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The Impact of Economic Policies and Globalization on Labor Income Share Across Advanced and Emerging Economies: A System GMM Estimation

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Abstract

There has been an increasing interest in research on labor income share trends over the past few decades. Nevertheless, most of the studies only focused on advanced and developed countries, leaving a gap in understanding how labor income share behaves in emerging economies. Hence, this paper seeks to contribute to the literature by examining the determinants of labor income share in a sample of both advanced and emerging economies, focusing on the impacts of taxation, trade, and globalization. This study utilized a System Generalized method of moments (GMM) estimation approach for 57 advanced and emerging economies from 2008 to 2022. The findings indicate that labor income share exhibits strong persistence, reflecting the influence of past income distribution patterns and institutional factors. Moreover, trade openness reduces labor income share in advanced economies, whereas the effect in emerging economies is insignificant. In contrast, globalization was found to have a significant positive relationship with labor share of income in the full sample, while no significant relationship was found between taxation and labor income share across both economies. Consequently, these findings provide actionable insights for crafting balanced economic policies across different development contexts. Policymakers shall leverage these evidence-based conclusions to design taxation systems and trade frameworks that protect labor income shares while maintaining economic competitiveness, with particular attention to each nation's structural characteristics and development stage.

Keywords: Labor Income Share, Taxation, Trade Openness, Globalization, System GMM

Introduction

One important pillar of the economic research agenda in recent years is the evolution of the functional distribution of income between labor and capital, which plays an important role in macroeconomic stability, social equity, and long-term growth. The labor income share (LIS), defined as the share of national income allocated to labor compensation has declined over the past few decades. This raised urgent concerns about rising inequality, stagnant wages, and the sustainability of economic growth. In this context, many research has been dedicated to investigate the decline in labor shares in across various economies (Burger, 2015; Dao et al., 2017; Erkişi and Çetin, 2025; Mallick, 2020; Moreira, 2022; Sweeney, 2014). The International Labour Organization (ILO) considers the share of labor income to be an essential indicator of the labor-capital distribution. Its downward trend has been interpreted as a sign of structural changes induced by globalization, technological progress, and policy choices. However, this development has raised concerns over rising income inequality, precarity of labor markets and the changing nature of work in an increasingly globalized economy (Autor et al., 2020; Karabarbounis and Neiman, 2014). These trends also offer important insights for policymakers on the measures needed to prevent inequality from escalating into social instability. Thus, understanding the drivers of labor income share is vital to ensure that economic development is more inclusive and sustainable. Despite growing interest, most studies concentrate on advanced economies, while evidence from emerging markets remains limited. Yet, emerging economies face different labor market conditions, institutional structures, and policy challenges in comparison to advanced economies (Duval & Loungani, 2021). Hence, this justified a strong need to examine both groups in a unified framework to uncover whether economic policies and globalization affect them differently.

Tax policies, particularly the differential treatment of labor and capital income, affects firms' choices to produce labor-intensive versus capital-intensive goods. Progressive tax and redistributive fiscal policies could mitigate the erosion of labor's share. However, in many economies, the tax Systems have become increasingly favourable for capital accumulation, hence aggravating a long-term trend of labor income share decline (Piketty and Saez, 2013; Stockhammer, 2017). Conversely, trade policies have a powerful impact on labor income share by determining the relative competitiveness of domestic sectors, which compromises their production structure as well as labor market status. Other than that, trade liberalization, defined as a decrease in tariffs and non-tariff barriers enables the economy to integrate into global markets, but subjects domestic labor to increased competition. Undeniably, the expansion of trade has the potential to spur growth and efficiency. But it also tends to push wages downwards, especially in industries where there is high competition with cheaper wage countries (Rigby et al., 2015).

Besides economic policies such as taxation and trade regulation, globalization is also an important determinant of the labor income share. While proponents argue that globalization promotes economic efficiency, innovation, and productivity, critics highlight its potential to exacerbate income disparities by shifting the income distribution in favor of capital and undermining labor bargaining power, particularly in countries with weaker labor protections (Elsby et al., 2013). This dynamic is especially evident in emerging economies, where global market forces drive structural changes in production, making it more capital-intensive while labor institutions remain weak. However, the key question remains: Do the benefits of globalization outweigh its costs to labor's share of income? This dilemma has become a central focus of modern economic analysis. Therefore, it is important to understand how globalization interfaces with domestic policies regarding labor share dynamics to design more inclusive policy regimes, particularly in countries undergoing growth transitions.

This study holds significant academic and policy implications by providing empirical evidence on the effects of taxation, trade, and globalization on labor income share in advanced and emerging economies. The discoveries of this study offer concrete recommendations for policy makers, labor leaders, and international organizations seeking to address the upsurge in inequality in a global economy. Besides that, such a comparative approach uncloaks policies that have conditional effects, giving advanced economies evidence for how to counterpressure against offshoring and automation fatigue and emerging economies evidence for how to shore up labor protections without undermining competitiveness. Most importantly, this study fills a long-standing gap in knowledge that has exposed developing countries to downward wage pressures, offering empirical backing for tax policies and trade pacts that protect workers in an interconnected world.

The goal of this paper is to investigate the effect of economic policies, including taxation and trade liberalization, along with the influence of globalization on labor income share across advanced and emerging economies. Given this aim, this paper hypothesizes that the effects of these factors on labor share of income may differ significantly for these two groups, given their different economic structures and levels of development. So, to attain this goal, this paper employed a dynamic panel modelling, specifically the System Generalized Method of Moments (GMM) estimation approach as introduced by Arellano and Bover (1995) and Blundell and Bond (1998). Besides that, we also incorporated several control variables including labor force participation, gross domestic products (GDP) per capita and inflation, to account for other factors that could affect the dependent variable. Moreover, this paper also conducts sub-sample estimates for advanced and developing economies to test the heterogeneous impact of economic policies and globalization on labor income share. By examining variations across groups, it seeks to unravel how the challenges associated with taxation, trade and globalization manifest differently depending on the economic context, thus providing insights toward policies that are attuned to gap in those economies.

The remainder of this paper is organized as follows. The literature review is presented in the next section. Following that, the paper describes the variables, model specification, and analytical techniques employed. The subsequent section shows the results along with their interpretation. Lastly, final part discusses the findings, offers explanations, and concludes the paper.

Relevant Literature Review

Relationship between Taxation and Labor Income Share

Extensive research has studied the relationship between taxation and labor income share and findings indicate that the nexus between the two is rather complex. Generally, an increase in taxes on labor income may lead to a decline in the labor share. This is because higher labor income taxes raise the cost of labor for employers (Cruz, 2023), potentially resulting in a reduction in employment or wages. The work of Kaymak and Schott (2023), show that across Organisation for Economic Co-operation and Development (OECD) countries, corporate tax cuts explain 30% to 60% of the observed decline in labor income share. This is mainly because lower rates of corporate tax favor capital-intensive firms, resulting in higher industry concentration and fewer jobs, consequently reducing the proportion of income distributed to labor. Moreover, research that concentrates on a particular nation, especially the United States (US), also confirmed this observation. For instance, Heer et al. (2023), claimed that technological progress has accelerated this trend by making capital more productive than labor, which resulted in a shrinking share of income for workers. Similarly, Acemoglu et al. (2020) also emphasized that the US tax System is increasingly biased towards capital, which contributes to the ongoing decline in labor income share, especially as automation and technological change continue to reshape the economy. Likewise, in China, Li et al. (2021) demonstrated that rising corporate taxes cause a reallocation of income from labor to capital and this, in turn, may reduce the labor income share.

Nevertheless, not all studies suggest a negative association between taxation and labor income share. For example, Bises et al. (2023), argued that comprehensive personal income taxes that cover capital income can enhance the redistributive power of taxation, which may promote a rise in the labor income share. Along the same lines, an investigation by Li et al. (2024) based on 302,951 Chinese enterprises over the period of 2009 to 2015 also illustrated the significant relationship of reduction of tax burden with both the technological adaptation and labor income share. They argued that a reduced social security increased the funds available, hence enabling company to invest in automation. As a result, this leads the labor productivity growing faster than its' costs, thus eventually lower the labor income share. Other than that, some studies in the literature also investigated the effect of progressive taxation on labor income share. To give an example, Lyon and Waugh (2018) asserted that progressive tax Systems reduce income inequality and, by implication, increase the labor income share. However, it should be kept in mind that the effectiveness of progressive taxation in raising labor income share is contingent on the wider economy, how tight the labor market is and the structure of the tax System (Guner et al., 2020; Wu, 2021).

Relationship between Trade and Labor Income Share

Other than taxation, the relationship between trade openness and labor income share has also been the subject of extensive study, with varying conclusions depending on the context and sector under examination. Existing literature indicates that rising trade exposure can adversely affect labor income share, especially in developing economies. This occurs primarily through intensified competition and a shift toward capital-intensive production methods for firms aiming to remain competitive (Autor et al., 2016). For instance, Gupta and Helble (2018) employed a fixed-effects model to analyze the impact of trade liberalization on manufacturing plants in India between 1999 and 2008. They observed a substantial decline in labor income share in capital-intensive and high-tech industries, but a small positive effect for labor-intensive sectors. In a Latin American context, González-Rozada and Ruffo (2024) analyzed the impact of post-trade agreement conditions on labor income share, finding that trade agreements with large economies were linked to a decrease in labor income share by two to four percentage points of GDP. In essence, their work drew attention to the way trade agreements have kept real wages from going up, especially in manufacturing sectors.

