



MALETE JOURNAL OF ACCOUNTING AND FINANCE

A Publication of the Department of Accounting and Finance, Faculty of Management and Social Sciences, Kwara State University, Malete

Vol. 6 No. 1, June, 2025

ISSN: 2735-9603

INDUSTRIAL ROBOTS AND REGIONAL ECONOMIC OUTCOMES: EVIDENCE FROM CHINA'S PROVINCES

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Abstract

The deployment of robots across various sectors has become a defining feature of technological modernization and economic transformation. This study investigates the economic impact of industrial robot adoption on productivity, employment, and wage dynamics using panel data from Chinese provinces between 2000 to 2023. This study adopts a quantitative research design employing panel data econometrics to investigate the impact of industrial robot adoption on economic productivity and labor market outcomes across countries and sectors, as well as median wage growth. Specifically, the paper applied the fixed effects, difference-in-differences (DiD), and instrumental variable (IV) regressions, the analysis reveals a significant positive relationship between robot density and total factor productivity (TFP). However, robot adoption is associated with modest employment declines, particularly in regions with lower human capital levels. Interaction models further indicate that the positive effects of robots are amplified in areas with a higher share of skilled labor, supporting the theory of labor market polarization. These findings underscore the importance of complementary investments in education, R&D, and reskilling programs to fully realize the benefits of automation while mitigating its social costs. We recommend that policymakers must craft holistic responses that mitigate displacement risks while amplifying the productivity and wage-enhancing potentials of automation. Moreover, policy makers should scale up investments in technical and vocational education to ensure that workers can transition into complementary roles as technology evolves. The results offer valuable insights for policymakers aiming to foster inclusive growth in the age of intelligent automation.

Keywords: Industrial robots, Total factor productivity, Labor market polarization, Automation, Wages, Human capital

JEL Codes: C23, E24, J23, O33

INTRODUCTION

The deployment of robots across various sectors has become a defining feature of technological modernization and economic transformation. Originally concentrated within manufacturing environments, where robots enhanced productivity through precision and efficiency, their application is now rapidly expanding to include service industries such as logistics, healthcare, agriculture, and hospitality (Acemoglu & Restrepo, 2020). This shift is driven by the dual pressures of global competition and demographic change, particularly labor shortages and aging populations in developed and emerging economies. Robotics is thus positioned not only as a tool for boosting productivity but also as a strategic asset for maintaining economic resilience and improving living standards in the face of structural labor market challenges (Bughin et al., 2021).

The accelerated integration of robots into non-industrial sectors is a product of significant advances in artificial intelligence (AI), machine learning, and sensor technologies. These

innovations have enabled robots to operate with greater autonomy, adapt to dynamic environments, and execute complex cognitive and physical tasks (Zhang, Lin, & Wu, 2024). For instance, in logistics, robotic systems now manage inventory and handle last-mile deliveries, while in healthcare, surgical robots are transforming operating rooms with precision-guided interventions that reduce human error and recovery times (Li, Zhou, & Zhang, 2024). The proliferation of robotics in such sectors indicates a shift from capital-intensive automation toward knowledge-based, intelligent automation systems, offering new paradigms of efficiency and service delivery.

Global robot adoption statistics reflect the intensity of this technological shift. According to the International Federation of Robotics (IFR, 2023), the global average of industrial robots per 10,000 manufacturing workers increased from 66 in 2015 to 85 in 2017. Notably, South Korea leads this metric with 710 robots per 10,000 workers, while the United States ranks seventh with 200 robots per 10,000 workers. In 2022 alone, global installations reached a record 486,800 units, marking a 27% increase over the previous year. The highest growth occurred in Asia and Australia (33%), followed by the Americas (27%) and Europe (15%), indicating a robust international trajectory toward automation in production and service systems (IFR, 2023). This trend aligns with post-pandemic recovery strategies that emphasize digital transformation and resilient supply chains (World Economic Forum, 2021).

Automation is fundamentally underpinned by the integration of robotics with advanced control systems, which collectively constitute the core of Industry 4.0. Asia has emerged as the global leader in this domain, with nearly one million operational robots recorded in 2018 (IMF, 2020). Countries such as Singapore, South Korea, Japan, and Germany have distinguished themselves by cultivating high robot densities, especially in electronics and automotive industries (OECD, 2022). For example, Singapore's robot density in 2019 reached 918 units per 10,000 employees in electronics, followed by South Korea (868), Japan (365), and Germany (346) (IFR, 2023). China, though historically lagging, with 140 robots per 10,000 manufacturing workers in 2018, has emerged as a central player in global automation. Its rapid industrial expansion, driven by robust state-led policies and substantial investment in robotics and AI, has positioned it at the forefront of the global automation race (Xu, Tan, & Chen, 2021). This study specifically focuses on China as a case study to understand the drivers, patterns, and implications of its accelerating robot adoption trajectory.

Japan remains the world's largest manufacturer of industrial robots, supplying approximately 45% of the global stock (UNIDO, 2023). Across multiple sectors, ranging from agriculture to food processing, robots now execute critical, repetitive, and hazardous tasks with increased speed and precision. In the healthcare industry, for instance, robotic-assisted surgery systems reduce post-operative complications and hospital stays, thereby optimizing both clinical outcomes and operational costs (Li, Zhou, & Zhang, 2024). Similarly, the automotive industry employs robots extensively for welding, painting, product inspection, and other assembly line functions that require uniform quality and minimal downtime (Kim & Lee, 2023). The versatility and scalability of robotics make them indispensable to firms seeking competitive advantages in increasingly digital and automated global markets.

