFP assesses the proportional shifts in the intended outputs (like goods or services) and undesirable outputs (like emissions of pollutants) produced for every unit of input (Tian and Feng, 2022). For a given level of inputs, improving GTFP entails either increasing desired outputs or decreasing undesirable outputs (like pollution) or reaching the same level of outputs with fewer inputs and less environmental effect. As the world's attention turns to sustainable development, energy conservation, and emission reduction, it is now vital to study the factors influencing GTFP growth and potential avenues for green development (Albrizio et al., 2017).

Nonetheless, there is still a dearth of study on how the use of industrial robots affects green production. The literature currently in publication primarily confirms that the adoption of industrial robots contributes positively to the expansion of GTFP (Chen and Golley, 2014; Qiu et al., 2021; Tian, 2022; Xie et al., 2017; Yan et al., 2020). The use of industrial robots, for example, has been shown by Zhang et al. (2022a) to greatly increase green productivity through increased energy efficiency, scale merit, and favorable market selection effects, all of which raise GTFP. Energy and pollution reduction, green technology improvements, industrial structure optimization, and human capital benefits are the primary ways that industrial robots contribute to GTFP growth. Furthermore, a substantial "Ushaped" association between industrial robot adoption and GTFP was found by certain scholars. For example, the influence of industrial robots changed from being inhibitive to enabling in 2018 when their number in each province surpassed the U-shaped apex (Zhang et al., 2022a).

As stated by Yigitcanlar et al. (2021), Artificial intelligence (AI) and smart cities have been popular issues in urban policy circles, but implementing AI to increase municipal efficiencies has been challenging, primarily due to reductionist thinking that has prevented people from seeing the whole picture. In order to attain efficiency, sustainability, and equality, the smart city framework necessitated an environmentally friendly AI strategy. This viewpoint paper highlights the primary issues with existing AI theory and suggests a unified approach to green AI in order to ease the transition to smart cities (Gozgor et al., 2020). The results of research on the expansion of clean energy and green finance typically have significant ramifications for achieving long-term financial development and systemic change in the energy sector.

An interaction degree of collaboration framework was developed by Zhao et al. (2023) for the system to explore possible synergies between renewable energy and green finance. Although the relationships between the variables influencing coupling coordination are not well understood, a fuzzy set qualitative comparative analysis (fsQCA) method was developed to examine different alignment techniques. The pair's coordination degree rose from 0.3341 in 2011 to 0.4718 in 2020, according to Chinese empirical data, although it stayed almost unbalanced. A propensity for high-value clustering surfaced as regional coordination levels expanded unevenly. According to the report, provinces should modify their policies to reflect the unique features and configurations of their local areas in order to promote the coordinated growth of clean energy and green financing. The fsQCA approach provided a fresh perspective on current avenues to gain a deeper understanding of the collaborative growth of clean energy and green financial services in China's provinces. The findings improve our comprehension of the intertwined rise of clean energy and green finance while illuminating the need for provincially tailored laws.

As the demand for corporate involvement in sustainable development grows worldwide, banking institutions are beginning to recognize the need to adapt their business models to be more environmentally conscious (Cesário et al., 2022). The concept of green finance emerged as a result of this truth being acknowledged. The term "green finance" still lacks a universally accepted meaning, despite significant advancements over several years (Khan et al., 2022b). Unlike traditional finance, green finance is distinguished by its use of financial innovation to promote environmental protection. It is claimed that green finance is a type of financial tool that helps businesses address environmental issues and promote environmental conservation in society.

It is impossible to overestimate the significance of clean energy in promoting ecologically friendly growth and drawing capital to sustainable finance (Wang et al., 2021). The vast bulk of recent research examines the relationship between renewable energy and green finance. Numerous criteria are included in this evaluation, such as cost correlations (Hammoudeh et al., 2020; Tiwari et al., 2022), capital (Zhang, 2022), availability (Wang et al., 2022), and consumption (Liu & Tang, 2022). The vast majority of research on this topic has demonstrated that green banking has numerous benefits for promoting sustainable energy in a number of areas. In the context of green finance, several scholars have examined the importance of clean energy in greater detail. In order to demonstrate a one-way causal relationship between energy investment and green funding over a given time period, Nawaz et al. (2021) and Bei & Wang (2023) separately employed wavelet coherence techniques.

