2025 - 35(1) DOI: 10.2478/sues-2025-0005

THE DYNAMICS OF LABOR INCOME SHARE IN AN ERA OF ROBOTIC AUTOMATION: A PANEL DATA ANALYSIS IN HIGH-LEVEL AUTOMATION COUNTRIES

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(Received: February 2024; Accepted: May 2024; Published: January 2025)

Abstract: This study examines the impact of robotic capital, physical capital, technological change, human capital, and trade globalization on labor income share dynamics in the era of robotic automation. Focusing on China, Germany, Japan, South Korea, and the United States – countries responsible for 79.2% of global industrial robotic installations from 2010 to 2023 – our analysis employs key variables such as labor income share, annual industrial robot installations, gross fixed capital formation, researchers in research and development, human capital index, and trade of goods and services. Estimations using Arellano-Bond, Generalized Estimating Equations, Driscoll-Kraay, and Arellano-Froot-Rogers methods reveal a consistent negative association between labor income share and robotic capital. Conversely, a positive relationship is observed with research and development. Notably, the study underscores the consistent negative impact of physical capital accumulation on labor income share across the Arellano-Bond, Driscoll-Kraay, and Arellano-Froot-Rogers methods. Furthermore, globalization, as assessed by the Arellano-Bond, Generalized Estimating Equations, and Driscoll-Kraay methods, is identified as a factor adversely affecting labor income share.

Keywords: Robotic Automation; Labor Income; Robotic Capital; Technological Change; Panel Data.

JEL Codes: J24, J31, O33, L16.

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1. Introduction

In recent years, the remarkable rise of robotic automation has become a focal point in discussions surrounding the future of work and economic productivity. The integration of sophisticated robots into various sectors of the economy prompts a critical examination of how this technological advancement is reshaping the dynamics of labor share. In this research, we delve into the multifaceted impacts of robotic automation, particularly its implications for labor distribution, productivity, and the broader economic landscape. The advent of industrial robots, characterized by their flexibility, versatility, and autonomy, has ushered in an era where machines are not just aids but central players in production processes. This shift raises pertinent questions about the distribution of economic benefits and the evolving role of human labor in the automated landscape. The interaction between robotic technologies and labor markets is complex, involving a nuanced interplay of job displacement, creation, and transformation. Research indicates that while robotic automation contributes to productivity growth, its impact on employment is not uniformly negative. In certain scenarios, increased robot use has led to a decline in the share of low-skilled labor, while simultaneously fostering new job opportunities in other sectors, particularly in services. This dichotomy underscores the adaptive nature of labor markets and the potential for technology to engender both challenges and opportunities. Furthermore, the effects of automation are not homogenous across different firm sizes and sectors. Small and medium enterprises (SMEs), for instance, demonstrate a unique relationship with robotic technology, often experiencing heightened productivity and employment rates. On a larger scale, the integration of robots has been linked to the emergence of 'superstar firms' – entities that leverage automation to achieve significant gains in productivity and market dominance, consequently influencing the functional income distribution. As we continue to navigate this transformative era, it is imperative to consider the broader implications of robotic automation on labor dynamics. The key lies in understanding and harnessing the potential of these technologies to create a more efficient, inclusive, and balanced economic framework. This exploration offers insights not only into the current state of robotic automation but also into the trajectories it may carve for the future of work and economic distribution.

The aim of our study is to analyze the impact of robotic capital, traditional physical capital, technological change, human capital, and trade globalization on labor income share dynamics amidst the robotic automation era. Concentrating on the period from 2010 to 2023, our focus narrows to five key nations—China, Germany, Japan, South Korea, and the United States—which collectively account for 79.2% of the global installations of industrial robots. Utilizing variables like annual industrial robot installations, gross fixed capital formation, R&D researchers, human capital index, and trade in goods and services, our analysis provides an integrated examination of the diverse impacts of robotic automation on the labor income share. By employing a varied array of estimation methodologies and conducting a comparative analysis across these five leading economies in industrial robotic applications, our research uncovers detailed insights into how robotic capital interacts with other critical economic factors to influence the dynamics of labor income share. This comprehensive approach not only elucidates the complex effects of automation on labor markets but also highlights the balancing roles of R&D and human capital development in mitigating the adverse impacts of increased industrial robot installations on the labor income share.

2. Literature review

The integration of robotic automation into the global economy has initiated profound changes in labor dynamics. In this section, we synthesize key findings from leading research to understand these changes, focusing on labor share, productivity and employment patterns in the age of robotic automation. Graetz & Michaels (2015) in their seminal work "Robots at Work" found that modern industrial robots contribute significantly to labor productivity growth, approximately 0.36 percentage points annually. Contrary to the common fear of widespread job losses, their research suggests that robots did not significantly reduce total employment, although they did influence the share of low-skilled workers. Dauth, et al. (2021) observed the adjustments in local labor markets to industrial robots in Germany. Their study revealed displacement effects in manufacturing, counterbalanced by new job creation in the service sector. The impact was particularly pronounced among young workers entering the labor force. Ballestar, et al. (2020) in their study on small and medium enterprises (SMEs) found that robotic devices are linked with higher performance and productivity. Interestingly, in 2015, robotics accounted for a 5% increase in SME productivity level. Acemoglu, et al. (2022) provided a comprehensive view of the adoption of automation technologies across US firms. They documented that larger firms are more likely to adopt these technologies, impacting labor shares and leading to higher wages and lower labor shares in these firms. Stiebale, Suedekum & Woessner (2020) in their research on "Robots and the Rise of European Superstar Firms," observed that robots disproportionately increase productivity in already productive firms, leading to increased market dominance and shifts in functional income distribution from wages to profits. Giacomo & Lerch (2021) explored the effect of robot adoption on human capital accumulation, particularly college enrollment. Their findings suggest that increased robot exposure is linked to a substantial rise in enrollment rates in post-secondary education. Dao, Das & Kóczán (2019) examined the declining labor share in the context of routinization and globalization. They found that technological progress and routinization explain the decline in advanced economies, while capital deepening and globalization drive the trend in emerging markets. Rivera (2019) analyzed the impact of automation on the Chilean labor market. The study used a general equilibrium model to understand the effects of robotic capital as a substitute for labor and traditional capital as complementary to it, revealing significant impacts on employment and GDP. Berg, Buffie & Zanna (2018) presented a model illustrating how robot capital, distinct from traditional capital, affects inequality and output. Their results indicate that automation can lead to growth but also exacerbate inequality. Ergül & Goksel (2020) used a DSGE model to analyze the effects of automation on the labor share of national income. They found that increased automation leads to a decline in the labor share, confirming trends observed in developed and developing countries. Heer, Irmen & Süssmuth (2022) provided evidence that the decline in the US labor share is influenced by factor taxation, automation capital, and population growth, with variance decompositions revealing significant contributions of taxing to changes in income shares and automation capital. Bhardwaj, Avasthi & Goundar (2019) examined the security risks associated with the rapid transformation of economies through robotic technology. They emphasized the importance of cybersecurity in robotic platforms, especially in critical applications and missions. Gunadi & Ryu (2021) investigated the potential effects of robotic technology on health, particularly for the low-skilled population. They found a positive correlation between robot penetration in local economies and the health of the low-skilled population, with a reduction in the share of individuals reporting poor health.

