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The Double Dividend of Automation: How Do Industrial Robots Affect Energy and Carbon Intensity?

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This paper investigates the effect of industrial robot deployment on energy and carbon intensity, using data from 60 countries over the period 2000–2019 and employing both homogeneous and heterogeneous panel data methods. The findings indicate that robot deployment decreases energy and carbon intensity, thereby improving efficiency in both domains. These effects are particularly pronounced at higher intensity levels, underscoring the critical role of robots in enhancing environmental and energy performance.

I. Introduction

Energy is a fundamental pillar of modern economies and an indispensable factor of production for sustainable growth and development. The world's energy demand is still largely met by fossil resources such as oil, natural gas, and coal (Athari, 2024). This reliance has increased the focus on sustainability since the 1987 Brundtland Report, with major international summits such as the 1992 Rio Conference, the 1997 Kyoto Protocol, and the 2015 Paris Agreement emphasizing the need to mitigate greenhouse gas emissions (GHGs) and promote the energy transition (Ulucak et al., 2019). However, the global fossil energy structure leads to increased emissions of carbon dioxide (CO₂) and other GHGs, thereby contributing to climate change and other serious environmental threats (Adebayo & Ullah, 2024). Moreover, dependence on fossil energy exposes countries to energy security risks, trade deficits linked to energy imports, and geopolitical vulnerabilities in energy-producing regions (Singh et al., 2025; S. Wang et al., 2023). Therefore, the reduction of energy and carbon intensity across production processes, combined with improvements in energy efficiency, represents a critical and urgent priority for the attainment of the SDGs (DeAngelo et al., 2021; E. Z. Wang et al., 2022).

On the other hand, in the Industry 4.0 era, the structural transformation driven by digitalization, automation, and the integration of artificial intelligence, which has been brought about by the Fourth Industrial Revolution, has made existing production processes more environmentally friendly and sustainable (M. Chen et al., 2021; Y. Chen et

al., 2022; Lee et al., 2022). The use of industrial robots, especially in industrial production, has continued to increase rapidly. In this context, the use of industrial robots has emerged as a significant area of debate concerning its effect on energy efficiency and environmental performance (Jin, 2024; Li et al., 2022). While the effect of robots on average energy and carbon intensity has been widely studied, recent research highlights new dimensions: Chen et al. (2025) examined the global industrial robot trade network, showing how robot flows between countries can affect energy and emissions, while Tang et al. (2025) analysed how industrial robot adoption, as a form of AI-driven automation, affects global embodied carbon flows, demonstrating that increased robot use in developing countries can significantly boost carbon outflows and risk carbon leakage. Building on these studies, this paper contributes to the contemporary literature by estimating the impact of industrial robots on energy and carbon intensity across countries with low, medium, and high levels of intensity, capturing the full distribution of outcomes. In addition, the paper explicitly examines how automation in industrial production influences both energy efficiency and carbon reduction, highlighting mechanisms through which structural changes in production affect environmental performance.

Theoretically, robots enhance energy efficiency by reducing human error in production processes and providing greater precision, speed, and continuity, thereby lowering the amount of energy consumed per unit of output (Lin & Xu, 2024). Through automation, production can be better planned, waste rates can be minimized, and resource utilization can become more efficient. These improvements

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have the potential to reduce both energy intensity and carbon dioxide emissions (Huang et al., 2022; Liu et al., 2024). Nevertheless, the extensive deployment of robots may lead to an increase in energy/electricity demand due to the rebound effect (E. Z. Wang et al., 2022); however, this debated effect can largely be offset by overall efficiency gains. Therefore, industrial robots have become an important subject of debate in the context of the relationship between production structure, energy, and the environment, and research on this topic continues to grow. Furthermore, by analysing countries across quantiles of energy and carbon intensity, the study captures heterogeneity among nations, showing how impacts differ between low, medium, and high-intensity economies. This approach provides insights into the uneven adoption of robots and associated environmental effects across diverse industrial and economic contexts.