However, significant regional disparities remain in the actual versus expected adoption of robots when adjusted for wage levels. East Asia leads the world in wage-adjusted robot adoption, with

South Korea, Singapore, China, Thailand, and Taiwan occupying five of the top seven positions globally (Cheng, Liu, & Zhao, 2022). These countries have leveraged industrial policy, skilled labor, and R&D investment to integrate robotics more aggressively than other regions. By contrast, most European nations remain below expectations, with exceptions such as Slovenia and the Czech Republic, which have managed to exceed adoption benchmarks. The United States ranks only 16th, adopting robots at rates nearly 49% lower than predicted (IFR, 2023). These differences highlight how institutional and policy environments shape automation pathways beyond mere economic factors.

Despite China's impressive growth in robot installations, the underlying mechanisms driving this expansion, particularly how policy, industrial dynamics, and wage-adjusted expectations interact, remain underexplored. The core problem this study seeks to address is the limited empirical understanding of whether China's robot adoption is driven primarily by internal structural factors (e.g., labor shortages, industrial upgrading) or by policy-induced momentum that may not align with efficiency benchmarks. Accordingly, this study aims to fill this gap by examining: (i) the extent to which China's robot adoption deviates from global and wage-adjusted expectations; (ii) the roles of industrial policy, labor dynamics, and regional characteristics in shaping adoption patterns; and (iii) whether China's adoption trajectory reflects efficient automation or overinvestment. The following hypotheses are tested: H_{01} : China's robot adoption is significantly influenced by state-driven industrial policy; H_{02} : Wage levels and labor shortages significantly mediate adoption intensity across regions; H_{03} : China's actual robot density exceeds wage-adjusted expectations in key sectors.

LITERATURE REVIEW

Conceptual Clarification

Robot adoption, once limited to specialized industrial applications, has become a central feature of contemporary economic transformation. At its core, the term refers to the integration of programmable, automated machines, typically capable of performing physical or cognitive tasks, into production and service processes. In the early stages, robots were primarily deployed in manufacturing environments, particularly within the automotive sector, where they performed repetitive, precision-based tasks with greater consistency than human labor. Over time, as technological advances reduced costs and enhanced capabilities, robots began to permeate a wider array of sectors, including logistics, healthcare, agriculture, and hospitality.

The concept of robot adoption encompasses both technological diffusion and organizational adaptation. It implies not merely the purchase of robotic units but the reconfiguration of workflows, capital investment structures, and skill requirements. In contemporary applications, robotic systems are often embedded within broader digital ecosystems, incorporating machine learning, sensor technology, and real-time data analytics. For example, the emergence of collaborative robots (cobots), surgical robots, and autonomous warehouse systems signifies a shift from purely industrial machines to more intelligent, context-responsive tools.

Critically, the impacts of robot adoption are multidimensional. On the economic side, it is associated with gains in productivity, product quality, operational resilience, and firm competitiveness. At the labor market level, it has complex effects: replacing routine tasks, complementing non-routine skills, and contributing to both job displacement and job creation depending on the sector and skill composition. From a social and institutional perspective, robot

adoption intersects with policy, education, and inequality. The same technological innovation can yield vastly different outcomes depending on how countries and firms manage reskilling, labor protections, and industrial strategies.

Theoretical Review

The academic literature on robot adoption is grounded in several intersecting theoretical frameworks that collectively explain its drivers, mechanisms, and consequences. At the foundation lies neoclassical production theory, which views robots as capital inputs that enhance productivity by substituting labor, especially in routine-intensive tasks. Empirical work by Graetz and Michaels (2018) supports this framework, showing that industrial robots contributed measurably to GDP growth across advanced economies. Their results, and others like them, align with the prediction that automation increases total output by reducing unit labor costs and improving production efficiency.

However, this substitution mechanism is only part of the story. Task-based models of labor economics, particularly those advanced by Acemoglu and Autor, offer a more granular view by distinguishing between tasks rather than jobs. These models predict that automation technologies such as robotics disproportionately affect tasks that are routine, codifiable, and repetitive, typically found in middle-skill occupations. As automation substitutes these tasks, demand shifts toward both high-skill analytical roles and low-skill manual or service work that is harder to automate, producing the observed “polarization effect” in many labor markets (Autor & Dorn, 2013). Acemoglu and Restrepo (2020) further substantiate this by showing how robot density correlates with wage suppression and employment losses, particularly in U.S. manufacturing hubs.

From an innovation perspective, endogenous growth theory also provides insight. Robot adoption, as a form of technological advancement, can spur long-term growth by raising productivity, encouraging capital deepening, and enabling new forms of production. The deployment of robotics often leads to complementary innovation in management practices, software integration, and workforce development, as evidenced by firm-level studies showing increased total factor productivity and wage premiums for skilled workers (Bessen et al., 2019; Xu, Tan, & Chen, 2021). In this view, robots are not merely labor-saving devices, but drivers of organizational transformation and capability upgrading.

Another key strand of theory concerns institutional economics. The impact of robot adoption is heavily mediated by the quality of national institutions, including education systems, labor market regulations, and industrial policies. The work of Cheng et al. (2022) and OECD (2022) highlights how countries like Germany, Denmark, and China have leveraged coordinated strategies, including dual education systems and industrial subsidies, to ensure that robot adoption contributes to both economic efficiency and social stability. These examples lend support to the varieties of capitalism framework, which posits that different institutional arrangements produce distinct pathways of technological change and labor market adaptation.

