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Labour or capital factors: Which influence industrial automation more?

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ABSTRACT

Objective: The purpose of the article is to determine which economic factors, specifically those related to labour and capital, have a more significant impact on the level of industrial automation. This assessment is based on robot density per 10 000 employees in the manufacturing sector.

Research Design & Methods: The empirical insights came from a broad array of statistical data spanning from 2000 to 2022, acquired from reputable international institutions. The study employs a methodological framework that integrates a review of pertinent literature, deductive reasoning, and an in-depth comparative analysis of selected time series. The central element of the research is the application of multiple regression analyses, primarily focusing on data from 2020 for 27 nations progressing in manufacturing automation.

Findings: Analysis of time series data on multifactor, labour, and capital productivity in countries with the highest robot densities shows a complex interplay between labour and capital productivity in the realm of industrial automation. Multiple regression analysis, particularly Model 1, substantiated hypothesis H2, revealing that capital-related factors, specifically gross domestic expenditures on R&D and foreign direct investment, emerged as statistically significant predictors of robot density (RD), both exhibiting positive correlations. This underscores the pivotal role of capital investments and technological advancements in fostering automation. Further analysis using Model 2, aggregating labour and capital variables, reaffirmed the predominance of capital factors in influencing industrial automation. The pronounced positive association between the capital index (CAP) and RD highlights the critical influence of capital-related variables, such as technological innovations and investments, in driving the adoption and density of industrial robots, thereby underscoring the foundational role of capital in the advancement of automation in the manufacturing sector.

Implications & Recommendations: The findings highlight a bidirectional influence between automation and productivity in the manufacturing sector, with capital access and utilization playing a pivotal role in automation disparities across economies. Economies reliant on labour-intensive methods lag in automation, underscoring the insufficiency of abundant labour for promoting automation. Instead, capital availability, particularly through R&D spending and foreign investment, emerges as crucial for advancing industrial automation. This necessitates a strategic realignment, where policymakers and industry leaders must prioritize capital investment and technological innovation as key automation enablers. The study calls for comprehensive strategies that emphasize capital investment, technological innovation, skill development, and quality education to effectively engage in the global automation landscape.

Contribution & Value Added: Contrary to the prevalent focus in existing literature on automation's impact on socio-economic factors, particularly labour productivity, this research adopts a reverse perspective by examining the influence of labour and capital factors on automation progression. The study's novel approach, asserting the paramountcy of capital in driving automation, suggests that active participation in the global automation landscape necessitates comprehensive efforts encompassing R&D investment, FDI attraction, workforce skill enhancement, and investment in quality education.

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INTRODUCTION

The contemporary global economy is increasingly explained by its reliance on knowledge and data, establishing these elements as pivotal in the cultivation of competitive advantage. This transition towards an information-centric paradigm has been significantly propelled by the advancements in information and telecommunication technologies (ICT). On the other hand, these developments have laid the groundwork for the emergence of Industry 4.0, a revolutionary phase in industrial evolution characterized by a focus on automation, data exchange, cloud computing, the Internet of Things (IoT), and innovative manufacturing technologies such as 3D printing, underpinned by the pervasive influence of artificial intelligence (AI). This technological leap has engendered a paradigm shift in how industries operate, fostering an environment where efficiency, connectivity, and smart automation are at the forefront.

Following the strides made in Industry 4.0, the concept of Industry 5.0 has surfaced, heralding a renaissance in the integration of the human element within the industrial matrix. Unlike its predecessor, Industry 5.0 emphasizes the symbiotic relationship between humans and advanced smart systems, including robotics and AI. This new industrial vision advocates for a human-centric design approach, where personalization, sustainability, and resilience are not just supplementary benefits, but foundational pillars. The ascension of Industry 5.0 is intrinsically linked to the rapid advancements in AI and robotics, suggesting a future where manufacturing processes are not only dictated by machine efficiency, but are also reflective of human values and ethics.

However, the discourse surrounding the impact of industrial automation, a cornerstone of Industry 4.0, often veers towards its potential negative repercussions, particularly concerning the labour market. Critics highlight issues such as job displacement and the widening skills gap as automation becomes more prevalent. However, it is crucial to acknowledge that the adoption and effects of industrial automation have been markedly uneven across different regions, predominantly concentrated in a handful of countries. This article aims to invert the traditional analysis by examining the influence of selected labour and capital factors on the progression of automation, as evidenced by the density of robots per 10 000 employees in the manufacturing sector. This approach seeks to offer a more refined understanding of the dynamics at play, bridging the gap between technological advancement and socio-economic factors, thereby contributing to a more holistic discourse on the future of industry in the global economy.

The article is structured to analyse the impact of labour and capital factors on industrial automation, utilizing empirical data and multiple regression models. It includes a literature review, a detailed methodological framework, and an evaluation of automation drivers, highlighting the dominant role of capital investments over labour-related factors.