This paper seeks to answer the following questions: What is the impact of robot adoption on energy efficiency and GHGs? Do these effects vary according to countries' energy structures and emission profiles? To this end, the paper investigates the effect of robot deployment on energy and carbon intensity by employing both homogeneous and heterogeneous panel data methods. By examining quantile distributions, the analysis captures not only average effects but also the heterogeneity of robot impacts across low, medium, and high energy and carbon intensity countries. Furthermore, the findings offer a comparative evaluation of how industrial robots contribute to global energy and environmental objectives, providing valuable insights into ongoing debates in the literature. Finally, the study provides important implications for policymakers and industry stakeholders in the development of greener and more sustainable production systems.

II. Methodology

A. Model and data

This paper investigates the effect of industrial robot deployment on energy and carbon intensity, using data from 60 countries over the period 2000–2019 (N=1200). These countries were selected as major users of industrial robots, ensuring that industrial automation is adequately represented in the sample. This selection allows us to focus on economies where robot deployment is meaningful, while the subsequent quantile analysis captures heterogeneity in energy and carbon intensity across countries, including variations in industrial sophistication. The panel is fully balanced, with observations available for all 60 countries across the 20-year period. The list of countries included in the analysis is reported in the Appendix (see [Table A](#)). To account for other influential factors, the model incorporates urbanization, industrialization, international trade, and economic growth as control variables. Industrial robot data are measured by the International Federation of Robotics (IFR), while data for other variables are obtained from the World Bank database.

The general regression model is specified as follows:

$$Y_{it} = \alpha + \beta_1 INDROB_{it} + \gamma' X_{it} + \varepsilon_{it} \quad (1)$$

The regression model uses Y_{it} as the dependent variable, representing either energy intensity (EI_{it}) or carbon intensity (CI_{it}) for country i at time t . Energy intensity is defined as total energy consumption divided by GDP (energy/GDP), while carbon intensity is measured as CO₂ emissions divided by GDP (CO₂ emissions/GDP). These GDP-based intensity measures are commonly employed in the literature to assess production efficiency and the degree of decoupling between economic activity and environmental pressure (Bilgili et al., 2017). Although such ratios may be sensitive to GDP fluctuations, they are particularly suitable for cross-country analysis and for evaluating how technological change, such as industrial automation, affects energy and carbon efficiency within production processes rather than per capita consumption patterns. The main explanatory variable is $INDROB_{it}$, which measures the level of industrial robot usage (number of industrial robots per 10,000 employees). The model also includes a vector of control variables X_{it} , which captures the effects of the urbanization rate (URB_{it} , the number of individuals living in urban areas per 1,000 people), industrial activity (IND_{it} , industry value added per mille (%) of GDP), trade openness (TRD_{it} , measured as the trade-to-GDP ratio in per mille terms), and the logarithm of real GDP per capita (GDP_{it} , in constant 2015 US dollars). The error term ε_{it} accounts for unobserved influences on the dependent variable.

The empirical investigation applies both ordinary least squares (OLS) and quantile regression methods. The OLS method estimates the average effect of industrial robot deployment on energy and carbon intensity across all countries and years. However, theoretical and empirical considerations suggest that the impact of industrial robots is unlikely to be uniform across countries with different levels of energy and carbon intensity (Unlu & Kocak, 2026). Countries with high energy or carbon intensity may experience stronger efficiency gains from automation due to the greater scope for technological upgrading, while low-intensity countries may face diminishing returns or rebound effects. Quantile regression is therefore particularly relevant, as it allows the estimated effects of industrial robots to vary across the entire distribution of energy and carbon intensity, rather than focusing solely on the conditional mean. By capturing heterogeneous effects at low, medium, and high quantiles, this approach provides deeper insights into how industrial automation influences energy-emissions efficiency under different structural and technological conditions. This dual-method framework enables a more nuanced and policy-relevant analysis by accounting for both average and distributional effects.

