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The Impact of Global Value Chain on Income Inequality: A PQR Analysis

Abstract. *The main objective of this study is to reveal the effects of the global value chain (GVC) on income inequality. For this purpose, data from 52 countries covering 1995-2020 have been used. Cointegration tests were applied to determine the cointegration relationship between the variables included in the analyses, and a cointegration relationship was detected among the variables. The panel quantile regression (PQR) method was preferred to estimate the long-term coefficients of variables with cointegration relationships. According to the PQR estimation results, GVC participation improves income distribution across all quantiles. Although the inequality-reducing effect of GVC participation is confirmed, it was determined that it is more potent in quantiles where the income distribution is more equal. Panel causality tests revealed a bidirectional causality relationship between GVC indicators and income inequality. The findings emphasise that countries with distorted income distribution should mainly focus on high value-added stages in integration into GVC and developing inclusive social policies.*

Keywords: *global value chain, income distribution, cointegration, panel quantile regression, causality.*

JEL Classification: C30, D33, D40, D63.

Received: 27 May 2025	**Revised: 28 February 2026**	**Accepted: 6 March 2026**

1. Introduction

Throughout history, technical and institutional advances have significantly affected how consumption and production are organised across space and time. At this point, a sharp break occurred due to the Industrial Revolution. Developments in maritime transportation during the 19^{th} century Industrial Revolution enabled the spatial separation of production from consumption. With this development, it became more economical to transport consumer goods produced in one country to other countries through transnational trade networks. However, spatial separation in production stages gained importance in the last quarter of the 20^{th} century. Particularly, transportation, communication, and organisational structure transformations enabled production to occur in a fragmented form. Parallel to these

DOI: 10.24818/18423264/60.1.26.13

developments, many countries' adoption of liberal policies, reduction of customs tariffs, limitation of barriers to international trade, and the formation of new market economies facilitated the spatial separation of production activities (Ponte et al., 2019, p. 1). As a result, companies fragmented their production activities and spread production stages on a global scale, taking into account advantages such as efficiency, cost, and specialisation. These developments have caused a significant portion of production activities to be distributed across different geographies and enabled global production organisation through 'Global Value Chains' (GVC) (Coveri et al., 2024, p. 382). The spread of GVCs has changed the geography of production and fundamentally altered the production process. With fragmentation in the production process, countries' roles and specialised functions in global production have come to the forefront rather than their products. This transformation in the production process has also profoundly affected the economic structure of nation-states. The first among these is the impact of global production networks on income distribution. GVCs combine gains, opportunities, and losses for economies. The distribution of gains along the chain is unequal between and within economies. Significant profit differences emerge between countries with a more substantial presence in global value chains and those at lower stages (Jithin et al., 2023, p. 2797). This emphasises the importance of countries improving their positions in global value chains worldwide. It is frequently emphasised in the literature that Global Value Chains (GVCs) affect not only inequalities between countries but also the internal income distribution of countries. In this context, two fundamental and opposing views stand out. The first view suggests that integration into GVCs deepens income inequality by creating winners and losers within countries, particularly increasing the gap between low-income and high-income groups. In contrast, the other view argues that participation in GVCs raises income levels across all social segments and that everyone benefits from this process (Carpa and Zarzoso, 2022, p. 270). Outside these two approaches, interpretations suggesting that internal dynamics such as a country's economic structure and labour quality can differentiate the effects of GVCs on income distribution also find a place in the literature. This framework states that demand for skilled labour will increase in developed economies positioned in the advanced stages of GVCs. At the same time, low-skilled jobs will be shifted more to developing countries. It is argued that this situation may increase income inequality in developed countries, favouring skilled labour at the expense of unskilled labour. On the other hand, the view that participation in GVCs in developing countries may increase labour productivity, leading to wage increases and thus having positive implications for income distribution, is also expressed (Carpa and Zarzoso, 2022, p. 270; Jithin, 2024, p. 2). Although the empirical literature examining the relationship between GVCs and income distribution is limited, studies on this research topic have accelerated recently with developments in GVC decomposition methods. Developed databases allow this literature to be enriched. Additionally, different models and analysis methods used also nourish the literature. When examining existing empirical research, it is observed that the effect of GVCs on income inequality varies according to the country's economic status (developed or developing country) and its structure in the value chain (forward and backward linkages upstream and downstream) (Carpa and Zarzoso, 2022, p. 282; Jithin, 2024, p. 13; Coveri et al., 2023, p. 21; Duarte et al., 2022, p. 327). This study, unlike others, aims to contribute to the existing literature by examining the heterogeneous effects of GVC participation and its components (forward and backward) on income distribution. For this purpose, the panel quantile regression (PQR) method was used in the study. The PQR method is a regression method that, unlike traditional panel regression analyses, focuses not only on the mean value of the dependent variable but also on different points (quantiles) of the distribution. With the PQR method, the impact of GVC participation on income distribution can be monitored by considering different income distribution groups. In this way, the effect of the involvement in GVCs on countries with varying distributions of income can be revealed more clearly. Therefore, this study is the first of its kind in the literature. The research utilized a data set from 53 developed and developing countries. As a result of the study, it was observed that GVC participation has a role in correcting income inequality at all income distribution levels. In addition, a bidirectional causal relationship between GVC and income distribution was detected. Considering these results, it is critically important for policymakers to develop policies that encourage participation in GVCs considering specialisation and establish strategic goals that will elevate countries' positions in the value chain to improve income distribution.