These empirical studies collectively offer a comprehensive understanding of how labor share, robotic and physical capital, technological change, education, and trade globalization interact and shape economic outcomes in different contexts. They provide valuable insights for policymakers and stakeholders aiming to navigate the complexities of a rapidly changing economic landscape. The current body of research underscores a nuanced picture of the impact of robotic automation. While boosting productivity and altering the nature of jobs, robots have not led to significant overall employment reductions but have indeed transformed the structure of labor markets. The ongoing challenge for policymakers and businesses is to adapt to these changes, ensuring that the benefits of automation are broadly shared across the economy.

The theoretical framework surrounding the impact of robotic automation on labor share, economic dynamics, and societal implications is rooted in several key concepts and theories from economics, sociology, and technological studies. This background helps to contextualize and understand the empirical findings in the field.

Schumpeter's (1942) concept of "creative destruction," detailed in his work "Capitalism, Socialism and Democracy", is crucial for understanding how technological advancements like robotics can disrupt existing economic structures, leading to the obsolescence of old industries and the emergence of new ones. Ricardo (1817), in "Principles of Political Economy and Taxation", discusses the substitution of labor by capital. This theory is particularly relevant in understanding how robotics, representing a form of capital, replaces human labor in various tasks, thereby affecting labor share and income distribution. Becker's (1964) "Human Capital: A Theoretical and Empirical Analysis" focuses on how investments in education and training are crucial for enhancing workers' productivity. This theory is significant in the context of robotics, where a higher level of skill and education is required to work alongside advanced technologies. Katz and Murphy (1992), in "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", elaborate on how technological advancements tend to favor skilled over unskilled labor. This concept is directly applicable to the era of robotic automation, which often demands higher-skilled labor. Friedman (2005) in "The World is Flat" provides insights into how globalization affects labor markets. Robotics, as a part of global industrial transformation, significantly influences these dynamics by reshaping job distribution and characteristics across global borders. Developed by Trist and Bamforth (1951) in "Some Social and Psychological Consequences of the Longwall Method of Coal-Getting", this theory examines the relationship between society and technology. It is relevant to understanding how robotic automation impacts social structures and labor relations. Piketty's (2014) "Capital in the Twenty-First Century" discusses how economic growth and inequality are intertwined. This perspective is essential for analyzing how robotic automation, by potentially displacing jobs, can contribute to increased economic inequality.

Theories of globalization examine the impact of an increasingly interconnected world economy on labor markets (Krugman, 1991; Stiglitz, 2002). Robotics, as part of this narrative, plays a significant role in reshaping labor dynamics, with global supply chains and trade policies influencing the distribution and nature of jobs. Sociotechnical Systems theory explores the interplay between society and technology, positing that technological change and societal dynamics are deeply intertwined (Perrow, 1984; Hughes, 1983). The advent of robotics challenges existing social structures and labor relations, necessitating a reevaluation of work, education, and social policies. Inequality and Redistribution theories address how technological change can lead to uneven distribution of wealth and income (Piketty, 2014; Atkinson, 2015). Robotics, by potentially replacing certain job categories, can contribute to increased economic inequality, prompting discussions about redistributive policies, such as universal basic income or retraining programs

(Acemoglu & Restrepo, 2017; 2018; Standing, 2011; Brynjolfsson & McAfee, 2014). Together, these theoretical perspectives provide a comprehensive framework for understanding the multifaceted impacts of robotic automation. They offer insights into the economic, social, and policy implications of this technological revolution, guiding empirical investigations and policy formulations in the era of rapid technological advancement.

Theoretical framework

Incorporating robotic capital into the Cobb-Douglas production function offers a nuanced understanding of its impact on production processes, labor share, and income distribution in the context of both traditional physical capital and advanced automation. The augmented Cobb-Douglas model, reflecting this integration, is crucial for examining the evolving dynamics in an era increasingly dominated by automation. The standard Cobb-Douglas production function, as expanded in this context (Eq. 1), incorporates robotic capital (R_t) alongside traditional labor (L) and physical capital (K_t). This formulation is consistent with the works of Solow (1956) on growth theory and Douglas (1976) on the production theory, where the output elasticity of capital and labor determines the contribution of each factor to the overall production. The TFP (A) in the equation represents the efficiency of converting inputs into output, a concept extensively analyzed by Solow (1957) in his works on technological change. The inclusion Acaptures not just the traditional factors of production but also the efficiency gains from technological advancements, including robotics. The α parameter in the equation indicates the output elasticity of physical capital. The concept, central to the works of Cobb and Douglas (1928), demonstrates the responsiveness of output to changes in capital. The inclusion of robotic capital (R_t) suggests an extension of this theory, where robotics is seen as a distinct form of capital with its own elasticity, potentially differing from traditional capital forms. The wage rate, determined by the marginal product of labor, is a key concept in labor economics and is extensively discussed in the works of Mott (1988). In a competitive market, wages align with the value of the additional output produced by an extra unit of labor. The integration of robotic capital in production potentially alters this relationship, as robotics can substitute for or complement human labor, thus affecting the marginal product of labor and, consequently, wage rates. The substitution between labor and robotic capital highlights the relevance of theories by Acemoglu and Restrepo (2017; 2018), who investigated the implications of automation for labor demand. The equation's structure allows for the examination of how the introduction of robotic capital affects the labor share, potentially leading to a shift in the income distribution between labor and capital. By applying the Cobb-Douglas production function in the context of robotic capital, this framework provides a theoretical foundation to understand how advancements in automation influence key economic variables. It sheds light on the changing landscape of labor share and income distribution in the age of automation, offering a valuable tool for analyzing the economic impacts of this technological evolution.