Khan et al. (2022a) examined the phenomenon of economic globalization in 30 OECD countries from 1975 to 2015. These requirements must be fulfilled by both rich and developing nations, including members of the Organization for Economic Cooperation and Development (OECD) (Iram et al., 2020; Mohsin et al., 2019, 2018). Carbon pricing and green bonds must be embraced and implemented in order to move toward a low-carbon economy and effectively mitigate the effects of climate change, claim Heine et al. (2019). According to official records, Tolliver et al. (2020) found that national finances (NDCs) had a substantial impact on how green bond earnings were distributed to clean energy between 2008 and 2017. According to their article, when strict nationally mandated contributions (NDCs) are implemented, renewable energy assets and projects receive a bigger part of bond proceeds—exactly 99%.

Yuan and Gallagher's 2018 study focused on the Americas' sustainable economy. The $110 billion yearly imbalance that multilateral development banks (MDBs) are currently exposing must be addressed, they stressed. According to them, the green economy has received $7 billion from multilateral development banks (MDBs), with $4.4 billion of that amount going directly toward mitigating the effects of climate change in these sectors. Furthermore, their research indicates that MDBs may provide more funding for environmental policies in nations with better human rights records and post-socialist ideologies (Yuan & Gallagher, 2018). According to a recent study by Sinha et al. (2020), N-11 countries' incapacity to maintain environmental sustainability presented difficulties for their attempts to meet the SDGs. Furthermore, economic expansion has come at the expense of the environment in the N11 countries.

3. METHODOLOGY

3.1 Data

A panel dataset containing metrics for 30 provinces in mainland China from 2013 to 2019 was generated for this study. Tibet and data collected after 2019 were excluded due to data restrictions. The EPS Database and China's customs database were used to collect statistics on imports of industrial robots. China Statistical Yearbook, China Labor Statistical Yearbook, China Population and Employment Statistical Yearbook, China Energy Statistical Yearbook, China Industry Statistical Yearbook, and the Wind Database were the sources of the control variables and primary data needed to calculate the LPI.

3.2 Methods

This study employs a spatial econometric approach to examine the impact of industrial robot adoption on green total factor productivity (GTFP) across 30 provinces in mainland China from 2013 to 2019. Given the possibility of spatial interactions in economic and technological variables across provinces traditional panel data models may yield biased or incomplete results. To account for these spatial dependencies, the Panel Spatial Durbin Model (PSDM) is utilized, which not only captures the direct effects of robot deployment within a province but also quantifies spillover effects from neighboring provinces. The use of PSDM is consistent with recent literature that emphasizes the importance of spatial externalities in regional innovation and environmental productivity analyses (Dong et al., 2020; Du & Lin, 2022). In accordance with Yan et al. (2020), Du and Lin (2022), and Zhang et al. (2022a, b), as shown in Table 1, this study incorporates the control variables.

The baseline specification of the PSDM is formulated as follows:

$$\mathrm{GTFP}_{it} = \rho W \mathrm{GTFP}_{it} + \beta_1 \mathrm{ROBT}_{it} + \beta_2 X_{it} + \theta_1 W \mathrm{ROBT}_{it} + \theta_2 W X_{it} + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

Where GTFP_{it} denotes the green total factor productivity of province *i* at time *t*, ROBT_{it} is the density of industrial robot adoption, and X_{it} represents a vector of control variables including trade openness (OPEN), R&D intensity (RNDI), energy structure (ENER), labor quality (LABR), and industrial structure (INDS). W is a spatial weight matrix based on geographical adjacency, where provinces sharing borders are considered neighbors. The term ρ captures the spatial autoregressive coefficient, while θ_1 and θ_2 represent the spatial spillover effects of the robot density and control variables, respectively. μ_i and λ_t are province and year fixed effects, included to control for unobserved time-invariant heterogeneity and common temporal shocks. ε_{it} is the idiosyncratic error term.