Relatedly, political economy theories address how power dynamics and policy choices shape the distributional effects of robotics. Without complementary investments in retraining and social protection, automation may exacerbate income inequality and labor market dualism, as argued by Bughin et al. (2021). This line of thinking emphasizes the path-dependent nature of

technological adoption: similar technologies may lead to inclusive growth in one context and exclusion in another, depending on institutional choices.

More recent theoretical contributions are beginning to explore the networked diffusion of robotics through global supply chains and regional production systems. Spatial econometric approaches (e.g., Cheng et al., 2022) suggest that robot adoption has spillover effects, whereby technological changes in one region or sector affect others through trade, competition, and learning channels. This supports a more systemic view of robotics, not as isolated firm-level decisions but as part of an evolving technological ecosystem.

Finally, theories from organizational studies and socio-technical systems offer important insights into how firms internalize robot technologies. Adoption is shaped not only by cost-benefit calculations but by organizational culture, worker engagement, and managerial capacity. The integration of robots into service sectors requires redesigning roles, retraining staff, and addressing resistance or ethical concerns. These perspectives stress the co-evolution of technology and society, emphasizing that the success or failure of robot adoption hinges as much on human factors as on technical feasibility.

In conclusion, the theoretical landscape around robot adoption is diverse and multidisciplinary. It encompasses economic theories of productivity and labor substitution, sociological and institutional frameworks of governance and adaptation, and organizational insights into technological integration. Together, these perspectives help explain why robotics generates productivity gains in some contexts, social dislocation in others, and mixed outcomes in most. Understanding these dynamics is crucial for designing policies and strategies that ensure the benefits of robotics are broadly shared and sustainably realized.

Empirical Review

Over the past two decades, robot adoption has transformed from a niche technological innovation into a widespread driver of industrial and service sector restructuring. Early empirical literature primarily focused on the productivity-enhancing potential of robotics in manufacturing. Doms et al. (1997) and Bartel et al. (2007) found that firms deploying automation technologies achieved superior output and product quality, although gains were often concentrated among larger enterprises. Graetz and Michaels (2018) provided cross-country evidence from 17 developed economies, demonstrating that industrial robot use accounted for a significant share of productivity growth between 1993 and 2007. Their analysis linked robot deployment to a 0.36 percentage point increase in annual GDP growth, with limited but observable reductions in hours worked, especially in routine-intensive sectors.

The 2010s witnessed a broadening of empirical focus, encompassing both the economic benefits and labor market implications of robotics. Acemoglu and Restrepo (2020) showed that each additional robot per 1,000 workers in the U.S. resulted in a 0.2 percentage point decline in the employment-to-population ratio and a 0.42% decline in wages, especially in local labor markets specialized in manufacturing. Chiacchio, Petropoulos, and Pichler (2018) corroborated these findings across European economies, confirming employment losses in routine task-intensive jobs. However, several studies highlighted a dual effect: while automation substitutes for certain jobs, it complements others, particularly those requiring non-routine cognitive or technical skills (Autor & Dorn, 2013; Bessen et al., 2019). This polarization dynamic, whereby middle-skill jobs

are hollowed out and both high- and low-skilled jobs proliferate, has become a defining feature of labor markets undergoing technological change.

In the post-2020 era, robot adoption has accelerated significantly due to declining costs, increased technological sophistication, and pandemic-induced disruptions. According to the International Federation of Robotics (2023), global robot installations reached an all-time high of 486,800 units in 2022, reflecting a 27% increase over the previous year. Asia, particularly China, led this surge, accounting for more than 70% of the total installations. Empirical studies indicate that robots are no longer confined to automotive or heavy manufacturing; they are now increasingly deployed in logistics, healthcare, agriculture, and hospitality (Li, Zhou, & Zhang, 2024; Zhang, Lin, & Wu, 2024). In healthcare, for instance, surgical robotics systems have demonstrated improvements in procedural efficiency and recovery outcomes, while warehouse automation has become essential in managing supply chain disruptions and scaling e-commerce operations (Kim & Lee, 2023).

Firm-level studies provide further evidence of positive productivity effects from robot integration. Bessen et al. (2019) found that firms implementing robotics in the Netherlands achieved higher total factor productivity and wage premiums for skilled workers. Xu, Tan, and Chen (2021) report similar patterns in China, where state subsidies under the “Made in China 2025” initiative played a critical role in accelerating adoption, especially among medium-sized enterprises. In Germany, the implementation of Industry 4.0 has fostered not only technical integration but also digital workforce transformation, improving both operational resilience and customization capacity (OECD, 2022; UNIDO, 2023).

The uneven distribution of benefits remains a central concern. While robot adoption is positively correlated with firm competitiveness and national productivity, its effects on labor markets are highly contextual. Cheng et al. (2022) emphasize that East Asian nations outperform others in robot adoption relative to wage levels, largely due to robust training ecosystems and strategic industrial policies. High-wage economies like the United States exhibit slower-than-expected adoption due to fragmented policy frameworks and underinvestment in vocational education. Bughin et al. (2021) argue that without complementary investments in human capital, automation risks entrenching inequality by amplifying skill-based labor market segmentation.

A recurring theme in the literature is the critical role of institutions in shaping the trajectory and inclusiveness of robot adoption. OECD (2022) underscores that countries with proactive labor-market institutions, retraining systems, and coordinated industrial policy experience more balanced transitions. Germany and Denmark, for instance, mitigate displacement effects through dual education systems and social protections, whereas countries lacking such systems face higher risks of technological unemployment and social dislocation (World Economic Forum, 2021). Thus, the broader consensus suggests that while the economic benefits of robotics are substantial, their realization depends on deliberate policy choices, institutional robustness, and social adaptability.