Following the article's introduction, the second section summarises the literature on the relationship between GVC participation and income distribution. The third section presents the empirical methodology, experimental strategy, dataset, and variables. The fourth section displays the results of the empirical method employed. Finally, the fifth section summarises the findings, evaluates the results, and provides policy recommendations.

2. Literature review

Research examining the relationship between global value chains (GVCs) and income inequality has gained momentum since the 2000s. In particular, the development of GVC decomposition methods and the creation of new datasets have allowed this research area to deepen. The existing literature shows that the relationship between GVCs and income inequality does not fit a single pattern. Research indicates that a country's income status, role in the chain, and position in forward or backward linkages significantly affect inequality. The literature uses widespread distribution indicators such as the Gini coefficient and labour-focused variables such as worker wages (e.g., skilled-unskilled wage premium) and labour share in national income to measure income inequality. This shows that both general distribution dynamics and the separate effects of income components in the production process are being evaluated. Carpa and Martínez-Zarzoso (2022) examined the relationship between GVC participation and income inequality. For this purpose, panel data analysis was conducted using data from 39 countries (developed and developing) for the period 1995-2016. In the study, countries' participation in GVCs and their GVC positions were calculated and reported separately, and a model was constructed with the calculated data. In the model, the Gini coefficient was used as the dependent variable. In contrast, GVC participation, GVC position, per capita income, foreign direct investment, research and development activities, and employment indicators were used as explanatory variables. The model was analysed using the GMM method. As a result of the research, it was observed that GVC participation positively affects income distribution in developing countries over the long-term process. Although some adverse effects were seen in short-term results, it was found that they were compensated for in the long term. No significant result was obtained for developed countries. Jithin et al. (2024) examined the asymmetric effect of GVC participation and its components (forward and backward participation) on income inequality. The 2004-2018 study used data from 29 OECD countries. In the study, data were analysed using the panel ARDL method. Additionally, the nonlinear ARDL method was included in the analysis. As a result of the research, it was found that participation in GVCs contributes to economic growth, job creation, and increased income levels in the long term, which has a positive effect on income inequality. In another study using data from 101 countries from 2003-2015, Coveri et al. (2024) examined the relationship between GVCs and income inequality. The research analysed the model using panel fixed effects and the two-stage GMM method. As a result of the study, it was first observed that countries' GVC positioning conditions the relationship between GVCs and income inequality. Additionally, evidence showed that foreign direct investments in more participation in knowledge-intensive GVC stages encourage technological upgrading of economies, support the creation of better-paid jobs, and reduce income inequality. Duarte et al. (2022) examined GVCs and within-country and between-country income inequalities using a multi-sector-multi-region (MRIO) and econometric approach. The research analysed data from 67 countries for the period 1995-2018. The results show different geographical patterns. The researchers found that participation in GVCs could reduce internal inequalities in Developed, African, Latin American, and Asian countries. In contrast, they observed that inequality increased in China and India. Cai et al. (2023) investigated the effect of the GVC position on income inequality theoretically and empirically. Their research first developed a theoretical model based on Daudey and Garcia-Penalosa's (2008) income inequality model to discuss how GVC position affects income inequality. Within the framework of the created theoretical model, they found that a country's GVC position would simultaneously increase the domestic labour share and the wage income difference of