LITERATURE REVIEW

In tracing the historical and theoretical perspectives on technological advancements and their impact on society and the economy, the seminal works of Babbage (2010) and Beniger (1986) lay the foundational understanding of the mechanization of industries and the onset of the information society. Babbage's exploration into the economy of machinery provides an early examination of the efficiency and division of labour brought about by technological innovations, a theme that resonates with contemporary discussions on automation and AI. On the other hand Beniger (1986) extends this discourse into the realm of the control revolution, delving into the technological and economic origins of the information society. His analysis offers a comprehensive view of how technological progress has shaped organizational structures and societal functions, setting a precedent for understanding the current digital transformation.

Further enriching this narrative, Braverman (1998) and Piketty (2014) offer critical insights into the socio-economic implications of technological change. Braverman's critique on the degradation of work in the twentieth century highlights the implications of industrial advancements on labour practices, presenting a perspective that compares the optimistic views on technology's potential to enhance human labour. In parallel, Piketty's extensive examination of capital in the twenty-first century sheds light on the economic disparities exacerbated by technological progress, offering a macroeconomic perspective on how technology influences wealth distribution and social stratification. These historical and theoretical explorations provide a nuanced understanding of the complex interplay between technology, economy, and society, serving as a crucial background for contemporary analyses of automation and AI's impact on the labour market.

Delving into the intricate dynamics between automation's role in job displacement and creation, the influential studies by Acemoglu and Restrepo (2017, 2019) provide a diverse perspective on the impact of robotics and automation in the US labour markets. Their research highlights the complex nature of technological advancements, echoing historical debates on machinery's dual capacity to enhance and replace human labour. This body of work emphasizes the necessity for societies to adapt and harness the positive aspects of automation, mirroring past transitions in labour dynamics induced by technological breakthroughs.

Furthering the discourse on the implications of technological change for the labour market, Autor's significant contributions (Autor, 2015; Autor *et al.*, 2001; Autor & Salomons, 2018) challenge the prevalent narrative of automation leading to widespread job loss. Instead, he argues for the enduring nature of employment, albeit transformed by technology's evolution. This perspective aligns with earlier concerns about labour transformation, suggesting that technological advancements tend to complement complex human skills, thereby reshaping job demands in favour of tasks that require complex problem-solving and interpersonal abilities.

Exploring the transformative effects of Industry 4.0 on various sectors, particularly in industrial automation and supply chain management, the study by Acharya *et al.* (2017) provides in-depth insights into how analytic hierarchy processes serve to navigate the complexities introduced by these technological advancements. Their research offers a detailed examination of the factors influencing industrial automation, revealing the complex interplay between technological capabilities and organizational needs. This aligns with the discussions by Acemoglu and Restrepo on the diversified impact of automation, further emphasizing the need for strategic adaptation to harness the full potential of technological innovations in the industrial landscape.

As concerns supply chain performance, the contributions of Fatorachian and Kazemi (2020) shed light on the pivotal role of Industry 4.0 technologies in reshaping production planning and control. Their analysis delves into the significant enhancements in efficiency and responsiveness that Industry 4.0 brings to supply chains, illustrating the profound implications of these technologies for global trade and logistics. This body of work complements the broader narrative on the impact of automation on labour markets by highlighting the complementary nature of technological advancements in optimizing operational processes and creating value across different industry sectors.

Furthermore, the comprehensive review by Sima *et al.* (2020) on the influences of the Industry 4.0 revolution on human capital development and consumer behaviour provides a holistic view of the socio-economic changes ushered in by these technological shifts. Their systematic exploration of the interconnectedness between Industry 4.0 and various aspects of human capital and consumer dynamics underscores the multifaceted effects of technological progress. This research not only echoes the labour market transformations discussed by Autor *et al.* (2001) but also extends the understanding of technology's impact by encompassing the broader socio-economic ecosystem, including changes in consumer behaviour and workforce development in the face of rapid technological innovation.

Building on the exploration of Industry 4.0's impact on supply chains and human capital, the discourse extends to the transformative potential of information technology on organizational structures and business performance, as exemplified in the work of Brynjolfsson and Hitt (2000). Their research provides empirical evidence on the correlation between technological adoption and enhanced business outcomes, emphasizing the strategic importance of digital transformation. This perspective merges with the efficiencies brought about by Industry 4.0, as discussed by Fatorachian and Kazemi, highlighting the broader implications of automation and technological innovation beyond the manufacturing floor and into the realm of organizational strategy and performance. Furthermore, the empirical study by Doms *et al.* (1997) and the recent work of Dinlersoz and Wolf (2023) on the effects of automation on labour share and productivity in U.S. manufacturing plants offer nuanced insights into the sector-specific impacts of technological advancements. These studies reveal the intricate relationship between technology adoption, workforce composition, and economic outcomes within the manufacturing sector, echoing the findings from the Industry 4.0 literature. They underscore the complex, multifaceted nature of technology's impact on labour markets, highlighting the necessity of strategic adaptation and the potential for innovation-led growth in a rapidly evolving technological landscape.