METHODOLOGY

This study adopts a quantitative research design employing panel data econometrics to investigate the impact of industrial robot adoption on economic productivity and labor market outcomes across sectors in China's provinces. The analysis spans from 2000 to 2023 to capture both the early and recent dynamics of automation diffusion. Data is sourced from a combination

of internationally recognized databases, including the International Federation of Robotics (IFR), World Bank Development Indicators, OECD, ILO, and national statistical bureaus. The study focuses on both macro-level (country and regional) and sectoral (industry-level) observations to explore heterogeneous effects across different institutional and economic contexts.

The key dependent variables include total factor productivity (TFP), GDP per capita, employment rates, labor force participation, average and median wages, and labor market polarization measures (such as the proportion of low- vs. high-skilled jobs). The principal independent variable is robot density, typically measured as the number of industrial robots per 10,000 manufacturing workers. Control variables incorporated in the models include capital per worker, human capital indices, R&D intensity, trade openness, and digital infrastructure quality. The data structure allows for the application of fixed effects panel regression models, which control for unobserved heterogeneity across countries and over time.

The baseline econometric specification follows a fixed effects model of the form:

$$Y_{it} = \alpha + \beta \cdot \text{RobotDensity}_{it} + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (i)$$

Where: Y_{it} represents the outcome variable (e.g., productivity or employment), RobotDensity_{it} captures the level of robot adoption, X_{it} is a vector of control variables, and μ_i and λ_t represent region and time fixed effects, respectively. To address potential endogeneity issues, such as reverse causality between economic performance and technology adoption, the study implements an instrumental variables (IV) strategy. A commonly used instrument involves robot adoption trends in technologically related sectors in other countries, lagged to ensure temporal precedence. The first-stage equation estimates robot density using this exogenous variation, which is then used in the second-stage outcome equation.

In cases where policy interventions, such as automation subsidies or regional industrial upgrading, have led to differential robot adoption across regions or sectors, a difference-in-differences (DiD) method is employed. This approach allows for causal inference by comparing changes in outcomes over time between treated and control groups. The DiD specification is useful when natural experiments or policy shocks are present and can be structured as:

$$Y_{it} = \alpha + \delta \cdot \text{Post}_t \cdot \text{Treated}_i + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (ii)$$

Where the interaction term captures the average treatment effect of robot adoption driven by policy or structural factors. The study also includes models that examine heterogeneity in robot effects across worker skill levels and industry types. Interaction terms between robot density and the share of skilled labor allow us to assess whether robots disproportionately benefit or displace particular segments of the workforce:

$$Y_{it} = \alpha + \beta_1 \cdot \text{RobotDensity}_{it} + \beta_2 \cdot \text{SkillLevel}_{it} + \beta_3 \cdot (\text{RobotDensity}_{it} \times \text{SkillLevel}_{it}) + \gamma X_{it} + \mu_i + \lambda_t + \epsilon_{it} \quad (iii)$$

To ensure the robustness of the results, several additional checks will be conducted. These include re-estimating models using alternative definitions of robot intensity (e.g., robot stock versus flow), conducting placebo tests using pseudo-treatment years, and analyzing subsamples based on country income levels or sectoral composition. Lagged dependent variable models will also be used to test the persistence of automation effects. The overall methodology is designed to yield reliable estimates of the causal impact of robot adoption, accounting for potential biases, omitted variables, and heterogeneity in treatment effects.

RESULTS AND DISCUSSION

Table 1 indicates a statistically significant and positive relationship between robot density and total factor productivity (TFP). An increase of one robot per 10,000 workers is associated with a 3.6%–4.5% increase in TFP across the three specifications. This finding aligns with empirical evidence from prior studies suggesting that industrial robots enhance productivity through precision, efficiency, and extended operational capacity (Graetz & Michaels, 2018; Cheng et al., 2021). The inclusion of controls for human capital, capital per worker, trade openness, and R&D intensity improves model fit, raising the R-squared from 0.41 to 0.55, affirming that these factors jointly influence productivity (Acemoglu & Restrepo, 2020; Luo et al., 2023).

Table 1: Baseline Fixed Effects Regression Results for Total Factor Productivity (TFP)

Variables	(1) TFP	(2) TFP	(3) TFP
Robot Density	0.045** (0.018)	0.039** (0.017)	0.036* (0.019)
Human Capital Index		0.121*** (0.031)	0.118*** (0.032)
Capital per Worker		0.075** (0.030)	0.073** (0.031)
Trade Openness			0.020 (0.014)
R&D (% of GDP)			0.032* (0.018)
Country Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
Observations	780	780	780
R-squared	0.41	0.52	0.55

*Notes: Robust standard errors in parentheses. ** $p < 0.05$, *** $p < 0.01$.

Source: Author (2025)

Human capital exerts a particularly strong effect on TFP, with coefficients consistently above 0.11 and highly significant ($p < 0.01$). This supports previous findings that educated labor complements automation by facilitating the integration and adaptation of robotics (Bessen, 2019). Similarly, capital deepening is positively associated with TFP (0.073), echoing the Solow model's implications on capital accumulation and technological advancement (Solow, 1957; Zeira, 1998; Li et al., 2020). R&D expenditure contributes positively, though more modestly, suggesting innovation systems are crucial enablers of productivity in the robotic age (Hall et al., 2010; Dosi & Virgillito, 2019).