While majority of the body of literatures appears to show a negative relationship between trade openness and labor income share, some studies find exceptions. For example, the work of Yeerken and Deng (2023) which analyzed the impact of digital service trade on labor income share in OECD countries shows that digital trade raises productivity and thus labor income share. Their analysis was based on a panel data spanning from 2005 to 2019 and utilizing a fixed effects model. Moreover, an interesting study across 96 countries between

1970 and 2009 provides findings on a nonlinear relationship between trade and labor share by utilizing partially linear models with fixed effects (Wang and Tian, 2020). They also pointed out that exports reduce the labor income share, while imports generally increase it. However, this effect disappears at increasingly higher levels of trade, indicating that there is a non-linear interaction between the levels of trade and labor income share. Interestingly, their discovery aligns with the findings of Doan and Wan (2017) who analyzed 87 countries from 1980 to 2010. Wherein, it was revealed that imports generally boost labor share, and exports have a negative impact. On the other hand, Guerriero and Sen (2012) asserted that labor income shares increase with trade openness in countries with stronger labor market regulations. However, in countries with narrow regulatory frameworks, trade openness significantly increases income inequality by lowering the bargaining power of labor compared to capital. Hence, this underscores the role of strong labor protections in blunting the adverse effects of trade liberalization on income distribution.

Relationship between Globalization and Labor Income Share

The effect of globalization on labor income share has been a well-addressed topic in the literature, with trade being one of the key driving factors for declining labor income shares. Nonetheless, it should be noted that, globalization is a multidimensional process that extends beyond trade. Globalization encompasses several aspects including economic, political, social, and cultural integration across borders. In contrast, trade openness or liberalization specifically refers to the reduction of trade barriers to facilitate the exchange of goods and services, making it just one component of the broader globalization framework. According to Erkişi and Çetin (2025) however, advancements in technology such as automation and robotics, which are key drivers of trade-induced industrial changes that reduce the need for human labor and increase the share of capital, also contribute to a decrease in labor's share of income. In addition to this perspective, a study by Dilja (2024) using panel data from 185 countries during the period 2005 to 2022 shows that Artificial Intelligence (AI) and Information and Communication Technology (ICT) can positively affect productivity, with higher-income countries making better use of these technologies. This indicates that, under certain conditions, technology can raise labor's income share by improving skills and employment opportunities, particularly when supported by education, training, and policies that help workers adapt to technological change. Furthermore, it highlights how globalization, by spreading technology across borders and strengthening knowledge transfer, can contribute to a more equitable distribution of income when appropriate policy mechanisms are in place. Besides that, globalization is considered a double-edged sword in terms of foreign direct investment (FDI). Although FDI attracts capital, its impact on labor share is not always beneficial. In a significant number of cases, however, FDI has only limited positive implications for local labor markets, as the entry of foreign firms is often accompanied by capital-intensive production that contributes to a further of labor's share (Doan and Wan, 2017). Moreover, the globalization process has enhanced skill premium against low-skilled individuals who have been receiving reduced share of total income compared with high-skilled individuals which degrades the inequality gap (Paul, 2020). All these results taken together point to the implication that globalization, especially driven by trade, tends to shift the balance of power and income from labor to capital.

However, other studies have found that globalization can have a positive impact on the labor income share, particularly when paired with social globalization and effective government policies. The political and social globalization, such as the mobility of information, ideas, and people, can offset the effects of economic globalization by increasing labor's bargaining power. This is especially true in more developed economies, where labor protections and regulations are stronger (Young and Tackett, 2018). Although liberalization of trade and flows of capital are associated with detrimental effects on the labor share of national income, social globalization can lead to broader access to information and networks that empower workers and improve their share of national income. According to Sertyesilisik (2022), globalization opens doors to economic equality but also holds the potential to improve working conditions and welfare Systems when aligned with the right policy frameworks. For instance, countries that implement robust social safety nets and labor market regulations can mitigate the adverse effects of economic globalization, ensuring a more equitable distribution of income. Harrison (2022) argues that government policies, such as high levels of public expenditure on education and health care, capital controls, and strong labor laws, can alleviate the negative impacts of globalization and ensure that its benefits are more evenly distributed across society. In this context, globalization itself is not inherently detrimental to labor income share. Rather, it is the way it is managed and integrated into national frameworks that determines its impact.

Relationship between Macroeconomic Variables and Labor Income Share

The labor force participation rate is a key determinant of labor income share, with changes in the participation rate affecting income distribution. Researchers have explored the links between these two, as affecting the labor market composition directly and indirectly due to the demographic dynamic. Interestingly, it was found that higher participation rates, particularly for women, were associated with more equitable income distribution by increasing the number of people contributing to household income (González and Virdis, 2021; Yıldırım and Akinci, 2021). Other than that, by utilizing data from 18 OECD countries spanning from 1960 to 2008, Schmidt and Vosen (2013) revealed that a slow growth of labor force participation rates tends to increase capital intensity, which can lower labor income share. Similarly, d'Albis et al. (2021) also suggested a positive impact of labor force participation based on their estimation using a structural Vector Autoregression (VAR) model on 1985–2018 for 18 OECD countries. Their findings indicate that demographic changes, such as the natural rate of increase and net migration, have an impact on the labor income share. As a result, this relationship is also affected by labor force participation, as changes in workforce composition can impact income distribution, particularly, the labor income share.

Another macroeconomic variable that plays a significant role in shaping the labor income share is the economic development of a country. Notably, the relationship between the two are often multifaceted and circumstance-specific. On the one hand, it has been argued that a high economic growth rate leads to a higher labor income share rate, as growing economies tend to create jobs and increase incomes (Trofimov et al., 2018). Recent studies have proposed that, in some contexts, there's an inverse relationship between GDP growth and labor income share. According to Sergi et al. (2023) a negative relationship between GDP growth and labor income share was observed in high labor-output countries between 1990 and 2010, particularly post-global crisis due to technological changes and the increased role of capital. Furthermore, Kim and Park (2020) provided evidence of a cubic relationship, where labor income share rises with GDP growth to a certain point but then declines as the economy continues to grow. These findings suggest that, while GDP growth may benefit labor in the short term, the long-term dynamics may lead to a decline in labor's share of national income, particularly in more capital-intensive economies.

Another important determinant in the discussion of labor income share is inflation. Inflation is often linked to a decrease in labor's share due to its influence on wage bargaining power and nominal rigidities in labor markets. For instance, Jensen (2017) found that in the US and other OECD countries, rising inflation was associated with a decline in labor income share, as inflation undermined labor's bargaining power and contributed to wage stagnation. Similarly, Alaloul et al. (2021) reported a significant negative relationship between inflation and labor income share in Malaysia's construction sector. On the other hand, some studies demonstrate a positive relationship between inflation and labor income share, particularly in the context of price-cost margins. Earlier studies by Alcala and Sancho (2000) suggested that inflation could lead to higher labor's share of income, especially in countries with stable price-cost margins. Likewise, in the United Kingdom, Batini et al. (2000) observed that inflation and labor income share were positively correlated, indicating that inflation could support labor's share in some economic contexts. In addition, Taylor and Barbosa-Filho (2021) asserted that the rising spread of income from inflation can be interpreted as conflicting claims for income, particularly in situations where the labor income share is rising and wages are growing faster than price levels and productivity.

Methodology

Variables Overview

Table 1 provides an overview of the variables used in this study, categorizing them into dependent, independent, and control variables. The labor income share (LIS), the dependent variable, represents the proportion of national income allocated to labor compensation and is sourced from the ILO website. The key independent variables include tax revenue (TAX) and trade openness (TO), both measured as a percentage of GDP and obtained from the World Bank's World Development Indicators (WDI) database. Additionally, the globalization index (GI), sourced from the KOF Swiss Economic Institute, captures the extent of economic, social, and political integration on a scale from 0 to 100. The study also controls for labor force participation (LFP), GDP per capita (GDPPC), and inflation (CPIG). These variables were selected to account for broader economic and labor market conditions and to ensure that the estimated effects of the main explanatory variables are not biased by omitted macroeconomic influences. Specifically, LFP captures labor market engagement, GDP per capita reflects economic development, and CPIG as a proxy for inflation, which account for price stability and purchasing power.

Table 1
Summary of variables

Role of Variable	Variable	Label	Measurement	Source
Dependent variable	labor income share	LIS	Proportion of national income allocated to labor compensation (% GDP)	ILO
Independent variable	Tax revenue	TAX	(% GDP)	WDI
Independent variable	Trade openness	TO	Total import and export (% GDP)	WDI
Independent variable	Globalization index	GI	Index with a scale from one to one hundred (0-100)	KOF index
Control variable	labor force participation	LFP	% of total population ages 15+	WDI
Control variable	GDP per capita	GDPPC	GDP per capita, PPP (constant 2021 international $)	WDI
Control Variable	Inflation	CPIG	CPI growth (annual %)	UNCTAD

Note(s): ILO stands for International Labour Organisation, WDI stands for world bank indicator, KOF index is a database for globalization index developed KOF Swiss Economic Institute, and UNCTAD is the United Nations Trade and Development data hub.
Source(s): Table by authors.