Transitioning from the discussion on the interplay between technology, organizational structures, and labour dynamics, the exploration of artificial intelligence (AI) and automation's broader societal impacts offers a further understanding layer. In their book on the economics of AI, Agrawal *et al.* (2018) delve into the concept of 'prediction machines,' framing AI as a pivotal tool for enhancing decision-making processes. This notion complements the insights from Brynjolfsson and Hitt regarding the strategic significance of technological adoption in organizations. Agrawal's *et al*. (2018) perspective underscores the transformative potential of AI to extend beyond mere efficiency improvements, driving innovation and redefining competitive landscapes across industries.

Furthermore, Ford's explorations in *Rise of the Robots* (2015) and *Rule of the Robots* (2022) provide a comprehensive analysis of the implications of AI and robotics for the future of work and the economy. Author highlights the dual nature of technological advancements: while they present unprecedented opportunities for innovation and efficiency, they also pose significant challenges in terms of potential mass unemployment and economic inequality. This dual narrative echoes the discussions on the nuanced impact of automation on labour markets presented by Autor *et al*. (2001), further emphasizing the need for a balanced approach to harnessing technology's benefits while mitigating its potential downsides.

Finally, the contributions of Hoff and Bashir (2015) and Susskind and Susskind (2022) broaden the scope of the discourse by examining the human element in the technological revolution. Hoff and Bashir's research into trust in automation highlights the critical importance of developing reliable and user-friendly systems to foster positive human-technology interactions. This aspect is crucial for ensuring the seamless integration of AI in both personal and professional spheres. Similarly, Susskind and Susskind's (2022) examination of the future of professions in the age of AI suggests a significant transformation in how professional expertise is accessed and utilized. Their work suggests a redefinition of roles and skills, highlighting the need for adaptability and lifelong learning in the workforce. These perspectives add depth to the discussion on technology's impact, suggesting that both technological capabilities and how individuals and societies adapt to these changes will shape the future.

Based on the conducted research, it is evident that the majority of literature focuses on the influence of automation on labour and capital-related domains in the economy, rather than the reverse. Specifically, numerous studies and analyses have been devoted to understanding how automation impacts employment rates, labour share of income, productivity, and the overall economic structure. These studies typically explore how the introduction of automation and technological advancements displaces certain types of labour, affects wage dynamics, and shifts the income distribution between labour and capital.

On the other hand, there is comparatively less evidence and fewer studies that specifically address the reverse assumption, *i.e.* how labour and capital incentives might drive the automation adoption rate. While some research does explore this aspect, indicating that factors such as labour supply, wage rates, and the strategic decision-making of firms can influence the adoption of automation technologies, these studies are less prevalent than those examining the impacts of automation on the economy.

For instance, Gaimon's research (1985) explores the decision-making process regarding the mix of automation and labour within organizations. It identifies the optimal mix to enhance productivity, considering incentives such as output increase, labour cost reduction, and compensation for limited labour supply. The dynamic model considers factors like technological improvement and wage rate changes, highlighting the complex interplay between labour and capital incentives and automation implementation. In turn, Romer (1990) provides a theoretical foundation that underscores the role of human capital, policy, and market structures in driving technological progress and, subsequently, its impact on labour and automation. In contrast, Fornino and Manera (2019) investigate the economic incentives for automation in scenarios where labour and machines are perfect substitutes. It reveals that even when labour is more costly than robots, firms may still employ it if they face risks and machine adjustments are costly. Moreover, labour can be flexibly managed. This underscores the role of labour flexibility and idiosyncratic firm risks in driving the deployment of automation technologies. Building on this discourse, Danzer *et al.* (2020) examined the impact of labour supply dynamics on automation innovation, uncovering a negative correlation between an abundant labour supply and the drive for labour-saving technological advancements, particularly in sectors heavily reliant on low-skilled workers.

In summary, it seems that the prevailing body of literature offers a more comprehensive examination of how automation impacts labour and capital in the economy, while fewer works devote attention to exploring how incentives related to labour and capital might influence the pace and trajectory of integrating automated technologies.

RESEARCH METHODOLOGY

The empirical findings presented in this study have been derived from an extensive collection of statistical data sourced from reputable organizations such as the International Federation of Robotics (IFR), OECD, The World Bank, the International Labour Organization (ILO), and UNCTAD, covering the period from 2000 to 2022. The methodological approach adopted in this research includes a thorough review of relevant literature and primary sources, complemented by deductive reasoning and a detailed comparative analysis of selected time series. A pivotal aspect of this study involves multiple regression analyses, predominantly utilizing data from the year 2020. In rare instances where data for 2020 were not available, figures from 2019 have been substituted to ensure analysis consistency.

To address the research objectives, the following main hypotheses have been established:

H1: In 27 countries with high and medium density of industrial robots, the key factors influencing the level of automation are those associated with labour as a critical production component.

H2: In the same cohort of countries, the extent of automation is significantly affected by capital-related factors.