B. Preliminary analysis

Descriptive statistics reveal substantial variation in both dependent and explanatory variables across countries. Energy intensity (EI) and carbon intensity (CI) show considerable dispersion, with means of 4.837 and 0.613, respectively. The main explanatory variable, industrial robot density (INDROB), averages 6.275 robots per 10,000 employees, ranging from 0 to 13.275, which indicates significant heterogeneity in automation levels. Control variables

Table 1. Descriptive statistics and stationarity

Variables	Mean	SD	Min	Max	LLC	CIPS
EI	4.837	2.504	1.280	26.390	-4.240***	-2.271***
CI	0.613	0.584	0.051	5.155	-4.706***	-2.358***
GDP	9.377	1.353	3.983	11.375	-2.824***	-1.903*
URB	7.050	1.818	2.437	10.000	-19.594***	-2.111**
TRD	8.912	5.956	1.583	43.732	-3.214***	-2.439***
IND	3.073	1.958	0.000	18.980	-4.177***	-3.239***
INDROB	6.275	3.622	0.000	13.275	-7.032***	-3.270***

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively.

such as GDP per capita, urbanization, trade openness, and industrial activity also exhibit wide variability. To ensure the validity of the panel regression framework, Levin, Lin, and Chu (LLC, 2002) and cross-sectionally augmented IPS (CIPS, Pesaran, 2007) unit root tests were applied, and the results confirm that all variables are stationary. These findings support the econometric robustness of the empirical model and justify the application of panel OLS and quantile regression techniques. The corresponding descriptive statistics and unit root test results are reported in [Table 1](#).

III. Results

[Table 2](#) presents the effect of industrial robot deployment on energy intensity using both panel OLS and quantile regression results. According to the panel OLS estimates, industrial robot density (INDROB) has a statistically significant negative effect on energy intensity ($\beta_1 = -0.098$, $p < 0.01$), indicating that robot adoption generally improves energy efficiency. The quantile regression estimations show that the magnitude of this effect varies across the distribution of energy intensity. At the lower quantile (0.10), the effect of robot adoption is positive but not statistically significant ($\beta_1 = 0.022$) and remains relatively small. However, at the median and higher quantiles (0.50, 0.75, and 0.90), the effect becomes statistically significant and negative, with the strongest negative impact observed at the upper tail of the distribution (e.g., $\beta_1 = -0.145$ at the 0.90 quantile, $p < 0.01$). This suggests that industrial robots reduce energy intensity more effectively in countries with higher initial energy intensity levels.

The overall significance of the model is confirmed by the F-statistic for the OLS regression and the Quasi-Likelihood Ratio (Quasi-LR) tests for the quantile regressions. The adjusted R^2 for the OLS model is 11%, while the pseudo- R^2 values for the quantile regressions range from 4% to 17% across quantiles. These results highlight the heterogeneous effect of robot deployment on energy intensity, with stronger energy-saving benefits observed in countries characterized by higher energy intensity.

It should be noted that, at the lower quantiles, particularly the 0.10 quantile, the estimated effect of robot adoption is statistically insignificant, suggesting that automation does not yield uniform energy efficiency gains across all countries. This highlights that the energy-saving ben-

efits of robots are not universal and tend to materialize mainly in relatively high energy-intensity economies.

[Table 3](#) presents the estimated effects of robot deployment on carbon intensity. The panel OLS results show that robot deployment (INDROB) has a statistically significant negative effect on carbon intensity ($\beta_1 = -0.023$, $p < 0.01$), suggesting that robot adoption plays a positive role in reducing carbon intensity. The quantile regression results show that the impact of robot deployment varies across the distribution of carbon intensity. At the lower quantile (0.10), the effect is negative but not significant, while at the 0.25 quantile, there is a significant negative effect ($\beta_1 = -0.007$, $p < 0.01$). At the median quantile, the effect is weak and insignificant. However, at the upper quantiles (0.75 and 0.90), robot adoption significantly reduces CO₂ intensity ($\beta_1 = -0.020$ and -0.037 , respectively, $p < 0.01$). This indicates that robots are particularly effective in improving carbon performance in countries with higher carbon intensity.