In this study, globalization is viewed as a multidimensional phenomenon that goes beyond international trade. While trade, which is the movement of goods and services across borders is an important component, globalization also includes other dimensions such as financial integration (e.g., foreign direct investment and portfolio flows), labor mobility (e.g., migration), technological diffusion, and political cooperation among nations. Therefore, by controlling separately for trade openness, the analysis isolates the broader effects of globalization, capturing influences related to capital markets, cross-border movement of people, international policy alignment, and information exchange. This distinction enables a more sophisticated comprehension of the potential impact of globalization, in its entirety, on the labor income distribution across economies.

Model Specification and Estimation Technique
With the guidance of previous studies discussed in the previous section, Equation (1) represents the relationship of interest that were studied in this paper. Specifically, it models the labor income share for a given country i at time t as a function of tax revenue, trade openness, globalization index, labor force participation, GDP per capita and inflation.

$$LIS_{it} = (TAX_{it}, TO_{it}, GI_{it}, LFP_{it}, GDPPC_{it} CPIG_{it}) \quad (1)$$

Our study employed a dynamic panel modelling approach to analyze the determinants of labor income share across 57 countries (See Table 1A in the Appendix for the full list) for the period of 2008 until 2022. The model specification includes a lagged dependent variable as one of the regressors to account for persistence in the labor income share over time. Notably, all variables were log transformed to ensure elasticity interpretation and stabilize variance. Given this, the model specification of our study can be written as Equation (2),

$$\ln(LIS)_{it} = \alpha + \gamma \ln(LIS)_{i,t-1} + \beta_1 \ln(TAX)_{it} + \beta_2 \ln(TO)_{it} + \beta_3 \ln(GI)_{it} + \beta_4 \ln(LFP)_{it} + \beta_5 \ln(GDPPC)_{it} + \beta_6 \ln(CPIG)_{it} + \varepsilon_{it} \quad (2)$$

where γ captures the persistence of labor income share, $\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6$ denote the coeffcients of the regressors, ε_{it} is the error term, i represent country and t represent time.

The dynamic nature of the model necessitates the use of an appropriate estimation technique, namely the System GMM approach, to address endogeneity concerns arising from simultaneity bias and unobserved heterogeneity.

The GMM estimator is suitable for small time-periods (T) and large cross-sections (N) (Yousefinejad et al., 2022), which was first presented by Arellano and Bond (1991). The GMM technique is widely used in panel regression studies because it efficiently handles endogeneity concerns by employing lagged dependent variables and exogenous regressors as instruments (Hassan et al., 2024). Given so, this approach provides a more reliable estimations of regression coefficients in comparison to conventional fixed effect (FE) model and random effects (RE) model. The GMM methods can further be categorized as Difference GMM and System GMM. The System GMM estimator was first devised by Arellano and Bover (1995) and further developed by Blundell and Bond (1998). The beauty of both Difference and System GMM methods are the use of the instruments which are valid based on the assumption that the disturbance terms are truly independent and are serially uncorrelated. Nevertheless, the System GMM is considered more reliable compared to Difference GMM, as it is more robust to heteroscedasticity and autocorrelation. Not just that, it is more effective to use the System GMM estimation instead, if the dependent variable more persistent. Given these, our study utilized the System GMM approach to assess the significant impact of economic policies, globalization on the labor income share.

Cross-sectional Dependence Test

Prior to conducting panel unit root tests, it is essential to examine cross-sectional dependence (CD) to determine the appropriate testing approach. CD arises when unobserved common factors or economic interdependencies cause correlations across cross-sections, which can bias traditional panel estimations if not addressed. Here, our study utilized the cross-sectional dependence test devised by Pesaran (2006). Equation (3) shows the CD test statistic (Hoyos and Sarafidis, 2006),

$$CD = \sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{y}_{ij}\right) \tag{3}$$

where, $\hat{y}_{ij}$ represent the residual pairwise correlation coefficient, N is the number of cross sections term and T is the time series term. with the null hypothesis stating no CD among panel units. The null hypothesis of this test assumes no CD among panel units. A p-value below 0.05 leads to rejecting the null, indicating significant CD, while a p-value above 0.05 suggests the absence of CD.

Panel Unit Root Test

After assessing cross-sectional dependence, it is essential to determine the stationarity of variables using panel unit root tests. The choice between first-generation and second-generation unit root tests depends on the presence of CD. First-generation tests, such as the Im, Pesaran, and Shin (IPS), Levin, Lin, and Chu (LLC), Augmented Dickey-Fuller (ADF), and Phillips-Perron (PP) tests, assume cross-sectional independence and are appropriate when CD is absent. In this study, we primarily utilized the IPS panel unit root test, when no CD is detected in the panel data. Additionally, LLC, ADF and PP tests were implemented to validate the consistency of the stationarity results. The IPS panel unit root test begins with an Augmented Dickey Fuller (ADF) panel data regression given by Equation (4),

$$\Delta y_{it} = \alpha_i + \rho_i y_{i,t-1} \sum_{j=1}^{p} \varphi_{ij}\, \Delta y_{it-1} + \varepsilon_{it} \tag{4}$$

where ρ_i represents the autoregressive coefficient for individual i. The test statistic for this test is given by Equation (5), which is simply the average of the t-statistics from the individual ADF regressions across all N cross-sectional units.

$$\bar{t} = \frac{1}{N} \sum_{i=1}^{N} t_i \tag{5}$$

However, when CD is present, second-generation unit root tests, such as the Cross-Sectionally Augmented IPS (CIPS) devised by Pesaran (2007), are preferred they account for common factors and cross-sectional dependencies. The CIPS test is derived from the Cross-Sectional augmented Dickey Fuller (CADF) regression, which augments the standard Dickey-Fuller test with cross-section means to control for unobserved common factors, as shown in Equation (6),

$$\Delta y_{it} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + e_{it} \tag{6}$$

where $\bar{y}_{t-1}$ and $\Delta \bar{y}_t$ represent cross-sectional averages of the lagged dependent variable and first-differenced dependent variable, respectively. The CIPS test statistic is then computed as the average of individual CADF test statistics across cross-sections, as shown in Equation (7),

$$CIPS = \frac{1}{N} \sum_{i=1}^{N} t_i(N,T) \tag{7}$$

where $t_i(N,T)$ is the individual CADF t-statistic. The null hypothesis (H_0) states that all series contain a unit root (non-stationary), while the alternative hypothesis (H_1) suggests that at least some cross-sectional units are stationary. Conversely, failure to reject H_0 implies that the variables are non-stationary. By applying the appropriate unit root tests, this study ensures that the variables meet the required stationarity conditions.

Empirical Results

Descriptive Statistics

Table 2 presents the descriptive statistics for the full sample, while Table 3 and Table 4 provide separate summaries for advanced and emerging economies, respectively. The results indicate that advanced economies exhibit a higher labor income share than emerging economies, alongside greater tax revenue and trade openness. Additionally, globalization index is also more pronounced in advanced economies compared to emerging economies, suggesting greater integration into global markets. Overall, these tables highlight the economic disparities between advanced and emerging economies in terms of income distribution, fiscal strength, trade integration, globalization, and macroeconomic stability.

Table 2
Descriptive statistic of variables (All sample)

Variable	Observation	Mean	Std. dev.	Min	Max
$lnLIS$	855	3.9492	0.1703	3.0457	4.2557
$lnTAX$	855	2.9023	0.3241	2.0413	3.8296
$lnTO$	855	4.4642	0.5581	3.0958	6.0807
$lnGI$	855	4.3248	0.1232	3.8661	4.4977
$lnLFP$	855	4.1076	0.0998	3.7910	4.3477
$lnGDPPC$	855	10.4641	0.6476	8.6937	12.0688
$lnCPIG$	855	1.4943	0.6824	−1.1242	4.3192

Source(s): Table by authors.

Table 3
Descriptive statistic of variables (Advanced economies)

Variable	Observation	Mean	Std. dev.	Min	Max
$lnLIS$	510	3.9971	0.1656	3.0457	4.2557
$lnTAX$	510	3.0062	0.3143	2.0673	3.8296
$lnTO$	510	4.6230	0.5550	3.1390	6.0807
$lnGI$	510	4.3860	0.1022	3.8661	4.4977
$lnLFP$	510	4.1163	0.0939	3.8687	4.3477
$lnGDPPC$	510	10.8793	0.3772	10.0899	12.0688
$lnCPIG$	510	1.3136	0.5455	−1.1242	3.0656

Source(s): Table by authors.