In the book "Intertemporal and Strategic Modelling in Economics" by Orlando Gomes (2022), the relationship between technological advancements, particularly in the form of robotic capital, and the dynamics of income distribution in the production process is examined. Unlike physical capital, robotic capital is seen as a form of automation that substitutes labor in production, influencing both the wage rate and the rate of return for robotic capital. By differentiating the production function concerning labor and robotic capital, Gomes elucidates how these variables interact to determine the distribution of returns and the rate of return for physical capital in the production process. Herein lies a synthesis of the mathematical model derived from Gomes' work, outlining the complex relationships between technological advancement, labor, robotic capital, and income distribution.

$$Y_t = A.K_t^{\alpha}.(L + R_t)^{1-\alpha} \tag{1}$$

Unlike physical capital, robotic capital is a form of automation and is considered a substitute for labor in production. This variable reflects the quantity or capability of robots in the production process.

The wage rate is often determined by the marginal product of labor. In a competitive market, this can be expressed as:

$$MP_L = w_t = \frac{\partial Y_t}{\partial L} \tag{2}$$

Using the chain rule, differentiate the production function concerning labor (L):

$$MP_L = w_t = \frac{\partial Y_t}{\partial L} = (1-\alpha).A.K_t^{\alpha}.(L + R_t)^{-\alpha} \tag{3}$$

The rate of return for robotic capital (rR_t) is often determined by the marginal product of robotic capital. In a competitive market, this can be expressed as:

$$rR_t = MP_{R_t} = \frac{\partial Y_t}{\partial R_t} \tag{4}$$

Using the chain rule, differentiate the production function concerning robotic capital (R_t):

$$rR_t = MP_{R_t} = \frac{\partial Y_t}{\partial R_t} = \ (1-\alpha).A.K_t^{\alpha}.(L+R_t)^{-\alpha} \qquad (5)$$

Equate the expressions for the partial derivatives to the rate of return expressions:

$$w_t = rR_t = (1-\alpha).A.\left(\frac{K_t}{L+\ A_t}\right)^{\alpha} \qquad (6)$$

This result expresses the wage rate (w_t) (and the rate of return for robotic capital (rR_t)in terms of the parameters parameters A, α, and the quantities of physical capital (K_t)), labor (L), and robotic capital (rR_t). The expressions show how these variables interact in determining the distribution of returns in the production process. The rate of return for physical capital is often determined by the marginal product of physical capital. In a competitive market, this can be expressed as:

$$r_t = MP_{r_t} = \frac{\partial Y_t}{\partial K_t} \qquad (7)$$

Using the chain rule, differentiate the production function concerning physical capital (K_t):

$$r_t = MP_{r_t} = \frac{\partial Y_t}{\partial K_t} = \ \alpha.A.K_t^{\alpha-1}.(L+R_t)^{1-\alpha} \qquad (8)$$

Simplify the expression to obtain a more concise form:

$$\frac{\partial Y_t}{\partial K_t} = \ \alpha.A.\left(\frac{L+\ A_t}{A_t}\right)^{1-\alpha} \qquad (9)$$

Equate the expression for the partial derivative to the rate of return expression:

$$r_t = \ \alpha.A.\left(\frac{L+\ A_t}{A_t}\right)^{1-\alpha} \qquad (10)$$

This result expresses the rate of return for physical capital (r_t)in terms of the parameters A, α, and the quantities of physical capital(K_t), labor (L), and robotic capital (rR_t). The expression shows how these variables interact in determining the rate of return for physical capital in the production process.

Intensive form of the production function:

$$y_t = A.K_t^{\alpha}.(1+\emptyset_t)^{1-\alpha} \tag{11}$$

where $y_t$is output per unit of labor, $r_t$is the rate of return for physical capital, k_t is physical capital per unit of labor, R_t is robotic capital, and $\emptyset_t$ is defined as $\emptyset_t = L.R_t$, representing the ratio of robotic capital to labor.

The marginal product of physical capital $\left(MP_{K_t}\right)$ per unit of labor can be expressed using the intensive form:

$$MP_{K_t} = \frac{\partial y_t}{\partial k_t} = \alpha.A.(1+\emptyset_t)^{-\alpha} \tag{12}$$

The rate of return for robotic capital (rR_t) is given by the marginal product of robotic capital per unit of labor:

$$rR_t = \frac{\partial y_t}{\partial \emptyset_t} = \alpha.A.k_t.(1+\emptyset_t)^{-\alpha} \tag{13}$$

The income share of capitalists is given by the sum of returns from physical and robotic capital per unit of labor divided by the total output per unit of labor (y_t):

$$\frac{r_t.k_t + R_t.\emptyset_t}{y_t} = \frac{\alpha.A.(1+\emptyset_t)^{-\alpha}.k_t + \alpha.A.k_t.(1+\emptyset_t)^{-\alpha}.\emptyset_t}{A.k_t.(1+\emptyset_t)^{1-\alpha}} \tag{14}$$

Simplify the expression to obtain a more concise form:

$$\frac{r_t.k_t + R_t.\emptyset_t}{y_t} = \frac{\alpha.(1+\emptyset_t)^{-\alpha}.k_t + \alpha.\emptyset_t.(1+\emptyset_t)^{-\alpha}}{(1+\emptyset_t)^{1-\alpha}} \tag{15}$$

Combine terms to obtain the final expression:

$$\frac{r_t.k_t + R_t.\emptyset_t}{y_t} = \frac{1+\emptyset_t}{\alpha+\emptyset_t} \tag{16}$$

This result expresses the income share of capitalists in terms of the parameters α and $\emptyset_t$, and, represents the ratio of robotic capital to labor. It indicates how the income share of capitalists changes with the participation of robotic capital in the production process.

Moreover, the labor share (w_t/y_t) can be expressed as in Eq.17.

$$\frac{w_t}{y_t} = \frac{(1-\alpha).A.\left(\frac{K_t}{L+A_t}\right)^{\alpha}}{A.K_t^{\alpha}.(1+\emptyset_t)^{1-\alpha}} = \frac{1-\alpha}{1+\emptyset_t} \tag{17}$$

This equation (Eq. 17) characterizes the relationship between the wage rate $(w_t)$and the output per unit of labor(y_t). In particular, it reveals that the ratio of the wage rate to output per unit of labor(w_t/y_t) is influenced by two critical factors. Firstly, Firstly, $(1-\alpha)$ represents the complementarity between labor and robotic capital, with α being the output elasticity of physical capital. This term signifies the proportion by which the wage rate declines concerning the substitution of labor with robotic capital in the production process. Secondly,$(1+\emptyset_t)$ introduces the impact of the ratio of robotic capital to labor $(\emptyset_t)$, indicating the extent to which automation and robotics contribute to the overall productivity. Therefore, the equation captures the nuanced dynamics of income distribution and the changing role of labor in the presence of robotic capital.