Table 1. List of variables for Model 1

Variable	Description	Data source	Dependent/independent
RD	Robot density per 10 000 employees	IFR (2021)	Dependent variable
EMP	Manufacturing employment (% of total)	ILO (2024)	Independent variable related to labour
UnEmp	Unemployment rate 25+ (%)	ILO (2024)	Independent variable related to labour
LProd	Output per worker (GDP constant 2015 USD)	ILO (2024)	Independent variable related to labour
GERD	Gross domestic expenditures on research and development (% of GDP)	WB (2024)	Independent variable related to capital
GFCF	Gross fixed capital formation (% of GDP)	WB (2024)	Independent variable related to capital
FDI	Foreign direct investment, net inflows (% of GDP)	WB (2024)	Independent variable related to capital

Note: WB – the World Bank.
Source: own study.

To evaluate the proposed hypotheses, two distinct econometric models have been subjected to rigorous analysis, leveraging normalized data from the year 2020. These models encompassed a consistent dataset pertaining to the following 27 countries: Australia, Austria, Belgium, Canada, China, Czechia, Denmark, Finland, France, Germany, Hong Kong, Hungary, Italy, Japan, Netherlands, Norway, Poland, Portugal, South Korea, Singapore, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom, and the United States. Model 1 delineates labour- and capital-related factors as separate variables, in contrast to Model 2, which constructs two composite measures treated as independent variables. These have been derived from the arithmetic mean of normalized indices, representing labour (L) and capital (C) as key determinants of industrial automation. Tables 1 and 2 systematically document the variables and metrics employed in each model.

Table 2. List of variables for Model 2

Variable	Description	Data source	Dependent/independent
RD	Robot density per 10 000 employees	IFR (2021)	Dependent variable
LAB	Labour-related composite measures including: 1) Output per worker (GDP constant 2015 USD) 2) Unemployment rate 25+ (%) 3) Average monthly earnings of employees in manufacturing (USD) 4) Qualification mismatch 5) Skills sub-index from Frontier Technology Readiness Index (FTRI)	1,2,3 – ILO (2024), 4 – OECD (2024), 5 – UNCTAD (2024).	Independent variable
CAP	Capital-related composite measures including: 1) Gross domestic expenditures on research and development (% of GDP) 2) Foreign direct investment, net inflows (% of GDP) 3) Gross fixed capital formation (% of GDP) 4) ICT sub-index from FTRI 5) Access to finance sub-index from FTRI	1,2,3 – WB (2024), 4,5 – UNCTAD (2024).	Independent variable

Note: WB – the World Bank.

RESULTS AND DISCUSSION

Although the common methods for analysing the growth of the industrial automation market primarily rely on data related to industrial robot installations and operational stock, segmented by country and industry, it seems that robot density provides the most objective measure of industrial automation's progress. The International Federation of Robotics (2020) defines robot density as 'the number of multipurpose industrial robots in operation per 10 000 employees.' This definition proves particularly useful for this article, as it highlights the relative specificity of the measure by comparing the 'world of machines' with the 'world of humans.'

From 2010 to 2020, the global density of industrial robots in manufacturing increased by over 150%, reaching 126 units (IFR, 2021). Furthermore, in 2021, the worldwide average growth of robot density climbed to 141 units (Statista, 2024), indicating that even the COVID-19 pandemic did not disrupt this clear upward trend. Between 2017 and 2021, the highest, record-breaking growth rate occurred in China, where robot density in manufacturing more than tripled. While the achievements of the next four countries in this respect – Switzerland, South Korea, the United States, and Sweden – were not as dramatic, with increases ranging from 86% in Switzerland to over 30% in the USA and Sweden (Statista, 2024), they were still significantly higher than those in other countries on the path to industrial automation.

As illustrated in Figure 1, the data from the IFR on robot density showcased significant disparities in the adoption of industrial automation across various countries from a broader perspective. The top 5 countries – South Korea, Singapore, Japan, Germany, and Sweden – demonstrated notable advancements in this area, highlighting their global leadership in the adoption of industrial robotics. Particularly, South Korea has shown an impressive trajectory, with its robot density soaring from 107 robots per 10 000 employees in 2000 to 932 in 2020, reflecting a dedicated and aggressive approach to automation aimed at boosting manufacturing efficiency and global competitiveness. In contrast, Japan's growth has been more moderate, indicating a potentially maturing market or a strategic phase of consolidation in robotics adoption. Two decades ago, Japan was the only country to surpass the threshold of 300 industrial robots per 10 000 employees. By 2020, only three additional countries – South Korea, Singapore, and Germany – had crossed this benchmark, with the first two leaving Japan significantly behind. Furthermore, despite China's improvements in industrial automation in recent years, it was not sufficient for the country to move from the group of automation followers, with a robot density in the range of 200-300 units, into the top 5, let alone close the gap with the leading countries in Southeast Asia.