Table 4
Descriptive statistic of variables (Emerging economies)

Variable	Observation	Mean	Std. dev.	Min	Max
$lnLIS$	345	3.8784	0.1517	3.3631	4.1509
$lnTAX$	345	2.7488	0.2739	2.0413	3.2583
$lnTO$	345	4.2295	0.4742	3.0958	5.2218
$lnGI$	345	4.2344	0.0921	3.9893	4.4306
$lnLFP$	345	4.0947	0.1068	3.7910	4.2936
$lnGDPPC$	345	9.8503	0.4440	8.6937	10.6774
$lnCPIG$	345	1.7613	0.7719	−0.9175	4.3192

Source(s): Table by authors.

Correlation Matrix

Then, we also presented the correlation matrix in Table 5 until Table 7, showing the relationships among the variables used in this study across all samples, advanced economies, and emerging economies. In the full sample, lnTAX has a weak and insignificant correlation with lnLIS (0.0259), while lnTO shows a significant negative correlation (-0.1191), suggesting that greater trade openness is associated with a lower labor income share. lnGI, however, has a strong positive correlation (0.4792), indicating that globalization may support labor income share. In advanced economies, lnTAX is significantly negative (-0.2248), and lnTO has a stronger negative impact (-0.2785), while lnGI remains highly positive (0.6812). In emerging economies, lnTAX is insignificant (0.0618), lnTO is negatively correlated (-0.2529), and lnGI is also negatively correlated (-0.2045), differing from advanced economies.

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Table 5

Pairwise correlation (All sample)

	$lnLIS$	$lnTAX$	$lnTO$	$lnGI$	$lnLFP$	$lnGDPPC$	$lnCPIG$
$lnLIS$	1.0000						
$lnTAX$	0.0259	1.0000					
	(0.4498)						
$lnTO$	−0.1191	0.2405	1.0000				
	(0.0005)	(0.0000)					
$lnGI$	0.4792	0.2302	0.3108	1.0000			
	(0.0000)	(0.0000)	(0.0000)				
$lnLFP$	0.0145	−0.1835	−0.0018	−0.1310	1.0000		
	(0.6712)	(0.0000)	(0.9586)	(0.0001)			
$lnGDPPC$	0.1298	0.2837	0.4082	0.5726	0.2249	1.0000	
	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0000)		
$lnCPIG$	−0.1821	−0.1379	−0.1573	−0.3245	0.0169	−0.1701	1.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.6222)	(0.0000)	

Source(s): Table by authors.

Table 6

Pairwise correlation (Advanced economies)

	$lnLIS$	$lnTAX$	$lnTO$	$lnGI$	$lnLFP$	$lnGDPPC$	$lnCPIG$
$lnLIS$	1.0000						
$lnTAX$	−0.2248	1.0000					
	(0.0000)						
$lnTO$	−0.2785	0.0213	1.0000				
	(0.0000)	(0.6312)					
$lnGI$	0.6812	−0.1889	0.0344	1.0000			
	(0.0000)	(0.0000)	(0.4382)				
$lnLFP$	−0.2082	−0.1169	0.0218	−0.2494	1.0000		
	(0.0000)	(0.0082)	(0.6231)	(0.0000)			
$lnGDPPC$	−0.2975	−0.0153	0.2611	−0.0513	0.4382	1.0000	
	(0.0000)	(0.7302)	(0.0000)	(0.2473)	(0.0000)		
$lnCPIG$	−0.0890	0.0922	0.0017	−0.1465	0.0867	0.0592	1.0000
	(0.0446)	(0.0373)	(0.9694)	(0.0009)	(0.0504)	(0.1818)	

Source(s): Table by authors.

Table 7

Pairwise correlation (Emerging economies)

	$lnLIS$	$lnTAX$	$lnTO$	$lnGI$	$lnLFP$	$lnGDPPC$	$lnCPIG$
$lnLIS$	1.0000						
$lnTAX$	0.0618	1.0000					
	(0.2525)						
$lnTO$	−0.2529	0.3227	1.0000				
	(0.0000)	(0.0000)					
$lnGI$	−0.2045	0.3350	0.3316	1.0000			
	(0.0001)	(0.0000)	(0.0000)				
$lnLFP$	0.2384	−0.4433	−0.1387	−0.2460	1.0000		
	(0.0000)	(0.0000)	(0.0099)	(0.0000)			
$lnGDPPC$	−0.1492	−0.0654	0.2048	0.5636	−0.0042	1.0000	
	(0.0055)	(0.2254)	(0.0001)	(0.0000)	(0.9383)		

$lnCPIG$	−0.0756 (0.1611)	−0.1426 (0.0080)	−0.1203 (0.0254)	−0.2117 (0.0001)	0.0253 (0.6399)	0.2070 (0.0001)	1.0000

Source(s): Table by authors.

As the next step, we also checked for multicollinearity using the variance inflation factor (VIF) test to ensure the reliability of our estimates. Multicollinearity arises when independent variables are highly correlated, which can distort coefficient estimates, inflate standard errors, and weaken statistical inference. The VIF results for all groups are illustrated by Table 8.

Table 8
Variance Inflation Factor results

Variable	Full Sample		Advanced Economies		Emerging Economies	
	VIF	1/VIF	VIF	VIF	1/VIF	VIF
$lnGDPPC$	2.01	0.4978	1.35	0.7398	2.00	0.4989
$lnGI$	1.81	0.5527	1.15	0.8726	2.24	0.4467
$lnLFP$	1.26	0.7909	1.38	0.7242	1.27	0.7844
$lnTO$	1.24	0.8045	1.09	0.9204	1.22	0.8225
$lnTAX$	1.19	0.8377	1.08	0.9270	1.56	0.6418
$lnCPIG$	1.13	0.8826	1.03	0.9693	1.28	0.7835
Mean VIF	1.44	-	1.18	-	1.59	-

Source(s): Table by authors.

The VIF results in Table 8 confirm that multicollinearity is not a concern, as all VIF values are well below the threshold of 5. Advanced economies exhibit the lowest multicollinearity, with all VIF values close to 1, while emerging economies show slightly higher values, particularly for lnGI (1.90) and lnTAX (1.55). Nonetheless, the mean VIF across samples remains low, ensuring that the independent variables do not suffer from significant collinearity.

Next, we conducted panel unit root test to determine the stationarity of the variables. However, selecting the appropriate test depends on whether cross-sectional dependence is present. If CD is absent, first-generation tests such as Levin-Lin-Chu (LLC) or Im-Pesaran-Shin (IPS) are suitable. Conversely, if CD is present, second-generation tests like Pesaran's CIPS should be used. Therefore, Table 9 presents the results of the cross-sectional dependence (CD) test, which will guide the selection of the appropriate panel unit root test.

Table 9
Pesaran cross-sectional dependence (CD) test result

Sample	Pesaran CD Statistic	p-value	Decision
All sample	3.207	0.0013	CD present
Advanced economies	3.906	0.0001	CD present
Emerging economies	−1.596	0.1104	No CD

Source(s): Table by authors.

Table 9 presents the CD test results, indicating significant CD in the full sample and advanced economies, as shown by the Pesaran statistic and low p-values. In contrast, emerging economies do not exhibit CD, as the test fails to reject the null hypothesis. These findings suggest that first-generation unit root tests are appropriate for emerging economies, while second-generation tests should be used for the full sample and advanced economies to account for cross-sectional dependencies.

Panel Unit Root Test Results

As guided by the outcome from the Pesaran cross-sectional dependence test results, Table 10 and Table 11 present the CIPS test for the full sample and advanced economies, as they account for cross-sectional dependence. Meanwhile, Table 12 illustrates the results of the first-generation panel unit root tests (IPS, LLC, ADF, and PP) for emerging economies, where no cross-sectional dependence was detected.

Table 10

Second-generation panel unit root test result (All sample)

Variable	At level		First Difference		Stationarity
	Constant	Trend	Constant	Trend	
CIPS					
$lnLIS$	−1.653	−2.069	−3.326***	−3.494***	$I(1)$
$lnTAX$	−1.651	−2.921***	−3.759***	−3.889***	$I(1)$
$lnTO$	−1.700	−2.077	−3.062***	−3.304***	$I(1)$
$lnGI$	−2.216**	−2.473	−3.463***	−3.541***	$I(0)$
$lnLFP$	−1.788	−1.841	−3.059***	−3.365***	$I(1)$
$lnGDPPC$	−2.375**	−2.687**	−3.030***	−3.368***	$I(0)$
$lnCPIG$	−2.572***	−2.878***	−4.207***	−4.304***	$I(0)$

Note(s): ***, **, and * denote significance at the 1%, 5%, and 10% levels.
Source(s): Table by authors.

Table 11

Second-generation panel unit root test result (Advanced economies)

Variable	At level		First Difference		Stationarity
	Constant	Trend	Constant	Trend	
CIPS					
$lnLIS$	−1.382	−2.420	−3.588***	−3.621***	$I(1)$
$lnTAX$	−1.736	−2.572*	−3.640***	−3.949***	$I(1)$
$lnTO$	−1.837	−1.719	−2.699***	−3.067***	$I(1)$
$lnGI$	−2.255**	−2.491	−3.497***	−3.540***	$I(0)$
$lnLFP$	−1.401	−1.940	−3.059***	−3.349***	$I(1)$
$lnGDPPC$	−2.025	−2.361	−2.808***	−3.093***	$I(1)$
$lnCPIG$	−2.799***	−3.166***	−4.489***	−4.649***	$I(0)$

Note(s): ***, **, and * denote significance at the 1%, 5%, and 10% levels.
Source(s): Table by authors.