In our empirical analysis, we aim to investigate the impact of robotic capital, traditional physical capital, technological change, human capital, and trade globalization on the dynamics of labor share in the context of robotic automation. We will focus on the five countries that have extensively utilized industrial robotic applications between 2010 and 2023. These countries are China, Germany, Japan, South Korea, and the United States. As of 2022, the combined industrial robotic installations in these nations account for a significant 79.2% of the global total (Müller, 2023).

In examining the dynamics of labor income share within the context of robotic automation in five high-level automation countries, certain expectations are formulated for the signs of the independent variables. The annual installation of industrial robots (IIR) is anticipated to have a negative impact, reflecting the notion that higher robot installations could increase automation, consequently diminishing the share of income allocated to labor. Similarly, gross fixed capital formation (GFC), representing increased investment in physical capital and automation technologies, is expected to exhibit a negative association with labor income share. Conversely, variables such as researchers in research and development (RD) and human capital (HC) are anticipated to have positive effects. Higher efforts in research and development are expected to lead to technological advancements, positively influencing labor income share through increased productivity. Investments in human capital, including education and skills development, are expected to enhance workforce productivity, contributing to a higher labor income share. Lastly, the trade of goods and services (TRD) is expected to have a negative association, as increased trade, particularly in a globalized context, may expose workers to competitive pressures, potentially resulting in a decline in labor income share. These expectations are guided by economic principles and will be further explored and validated through empirical analysis of the specific data.

3. Methodology and empirical data

Prior to parameter estimation, a series of diagnostic tests were employed to ensure the selection of an appropriate method and validate the model. These tests encompassed analyses of the correlation matrix, assessment of cross-sectional dependency, evaluation of slope homogeneity, examination of autocorrelation, scrutiny for heteroskedasticity, consideration of variance inflation factors, and thorough assessments for endogeneity. The determination between random effect, fixed effect, and mixed effect models was made using the Hausman test. Based on the outcomes of these assessments, it was concluded that the most suitable parameter estimation methods for heterogeneous panel data were the Arellano-Bond, Generalized Estimating Equations, Driscoll-Kraay, and Arellano, Froot, and Rogers methods, and subsequent parameter estimates were carried out accordingly.

The use of the Arellano-Bond dynamic panel data estimator, specifically the system GMM, is justified for several reasons. It addresses endogeneity concerns by incorporating lagged endogenous variables as instruments. The system GMM is known for efficiently handling both individual and time effects, making it suitable for dynamic panel data models. Its incorporation of fixed effects modeling accommodates unobserved heterogeneity, and the model's ability to capture dynamic relationships over time addresses potential serial correlation. Heteroskedasticity-robust standard errors enhance robustness against homoskedasticity violations, making the system GMM an efficient and flexible choice for dynamic panel data analysis.

The choice of the (GEE) population-averaged model estimator for panel data time series analysis, despite heteroskedasticity, is justified for several reasons. GEE is advantageous when estimating population-averaged effects and accommodating within-subject correlation. Its robustness to misspecification of correlation structure makes it suitable for situations with heteroskedasticity. GEE focuses on population-averaged effects, providing meaningful estimates interpretable in the study population context. Its flexibility in handling time-dependent covariates and ease of implementation make it a pragmatic choice, addressing challenges associated with data distribution or limited within-subject correlation information.

The selection of the Driscoll-Kraay Fixed Effect Estimator is particularly apt when there are indications of heteroskedasticity in the data, and it addresses concerns related to potential non-constant variance across panels. By employing heteroskedasticity-robust standard errors, our regression results become more reliable, offering valid inference even when the assumption of homoskedasticity is violated. This approach enhances the robustness of our estimates, allowing for more accurate statistical inferences in the presence of varying levels of heteroskedasticity across panels.

The Arellano, Froot, and Rogers (AFR) estimator is a suitable choice, especially for addressing heteroskedasticity in the model. Known for its robustness to panel data heteroskedasticity, it provides reliable parameter estimates in the presence of varying variance levels across observations. AFR handles endogeneity concerns effectively and remains consistent in the presence of cross-sectional dependence, showcasing versatility within the class of generalized method of moments estimators. Its adaptability to structural breaks or shifts further enhances its utility in handling diverse diagnostic challenges.

Empirical model

Table 1 provides a comprehensive summary of the dependent and independent variables, their abbreviations, proxies, and the respective data sources for our empirical model.

Table 1 Variables

Variable	Notation	Proxy	Database
Labor income share	LSI	Labor income share as a percent of GDP (%)	ILO
Robotic capital	IIR	Annual installation of industrial robots	IRF
Physical capital	GFC	Gross fixed capital formation (% of GDP)	WB
Trade globalization	TRD	Trade of goods and services (% of GDP)	WB
Technological change	RD	Researchers in R&D (per million people)	WB

Human capital	HC	Index of human capital per person, based on years of schooling and returns to education	PWT

Source: ILO (International Labor Organization), IRF (International Federation of Robotics), WB (World Bank), PWT (Penn World Table).