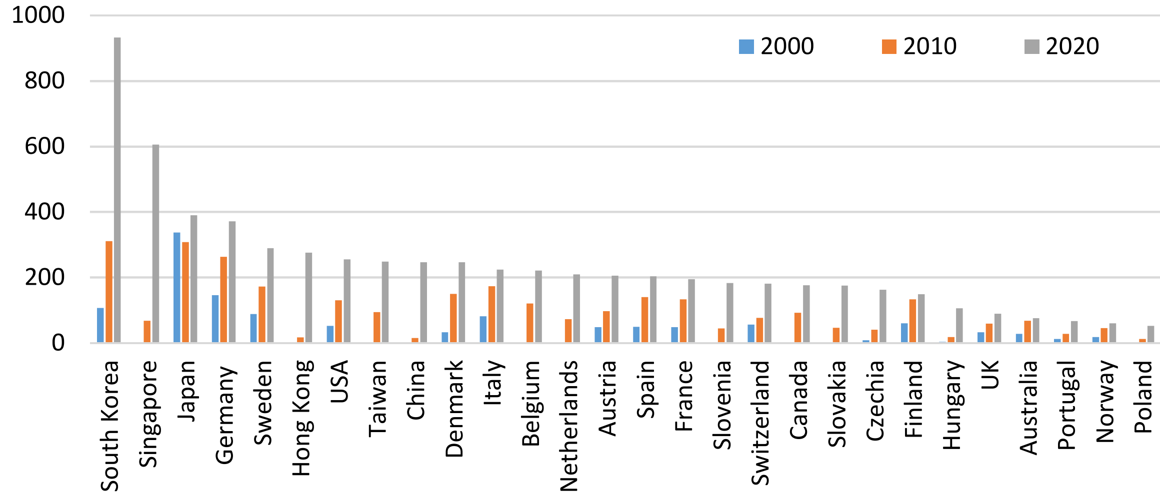

Figure 1. Robot density per 10 000 employees in manufacturing, 2000-2020
Source: own elaboration based on IFR (2020, 2021, 2024).

In contrast, we may link the disparity in robot density among Central European countries to a variety of factors. With their significant share of advanced manufacturing sectors like automotive and electronics, Slovakia and Czechia may have created a more favourable setting for embracing robotics. These industries often feature higher automation levels, benefiting from the complex, repetitive tasks that robotic systems excel at handling. Conversely, Hungary and Poland might possess a higher proportion of sectors that rely less on automation, but more on cheaper low- and medium-skilled labour, such as food processing, furniture making, textiles, or traditional manufacturing, which could account for their lower robot densities. Furthermore, we cannot overstate the role of economic strategies and investments in technological infrastructure. Slovakia and Czechia have been more effective in attracting foreign direct investments that not only supply capital but also bring technological expertise and elevate automation standards. Meanwhile, Hungary and Poland may have encountered obstacles in these areas, potentially due to unfavourable economic policies, inadequate investment in technology and innovation, or a belated effort to adopt industrial automation solutions.

As Figure 2 shows, we may partially attribute the trend in multifactor productivity from 2000 to 2022 to the growing role of automation in enhancing economic efficiency across selected economies. With the rise in robot densities, particularly in countries leading in automation such as South Korea, there has been a significant increase in multifactor productivity (MFP) indices. This suggests that we may treat the widespread adoption of robotics as a key factor in optimizing resource utilization and increasing productivity. This trend highlights the direct impact of automation on manufacturing processes and its wider implications for the economy, illustrating how technological advancements are pivotal in making industries more efficient and productive.

Significant additional observations emerge from the data presented in Figures 3 and 4. Integrating trends in robot density in manufacturing and multifactor productivity with labour and capital productivity data revealed compelling patterns, particularly in the comparison between the automation leader, South Korea, and its close followers. South Korea has made exceptional strides not only in robot density but also in labour productivity, with GDP per hour worked exhibiting steady growth from 2015 onward. This can suggest a likely direct link between increased automation and labour efficiency, implying that the introduction of industrial robots has substantially contributed to improving workforce productivity. Conversely, economies such as Germany, Japan, Sweden, and the USA, while also experiencing enhancements in labour productivity, demonstrate a velocity and magnitude that are particularly noteworthy in South Korea, emphasizing its superiority in industrial automation. This is further evident in capital productivity trends, where South Korea, despite a slight decline, sustains a commendably high level of efficiency in capital utilization, including undoubtedly investments in robotics and technology. This indicates that South Korea's assertive investment in automation not only maximizes labour output but also ensures efficient capital utilization, fostering overall economic productivity.