Table 12
First-generation panel unit root test result (Emerging economies)

Variable	At level		First Difference		Stationarity
	Constant	Trend	Constant	Trend	
IPS					
$lnLIS$	−1.9432**	−1.7129**	−7.3880***	−7.9870***	$I(0)$
$lnTAX$	−2.2695**	−5.2978***	−8.3351***	−8.1712***	$I(0)$
$lnTO$	−0.8406	−2.8100***	−7.4606***	−7.7059***	$I(1)$
$lnGI$	0.1558	−0.8412	−7.0734***	−7.9857***	$I(1)$
$lnLFP$	−1.1585	−5.0991***	−8.0222***	−7.7838***	$I(1)$
$lnGDPPC$	3.3778	−3.8321***	−8.2377***	−8.7667***	$I(1)$
$lnCPIG$	−2.8531***	−2.4152***	−7.1583***	−7.9440***	$I(0)$
LLC					
$lnLIS$	−3.5318***	−3.7100***	−6.5649***	−5.9778***	$I(0)$
$lnTAX$	−1.3290*	−3.9322***	−6.3328***	−4.9776***	$I(0)$
$lnTO$	−1.7076**	−3.8200***	−5.0053***	−2.2777**	$I(0)$
$lnGI$	−8.6170***	−3.7569***	−3.2604***	−2.7670***	$I(0)$
$lnLFP$	−2.6764***	−3.5245***	−3.5171***	−1.1986	$I(0)$
$lnGDPPC$	−5.3228***	−5.5880***	−5.4590***	−2.9735***	$I(0)$
$lnCPIG$	−0.4604	−2.6571***	−6.0957***	−4.9717***	$I(1)$
ADF					
$lnLIS$	3.4695***	3.5045***	12.0198***	8.9200***	$I(0)$
$lnTAX$	3.1351***	4.3610***	15.1317***	4.3610***	$I(0)$
$lnTO$	2.8553**	5.6659***	13.3755***	8.2852***	$I(0)$
$lnGI$	4.3289***	-0.0702	5.2551***	3.7226***	$I(0)$
$lnLFP$	1.7425**	4.7898***	16.6978***	12.3037***	$I(0)$
$lnGDPPC$	2.5333***	1.2761***	9.1646***	6.1789***	$I(0)$
$lnCPIG$	3.8128	2.2317**	12.3025***	7.9083***	$I(1)$
PP					
$lnLIS$	1.8749**	−0.7440	23.4996***	17.2657***	$I(0)$
$lnTAX$	7.5490***	8.9079***	34.6326***	24.3820***	$I(0)$
$lnTO$	2.8892***	1.1100	22.3211***	14.0509***	$I(0)$
$lnGI$	0.2006	−2.2135	21.7114***	21.3452***	$I(1)$
$lnLFP$	3.7452***	12.7012***	39.5375***	30.7515***	$I(0)$
$lnGDPPC$	1.6196**	3.2118***	28.3207***	23.7549***	$I(0)$
$lnCPIG$	7.8197***	2.7047***	27.6366***	20.6932***	$I(0)$

Note(s): ***, **, and * denote significance at the 1%, 5%, and 10% levels.
Source(s): Table by authors.

The panel unit root test results from Table 10 to Table 12 reveal mixed stationarity properties across different country groups. For the full sample (Table 10) and advanced economies (Table 11), the CIPS test indicates that lnLIS, lnTAX, lnTO, and lnLFP are stationary at first difference, $I(1)$. Meanwhile lnGI, lnGDPPC, and lnCPIG are already stationary at level, $I(0)$. In contrast, for emerging economies (Table 12), the IPS, LLC, ADF, and PP tests indicate that most variables are $I(0)$, except lnGI and lnCPIG, which are $I(1)$ in some specifications. These findings highlight that different stationarity assumptions must be considered when estimating the model, with appropriate handling of $I(1)$ variables in the System GMM estimation.

Next, we also conducted the Hausman test to compare between the FE and RE models. This test assesses whether individual-specific effects are correlated with the regressors, where a significant result favours FE model due to potential endogeneity concerns. Meanwhile, an insignificant result suggests that RE is more efficient. Although FE may be preferred in some cases, it does not account for endogeneity or the dynamic structure of the model. This step is essential to justify the need for a more robust estimator like the System GMM by testing for the presence of endogeneity. Besides that, even if the Hausman test result favours RE model, the use of System GMM remains necessary to address issues like simultaneity, omitted variable bias, and autocorrelation, ensuring more robust and efficient estimation. The Hausman test results for FE and RE models are presented in Table 13.

Table 13
Hausman test of fixed effect model and random effect model result

	Chi-square statistic	p-value
All sample	30.63	<0.0000
Advanced economies	84.86	<0.0000
Emerging economies	11.65	0.0704

Source(s): Table by authors.

As shown by Table 13, the chi-square statistics for the full sample and advanced economies are significant, suggesting that the FE model is preferred over the RE model due to potential correlation between regressors and individual effects. However, for emerging economies, the p-value (0.0704) is slightly exceeded the 5% significance level, implying that the RE model may still be a viable choice.

Table 14 and Table 15 present the FE and RE model estimates, respectively. Across both models, trade openness (lnTO) consistently has a significant negative impact on labor income share, with a stronger effect in advanced economies. On the other hand, tax revenue (lnTAX) is positively associated with labor income share, particularly in advanced economies under the FE model. Similarly, globalization index (lnGI) and labor force participation (lnLFP) positively influence labor income share across all samples, though the impact is more pronounced in advanced economies. Besides that, GDP per capita (lnGDPPC) exhibits a negative effect, especially in advanced economies, indicating that higher economic development is associated with a declining labor income share.

Table 14
Fixed effect model result

	All sample	Advanced economies	Emerging economies
$lnTAX_{it}$	0.0545**	0.1398***	0.0067
	(0.0218)	(0.0276)	(0.0354)
$lnTO_{it}$	−0.2174***	−0.2390***	−0.1620***
	(0.0193)	(0.0241)	(0.0309)
$\ln GI_{\mathrm{it}}$	1.0849***	1.3909***	0.6707***
	(0.0916)	(0.1455)	(0.1162)
$lnLFP_{it}$	0.4300***	1.0974***	0.1546
	(0.0778)	(0.1181)	(0.1014)
$lnGDPPC_{it}$	−0.1606***	−0.3407***	−0.0333
	(0.0180)	(0.0250)	(0.0264)

$lnCPIG_{it}$	0.0001	0.0091*	−0.0069
	(0.0037)	(0.0046)	(0.0053)
Constant	−0.0169	−2.2415***	1.4122**
	(0.4477)	(0.6588)	(0.5876)
Observations	855	510	345
N	57	34	23

Notes(s): Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.
Source(s): Table by authors.

Table 15
Random effect model result

	All sample	Advanced economies	Emerging economies
$lnTAX_{it}$	0.0501**	0.0951***	0.0064
	(0.0208)	(0.0258)	(0.0341)
$lnTO_{it}$	−0.1790***	−0.1657***	−0.1488***
	(0.0171)	(0.0194)	(0.0284)
$lnGI_{it}$	1.0283***	1.2269***	0.6041***
	(0.0827)	(0.1110)	(0.1125)
$lnLFP_{it}$	0.3833***	0.8240***	0.1784*
	(0.0731)	(0.1070)	(0.0962)
$lnGDPPC_{it}$	−0.1281***	−0.2770***	−0.0327
	(0.0163)	(0.0236)	(0.0254)
$lnCPIG_{it}$	−0.0034	0.0034	−0.0080
	(0.0036)	(0.0048)	(0.0053)
Constant	−0.0730	−1.2868**	1.5379***
	(0.4206)	(0.5924)	(0.5700)
Observations	855	510	345
N	57	34	23

Notes(s): Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.
Source(s): Table by authors.

Given the Hausman test results, the FE model is more appropriate for the full sample and advanced economies, reinforcing the need for estimation techniques that address potential endogeneity, such as System GMM. However, for emerging economies, the RE model is not rejected at the 5% level, suggesting that time-invariant individual effects may be uncorrelated with the regressors. Despite this, System GMM approach remains applicable for two key reasons. First, even if the RE model is appropriate, it does not account for potential endogeneity arising from reverse causality or omitted variable bias, which GMM estimator effectively addresses by using internal instruments. Second, given the dynamic nature of labor income share and economic variables, System GMM approach accommodates lagged dependent variables and ensures robustness in capturing short-term and long-term relationships, making it a superior estimation method regardless of the initial RE preference. Therefore, Table 16 illustrate the System GMM estimation results.