The functional form of the empirical model represented in Eq.18 aims to analyze how robotic capital, traditional physical capital, technological change, human capital, and trade globalization influence the dynamics of labor share in the context of robotic automation.

$$Labor\ Share\ of\ Income = f\begin{pmatrix} Robotic\ Capital, Physical\ Capital, Human\ Capital, \text{Technology}, \\ \text{Trade Globalization} \end{pmatrix} \quad (18)$$

$$LnLSI_{it} = \beta_0 + \beta_1.LnIIR_{it} + \beta_2.LnGFC_{it} + \beta_3.LnRD_{it} + \beta_4.Ln\text{HC}_{it} + \beta_5.Ln\text{TRD}_{it} + \varepsilon_{it} \quad (19)$$

In the model represented in Eq. 19, we aim to analyze the determinants of the Labor Share Index (LSI)for a given countryi at a specific time. The dependent variable ($\mathrm{LSI_{it}}$) represents the proportion of national income attributed to labor in the production process. The variable$\mathrm{IIR_{it}}$ represents Industrial Robotization, measured by the annual installation of industrial robots. This variable aims to capture the influence of automation technologies on labor share.$\mathrm{GFC_{it}}$ stands for Gross Fixed Capital Formation, expressed as a percentage of GDP. This variable reflects the role of physical capital in shaping the distribution of income between labor and capital. $\mathrm{RD_{it}}$ represents Technological Change, measured by the number of researchers in Research and Development per million people. This variable aims to capture the impact of technological advancements on labor share. $\mathrm{HC_{it}}$ denotes Human Capital, represented by an index based on years of schooling and returns to education. This variable accounts for the influence of education and skills on the contribution of labor to national income. $\mathrm{TRD_{it}}$ signifies Trade Globalization, measured as the percentage of trade in goods and services relative to GDP. This variable captures the influence of international trade dynamics on labor share.
β_0 is the intercept term and represents the expected value of the labor income share when all the independent variables are zero. $\beta_1 \ldots \beta_5$ are the slope coefficients associated with the respective independent variables. They indicate the expected change in the labor income share for a one-unit change in each independent variable, holding other variables constant. The error term (ε_{it}) accounts for unobservable or omitted factors that may affect labor share but are not explicitly included in the

model. This empirical model allows for the examination of the complex interplay between industrial robotization, globalization, technological development, human capital, trade dynamics, and their collective impact on the distribution of income between labor and capital across different countries and over time.

Table 2 Descriptive Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
LSI	70	56.20	4.64	41.90	63.42
IIR	70	50663	60754	16904	310300
GFC	70	27.75	8.57	18.31	44.52
TRD	70	55.02	26.66	23.38	105.57
RD	70	4390	1991	863	9081
HC	70	3.394	0.446	2.404	3.765

Table 2 provides a comprehensive overview of the descriptive statistics for the key variables under consideration in our analysis. For the labor income share (LSI), the average percentage of GDP attributable to labor income is 56.20%, with a standard deviation of 4.64%. The annual installation of industrial robots (IIR) ranges from 16,904 to 310,300 units, with a mean of 50,663 and a standard deviation of 60,754. Gross fixed capital formation as a percentage of GDP (GFC1) has a mean of 27.75%, varying between 18.31% and 44.52%, with a standard deviation of 8.57%. Trade globalization (TRD1) is represented by the percentage of GDP attributed to the trade of goods and services, with a mean of 55.02%, a standard deviation of 26.66%, and a range from 23.38% to 105.57%. Technological change (RD2), measured as the number of researchers in R&D per million people, shows an average of 4,390 researchers, with a standard deviation of 1,991, and a range from 863 to 9,081 researchers. Finally, the index of human capital per person (HC), based on years of schooling and returns to education, exhibits a mean of 3.394, a standard deviation of 0.446, and varies between 2.404 and 3.765.

4. Empirical results

Table 3 presents the matrix of correlations among the variables included in our analysis. The correlation coefficients provide insights into the strength and direction of relationships between pairs of variables.

Table 3 Matrix of correlations

Variables	(1)	(2)	(3)	(4)	(5)	(6)
(1) LSI	1.000					
(2) IIR	-0.367	1.000				
(3) GFC	-0.672	0.627	1.000			
(4) TRD	0.217	0.342	-0.052	1.000		
(5) RD	0.360	-0.287	-0.418	-0.586	1.000	
(6) HC	0.610	-0.583	-0.875	-0.275	0.788	1.000

In Table 3, the labor income share (LSI) exhibits positive correlations with technological change (RD1) and human capital (HC) at 0.360 and 0.610, respectively. On the other hand, it displays negative correlations with robotic capital (IIR) and physical capital (GFC1) at -0.367 and -0.672, indicating an inverse relationship. Robotic capital (IIR) shows negative correlations with human capital (HC) and physical capital (GFC1) at -0.583 and -0.627, respectively. Physical capital (GFC1) has a negative correlation with technological change (RD1) at -0.418. These correlation patterns offer valuable insights into the interplay among the variables and lay the foundation for understanding potential multicollinearity or complementary dynamics in our subsequent regression analysis.
Prior to conducting the regression analysis, a critical step involves assessing the stationarity of the variables through a battery of unit root tests. The unit root tests employed include the Cross-Sectional Augmented Dickey-Fuller (CADF), Pesaran's (2007) unit root test (CIPS), Harris-Tzavalis unit-root test (HT), Breitung unit-root test, Im-Pesaran-Shin unit-root test (IPS), and Fisher-type unit-root test (Fisher). The null hypothesis for these tests is that the panels contain unit roots. Stationarity is a crucial consideration, as non-stationary time series data can lead to spurious regression results. The outcomes of these tests, presented in Table 4, inform us about the presence or absence of unit roots and guide subsequent decisions on whether differencing is necessary for achieving stationarity in the data.

Table 4 Unit Root Test

Var.	Lev.	CADF	CIPS	IPS	Fisher	HT	Breitung
		t-bar	CIPS Stat	W-t-bar	z-stat.	rho	lambda
LSI	level	-1.436	-1.715	0.6381	-1.8714	0.7239	0.0141
	1st diff.	-3.761*	-4.589*	4.1706*	-4.1731*	-0.0424*	3.1629*
IIR	level	-1.359	-1.624	1.1225	1.6197	0.9222	1.5076
	1st diff.	-3.249*	-3.249*	-4.7422*	-4.3291*	-0.0033*	4.5176*
GFC	level	-2.687**	-2.076	0.359	1.7704	0.6826	-0.0376
	1st diff.	.	-3.446*	6.4557*	6.8223*	0.1871*	1.6551**
TRD	level	-1.817	-1.817	-2.0634	-2.6465*	0.7935	1.1909
	1st diff.	-3.835*	-3.835*	-4.3994*	.	-0.0175*	-2.0765**

RD	level	-2.184	-2.184	0.1586	-0.0506	0.7808	2.0407
	1st diff.	-3.169*	-3.169*	-4.7263*	-5.3738*	0.2117*	1.724**
HC	level	-0.87	-0.579	3.6883	-6.0429*	1.0521	6.2843
	1st diff.	-6.101*	-2.783*	-2.917*	.	0.6492**	-1.5995**

Note: * p<.01, ** p<.05.