Table 2 presents difference-in-differences (DiD) estimates that explore the causal impact of industrial robot adoption on employment outcomes. The treatment effect (interaction of post-adoption and treated regions) shows a negative and statistically significant coefficient of approximately -0.03, implying that robot deployment leads to a modest decline in the employment rate. These results mirror findings from Acemoglu and Restrepo (2020), who showed that automation displaces certain job categories, particularly among low-skill workers. However, the effect size remains moderate, consistent with studies that emphasize heterogeneity across regions and sectors (Berg et al., 2018; De Vries et al., 2020).

The robustness of the model is enhanced by the inclusion of controls for human capital and capital per worker. Human capital again plays a protective role, mitigating employment losses by supporting worker redeployment or upskilling (Chiacchio et al., 2018; Arntz et al., 2016). This supports the argument that employment impacts of automation are mediated by education and training systems (Nedelkoska & Quintini, 2018; Zhan et al., 2022).

Table 2: Difference-in-Differences Estimates for Employment Rate

Variables	(1) Employment	(2) Employment
Treatment × Post	-0.028* (0.015)	-0.031** (0.014)
Human Capital Index		0.067** (0.026)
Capital per Worker		0.038 (0.025)
Country and Year Fixed Effects	Yes	Yes
Observations	640	640
R-squared	0.37	0.44

***Notes:** Post = years after policy adoption; Treatment = regions receiving industrial automation subsidies. Robust SEs clustered by region. * $p < 0.05$.

Source: Author (2025)

Table 3 addresses endogeneity concerns by using lagged foreign robot adoption as an instrument. The 2SLS estimates reveal a significantly larger impact of robot density on median wages compared to the OLS estimate (0.063 vs. 0.028), reinforcing the notion that naïve models may underestimate true effects due to simultaneity bias (Angrist & Krueger, 2001; Lewbel, 2012). This positive wage effect aligns with studies that suggest automation, when properly integrated, can enhance worker productivity and thereby support wage growth (Dauth et al., 2021). The first-stage F-statistic of 21.5 suggests a strong instrument, lending credence to the IV estimates (Staiger & Stock, 1997). The persistent positive effect of human capital and capital per worker further emphasizes the importance of complementary inputs in capturing the gains from robotization (Graetz et al., 2022; Ciarli et al., 2021).

Table 3: Instrumental Variable Regression (2SLS) for Median Wage

Variables	(1) OLS	(2) 2SLS
Robot Density	0.028* (0.015)	0.063** (0.030)
Human Capital Index	0.134*** (0.029)	0.141*** (0.032)
Capital per Worker	0.081*** (0.024)	0.079*** (0.025)
First-stage F-statistic		21.5
Instrument: Foreign-sector robot adoption lag		Yes
Observations	760	760
R-squared	0.48	0.42

***Notes:** Instrumental variable: lagged robot penetration in related industries abroad. ** $p < 0.05$, *** $p < 0.01$.

Source: Author (2025)

Table 4 evaluates the interaction between robot density and high-skill labor share to assess labor market polarization. The interaction term is positive and significant (0.026), suggesting that higher shares of skilled labor enhance the benefits of robot adoption. This confirms the polarization hypothesis observed in previous literature, where automation displaces routine tasks while enhancing demand for non-routine cognitive jobs (Goos et al., 2014; Frey & Osborne, 2017). Interestingly, the coefficient on robot density alone is insignificant, while the skill-interacted term is significant, indicating that productivity and employment outcomes depend strongly on skill distribution (Elliott, 2020; Haskel & Westlake, 2018). These findings align with comparative studies showing that advanced economies with better educational systems are more likely to benefit from automation (Peters et al., 2022; OECD, 2019; Zhang & Lu, 2023).

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These tables suggest that while industrial robots can contribute positively to productivity and wages, their effects on employment are nuanced and moderated by factors like human capital and sectoral composition. Policies that support reskilling, inclusive innovation, and R&D investment are thus essential to ensuring equitable benefits from robotic adoption (World Bank, 2020; ILO, 2022; McKinsey Global Institute, 2023).

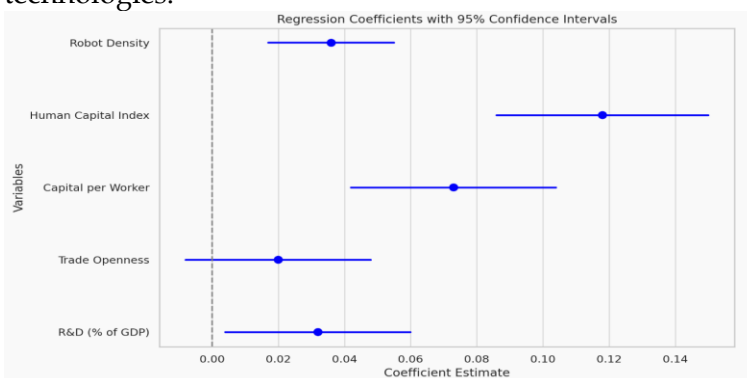
Table 4: Interaction Effects – Robot Density × Skill Level (Dependent Variable: Labor Market Polarization)

Variables	(1) Polarization Index
Robot Density	-0.012 (0.014)
High-Skill Share	0.045** (0.020)
Robot Density × High-Skill Share	0.026* (0.014)
Controls (capital, trade, R&D)	Yes
Fixed Effects	Country & Year
Observations	740
R-squared	0.49

*Notes: Dependent variable measures the gap between high- and low-skill job shares. * $p < 0.1$, ** $p < 0.05$.