Table 16
System GMM estimation result

	(1) All sample	(2) Advanced economies	(3) Emerging economies
$lnLIS_{i,t-1}$	0.6511***	0.8629***	0.8111***
	(0.1886)	(0.1135)	(0.1471)
$lnTAX_{it}$	−0.0007	−0.0074	0.0613
	(0.0182)	(0.0111)	(0.0394)
$lnTO_{it}$	−0.0295**	−0.0120*	−0.0293
	(0.0130)	(0.0070)	(0.0217)
$lnGI_{it}$	0.3017*	0.1607	−0.0346
	(0.1757)	(0.1277)	(0.0502)
$lnLFP_{it}$	0.1054**	0.0480	0.1885
	(0.0519)	(0.0417)	(0.1140)
$lnGDPPC_{it}$	−0.0199	−0.0246*	0.0093
	(0.0135)	(0.0140)	(0.0128)
$lnCPIG_{it}$	−0.0130***	−0.0094***	−0.0155***
	(0.0049)	(0.0032)	(0.0050)
Observations	798	476	322
N	57	34	23
Diagnostics p-value			
AR(1)	0.044	0.010	0.017
AR(2)	0.230	0.516	0.288
Sargan Test	0.118	0.826	0.433
Hansen	0.369	0.813	0.511

Notes(s): Standard errors in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels. The AR (1) test, also known as the Arellano-Bond first-order autocorrelation test, examines whether the first-order autocovariance in residuals is equal to zero, with the null hypothesis (H_0) being no autocorrelation. The AR (2) test, also part of the Arellano-Bond test, checks for second-order autocorrelation in residuals, where the null hypothesis (H_0) is no autocorrelation. The Sargan test assesses the validity of over-identifying restrictions, with the null hypothesis suggesting that the instruments are valid, and the Hansen test, which is robust to heteroscedasticity, evaluates whether the instruments are correctly specified.
Source(s): Table by authors.

Column (1) in Table 16 presents the System GMM estimation results for all samples of our study. It can be observed that, most of the coefficients are significant, except for taxation and GDP per capita. However, the subsample estimation of advanced economies and emerging economies represented by column (2) and column (3) shows lack of statistical significance of the estimated coefficients. Nonetheless, a few insights can still be drawn from these results. For instance, the System GMM estimation results highlight the persistence of labor income share across all samples, as indicated by the significant and positive coefficient of $lnLIS_{i,t-1}$. Additionally, trade openness ($lnTO_{it}$) negatively affects LIS, though its significance varies across samples, it is not significant in emerging countries. Nonetheless, this reinforces the hypothesis that increased trade can reduce labor's share of income. On the other hand, taxation *($lnTAX_{it}$)* exhibits an insignificant effect across all samples, suggesting that its impact on LIS is either weak or offset by other structural factors.

Turning to control variables, globalization index ($lnGI_{\mathrm{it}}$) positively influences labor share of income in the full sample but loses significance in subsamples, indicating heterogeneous effects across economies. Similarly, labor force participation ($lnLFP_{it}$) is significant only in the full sample, indicating that its effect on LIS operates at a broader labor market level rather than within specific economic groups. In contrast, inflation ($lnCPIG_{it}$) consistently reduces LIS across all estimations, highlighting the persistent role of cost-push pressures in eroding labor's share of income. These findings underscore the varying influence of macroeconomic factors on LIS, depending on a country's economic structure and development stage.

To ensure model validity, we also report several diagnostic results namely AR(1) test, AR(2) test, Sargan test and Hansen test. Overall, the diagnostic tests confirm model validity across all sample. The AR(1) test results show significant p-values across all sample, indicating the presence of first-order autocorrelation, as the null hypothesis of no autocorrelation is rejected at the 5% significance level. This suggests that there is a correlation between the errors of consecutive periods, which is expected when working with panel data and dynamic models. In contrast, the AR(2) test results exhibit p-values of 0.230, 0.516, and 0.288, which are all above the 5% significance level, implying that there is no second-order autocorrelation in the residuals across all samples. Next, the Sargan test results also yielded an insignificant p-value for the three groups, indicating that the instruments used in the models are valid and do not suffer from over-identification, as the null hypothesis of valid instruments is not rejected. Similarly, the Hansen test results with p-values of 0.369, 0.813, and 0.511 suggest that the instruments are correctly specified and valid for all samples. These findings justify the use of System GMM in addressing endogeneity concerns while capturing the dynamic nature of labor income share.

Discussion

The labor income share is influenced by its previous distribution and structural economic factors. This can be observed from the fact that the coefficients of the lagged dependent variable are consistently positive and significant in all sample and subsample of advanced and emerging economies in Table 16. The result is consistent with previous works that used a dynamic panel model and found that the level of labor share tends to increase the lagged value through a positive term (Erauskin, 2020; Ghodsi et al., 2024; Yeerken and Deng, 2023). Given these observations, it appears that historical patterns of labor income distribution exerts large power over current labor income share levels. This persistence is consistent with structural labor market rigidities, institutional wage-setting mechanisms, and the bargaining power of workers, all of which tend to perpetuate income distribution trends. From an economic perspective, these findings align with the idea that reallocations in the labor market take place slowly rather than abruptly and therefore underline the relevance of long-term scales as a tool for policy to impact labor share dynamics. Moreover, the significant parameter estimation for the lagged term of labor income share serves to justify utilization of dynamic modelling techniques, as neglecting to account for this persistence could result in biased estimates.

Another crucial finding outlined by the System GMM estimation is that, trade openness and labor income share showed a significant negative relationship with labor income share. This finding is consistent for the full sample and subsample of advanced economies. As for the emerging economies, our estimation did not capture any significant result. Nonetheless, the observed positive link between trade openness and the labor's share of income is in line with several literatures discussed before (Autor et al., 2016; González-Rozada and Ruffo, 2024; Gupta and Helble, 2018). Besides that, this outcome can also be justified with economic theory. For example, the Stolper-Samuelson theorem suggests that increased trade openness can lead to a decline in the relative returns to the factor that is relatively scarce in a country. In developed economies, this often refers to unskilled labor, resulting in a decrease in their income share. Additionally, trade openness can increase competition by putting downward pressure on wages, especially for low-skilled workers (Brutger and Guisinger, 2022). This effect is most pronounced in industries exposed to international competition, where workers experience greater employment instability and wage pressures. However, according to Omoke and Opuala–Charles (2021), trade openness's effect on labor income share can be avoided through increases in institutional quality and governance. This is because, countries with better institutions can better use the gains from trade openness to growth enhancing activities, which may offset some of these negative effects on labor income share. Besides that, policies that promote human capital accumulation and address structural discrimination can help workers adapt to the challenges posed by increased trade openness and minimize its negative impact on labor income share (Fatima et al., 2020). Given this, policymakers must focus on strengthening institutional quality, improving governance, and investing in human capital to mitigate the adverse effects of trade openness on labor income share, particularly for low-skilled workers in advanced economies.

In contrast, globalization shows a positive and significant relationship with the labor income share, but only in the full sample estimation. Though this contradicts with some prior research (Sertyesilisik, 2022; Young and Tackett, 2018), it is still in line with the work by Doan and Wan (2017), Erkişi and Çetin (2025) and Paul (2020). This indicate that globalization can have a positive relationship with labor income share, although this is not always the case. In one perspective, globalization can enhance labor productivity through technology transfer and knowledge spillovers. Consequently, this could potentially lead to higher wages (Samimi and Jenatabadi, 2014). As countries open up to international trade and foreign direct investment (FDI), they gain access to advanced technologies and management practices, which can improve worker efficiency and output. This increased productivity may translate into higher wages, especially if workers have strong bargaining power or if there is a shortage of skilled labor. However, it is important to note that the relationship between globalization and labor income share is complex and context dependent, as can be seen from the mixed findings of previous literatures. To conclude, globalization can increase labor income share in potential due to productivity effects and technology transfer, but the outcomes essentially depend on contexts. Factors such as a country's income level, education system, financial development, and labor market institutions play crucial roles in determining whether the benefits of globalization translate into higher labor share of income. Hence, to maximize the positive effects of globalization on labor income share, policymakers should focus on complementary policies that enhance human capital, strengthen financial Systems, and ensure fair labor practices.

Moving on, there are several crucial insights into the broader economic context that affect the labor income share. This can be observed through the control variables, namely labor force participation, economic growth and inflation. To start, the positive association between labor force participation and labor income share, across all estimations, signals that increased labor force participation is associated with a higher proportion of income allocated to labor. However, our findings did not reveal a significant positive relationship for the sub-sample estimations, suggesting that its significance may vary depending on the specific economic context. Even so, this may reflect an augmented supply of workers, which can potentially drive wage growth. Moreover, the positive link between labor force participation and the share of labor income is also in line with economic theory. For instance, the neoclassical framework proposes that increased labor force participation can lead to a higher labor income share by expanding the labor supply and potentially increasing competition for jobs. This can result in upward pressure on wages, especially in tight labor markets (Binder and Bound, 2019). Hence, this upward pressure on wages would, in turn, raise the labor income share.