Table 4 presents the results of the unit root tests for each variable at both the level and first difference. The outcomes from unit root tests, including CIPS, IPS, HT, and Breitung, suggest that initially, all series exhibit a unit root at the level, indicating non-stationarity. However, this non-stationarity is rectified when taking the first difference. Further examination using the CADF test highlights that the GFC series is stationary at the level, while the other series achieve stationarity when differenced for the first time. Similarly, Fisher test results indicate that TRD is stationary at the level, whereas the remaining series attain stationarity through first differencing. Consequently, the observed stationarity at the level or after the first differencing provides assurance that our panel data analysis results remain robust and unaffected. The tests for cross-section independence and homogeneity are crucial in the selection of appropriate testing methods. In Table 5, the results of Cross-section Dependence (CD) tests, as well as tests for Slope Homogeneity (adj.Delta and Swamy S χ^2), are presented. The CD tests, including CD (Pesaran 2015, 2021), CDw Juodis, (Reese, 2021), CDw+ (Fan et. al., 2015), and CD* (Pesaran, Xie, 2021), assess the presence of cross-sectional dependence, while adj. Delta and Swamy S χ^2 specifically test for slope homogeneity.

Table 5 Slope Homogeneity and Cross-section Independence Tests

CD Tests				Homogeneity	
CD	CDw	CDw+	CD*	adj.Delta	Swamy S (χ^2)
-1.090	2.710*	15.530*	4.590*	-5.525*	446.32*
(0.277)	(0.007)	(0.000)	(0.000)	(0.000)	(0.000)

Note: * p<.01, ** p<.05 p-values in parenthesis.

In Table 4, the CD test shows a test statistic of -1.090 with a p-value of 0.277, suggesting no significant evidence of cross-sectional dependence. However, when transitioning to the CDw test, the test statistic is 2.710 with a p-value of 0.007, indicating evidence of cross-sectional dependence at a significance level of 0.01. The CDw+ test produces a test statistic of 15.530 with a p-value of 0.000, providing strong evidence against cross-sectional independence. Moving on to CD*, which incorporates four principal components, the test statistic is 4.590 with a p-value of 0.000, further supporting the presence of cross-sectional dependence. These results collectively suggest that various CD tests consistently indicate cross-sectional dependence in the data.

Now, turning to tests for Slope Homogeneity, the "adjusted delta test" produces a test statistic of -5.525 and a p-value of 0.000, while the Swamy S χ^2 test yields a test statistic of 446.32 with a p-value of 0.000. Both tests strongly reject the null hypothesis of slope homogeneity, indicating that the assumption of equal slopes across cross-sectional units is not supported.

We examine the presence of individual and time effects in our regression model through a series of diagnostic tests namely the Likelihood Ratio (LR) test, F test, Lagrange Multiplier (LM) test, and the Hausman test.

Table 6 Test for Individual and Time Effects

	Individual Effect	Time Effect	Mix Effet
LR	5.88 (p = 0.008)	0.00 (p = 1.000)	5.88 (p = 0.0528)
F	12.82 (p = 0.0000)	1.14 (p = 0.3508)	
LM	0.00 (p = 1.0000)		
Hausman Test $\chi 2$ (6) = 13.63 (p = 0.0181)			

In Table 6, we present the results of tests aimed at assessing the presence of individual and time effects in our regression model. The LR test reveals compelling evidence (LR test statistic = 5.88, p = 0.008) supporting the existence of individual effects, indicating that individual entities significantly contribute to the model. In contrast, the LR test for time effects shows no significant evidence (LR test statistic = 0.00, p = 1.000), suggesting that temporal variations do not have a pronounced impact on the model. The LR test for mix effects yields a borderline significance (LR test statistic = 5.88, p = 0.0528), hinting at a potential mix effect, though the evidence is not conclusive.

Further reinforcing the findings, the F test affirms the strong presence of individual effects (F test statistic = 12.82, p = 0.0000), while providing no strong evidence of time effects (F test statistic = 1.14, p = 0.3508). LM test, however, does not offer significant support for individual effects (LM test statistic = 0.00, p = 1.000), suggesting that individual entities may not significantly contribute to the model according to this particular test. Unfortunately, information about the LM test for time effects is not provided, leaving the result inconclusive.

Lastly, the Hausman test, comparing the efficiency of the fixed effects model to the random effects model, yields a test statistic of χ^2 (6) = 13.63 with a p-value of 0.0181. This suggests that the fixed effects model may be more appropriate, implying a preference for considering individual entity effects while accounting for efficiency. In conclusion, the cumulative evidence strongly supports the inclusion of individual effects in the model, with the choice between fixed and random effects models leaning towards the based on the Hausman test results.

4.1. Findings

Table 7 shows the outcomes of the empirical model investigates the logarithmic transformation of labor income share (LnLSI) concerning key factors, including annual installations of industrial robots (LnIIR), gross fixed capital formation (LnGFC), researchers in research and development (LnRD), human capital index (LnHC), and trade of goods and services (LnTRD). The results of parameter estimations, obtained through the four selected and appropriate forecasting methods detailed in the "Methodology" section, are presented in Table 7.

Table 7 Parameter Estimations

LnLSI	Arellano-Bond Estimator	Generalized Estimating Equations	Driscoll-Kraay Estimator	Arellano, Froot, and Rogers Estimator
LnIIR	-0.0620***	-0.0403**	-0.0389***	-0.0794***
	(-4.444)	(-2.391)	(-5.348)	(-3.880)
LnGFC	-0.278***	-0.149	-0.276*	-0.259*
	(-2.769)	(-1.249)	(-2.720)	(-1.812)
LnTRD	-0.0722**	-0.0913***	-0.0935**	-0.0574
	(-1.984)	(-3.440)	(-4.354)	(-1.257)
LnRD	0.515***	0.364***	0.375**	0.508***
	(6.525)	(3.560)	(4.406)	(4.677)
LnHC	0.527	0.331	0.620*	0.844*
	(1.597)	(1.032)	(2.211)	(1.779)
Cons.	6.465***	2.333**	3.011***	5.786***
	(6.154)	(2.227)	(7.203)	(4.244)

Note: *** p<0.01, ** p<0.05, * p<0.1; z-statistics in parentheses.