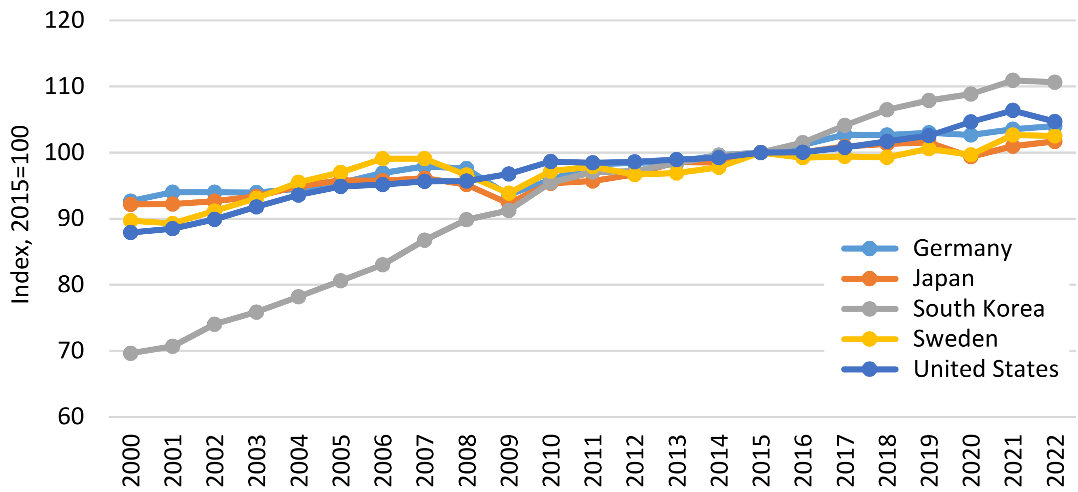

Figure 2. Comparative multifactor productivity (MFP) in selected automation leader countries, 2000-2022

Source: own elaboration based on OECD (2024).

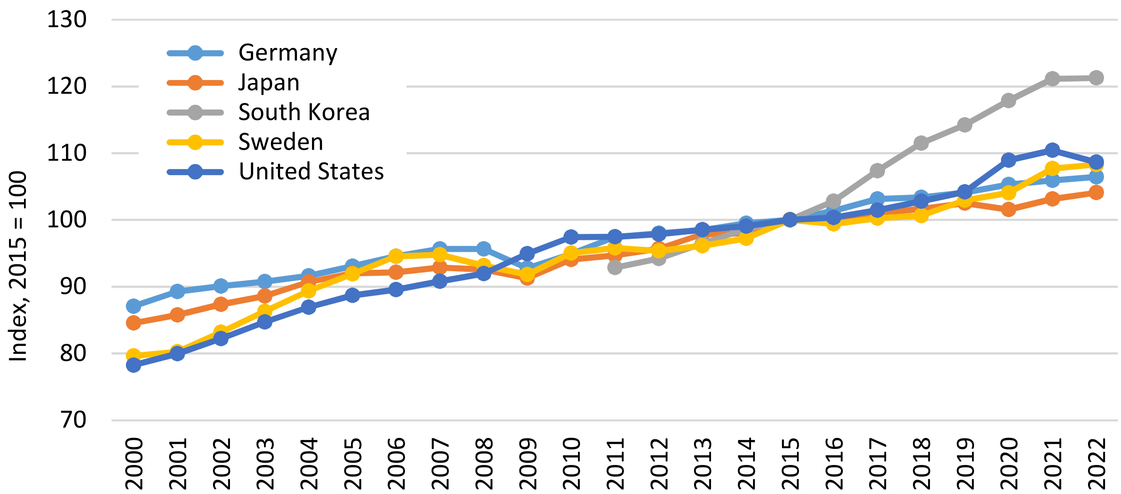

Figure 3. Comparative labour productivity in selected automation leader countries, 2000-2022

Source: own elaboration based on OECD (2024).

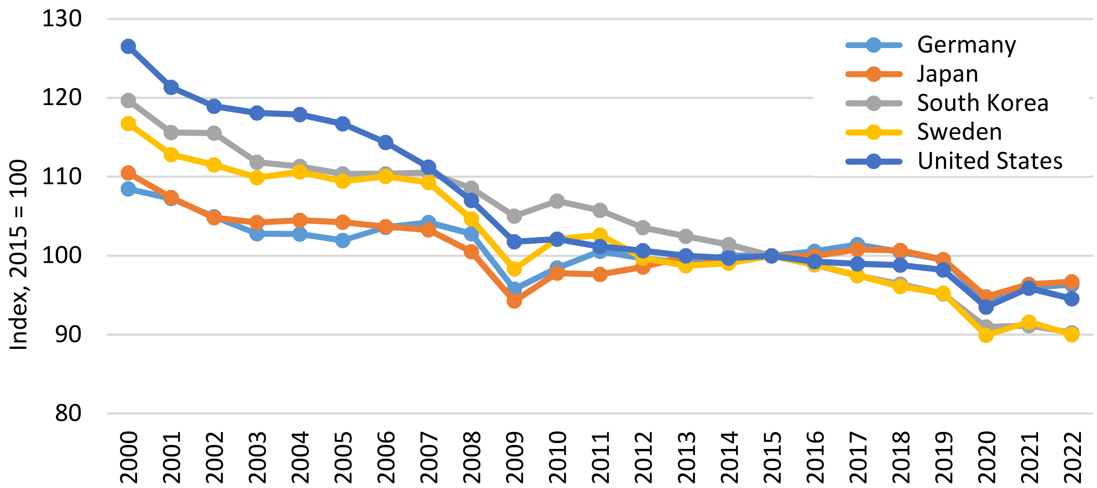

Figure 4. Comparative capital productivity in selected automation leader countries, 2000-2022

Source: own elaboration based on OECD (2024).