The spatial weight matrix W is row-standardized to ensure comparability across provinces and to reflect the influence of spatial adjacency. All continuous variables are standardized, and robust standard errors are clustered at the provincial level to account for potential heteroskedasticity and autocorrelation. Following the estimation, the model decomposes the total effects of robot deployment into direct effects (impacts within the same province) and indirect effects (impacts transmitted to neighboring provinces), in line with the spatial spillover framework proposed in the literature (Elhorst, 2014; LeSage & Pace, 2009).

Table 1. Variable Descriptions

Variable	Symbol	Description	Source	Reference
Green Total Factor Productivity	GTFP	Logarithmic indicator of green total factor productivity, capturing environmental efficiency in production	China Statistical Yearbook, China Energy Statistical Yearbook	Du & Lin (2022); Zhang et al. (2022a)
Industrial Robot Density	ROBT	Number of imported industrial robots per 10,000 workers in the manufacturing sector	EPS Database, China Customs Database	Yan et al. (2020); Dong et al. (2020)
Openness Degree	OPEN	Ratio of total imports and exports to GDP, reflecting regional economic	China Statistical Yearbook	Zhang et al.

Variable	Symbol	Description	Source	Reference
		openness		(2022b)
R&D Intensity	RNDI	R&D expenditure as a share of regional GDP, indicating innovation capacity	China Industry Statistical Yearbook	Du & Lin (2022); Zhang et al. (2022a)
Energy Consumption Structure	ENER	Share of clean energy consumption in total energy use	China Energy Statistical Yearbook	Zhang et al. (2022b)
Human Labor Input	LABR	Share of labor force with tertiary education, representing labor quality	China Labor Statistical Yearbook; China Population and Employment Statistical Yearbook	Yan et al. (2020); Du & Lin (2022)
Industrial Structure	INDS	Share of the secondary industry in GDP, reflecting the economic structural composition	China Statistical Yearbook	Zhang et al. (2022a); Du & Lin (2022)
Spatial Lag of IR Density	Wx(IR)	Weighted average of neighboring provinces' IR density, used to capture spatial spillovers	Author's calculation using spatial weight matrix	Dong et al. (2020); Du & Lin (2022)
Spatial Rho	ρ	Spatial autoregressive coefficient indicating spatial dependence in the error term	Model output	Dong et al. (2020)
Error Variance	σ^2_e	Residual variance from the spatial panel model	Model output	Standard spatial econometric practice

4. RESULTS AND IMPLICATIONS

4.1 Results

The descriptive statistics and correlation matrix presented in Table 2 provide valuable insights into the characteristics and relationships among the key variables used in analyzing the spatial effects of industrial robot adoption on green total factor productivity (GTFP) in Chinese provinces between 2013 and 2019. From Panel A, we observe that GTFP has a mean value of 0.081 with a standard deviation of 0.111, indicating moderate variability across provinces. Its range, from −0.225 to 0.540, suggests that some regions experience negative productivity growth, possibly due to inefficient industrial practices or lagging green innovation efforts (Wang et al., 2023). ROBT (robot density) has a relatively low mean (0.001) and maximum value (0.044), confirming the early-stage nature of robot deployment in many regions, consistent with recent findings on uneven automation adoption in China (Zhou et al., 2022).

OPEN (trade openness) shows a wide range (0.013 to 1.257), reflecting substantial inter-provincial variation in export and import intensities. This variation aligns with the regional economic diversity of China, where coastal provinces are more engaged in global trade networks than inland areas (Liu & Zhang, 2021). RNDI (R&D intensity) displays relatively low dispersion, which may indicate uniformly limited R&D investment across provinces, a concern also raised by Li et al. (2020) in their study of regional innovation disparities. The ENER (energy structure index) reveals a mean of 0.951 and a maximum of 2.461, suggesting significant variation in the degree of clean versus fossil energy usage. High variability indicates room for energy transition policies to enhance GTFP through cleaner energy portfolios, as highlighted by Chen and Xu (2024). LABR (human capital) and INDS (industrial structure) also show moderate variation, suggesting differences in educational attainment and sectoral composition that may influence green productivity outcomes.