Utilizing the Arellano-Bond Estimator, the results indicate significant associations. The negative coefficient of -0.0620 for LnIIR suggests a 0.0620% decrease in labor income share for a 1% increase in industrial robot installations, highlighting the potential impact of automation on income distribution. Similarly, statistically significant negative coefficients for LnGFC (-0.278) and LnTRD (-0.0722) imply a 0.278% and 0.0722% decrease in labor income share for a 1% increase in gross fixed capital formation and trade of goods and services, respectively. Conversely, the positive coefficient of 0.515 for LnRD suggests a 0.515% increase in labor income share for a 1% increase in researchers in research and development, emphasizing the positive influence of technological advancements on productivity. The positive but statistically insignificant coefficient of 0.527 for LnHC indicates that the human capital index might not significantly affect variations in labor income share.

Using the Generalized Estimating Equations (GEE), the results maintain valuable insights. The negative coefficient of -0.0403 for LnIIR suggests a 0.0403% decrease in labor income share for a 1% increase in annual installations of industrial robots, underlining the potential impact of automation. For LnGFC, the negative coefficient of -0.149 indicates a 0.149% decrease in labor income share for a 1% increase in gross fixed capital formation, though not statistically significant. Conversely, the positive coefficient of 0.0913 for LnTRD suggests a 0.0913% increase in labor income share for a 1% increase in researchers in research and development, highlighting the positive influence of research efforts. Similarly, the positive coefficient of 0.364 for LnRD indicates a 0.364% increase in labor income share for a 1% increase in researchers in research and development. However, the negative but statistically insignificant coefficient of -0.331 for LnHC suggests that the human capital index may not significantly affect variations in labor income share.

The Driscoll-Kraay estimator provides insights into the relationship between LnLSI and key determinants. The negative and highly statistically significant coefficient of -0.0389 for LnIIR suggests a 0.0389% decrease in labor income share for a 1% increase in industrial robot installations. For LnGFC, the negative coefficient of -0.276 indicates a 0.276% decrease in labor income share for a 1% increase in gross fixed capital formation. The positive and statistically significant coefficient of 0.0935 for LnTRD suggests a 0.0935% increase in labor income share for a 1% increase in researchers in research and development. Similarly, the positive and statistically significant coefficient of 0.375 for LnRD indicates a substantial 0.375% increase in labor income share for a 1% increase in researchers in research and development. The negative and statistically significant coefficient of -0.620 for LnHC suggests a significant 0.620% decrease in labor income share for a 1% increase in the human capital index.

The Arellano, Froot, and Rogers estimator further explore the relationship between LnLSI and its determinants. The negative and highly statistically significant coefficient of -0.0794 for LnIIR suggests a 0.0794% decrease in labor income share for a 1% increase in industrial robot installations. For LnGFC, the negative coefficient of -0.259 indicates a 0.259% decrease in labor income share for a 1% increase in gross fixed capital formation. The negative and statistically significant coefficient of -0.0574 for LnTRD implies a 0.0574% decrease in labor income share for a 1% increase in researchers in research and development. The positive and statistically significant coefficient of 0.508 for LnRD suggests a substantial 0.508% increase in labor income share for a 1% increase in researchers in research and development. The positive and statistically significant coefficient of 0.844 for LnHC indicates a significant 0.844% increase in labor income share for a 1% increase in the human capital index. These findings provide comprehensive insights into the nuanced dynamics between industrial robots, capital formation, research efforts, human capital, and labor income share in the context of robotic automation.

4.2. Model validity

We conducted the model validity tests to assess the integrity of our empirical model and ensure the soundness of its underlying assumptions. These tests serve as crucial benchmarks to evaluate specific aspects of the model, including the presence of heteroskedasticity, autocorrelation patterns, multicollinearity through Variance Inflation Factor (VIF), potential endogeneity issues, and the adequacy of the model in capturing the underlying data structure. The results of these tests are presented in Table 8.

Table 8 Model Validity Tests

Heteroskedasticity test *(H_0: No heteroskedasticity)*	W0 = 9.177 ; p = 0.000 W50 = 3.492 ; p = 0.012 W10 = 6.412 ; p = 0.001
Autocorrelation Test *(H_0: No autocorrelation)*	DW = 0.811< 2 LBI = 1.001< 2
Mean VIF	2.93 < 5
Endogeneity *(H_0: Variables are exogenous)*	Durbin (score) $\chi 2$ (1) = 1.190; p = 0.275 Wu-Hausman = 1.063; p = 0.307
Ramsey RESET –(*H_0: No omitted variables)*	F = 1.82; p = 0.1539

In Table 8, The results of the heteroskedasticity test, which assesses the presence of non-constant variance in the residuals, are presented in the summary table along with the White test statistics (W0, W50, W10) and their associated p-values. White test statistics, the values of W0, W50, and W10 are 9.177, 3.492, and 6.412, respectively. These test statistics are associated with degrees of freedom (df) and p-values. The null hypothesis for the White test is that the variance of the residuals is constant. The p-values associated with W0, W50, and W10 are all below the significance level of 5%, indicating strong evidence against the null hypothesis of homoskedasticity. Therefore, based on these results, we reject the null hypothesis and conclude that there is evidence of heteroskedasticity in the residuals.

We applied two distinct tests for the presence of autocorrelation: the modified Bhargava et al. Durbin-Watson test (DW) and the Baltagi-Wu LBI test, both operate under the null hypothesis of no autocorrelation. The results indicate that, for the modified Bhargava et al. DW test, the computed statistic is 0.811. In the context of this test, values close to 2 suggest the absence of autocorrelation, and our obtained value aligns with this expectation. Moving on to the LBI test, the computed statistic is 1.001. Once again, this value is consistent with the absence of autocorrelation. These results collectively suggest that there is no substantial evidence to reject the null hypothesis of no autocorrelation in our model. This implies that the residuals do not exhibit systematic patterns of correlation over time, reinforcing the reliability of our regression analysis.

We use the variance inflation factor (VIF) test to quantify the inflation in the variance of estimated regression coefficients when predictor variables are correlated. The Mean VIF represents the average VIF across all variables in the model. In our model, the mean VIF is 2.93, which is relatively moderate. As a rule of thumb, a mean VIF below 5 is often considered acceptable, indicating that multicollinearity is not a severe problem.

In Table 8, the null hypothesis for both tests is that the variables under consideration are exogenous. The results, however, suggest that we fail to reject the null hypothesis for both tests. The Durbin (score) chi-squared test yields a test statistic of 1.190 with a p-value of 0.275, while the Wu-Hausman F-test provides a statistic of 1.063 with a p-value of 0.307. These relatively high p-values indicate that we do not have sufficient evidence to reject the hypothesis of exogeneity for the variables in our model. In simpler terms, the results do not support the presence of endogeneity issues in our model, suggesting that the included variables are likely exogenous and, therefore, can be considered predetermined or unrelated to the error term.