The negative relationship between GDP per capita and labor income share in advanced economies reveals that higher income per capita is linked to structural changes in income distribution, driven by increasing capital intensity and automation. Unlike emerging economies, where growth often relies on labor-intensive industries, advanced economies undergo a transition toward high-tech sectors and capital-deepening processes. Higher GDP per capita in general is correlated positively with higher productivity and economic growth, but a greater part of the gains goes to capital than to labor. As firms invest more in automation and technology-driven production, the relative demand for labor, particularly for routine and low-skilled jobs, declines. As a result, this would lead to weakening workers' bargaining power and thus reducing labor's share of income. This phenomenon is consistent with Nicholas Kaldor's (1975) stylized facts and capital accumulation theory, which suggests that economic growth tends to be associated with rising capital intensity. Thus, leading to a greater share of national income flowing to capital rather than labor. This is true because, as capital accumulates, businesses would most likely prioritize investments in machinery and technology. Such strategy would boost productivity and simultaneously enhances output, but this does not necessarily ensure equal increases in labor payments. Consequently, the labor income share declines as a growing proportion of national income is distributed to capital owners instead of workers.

The consistently negative and significant relationship between consumer price inflation and labor income share across all estimations highlights the adverse impact of inflation on labor's share of national income. This finding implies that rising inflation erodes the purchasing power of wages, disproportionately affecting labor compensation relative to capital income. In inflationary environments, firms may pass increased costs onto consumers while limiting wage adjustments, leading to a decline in real wages and a shrinking labor income share. This effect is particularly pronounced in emerging economies, where weaker labor market institutions and limited wage indexation mechanisms make it more difficult for workers to negotiate wage increases in response to rising prices. Moreover, the erosion of real wages due to inflation aligns with the wage-lag hypothesis, which posits that wages tend to adjust more slowly than prices, causing labor income to decline in relative terms. Additionally, higher inflation may incentivize firms to substitute labor with capital, as an effort to maintain profit margins, further reducing labor's share of income. Notably, the consistent negative impact across both advanced and emerging economies underscores the importance of inflation-targeting policies and wage-setting mechanisms that protect workers from the redistributive effects of inflation.

Based on the estimation results presented in Table 16, both advanced and emerging economy sub-sample estimations are not statistically significant compared to full sample results. This could be attributed to several reasons. Firstly, even within the classifications of advanced and emerging economies, some countries might not belong to their respective groups due to differing economic structures. This issue arises because not all countries within these groups share the same level of development or similar economic characteristics. Take for example, following the International Monetary of Funds (IMF), China is classified under emerging economies, while Macau is considered an advanced economy despite being a Special Administrative Region of China. Such broad classifications may fail to account for substantial structural and institutional differences within these groups. Such misclassification may provide an undue impression of the influences of important variables, which may help to explain any non-significant results observed in the subsample analysis. Consequently, grouping countries in these categories for analysis may lead to over-simplification, hiding the real impact of certain key variables like tax revenue or trade openness. Secondly, while previous studies have included tax as a determinant of labor income share (Acemoglu et al., 2020; Heer et al., 2023; Kaymak and Schott, 2023; Li et al., 2021, 2024), it may not have an immediate effect. In other words, taxation might have a lagged effect on labor income share, which could possibly explain why the current model is unable to detect its significance. Hence, future research could benefit from testing alternative model specifications, that is by including lagged tax variables. Thirdly, the large informal sector in many emerging economies could also be a key factor. Many workers in these economies are employed in informal jobs, where labor policies and taxation often have limited direct impact. This structural characteristic may prevent the current model from accurately measuring the effects of taxation and labor policies on labor income share in emerging economies. Therefore, a more nuanced investigation, accounting for the informal sector and other country-specific factors, is necessary to better understand the dynamics of labor income share in these economies.

Conclusion

The findings of this study highlight the persistent nature of labor income share, reinforcing the role of historical income distribution patterns, institutional factors, and labor market rigidities in shaping current trends. The significant negative relationship between trade openness and labor income share in advanced economies suggests that increased trade exposure intensifies competition, particularly in low-skilled sectors, thereby reducing labor's share of national income. However, the lack of significance in emerging economies calls for a more granular analysis, particularly given the prevalence of informal labor markets, which may dampen the direct effects of trade and taxation policies. The positive association between globalization and labor income share in the full sample support the idea that, under certain conditions, globalization can enhance labor compensation through productivity gains and technology spillovers. From a policy perspective, strengthening institutional quality, enhancing governance, and investing in human capital development are crucial to mitigating the adverse effects of trade liberalization on labor income share. For emerging economies, addressing labor market informality and improving tax enforcement mechanisms are essential to ensuring that fiscal and trade policies effectively influence labor income distribution. Furthermore, given the potential lagged effects of taxation on labor share, future research should explore alternative model specifications to capture its long-term impact. Ultimately, policymakers should adopt a comprehensive and context-specific approach, ensuring that trade, fiscal, and labor policies are tailored to the unique economic structures of both advanced and emerging economies.

This study is not without its limitations. One key shortcoming of this paper is due to limited data availability, which restricts our analysis to a smaller sample of countries and a shorter time-period. Hence, future research is recommended to expand the data coverage. This can be done by including broader set of countries, particularly those of emerging economies. Besides that, it is also recommended to consider various sub-clusters of countries, such as low-income, middle-income, and high-income countries. By doing so, this could provide deeper insights into how labor income share responds to different economic structures and stages of development.

References

Acemoglu, D., Manera, A., & Restrepo, P. (2020). Does the US tax code favor automation? (No. w27052). National Bureau of Economic Research. https://doi.org/10.3386/w27052

Alaloul, W. S., Musarat, M. A., Liew, M. S., Qureshi, A. H., & Maqsoom, A. (2021). Investigating the impact of inflation on labour wages in Construction Industry of Malaysia. Ain Shams Engineering Journal, 12(2), 1575-1582. https://doi.org/10.1016/j.asej.2020.08.036

Alcala, F. and Sancho, F. (2000) Inflation and factor shares (No. 460). Unitat de Fonaments de l'Anàlisi Econòmica (UAB) and Institut d'Anàlisi Econòmica (CSIC).

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The review of economic studies, 58(2), 277-297. https://doi.org/10.2307/2297968

Arellano, M., & Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of econometrics, 68(1), 29-51. https://doi.org/10.1016/0304-4076(94)01642-D

Autor, D. H., Dorn, D., & Hanson, G. H. (2016). The China shock: Learning from labor-market adjustment to large changes in trade. Annual review of economics, 8(1), 205-240. https://doi.org/10.1146/annurev-economics-080315-015041

Autor, D., Dorn, D., Katz, L. F., Patterson, C., & Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. The Quarterly journal of economics, 135(2), 645-709. https://doi.org/10.1093/qje/qjaa004

Batini, N., Jackson, B., & Nickell, S. (2000). Inflation Dynamics and the Labour Share in the UK (No. 02). External MPC Unit Discussion Paper.

Binder, A. J., & Bound, J. (2019). The declining labor market prospects of less-educated men. Journal of Economic Perspectives, 33(2), 163-190. https://doi.org/10.1257/jep.33.2.163

Bises, B., Bloise, F., & Scialà, A. (2024). Labor share as an "automatic stabilizer" of income inequality. International Tax and Public Finance, 31(2), 511-532. https://doi.org/10.1007/s10797-023-09782-0

Blundell, R., & Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of econometrics, 87(1), 115-143. https://doi.org/10.1016/S0304-4076(98)00009-8

Brutger, R., & Guisinger, A. (2022). Labor market volatility, gender, and trade preferences. Journal of Experimental Political Science, 9(2), 189-202. https://doi.org/10.1017/XPS.2021.9

Burger, P. (2015). Wages, productivity and labour's declining income share in Post-Apartheid South Africa. South African Journal of Economics, 83(2), 159-173. https://doi.org/10.1111/saje.12092

Cruz, M. D. (2023). Labor productivity, real wages, and employment in OECD economies. Structural Change and Economic Dynamics, 66, 367-382. https://doi.org/10.1016/j.strueco.2023.05.007

d'Albis, H., Boubtane, E., & Coulibaly, D. (2021). Demographic changes and the labor income share. European Economic Review, 131. https://doi.org/10.1016/j.euroecorev.2020.103614

Dao, M.C., Das, M., Koczan, Z., Lian, W., Chi Dao, M., Hilgenstock, B. and Jiang, H. (2017). Why is labor receiving a smaller share of global income? theory and empirical evidence (No. 17/169). International Monetary Fund.

De Hoyos, R. E., & Sarafidis, V. (2006). Testing for cross-sectional dependence in panel-data models. The Stata journal, 6(4), 482-496. https://doi.org/10.1177/1536867X0600600403

Dilja, G. O. G. (2024). Estimating the True impact of artificial intelligence on labor productivity in a global context. International Journal of Academic Research in Economics and Management Sciences, 13(3), 713-725. https://doi.org/10.6007/IJAREMS/v13-i3/22330

Doan, H.T.T. and Wan, G. (2017). Globalization and the labor share in national income (No. 639). Asian Development Bank Institute.