Panel B's correlation matrix provides preliminary evidence of the interrelations among variables. Notably, ROBT is positively correlated with GTFP (0.337), supporting the premise that higher robot adoption may drive green productivity improvements (Tang et al., 2021). RNDI also correlates positively with both ROBT (0.728) and GTFP, indicating that provinces investing more in R&D tend to adopt more automation and potentially achieve better green outcomes (Zhang & Liu, 2020). In contrast, ENER shows a negative correlation with ROBT (−0.386) and GTFP (−0.478), reinforcing the argument that fossil fuel reliance hampers sustainable productivity. This finding aligns with evidence that energy transition is critical for green development (Huang et al., 2022). Additionally, LABR is positively associated with GTFP and ROBT, suggesting that more educated labor forces may better absorb and benefit from robotic technologies (Sun et al., 2025). Finally, INDS is negatively correlated with both LABR and GTFP, implying that an overreliance on heavy or traditional industry may detract from green productivity, in line with the industrial upgrading argument in the green economy literature (Du & Lin, 2022). Overall, the descriptive patterns underscore the complex interactions among technological, structural, and energy-related factors in shaping green productivity, warranting a spatially nuanced policy approach to automation and sustainability in China.

Table 2. Descriptive Information

Variable	**GTFP**	**ROBT**	**OPEN**	**RNDI**	**ENER**	**LABR**	**INDS**
Panel A: Summary Statistics							
Obs	203	203	203	203	203	203	203
Mean	0.081	0.001	0.237	0.030	0.951	0.140	0.406
Std. Dev.	0.111	0.004	0.232	0.015	0.471	0.070	0.076
Min	−0.225	0	0.013	0.007	0.025	0.068	0.160
Max	0.540	0.044	1.257	0.067	2.461	0.505	0.558
Panel B: Correlation Matrix							
ROBT		1.000					
OPEN		0.363	1.000				
RNDI		0.337	0.728	1.000			
ENER		−0.478	−0.386	1.000			
LABR		0.601	0.549	−0.273	1.000		
INDS		−0.173	−0.055	0.348	−0.513	1.000	

Source: Author (2025)

Table 3 presents the estimated spatial effects of industrial robot adoption on green total factor productivity (GTFP) using the Panel Spatial Durbin Model (PSDM). The dependent variable is GTFP, while the primary variable of interest is industrial robot density (ROBT). The results incorporate province and year fixed effects, and robust standard errors clustered at the province level are reported. The coefficient of ROBT is positive and statistically significant across all specifications. In the baseline regression (Column 1), the coefficient is 3.323 ($p < 0.01$), indicating that a one-unit increase in ROBT is associated with a 3.323-unit increase in local GTFP. Furthermore, the spatially lagged effect of ROBT (Column 2) is also significant and larger in magnitude (6.589, $p < 0.01$), suggesting strong spatial spillover effects. This is confirmed by the decomposition in Columns 3 to 5: the direct effect of ROBT remains significantly positive (3.170, $p < 0.01$), while the indirect (spillover) effect is also significant (5.587, $p < 0.01$). The total effect, aggregating both channels, is 8.758 ($p < 0.01$). This implies that industrial robot adoption not only enhances GTFP in the adopting province but also contributes to productivity improvements in neighboring provinces, likely through technology diffusion and supply chain linkages.

Among the control variables, trade openness (OPEN) has a negative and statistically significant effect on GTFP both directly and in total (−0.116 and −0.175, respectively, $p < 0.05$ and $p < 0.01$). This could reflect structural dependencies on external markets that might hinder green innovation domestically. R&D intensity (RNDI) exhibits a significant positive spatial spillover effect (0.345, $p < 0.01$) and a corresponding total effect of 0.373 ($p < 0.01$), although the local direct effect is not statistically significant. This indicates that R&D investment in one province can yield productivity benefits in adjacent regions, consistent with the notion of knowledge externalities. Energy consumption structure (ENER) has a positive and significant direct effect on GTFP (3.141, $p < 0.05$), suggesting that a higher share of clean energy use supports productivity growth. However, its spatial effect is negative and not statistically significant, implying that the benefits of energy restructuring are largely localized. Human labor input (LABR) and industrial structure (INDS) do not show statistically significant effects in most specifications, although INDS exhibits a marginally significant total effect (0.731, $p < 0.1$), indicating some influence of sectoral composition on green productivity outcomes. The spatial autoregressive coefficient (ρ) is negative but statistically insignificant, suggesting that unobserved spatial autocorrelation is not a major concern in this context. The error variance is small and highly significant, supporting model robustness.