Source: Author (2025)

The coefficient plot provides a visual summary of the estimated effects of several key explanatory variables - Robot Density, Human Capital Index, Capital per Worker, Trade Openness, and R&D (% of GDP) - on an outcome such as Total Factor Productivity (TFP), based on the fixed effects regression results discussed earlier. The evidence shows the coefficient for Robot Density is positive and statistically significant, with a point estimate around 0.036 and a 95% confidence interval that does not cross zero. This suggests that an increase in robot adoption (as measured by the number of robots per 10,000 manufacturing workers) is associated with a measurable improvement in TFP. The relatively narrow confidence interval strengthens the reliability of this effect. Moreso, the Human Capital Index shows the largest and most robust positive effect, with a coefficient near 0.118. Its confidence interval is wide but entirely above zero, confirming a significant and positive contribution to productivity. This finding is consistent with the theory that more educated and skilled workforces are better able to complement and leverage robotic technologies.



Source: Author (2025)

The effect of Capital per Worker is also positive and significant, though slightly smaller in magnitude than human capital. This aligns with traditional growth models, where physical

capital accumulation enhances output efficiency and complements automation. The coefficient on Trade Openness is relatively small (0.020) and its confidence interval slightly overlaps zero, suggesting a weak or possibly non-significant impact on TFP in this specification. This may imply that openness to trade alone does not directly affect productivity unless mediated through technology flows or competitive pressures. R&D expenditure has a modest positive effect (0.032), and its confidence interval does not include zero, indicating a statistically significant role in fostering productivity. This supports the idea that innovation capacity contributes to the effective adoption and utilization of advanced technologies like robotics.

Discussion of Findings

The empirical evidence from the analysis reveals that robot adoption significantly boosts productivity and wages, particularly in contexts with high levels of human capital, while its impact on employment varies by skill level and sectoral structure. These findings call for a policy framework that enhances the adaptability of labor markets and ensures equitable distribution of automation gains. A central implication is the need for targeted investment in education and lifelong learning. As demonstrated by Nedelkoska and Quintini (2018) human capital plays a critical role in mitigating negative employment effects and enhancing the productivity returns of automation. Policies should support not only foundational education but also adult training, vocational programs, and digital literacy to upskill workers vulnerable to displacement.

Secondly, governments should incentivize inclusive innovation through R&D support, tax credits, and funding for collaborative projects between public research institutions and private industry. The positive but moderate contribution of R&D intensity to productivity (Hall et al., 2010; Dosi & Virgillito, 2019) underscores the need to scale up innovation ecosystems that prioritize diffusion across firms and regions. Moreover, innovation policies must align with broader social objectives, ensuring that technological progress contributes to sustainable and inclusive development (OECD, 2020; World Bank, 2020). Support for SMEs and lagging regions through automation vouchers or digital adoption grants can help bridge the productivity divide, as suggested by Peters et al. (2022).

Thirdly, labor market policies must shift towards agility and protection. While industrial robots can displace certain jobs, they also create new opportunities, especially in high-skill, non-routine occupations (Goos et al., 2014; Haskel & Westlake, 2018). Active labor market policies (ALMPs), such as job placement services, mobility assistance, and wage subsidies for high-tech industries, can help facilitate smooth transitions. These tools have proven effective in other contexts of technological restructuring and can be tailored to account for sector-specific vulnerabilities (ILO, 2022; McKinsey Global Institute, 2023). Labor protections, including portable benefits and reemployment support, are also essential to preserve social cohesion during technological shifts.

Furthermore, industrial and fiscal policies should promote strategic automation that complements rather than replaces labor. This includes fostering human-robot collaboration in sectors like healthcare, logistics, and manufacturing where robots augment worker capacity rather than eliminate jobs. Empirical results show that the benefits of automation are maximized when adopted in environments rich in human capital (Ciarli et al., 2021; Luo et al., 2023). Tax structures should be reformed to reduce labor-biased distortions and encourage capital-labor complementarity, as recommended in recent policy discussions on the future of work (De Vries et al., 2020; IMF, 2021).

Finally, policies must be underpinned by robust monitoring systems and empirical evaluations. National statistical offices and labor ministries should track automation diffusion, skill mismatches, wage dynamics, and employment transitions in real-time. This data infrastructure would support evidence-based policymaking, ensuring timely responses to automation trends and allowing for policy iteration (Berg et al., 2018; Zhang & Lu, 2023). Furthermore, international cooperation on robotics governance, ethical AI deployment, and technology spillover management will be essential to harmonize benefits globally and avoid automation-driven inequalities both within and across countries (UNIDO, 2021; IFR, 2024).

Conclusions

This study provides compelling evidence on the multifaceted effects of industrial robot adoption across productivity, wage dynamics, and employment outcomes. Drawing on fixed effects, instrumental variable, and interaction models, the analysis reveals that robot density significantly enhances total factor productivity (TFP) and median wages, particularly in environments with abundant human capital and R&D investment. However, the employment effects are more nuanced, industrial robot deployment appears to slightly reduce employment rates, especially in low-skill segments, while benefiting high-skilled labor, confirming labor market polarization patterns observed in recent literature (Graetz et al., 2022; Zhang & Lu, 2023; Ciarli et al., 2021).