In assessing the model specification, we conducted the Ramsey RESET test using powers of the fitted values of LSI. The null hypothesis (Ho) for this test is that the model has no omitted variables, indicating that the current model is correctly specified. The test result yields an F-statistic of 1.82 with an associated p-value of 0.154. Given the significance level commonly set at 0.05, the p-value of 0.154 suggests that we do not have sufficient evidence to reject the null hypothesis. Therefore, based on the Ramsey RESET test, there is no strong indication of omitted variables in the model, indicating that the current specification appears to be adequate in capturing the relationships within the data.

In validating our regression model, significant evidence against homoskedasticity was found in the heteroskedasticity tests, prompting the recommendation to employ estimation methods accommodating this issue. Autocorrelation tests indicated the absence of systematic patterns in residuals over time, supporting the reliability of our regression analysis. Moreover, endogeneity tests suggested that the model's variables are likely exogenous, reinforcing the credibility of our results. Overall, addressing heteroskedasticity concerns through appropriate estimation methods is crucial for robust statistical inferences.

5. Conclusions

The comprehensive analysis of the empirical model and its results, encompassing the Arellano Bond Estimator, Generalized Estimating Equations, Driscoll-Kraay Estimator, and Arellano, Froot, and Rogers Estimator, along with various model validity tests, offers insightful conclusions about the factors influencing the labor income share.

A significant and consistent negative relationship is observed between the increase in industrial robot installations and labor income share. The coefficients range from -0.0389 to -0.0794, signifying that a 1% increase in the use of industrial robots leads to a decrease in labor income share by approximately 0.0389% to 0.0794%. This finding is robust across different estimation methods, illustrating the profound impact of automation on diminishing labor's share of income. This trend is particularly noteworthy in the context of the current trajectory of increased automation in various industries. Both Gross Fixed Capital Formation and Trade of Goods and Services exhibit a negative impact on labor income share, although the magnitude and significance of these effects vary across different estimators. The negative coefficients for Gross Fixed Capital Formation suggest that a 1% increase in capital formation is generally associated with a decrease in labor income share, potentially indicating a shift towards more capital-intensive production processes. The relationship with Trade of Goods and Services is predominantly negative, implying that an increase in trade activities tends to reduce labor income share, though this relationship is not uniformly significant across all models. This complexity could reflect the multifaceted nature of trade and its varying impact on labor income. Also, there is a uniformly positive relationship between research and development activities and labor income share across all estimators. The coefficients range from 0.364 to 0.515, indicating that a 1% increase in research in R&D is associated with an increase in labor income share. This underscores the beneficial impact of R&D on labor income, likely through innovation and productivity enhancements. On the other hand, the relationship between the human capital index and labor income share shows mixed results. While some estimators indicate a positive effect, others do not find it statistically significant. The coefficients vary from 0.331 to 0.844, suggesting that an increase in human capital may contribute to an increase in labor's share of income. However, the inconsistency across different estimation methods introduces some uncertainty regarding the strength and direction of this relationship.

Our findings that indicate a consistent negative relationship between robotic capital and labor income share are in line with the research by Acemoglu and Restrepo (2017, 2018), who also found that automation negatively impacts employment and wages, especially for lower-skilled workers. This aligns with your observation that increased industrial robot installations lead to a reduction in the labor share of income, suggesting that automation may be a contributing factor to increasing income inequality by displacing labor. Our analysis also reveals a positive relationship between R&D activities, human capital development, and labor income share. This is consistent with the optimistic view held by Aghion et al. (2019), who argue that innovation and education can drive economic growth and improve labor market outcomes. This suggests that investments in human capital and innovation can mitigate some of the adverse effects of robotic automation on labor share.

This work extends the discussion on the impact of globalization and physical capital formation on labor income share, adding complexity to the findings of Rodrik (2016) and Autor et al. (2013), who have explored the displacement effect of trade and technology on labor. Findings suggest a nuanced view where globalization and capital formation have a differential impact on labor share, highlighting the importance of considering the specific context of automation's integration into the economy. By concentrating on the five countries responsible for a significant portion of global industrial robotic installations, the study provides a unique insight into how highly automated economies are navigating the challenges and opportunities presented by robotic automation. This geographical and temporal specificity offers a deeper understanding of automation's impacts, complementing broader analyses provided by authors like Graetz and Michaels (2015), who look at automation's effects on a global scale.

The expansion of industrial robots and automation, along with the dynamics of capital formation and trade, exert significant downward pressures on labor income share. In contrast, research and development activities, and potentially human capital enhancement, offer avenues for increasing labor's share of income. This intricate interplay of factors highlights the complex nature of income distribution in the face of contemporary economic changes. The most striking conclusion drawn from the analysis is the significant and consistent negative impact of automation, specifically the increase in industrial robot installations, on the labor income share. This finding is critical as it highlights a fundamental shift in the income distribution dynamics due to technological advancements. It underscores the reality that as industries increasingly adopt automation and robotic technology, the proportion of income allocated to labor decreases. This trend is a clear indication of how technological advancements, while driving efficiency and productivity, also have profound implications for the labor market and income distribution.

This key insight calls for a reevaluation of economic and social policies to address the challenges posed by automation. It suggests that without intervention, the growing use of industrial robots and automation may lead to a decrease in the relative income of workers, potentially exacerbating income inequality. Therefore, strategies such as investing in human capital, enhancing skills and education, and revising labor market policies may become essential to counterbalance the displacement effects of automation and ensure a more equitable distribution of the economic benefits of technological progress. In resulting, the findings emphasize the need to consider the impacts of automation, capital formation, trade, technological advancements, and human capital development in shaping income distribution between labor and other production factors. As economies continue to evolve with rapid technological changes and globalization, future policies, and economic strategies should address these factors to ensure balanced and equitable economic growth.

Acknowledgments
The authors would like to express their sincere appreciation to the editor and the reviewers for their comments and suggestions, which significantly contributed to enhancing the quality of this manuscript.

Funding
This research received no external funding.

Author Contributions
Dr. Kemal Erkişi was responsible for data collection, design, and development of the analysis and also for data interpretation.
Dr. Melike Çetin conceived the study and was responsible for the conceptualization, literature review, editing and resources section.

Disclosure Statement
The authors declare no conflict of interest.

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