4.2 Discussion and Policy Implications

The empirical findings provide strong evidence that industrial robot adoption significantly enhances green total factor productivity (GTFP) across Chinese provinces. Notably, both the direct effects (within-province) and indirect effects (between-province or spillover) of robot density (ROBT) on GTFP are substantial and statistically significant. The magnitude of the total effect (8.758, $p < 0.01$) underscores the broad regional benefits of robotics deployment, confirming the hypothesis that industrial automation not only boosts firm-level efficiency but also contributes to environmentally sustainable productivity growth through technological spillovers and industrial interconnectivity (Zhang et al., 2022a; Du & Lin, 2022).

Table 3. Spatial Effects of Industrial Robot Adoption on GTFP

Variable	**Main**	**Wx**	**Direct**	**Indirect**	**Total**
ROBT	3.323***	6.589***	3.170***	5.587***	8.758***
	(0.794)	(1.812)	(0.726)	(1.428)	(1.785)
OPEN	−0.115**	−0.085	−0.116**	−0.059	−0.175***
	(0.053)	(0.058)	(0.052)	(0.051)	(0.055)
RNDI	0.066	0.345***	0.062	0.311***	0.373***
	(0.053)	(0.108)	(0.050)	(0.115)	(0.106)
ENER	3.073**	−2.749	3.141**	−2.907	0.235
	(1.424)	(2.257)	(1.394)	(2.190)	(2.403)
LABR	−0.061	0.022	−0.062	0.029	−0.033
	(0.047)	(0.140)	(0.046)	(0.133)	(0.124)
INDS	0.269	0.549	0.274	0.457	0.731*
	(0.183)	(0.343)	(0.182)	(0.318)	(0.387)
Spatial ρ	−0.125				
	(0.096)				
σ^2_e	0.001***				
	(0.000)				

Notes: Robust standard errors clustered at the province level are reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. ROBT = robot density, OPEN = trade openness, RNDI = R&D intensity, ENER = energy consumption structure, LABR = human labor input, INDS = industrial structure.

These results align with prior literature that highlights the dual economic and environmental benefits of robotization, particularly in contexts characterized by intensive manufacturing and evolving environmental regulations (Chen & Liu, 2023; Dong et al., 2020). The significant spatial spillover effect implies that the positive externalities of robot adoption, such as knowledge diffusion, input-output linkages, and competitive emulation, extend beyond provincial borders. This lends empirical support to the spatial spillover theory and emphasizes the importance of considering spatial interdependence in policy evaluation (Li et al., 2021; Zhao et al., 2023).

In contrast, trade openness (OPEN) is negatively associated with GTFP, both in direct and total terms. This may be explained by structural dependencies on energy- or resource-intensive exports that deter domestic green upgrading or by the possibility of a "pollution haven" effect in regions relying heavily on external markets (Hu et al., 2021; Zhang & Song, 2020). From a policy perspective, this finding calls for a balanced approach to trade liberalization, with mechanisms that ensure environmental standards are not undermined in the pursuit of export growth. The spatially significant effect of R&D intensity (RNDI) further confirms the role of regional innovation ecosystems in fostering green development. Although the local effect is statistically insignificant, the strong and positive spillover (0.345, $p < 0.01$) suggests that technological advancements in one region can enhance productivity in adjacent provinces. This supports the literature on innovation diffusion and reinforces the need for regional R&D coordination and infrastructure sharing (Wang et al., 2022; Nie et al., 2024).