The overall model significance is confirmed by the F-statistic for the OLS regression and the Quasi-Likelihood Ratio (Quasi-LR) tests for the quantile regressions. The adjusted R^2 for the OLS model is around 31%, while pseudo- R^2 values for the quantile regressions range between 19% and 35%. These findings highlight the heterogeneous effect of robot deployment on carbon intensity across its distribution, with stronger carbon reduction effects in countries characterized by higher carbon intensity. Similarly, the insignificant estimates at the median quantile indicate that the carbon-reducing impact of robot adoption is not pervasive across the entire distribution but becomes economically and statistically meaningful primarily at higher carbon intensity levels.

As a robustness check, the baseline findings are further re-estimated using fixed effects (FEM) models and dynamic panel GMM estimators to account for unobserved country-specific heterogeneity and potential endogeneity concerns related to industrial robot adoption. The results from these additional estimations are fully consistent with the main findings obtained from the panel quantile regressions. These robustness results are reported in the Appendix (see [Table B](#)).

Finally, the higher explanatory power observed in the carbon intensity models (OLS $R^2 = 31\%$) relative to the energy intensity models (OLS $R^2 = 11\%$) reflects differences in the structural composition of the dependent variables

Table 2. Regression results on the impact of robot adoption on energy intensity

Variables	Quantile regression					
	OLS	0.10	0.25	0.50	0.75	0.90
GDP	-0.554*** (0.096)	-0.206*** (0.078)	-0.194** (0.085)	-0.013 (0.096)	-1.119*** (0.221)	-1.740*** (0.162)
URB	0.099 (0.061)	-0.077** (0.039)	0.004 (0.030)	-0.047 (0.052)	0.497*** (0.107)	0.765*** (0.111)
TRD	-0.027** (0.011)	-0.011 (0.010)	-0.015** (0.006)	-0.014 (0.010)	-0.076*** (0.015)	-0.134*** (0.007)
IND	-0.016 (0.041)	-0.006 (0.031)	0.068 (0.051)	0.312*** (0.078)	0.179 (0.141)	0.081 (0.214)
INDROB	-0.098*** (0.020)	0.022 (0.024)	-0.025 (0.021)	-0.038* (0.020)	-0.077** (0.034)	-0.145*** (0.032)
Constant	10.199*** (0.670)	5.220*** (0.645)	5.201*** (0.748)	4.086*** (0.602)	13.468*** (1.297)	20.169*** (1.291)
F-Statistic	30.664	-	-	-	-	-
Prob (F stat)	0.000	-	-	-	-	-
Quasi-LR statistic	-	87.491	84.072	82.152	132.410	250.051
Prob (Quasi-LR stat)	-	0.000	0.000	0.000	0.000	0.000
Adj. R ²	0.11	-	-	-	-	-
Pseudo R ²	-	0.06	0.04	0.04	0.08	0.17

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. Standard errors are reported in parentheses.

Table 3. Regression results on the impact of robot adoption on carbon intensity

Variables	Quantile regression					
	OLS	0.10	0.25	0.50	0.75	0.90
GDP	-0.271*** (0.019)	-0.094*** (0.009)	-0.102*** (0.008)	-0.137*** (0.017)	-0.334*** (0.018)	-0.529*** (0.020)
URB	0.020 (0.012)	-0.025*** (0.004)	-0.012*** (0.004)	-0.031*** (0.011)	0.017* (0.010)	0.093*** (0.018)
TRD	0.006*** (0.002)	0.002** (0.001)	0.001** (0.0007)	0.003*** (0.0008)	-0.0003 (0.001)	-0.012*** (0.001)
IND	-0.066*** (0.008)	-0.030*** (0.004)	-0.021*** (0.006)	0.002 (0.047)	0.063*** (0.014)	-0.021 (0.026)
INDROB	-0.023*** (0.004)	-0.001 (0.003)	-0.007*** (0.002)	-0.001 (0.002)	-0.020*** (0.003)	-0.037*** (0.006)
Constant	3.287*** (0.139)	1.404*** (0.087)	1.473*** (0.081)	1.870*** (0.262)	3.718*** (0.172)	5.871*** (0.208)
F-Statistic	107.759	-	-	-	-	-
Prob (F stat)	0.000	-	-	-	-	-
Quasi-LR statistic	-	478.643	646.426	884.707	1090.801	822.099
Prob (Quasi-LR stat)	-	0.000	0.000	0.000	0.000	0.000
Adj. R ²	0.31	-	-	-	-	-
Pseudo R ²	-	0.22	0.19	0.22	0.27	0.35

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. Standard errors are reported in parentheses.

rather than a weaker linkage between industrial robots and energy efficiency. While industrial robot adoption directly contributes to energy efficiency improvements, energy intensity is also affected by macro-level factors such as energy prices, the energy mix, and climatic conditions that are not fully captured in the model, leading to lower overall explanatory power.