However, in comparing these trends, it is essential to recognize that although South Korea leads in automation and labour productivity, the difference in capital productivity with countries such as Germany and the USA was narrowing in the analysed period. This suggests that despite lower robot densities, these nations employ their capital in ways that sustain competitive productivity levels. We may view this as further evidence of the intricate relationship between labour and capital productivity in the context of automation, where the influence of robotics transcends manufacturing efficiency to affect broader economic indicators.

The presented data underscores the vital importance of automation in defining the contours of productivity landscapes. The example of South Korea demonstrates how substantial investments in robotics can enhance both labour and capital productivity, establishing a benchmark for other economies. Meanwhile, countries closely following the automation journey, despite their progress, display a sophisticated interplay between capital investment, labour efficiency, and technological adoption, providing insightful perspectives on the comprehensive impact of automation on economic productivity.

To understand how various labour and capital-related factors affect the adoption and density of robots in the manufacturing industry, the multiple regression model has been utilized. The proposed econometric model was:

$$RD = \beta_0 + \beta_1 \times EMP + \beta_2 \times UnEmp + \beta_3 \times LProd + \beta_4 \times GERD + \beta_5 \times GFCF + \beta_6 \times FDI + \varepsilon \tag{1}$$

in which:

RD - (robot density per 10 000 employees) is the dependent variable;

EMP, *UnEmp*, *LProd*, $GERD$, $GFCF$, and FDI - independent variables, as described in Table 1;

ε **-** significance of the particular component in question.

The analysis of the proposed multiple regression model, which explored the influence of various economic factors on robot density (RD) within the manufacturing sector, yielded critical insights (see Table 3). The model accounted for approximately 59.06% of the variance in RD as indicated by an R^2 value of 0.5906. It demonstrated a significant overall fit. Among the independent variables, gross domestic expenditures on R&D (GERD) and foreign direct investment (FDI) emerged as statistically significant predictors of RD, both showing positive correlations. Meanwhile, GERD, with a p-value of 0.000101, underscored the pivotal role of research and development investments in driving technological advancements and automation in manufacturing. Similarly, FDI's significance (p-value of 0.011586) suggests that foreign investments contributed substantially to the adoption and density of robotics, likely through technology transfer and enhanced industrial capabilities.

Table 3. Multiple regression analysis results for model (1)

N=27	b*	Std. error of b*	b	Std. error of b	t(20)	p
Intercept	–	–	-0.227442	0.239397	-0.950061	0.353421
EMP	0.144870	0.293516	0.116765	0.236572	0.493570	0.626986
UnEmp	0.269677	0.166307	0.270086	0.166560	1.621556	0.120558
LProd	-0.279652	0.260372	-0.220595	0.205386	-1.074046	0.295590
GERD	**1.014221**	**0.209894**	**0.882824**	**0.182701**	**4.832069**	**0.000101**
GFCF	-0.065742	0.177003	-0.066661	0.179477	-0.371420	0.714231
FDI	**0.568964**	**0.204750**	**0.514847**	**0.185275**	**2.778829**	**0.011586**

Note: R= 0.76851122, R^2= 0.59060950, corr. R2= 0.46779235, F(6,20)=4.8089, p<0.00345, est. std. error: 0.15045.
Source: own elaboration using Statistica software.

Conversely, the model revealed that labour-related factors, such as manufacturing employment (EMP), unemployment rate (UnEmp), and output per worker (LProd), did not significantly influence RD within the context of this analysis. The lack of significance of these labour variables, coupled with the pronounced impact of capital-related factors (GERD and FDI), suggests that capital investments, particularly in innovation and foreign capital inflows, played a more critical role in determining the level of automation in the manufacturing sector than labour-related factors. This distinction highlights the importance of technological infrastructure and investment in innovation for enhancing automation, suggesting that strategies aimed at increasing robot density might benefit more from focusing on capital-related factors, such as R&D and attracting FDI, rather than adjustments in labour market characteristics.

To support these insights, an additional econometric model for multiple regression analysis has been developed. In this model, robot density (RD) serves as the dependent variable, while two composite indices – as independent variables: one for labour-related factors and the other for capital-related factors. The proposed econometric model is expressed as follows:

$$RD = \beta_0 + \beta_1 \times LAB + \beta_2 \times CAP + \varepsilon \quad (2)$$

in which:

RD - (robot density per 10 000 employees) is the dependent variable;

LAB, CAP - independent variables, as described in Table 2;

ε - is the error term, accounting for the variation in robot density not explained by the model.