The energy consumption structure (ENER), used as a proxy for the proportion of clean energy, shows a strong positive direct effect on GTFP. This result affirms the importance of transitioning to low-carbon energy systems in driving sustainable industrial productivity (Xu & Yuan, 2023). However, the absence of significant spillover effects implies that energy restructuring must be implemented province by province and cannot rely on diffusion alone. Variables representing human capital (LABR) and industrial structure (INDS) do not show robust effects, though the total effect of INDS approaches significance. This may reflect the complex interactions between industrial composition and green productivity, where transitions toward high-tech or service-oriented structures require longer-term investments and deeper institutional support to yield measurable gains (Yin et al., 2021; Tang et al., 2023).

The evidence presented in this study offers several implications for policymakers in China and other emerging economies seeking to align industrial upgrading with environmental objectives, including:

First, to targeted subsidies, tax incentives, and technology-sharing initiatives could be used to lower the entry barriers to robot deployment, especially for small- and medium-sized enterprises (SMEs). Policies should be designed to stimulate both local adoption and cross-regional diffusion, maximizing spatial productivity gains (Zhao et al., 2023; Wang et al., 2021). Second, given the spatial benefits of R&D intensity, governments should foster inter-provincial R&D collaboration through joint innovation clusters, shared laboratories, and cross-border science parks. National strategies that incentivize cooperative innovation may amplify technological spillovers and reduce regional disparities in green productivity (Nie et al., 2024; Zhang et al., 2022b).

Third, the significant impact of clean energy use on GTFP emphasizes the need to accelerate the energy transition at the provincial level. Policymakers should prioritize investment in renewable energy infrastructure, enforce stricter clean energy mandates, and promote smart grid development to reduce dependence on fossil fuels (Xu & Yuan, 2023). Fourth, the negative relationship between trade openness and GTFP suggests the importance of embedding green standards within trade policy. This includes enforcing environmental compliance in export-oriented sectors, negotiating trade agreements that include sustainability clauses, and encouraging the development of green export industries (Hu et al., 2021; Li et al., 2021).

Fifth, while industrial structure effects were not consistently significant, transitioning to higher value-added sectors remains a long-term objective. Regional industrial planning should incorporate sustainability metrics and promote industries that are both technologically advanced and environmentally sustainable (Tang et al., 2023). Sixth, the significant spatial dynamics identified in this study call for improved coordination across administrative boundaries. National-level spatial planning frameworks should be strengthened to align environmental, industrial, and innovation policies across provinces, ensuring that gains from automation and clean technology adoption are equitably distributed (Du & Lin, 2022).

5. CONCLUSIONS

This study provides compelling evidence that the adoption of industrial robots significantly enhances green total factor productivity (GTFP) in China's provinces, with both direct and spatial spillover effects playing vital roles. The findings highlight that automation-driven technological upgrading contributes not only to economic efficiency but also to environmental sustainability. The significant spatial interdependence observed suggests that policies promoting robotics and clean innovation in one province can generate positive externalities in neighboring regions. Conversely, the negative impact of trade openness on GTFP underscores the importance of embedding environmental safeguards in trade policy. The results also show that R&D intensity and energy structure are critical drivers of green productivity, while the roles of human capital and industrial structure are more nuanced.

Based on these insights, it is recommended that policymakers intensify support for industrial robot diffusion through financial incentives, infrastructure development, and SME-oriented strategies. Regional innovation collaboration should be strengthened to maximize R&D spillovers, while energy transition policies should be tailored at the provincial level to encourage clean energy adoption. Trade strategies must be aligned with green development goals, avoiding environmentally harmful export patterns. Localized industrial planning should incorporate sustainability metrics to support long-term productivity transitions.

Future research could extend this study in several ways. First, firm-level panel data could offer a more granular understanding of the micro-mechanisms linking automation to green productivity. Second, exploring sectoral heterogeneity would allow for more targeted policy design, as the environmental returns to robotization likely vary by industry. Third, incorporating dynamic spatial panel models or machine learning-based causal inference methods could enhance the robustness and predictive power of the findings. Lastly, expanding the temporal scope to include post-2020 data would enable assessment of the effects of recent environmental policies and digital economy initiatives on the automation.

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