These findings are consistent with prior empirical studies showing that industrial robot adoption enhances energy efficiency and reduces emissions through technological upgrading and process optimization (e.g., Huang et al., 2022; E. Z. Wang et al., 2022). However, they contrast with studies suggesting that automation may increase energy demand due to scale and rebound effects (e.g., Liu et al., 2024). The heterogeneous effects identified across quantiles help rec-

oncile these mixed findings in the literature by demonstrating that the environmental benefits of robot adoption are not uniform but depend on countries' initial energy and carbon intensity levels.

IV. Conclusion

This study explores the effect of robot deployment on energy and carbon intensity. The results indicate that robot deployment generally leads to significant reductions in both energy and carbon intensity. However, the magnitude and direction of these effects vary across different quantiles of energy and carbon intensity. Robot adoption significantly reduces energy intensity at the median and higher quantiles, suggesting that countries or sectors with high

energy intensity benefit more in terms of energy efficiency from adopting robot technology. Similarly, the negative effects on carbon intensity are consistent and significant at the middle and higher quantiles, highlighting the substantial potential of automation technologies to reduce carbon emissions. These findings underscore the importance of considering distributional heterogeneity beyond average effects when evaluating the environmental impacts of technological change and suggest that robotic automation can be an effective strategy for enhancing environmental sustainability, especially in contexts with high energy and carbon intensity.

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Appendix

Table A. List of countries

Argentina	Croatia	Hungary	Morocco
Australia	Czech Republic	India	Netherlands
Belgium	Denmark	Indonesia	New Zealand
Belarus	Egypt	Ireland	Norway
Bosnia & Herzegovina	Estonia	Israel	Pakistan
Brazil	Finland	Italy	Peru
Canada	France	Japan	Philippines
Chile	Germany	Kuwait	Poland
China	Greece	Latvia	Portugal
Colombia	Hungary	Lebanon	Qatar
Lithuania	Saudi Arabia	Singapore	Slovakia
South Africa	South Korea	Spain	Sweden
Switzerland	Thailand	Tunisia	Turkey
UAB	Ukraine	United Kingdom	United States
Vietnam	Malaysia	Malta	Uzbekistan

Table B. Endogeneity checks

Variables	Energy intensity		Carbon intensity	
	FEM	GMM	FEM	GMM
EI (-1)	-	0.095*** (0.014)	-	-
CI (-1)	-	-	-	0.087*** (0.022)
GDP	-0.598*** (0.096)	-0.085*** (0.028)	-0.274*** (0.022)	-0.068*** (0.019)
URB	0.127** (0.061)	-0.132*** (0.017)	0.022* (0.013)	-0.077*** (0.009)
TRD	-0.020* (0.012)	-0.028*** (0.003)	0.006*** (0.002)	-0.015*** (0.002)
IND	-0.019 (0.041)	0.012* (0.007)	-0.066*** (0.009)	0.019*** (0.004)
INDROB	-0.056*** (0.021)	-0.013** (0.002)	-0.020*** (0.004)	-0.008** (0.003)
Constant	10.090*** (0.668)	-	3.281*** (0.141)	-
Fixed effects	YES	-	YES	-
Adj. R ²	0.12	-	0.30	-
J-Statistic	-	38.248	-	43.385
Prob. (J stat)	-	0.28	-	0.16
AR (2)	-	-0.299	-	1.135
Prob. (AR (2))	-	0.76	-	0.26

Note: ***, **, and * indicate statistical significance at 1%, 5% and 10% level, respectively. Standard errors are reported in parentheses.