Table 4. Multiple regression analysis results for model (2)

N=27	b*	Std. error of b*	b	Std. error of b	t(24)	p
Intercept	–	–	-0.224585	0.145633	-1.542129	0.136126
LAB	-0.097685	0.196370	-0.132102	0.265556	-0.497454	0.623396
CAP	**0.596952**	**0.196370**	**1.119710**	**0.368334**	**3.039931**	**0.005643**

Note: R= 0. 55442984, R^2= 0.30739244, corr. R2= 0.24967515, F(2,24)=5.3258, p<0.01219, est. std. error: 0.17864
Source: own elaboration using Statistica software.

In this approach, the regression analysis exploring the determinants of robot density (RD) within the manufacturing sector underscores the critical role of capital-related factors. The significant positive relationship between the capital index (CAP) and RD, indicated by a p-value of 0.005643, highlights that variables associated with capital, such as technological advancements and investments, were key automation drivers. This significant correlation suggests that increased emphasis on capital-intensive activities within the sector is closely linked to higher adoption and density of robots, emphasizing the importance of capital investments in promoting automation.

In contrast, the labour index (LAB), which encompasses labour costs, workforce size, and productivity, does not exhibit a statistically significant influence on RD, as evidenced by its p-value of 0.623396. This lack of significance suggests that within the confines of this analysis, labour-related factors might not play a crucial role in determining the automation level, as represented by robot density. This finding indicates that while labour dynamics are integral to the manufacturing sector, they may not directly impact the adoption and integration of robotics within the industry.

Overall, this supplemental model's explanatory power, with an R^2 value of 0.3074, reveals that the included variables capture a substantial portion of the variance in RD. However, there remains a significant portion unexplained, suggesting the presence of other influential factors not represented by the LAB and CAP indices. Nonetheless, the analysis sheds light on the complex interplay between economic forces and automation trends, with capital-related factors emerging as particularly influential in driving the adoption of robotics. This in-depth understanding is crucial for stakeholders in the manufacturing sector, emphasizing the need for strategic capital investments to enhance automation and productivity.

CONCLUSIONS

The analyses validated the research hypothesis H2, namely the impact of capital factors on robot density, which we may interpret as an indicator of the level of industrial production automation. As outlined in the literature review, the context of automation often examines its consequences for industry efficiency and employment. However, the IFR data on the development of robotization in recent decades indicate that progress in this area is particularly prevalent in economies well-endowed with capital. However, the models presented in this article are characterized by several limitations. Primarily, it is challenging to gather a sufficient dataset that allows for the extension of analyses to a larger number of countries. Moreover, many of the indicators used in the analyses are composite and therefore do not fully describe the particular situation in the manufacturing industry. Developing a model based on a larger set of more detailed variables would thus allow for more precise and meaningful outcomes. Moreover, the demonstrated greater significance of capital factors does not imply a lack or minimal influence of labour-related factors. The progress in robotization results from the interaction of various, often difficult-to-measure parameters, such as the legal and regulatory environment, support systems for investment in robotization, the level of education and efficiency of workers, dominant industrial sectors in a country (labour-intensive vs. capital-intensive), and the existing international specialization of a given economy.

This last aspect may be particularly significant in economies, where the service sector accounts for the largest share of GDP and employment. In these countries, which include most high and middle-income per capita economies, robotization may progress relatively slowly because the manufacturing sector does not play a significant role.

However, in some Asian countries, Germany, and Sweden, where the importance of the manufacturing sector is still relatively high (World Bank, 2024), the pace of industrial automation is significantly higher than in other economies, where other areas related to Industry 4.0, especially artificial intelligence solutions, seem much easier to implement in the service sector. Based on current observations, these advancements in artificial intelligence are likely to become increasingly important compared to agriculture and industry. Furthermore, similar to robotization, the disruptive shifts observed in the field of AI and their immediate impact on the service sphere are likely to be, to a large extent, conditioned by access to capital, as investments in the broadly understood ICT infrastructure contribute to the rapid development of artificial intelligence.

Noteworthy, continuing and rapid advancements in artificial intelligence, as a key part of the Industrial Revolution 5.0, can also have consequences for industrial automation progress. On the one hand, growing investment in AI and its practical deployment, especially in the service sector, can lead to diminishing investment in industrial robots. In such a scenario, we may observe a gradual transition from robotics to AI-related fields in R&D and investment in the near future. On the other hand, as the primary objective of Industry 5.0 is to achieve a balance between automated production systems and human ingenuity, investment in AI can simultaneously attract interest in the development of more sophisticated, smart automation systems, like collaborative robots. In such a case, where capital will still be crucial for consequential developments, the role of labour-related factors may be diminishing. In other words, capital-driven investment in AI may make human labour, especially low and medium-skilled, obsolete, with the acceleration of human replacement both in the service sector (by AI itself), and in the manufacturing sector (by industrial robots and cobots controlled and managed by AI).

The primary limitation of this research lies in the insufficient availability of comprehensive and consistent data on robot density across all countries, which may impede cross-country comparisons and limit the generalizability of the results. Future studies could focus on applying classification methods to evaluate the combined effects of robot density and AI deployment on the progression of industrial automation. Moreover, research should explore how these trends vary across nations with differing levels of capital endowment and ICT infrastructure.

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Conflict of Interest

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