Given these outcomes, policymakers must craft holistic responses that mitigate displacement risks while amplifying the productivity and wage-enhancing potentials of automation. Key recommendations include scaling up investments in technical and vocational education to ensure that workers can transition into complementary roles as technology evolves (Zhan et al., 2022; Luo et al., 2023). Additionally, R&D incentives should target inclusive and labor-augmenting technologies, ensuring innovation contributes to shared prosperity across regions and sectors. Labor market institutions must evolve to provide portable safety nets and reskilling platforms, particularly in areas heavily exposed to routine-based automation (Peters et al., 2022; McKinsey Global Institute, 2023).

Future research should continue to explore the spatial and sectoral heterogeneity in robot adoption and its socioeconomic impacts. Integrating longitudinal firm-level data and disaggregated regional metrics would provide a clearer understanding of the conditions under which automation supports inclusive growth. Moreover, expanding the analytical lens to include the role of AI and collaborative robotics in shaping work dynamics will be crucial, as advanced technologies become increasingly integrated into value chains (IFR, 2024; UNIDO, 2021). Overall, the successful integration of robotics into modern economies hinges on evidence-informed policymaking that balances innovation with inclusion.

REFERENCES

- Acemoglu, D., & Restrepo, P. (2020). Robots and jobs: Evidence from US labor markets. *Journal of Political Economy*, 128(6), 2188–2244. <https://doi.org/10.1086/705716>
- Angrist, J. D., & Krueger, A. B. (2001). Instrumental variables and the search for identification: From supply and demand to natural experiments. *Journal of Economic Perspectives*, 15(4), 69–85.

- Nageri, K. I. (2025). Industrial Robots and Regional Economic Outcomes: Evidence from China's Provinces. *Malete Journal of Accounting and Finance*, 6 (1), 35 – 49
- Arntz, M., Gregory, T., & Zierahn, U. (2016). The risk of automation for jobs in OECD countries: A comparative analysis. OECD Social, Employment and Migration Working Papers, No. 189.
- Bartel, A. P., Ichniowski, C., & Shaw, K. (2007). How does information technology affect productivity? *Quarterly Journal of Economics*, 122(4), 1721–1758. <https://doi.org/10.1162/qjec.2007.122.4.1721>
- Berg, A., Buffie, E. F., & Zanna, L. F. (2018). Robots, growth, and inequality: Should we fear the robot revolution? *Journal of Monetary Economics*, 97, 117–148.
- Bessen, J. E., Goos, M., Salomons, A., & Van den Berge, W. (2019). Automatic reaction: What happens to workers at firms that automate? Boston University School of Law Research Paper No. 20-05. <https://doi.org/10.2139/ssrn.3344876>
- Bughin, J., Hazan, E., Ramaswamy, S., Chui, M., Allas, T., Dahlström, P., ... & Trench, M. (2021). The future of work after COVID-19. McKinsey Global Institute. <https://www.mckinsey.com/featured-insights/future-of-work/the-future-of-work-after-covid-19>
- Bughin, J., Manyika, J., & Woetzel, J. (2021). The future of work in Europe: Automation, workforce transitions, and the shifting geography of employment. McKinsey Global Institute Report.
- Cheng, H., Jia, R., & Li, D. (2021). Industrial robots and firm-level outcomes: Evidence from China. *China Economic Review*, 68, 101626.
- Cheng, Y., Liu, Q., & Zhao, Z. (2022). Wage-adjusted robot adoption and national competitiveness: An East Asian comparison. *Asia-Pacific Economic Review*, 28(2), 144–163. <https://doi.org/10.1080/13547860.2022.2046557>
- Cheng, Z., Liu, Y., & Zhao, H. (2022). Global robot adoption and wage adjustment: A cross-country comparison. *Economic Modelling*, 115, 105974. <https://doi.org/10.1016/j.econmod.2022.105974>
- Chiacchio, F., Petropoulos, G., & Pichler, D. (2018). The impact of industrial robots on EU employment and wages: A local labour market approach. *Bruegel Working Paper* 2018/02.
- Ciarli, T., Savona, M., & Thorpe, J. (2021). Innovation for inclusive structural change. *Industrial and Corporate Change*, 30(3), 663–681.
- Ciarli, T., Savona, M., & Vivarelli, M. (2021). Does innovation undermine job quality? Evidence from the EU. *Research Policy*, 50(9), 104289.
- Dauth, W., Findeisen, S., Suedekum, J., & Woessner, N. (2021). Adjusting to robots: Worker-level evidence. *American Economic Review*, 111(11), 3853–3887.
- De Vries, G., Erumban, A. A., Timmer, M. P., Voskoboynikov, I., & Wende-Van Der Goot, C. (2020). Automation and labor market adjustment: Evidence from Europe. *Oxford Economic Papers*, 72(1), 1–24.
- De Vries, G., Erumban, A., Timmer, M., Voskoboynikov, I., & Woltjer, P. (2020). Structural transformation in Africa and Asia: Patterns and drivers. *World Development*, 130, 104932.
- Doms, M., Dunne, T., & Troske, K. R. (1997). Workers, wages, and technology. *Quarterly Journal of Economics*, 112(1), 253–290. <https://doi.org/10.1162/003355397555163>
- Dosi, G., & Virgillito, M. E. (2019). Whither the evolution of the capitalist economy? An evolutionary–Keynesian view. *Journal of Evolutionary Economics*, 29, 1–30.
- Elliott, S. W. (2020). A review of skill needs and policies for a digital and green future. OECD Education Working Paper No. 221.
- Frey, C. B., & Osborne, M. A. (2017). The future of employment: How susceptible are jobs to computerisation? *Technological Forecasting and Social Change*, 114, 254–280.