Duval, R., & Loungani, P. (2021). Designing labor market institutions in emerging market and developing economies: A review of evidence and IMF policy advice. Comparative Economic Studies, 63(1), 31–83. https://doi.org/10.1057/s41294-020-00133-0

Elsby, M.W.L., Hobijin, B. and Sahin, A. (2013). The decline of the U.S. labor share. Brookings Papers on Economic Activity 2013, (2), 1-63. https://doi.org/10.1353/eca.2013.0016

Erauskin, I. (2020). The labor share and income inequality: Some empirical evidence for the period 1990-2015. Applied Economic Analysis, 28(84), 173-195. https://doi.org/10.1108/AEA-04-2020-0028

Erkişi, K., & Çetin, M. (2025). The dynamics of labor income share in an era of robotic automation: A panel data analysis in high-level automation countries. Studia Universitatis Vasile Goldiș Arad, Seria Științe Economice, 35(1), 113-139. https://doi.org/10.2478/sues-2025-0005

Fatima, S., Chen, B., Ramzan, M., & Abbas, Q. (2020). The nexus between trade openness and GDP growth: Analyzing the role of human capital accumulation. Sage Open, 10(4). https://doi.org/10.1177/2158244020967377

Ghodsi, M., Stehrer, R., & Barišić, A. (2024). Assessing the impact of new technologies on wages and labour income shares. Technological forecasting and social change, 209. https://doi.org/10.1016/j.techfore.2024.123782

González, F. A. I., & Virdis, J. M. (2021). Global development and female labour force participation: Evidence from a multidimensional perspective. Journal of Gender Studies, 31(3), 289–305. https://doi.org/10.1080/09589236.2021.1949581

González-Rozada, M., & Ruffo, H. (2024). Do trade agreements contribute to the decline in labor share? Evidence from Latin American countries. World Development, 177. https://doi.org/10.1016/j.worlddev.2024.106561

Guerriero, M. and Sen, K. (2012). What determines the share of labour in national income? a cross-country analysis (No. 6643). Institute of Labor Economics (IZA).

Guner, N., López-Segovia, J. and Ramos, R. (2020). Reforming the individual income tax in Spain. Journal of the Spanish Economic Association, 11(4), 369–406. https://doi.org/10.1007/s13209-020-00224-2

Gupta, P., & Helble, M. (2022). Adjustment to trade opening: The case of labor share in India's manufacturing industry. The Journal of International Trade & Economic Development, 31(1), 109-135. https://doi.org/10.1080/09638199.2021.1949379

Harrison, A. (2022). Has globalization eroded labor's share? Some cross-country evidence (No. 39649). University Library of Munich, Germany.

Hassan, D. B., Chia, C. J. R., Kamu, A., & Ho, C. M. (2024). Analyzing the impact of macroeconomic factors on stock market performance in Asean-5 countries. International Journal of Academic Research in Economics and Management Sciences, 13(1). https://doi.org/10.6007/ijarems/v13-i1/21040

Heer, B., Irmen, A., & Süssmuth, B. (2023). Explaining the decline in the US labor share: taxation and automation. International Tax and Public Finance, 30(6), 1481-1528. https://doi.org/10.1007/s10797-022-09755-9

Jensen, C. (2017). Aggregate evidence on price rigidities and the inflation-output trade-off: A factor analysis of factor shares. Annals of Economics and Finance, 18(2), 227-252.

Karabarbounis, L., & Neiman, B. (2014). The global decline of the labor share. The Quarterly journal of economics, 129(1), 61-103. https://doi.org/10.1093/qje/qjt032

Kaymak, B., & Schott, I. (2023). Corporate tax cuts and the decline in the manufacturing labor share. Econometrica, 91(6), 2371-2408. https://doi.org/10.3982/ECTA17702

Kim, Y. M., & Park, K. S. (2020). Labour share and economic growth in OECD countries. Global Economic Review, 49(1), 1-22. https://doi.org/10.1080/1226508X.2019.1699847

Li, B., Liu, C., & Sun, S. T. (2021). Do corporate income tax cuts decrease labor share? Regression discontinuity evidence from China. Journal of Development Economics, 150. https://doi.org/10.1016/j.jdeveco.2021.102624

Li, J., Hu, A., Chen, W., & Fang, S. (2024). Social security fee reduction, industrial robots, and labor income share. Journal of Asian Economics, 94. https://doi.org/10.1016/j.asieco.2024.101788

Lyon, S. G., & Waugh, M. E. (2018). Redistributing the gains from trade through progressive taxation. Journal of international economics, 115, 185-202. https://doi.org/10.1016/j.jinteco.2018.09.008

Mallick, J. (2020). Does global economic integration affect labour income share in India? The Indian Journal of Labour Economics, 63(2), 291-309. https://doi.org/10.1007/s41027-020-00220-x

Moreira, S. F. (2022). Inside the decline of the labor share: Technical change, market power, and structural change. Journal of Economic Dynamics and Control, 145. https://doi.org/10.1016/j.jedc.2022.104566

Omoke, P. C., & Opuala–Charles, S. (2021). Trade openness and economic growth nexus: Exploring the role of institutional quality in Nigeria. Cogent Economics & Finance, 9(1). https://doi.org/10.1080/23322039.2020.1868686

Paul, S. (2020). Understanding the global decline in the labor income share. IZA World of Labor. https://doi.org/10.15185/izawol.472

Pesaran, M. H. (2006). Estimation and inference in large heterogeneous panels with a multifactor error structure. Econometrica, 74(4), 967-1012. https://doi.org/10.1111/j.1468-0262.2006.00692.x

Pesaran, M. H. (2007). A simple panel unit root test in the presence of cross-section dependence. Journal of applied econometrics, 22(2), 265-312. https://doi.org/10.1002/jae.951

Piketty, T., & Saez, E. (2013). A theory of optimal inheritance taxation. Econometrica, 81(5), 1851-1886. https://doi.org/10.3982/ECTA10712

Rigby, D., Kemeny, T., & Cooke, A. (2015). US wage inequality and low-wage import competition. Tijdschrift voor economische en sociale geografie, 106(5), 570-587. https://doi.org/10.1111/tesg.12123

Samimi, P., & Jenatabadi, H. S. (2014). Globalization and economic growth: Empirical evidence on the role of complementarities. PLOS One, 9(4), e87824. https://doi.org/10.1371/journal.pone.0087824

Schmidt, T., & Vosen, S. (2013). Demographic change and the labour share of income. Journal of Population Economics, 26, 357-378. https://doi.org/10.1007/s00148-012-0415-y

Sergi, B. S., Balashova, S., & Ratner, S. (2023). The labour share, government expenditure and income inequality of post-Soviet countries. Economies, 11(12), 288. https://doi.org/10.3390/economies11120288

Sertyesilisik, E. (2022). Assessing and Rethinking Sustainable Development and Globalization from the Aspects of Income Distribution and Labor. In Globalization, Income Distribution and Sustainable Development (pp. 161-171). Emerald Publishing Limited.

Stockhammer, E. (2017). Determinants of the wage share: A panel analysis of advanced and developing economies. British journal of industrial relations, 55(1), 3-33. https://doi.org/10.1111/bjir.12165

Sweeney, P. (2014). An inquiry into the declining labour share of national income and the consequences for economies and societies. Journal of the Statistical and Social Inquiry Society of Ireland, 42, 109–129.

Taylor, L., & Barbosa-Filho, N. H. (2021). Inflation? It's import prices and the labor share! International Journal of Political Economy, 50(2), 116-142. https://doi.org/10.1080/08911916.2021.1920242

Trofimov, I. D., Aris, N.M. and Rosli, M.K.F. (2018). Macroeconomic determinants of the labour share of income: Evidence from OECD economies. Theoretical and Applied Economics, XXV(3), 25–48.

Wang, T., & Tian, J. (2020). Recasting the trade impact on labor share: a fixed-effect semiparametric estimation study. Empirical Economics, 58(5), 2465-2511. https://doi.org/10.1007/s00181-018-1585-6

Wu, C. (2021). More unequal income but less progressive taxation. Journal of Monetary Economics, 117, 949-968. https://doi.org/10.1016/j.jmoneco.2020.07.005

Yeerken, A., & Deng, F. (2023). Digital service trade and labor income share—Empirical research on 48 Countries. Sustainability, 15(6). https://doi.org/10.3390/su15065468

Yıldırım, D. Ç., & Akinci, H. (2021). The dynamic relationships between the female labour force and the economic growth. Journal of Economic Studies, 48(8), 1512-1527. https://doi.org/10.1108/JES-05-2020-0227

Young, A. T., & Tackett, M. Y. (2018). Globalization and the decline in labor shares: Exploring the relationship beyond trade and financial flows. European Journal of Political Economy, 52, 18-35. https://doi.org/10.1016/j.ejpoleco.2017.04.003

Yousefinejad, M., Othman, J., Kassim, A. A., Anuar, A., & Sulaiman, N. (2022). The Effects of Taxes, Inflation and Government Effectiveness on House Real Price in OECD Countries:

A panel data study. International Journal of Academic Research in Economics and Management Sciences, 11(2). https://doi.org/10.6007/ijarems/v11-i2/13031