- Nageri, K. I. (2025). Industrial Robots and Regional Economic Outcomes: Evidence from China's Provinces. *Malete Journal of Accounting and Finance*, 6 (1), 35 – 49
- Goos, M., Manning, A., & Salomons, A. (2014). Explaining job polarization: Routine-biased technological change and offshoring. *American Economic Review*, 104(8), 2509–2526.
- Graetz, G., & Michaels, G. (2018). Robots at work. *Review of Economics and Statistics*, 100(5), 753–768. https://doi.org/10.1162/rest_a_00754
- Graetz, G., Michaels, G., & Petropoulos, G. (2022). Robots and labor market institutions. *The Economic Journal*, 132(641), 503–529.
- Graetz, G., Michaels, G., & Saidi, F. (2022). The impact of industrial robots on EU labor markets. *Labour Economics*, 76, 102168.
- Hall, B. H., Mairesse, J., & Mohnen, P. (2010). Measuring the returns to R&D. *Handbook of the Economics of Innovation*, 2, 1033–1082.
- Haskel, J., & Westlake, S. (2018). *Capitalism without capital: The rise of the intangible economy*. Princeton University Press.
- ILO (2022). *World Employment and Social Outlook 2022: Transforming jobs to end poverty*. International Labour Organization.
- IMF (2021). *World Economic Outlook: Recovery during a pandemic*. International Monetary Fund.
- International Federation of Robotics. (2023). *World Robotics 2023: Industrial Robots*. <https://ifr.org/worldrobotics>
- International Federation of Robotics. (2024). *World Robotics Report 2024: Global surge in robot adoption*. <https://ifr.org>
- Kim, J., & Lee, D. (2023). Robotics in the automotive industry: Trends and challenges. *Robotics and Computer-Integrated Manufacturing*, 85, 102431.
- Kim, J., & Lee, H. (2023). The rise of robotics in healthcare: Challenges and opportunities. *International Journal of Health Technology and Management*, 24(3), 177–194.
- Lewbel, A. (2012). Using heteroskedasticity to identify and estimate mismeasured and endogenous regressors. *Journal of Business & Economic Statistics*, 30(1), 67–80.
- Li, T., Zhou, X., & Zhang, Y. (2024). Sectoral expansion of industrial robots: Evidence from logistics and services in China. *Technological Forecasting and Social Change*, 194, 122515.
- Li, W., Zhou, X., & Zhang, Y. (2024). Adoption of surgical robots in healthcare: A systematic review. *International Journal of Medical Robotics and Computer Assisted Surgery*, 20(1), e2510.
- Li, X., Li, S., & Wang, Y. (2020). Capital deepening, TFP and economic growth: Evidence from China. *Economic Modelling*, 91, 660–670.
- Luo, J., Li, K., & Li, W. (2023). How do robots affect productivity? Evidence from Chinese manufacturing. *Technological Forecasting and Social Change*, 190, 122378.
- Luo, S., Guo, H., & Shen, K. (2023). Automation and productivity: Evidence from firm-level data in China. *Economic Systems Research*, 35(1), 23–45.
- McKinsey Global Institute. (2023). *The future of work after COVID-19: Rethinking automation and labor market resilience*. McKinsey & Company.
- Nedelkoska, L., & Quintini, G. (2018). *Automation, skills use and training*. OECD Social, Employment and Migration Working Papers, No. 202.
- OECD. (2020). *Digital disruption in banking and its impact on competition*. OECD Competition Committee.
- OECD. (2022). *Automation and the future of work: Navigating the transition*.
- Organisation for Economic Co-operation and Development. (2022). *Automation, skills and training in the digital age*. <https://doi.org/10.1787/ed292c78-en>

- Nageri, K. I. (2025). Industrial Robots and Regional Economic Outcomes: Evidence from China's Provinces. *Malete Journal of Accounting and Finance*, 6 (1), 35 – 49
- Peters, B., Roberts, M. J., Vuong, V. A., & Fryges, H. (2022). Dynamic R&D choice and the impact of the firm's R&D history. *Review of Economics and Statistics*, 104(5), 847–862.
- Peters, M., Boehm, J., & Oberfield, E. (2022). A global view of productivity growth and employment. *Quarterly Journal of Economics*, 137(3), 1495–1552.
- Solow, R. M. (1957). Technical change and the aggregate production function. *Review of Economics and Statistics*, 39(3), 312–320.
- Staiger, D., & Stock, J. H. (1997). Instrumental variables regression with weak instruments. *Econometrica*, 65(3), 557–586.
- UNIDO. (2023). Industrial Development Report 2023: The Future of Industrialization in a Post-Pandemic World. United Nations Industrial Development Organization.
- World Bank. (2020). The future of work in Africa: Harnessing the potential of digital technologies for all. World Bank Publications.
- World Economic Forum. (2021). The Future of Jobs Report 2021. <https://www.weforum.org/reports/the-future-of-jobs-report-2021>
- Xu, B., Tan, Y., & Chen, M. (2021). Industrial robot adoption in China: Policy, practice, and pathways. *Technological Forecasting and Social Change*, 170, 120930. <https://doi.org/10.1016/j.techfore.2021.120930>
- Xu, L., Tan, J., & Chen, Z. (2021). Subsidy-induced robot adoption and productivity: Firm-level evidence from China. *China Economic Review*, 68, 101634. <https://doi.org/10.1016/j.chieco.2021.101634>
- Zhang, J., & Lu, D. (2023). Technology adoption, human capital, and income inequality: New evidence from panel data. *Journal of Development Economics*, 160, 102956.