heterogeneous labour, thus changing the level of domestic income inequality between and within factors (labour). In the second part of the study, using data from 38 countries between 1995-2009, they examined "the channels and direction of impact of GVC position on domestic income inequality." The empirical analysis showed that the rise in GVC position would reduce local income inequality for developed or less developed countries. The channels through which the GVC position affects local income inequality are labour share and wage difference. Although a rising GVC position improves local income inequality by increasing the wage difference, it will further reduce local income inequality by increasing the labour share. The overall effect of both effects will be to reduce regional income inequality. In addition to the Gini coefficient, which is used as a standard distribution indicator in the literature, some studies have focused on labour-oriented measurements such as wages and labour share. Dao et al. (2017) examined why labour share in total income globally decreased after 1980. The research utilised different analysis methods, using samples from 49 countries for general analysis, 37 for sectoral analysis, and 37 for skill-based analysis. The study first observed that technological change and automation reduced labour demand by causing machines to replace low- and medium-skilled workers, decreasing the labour share in income. Additionally, it was found that participation in the global value chain negatively affects the share of income received by labour. The decline of unions and collective bargaining mechanisms, market concentration, and increased corporate power have increased capital gains while decreasing labour's share of income. Riccio et al. (2023) examined the impact of participation in GVCs on labour income and inter-occupational income inequality using industry-level input-output tables from the World Input-Output Database (WIOD) (Timmer et al., 2014) and Socio-Economic Accounts (SEA). The analyses showed that GVCs are hierarchically structured and that developed countries specialise in upstream functions across global production networks. They found that production workers are the biggest losers in this process, accounting for most of the decline in labour share in developed and developing countries. Reshef and Santoni (2023) focus on labour shares by considering the position of 39 developed and developing countries in the global value chain between 1995 and 2014. The first main finding of the research is the observed decline in labour shares with the deepening of forward GVC participation between 2001-2007. This indicates the use of capital-intensive intermediate inputs or primary goods in exports. After 2007, an increase in the share of skilled labour was observed, while decreases were seen in the share of general labour. Furthermore, the research attributes the decline in labour share, especially in developed countries, to China's membership in the WTO. In addition to these studies, Zhu and Trefler (2005) analyse the effects of free trade on income distribution in developing countries using a general equilibrium model. The study focuses particularly on the impact of trade on low-skilled and high-skilled workers. In a framework derived from the classical Heckscher-Ohlin model, the authors draw attention to differences in factor prices between developed and developing countries to explain technology differences and skill premiums. As a result of the study, it was observed that free trade does not automatically reduce income inequality in developing countries; on the contrary, it can increase inequality under certain conditions. Despite the extensive use of studies in the literature, no study appears to have analysed the effects of the global value chain on the income distribution using panel quantile regression.

3. Model specification

[1] Data

The study covers data from 52 countries, including 33 high-income and 19 middle-income countries. The World Bank's "country classification according to income level" system was used to classify these countries. In the classification, Australia, Austria, Belgium, Canada, the Czech Republic, Estonia, Denmark, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Latvia, Lithuania, New Zealand, the Netherlands, Norway, Portugal, Poland, Slovakia, Slovenia, Spain, South Korea, Sweden, Switzerland, the United Kingdom, the USA, and Singapore are considered high-income; In contrast, Argentina, Bangladesh, Brazil, China, Kazakhstan, Indonesia, Philippines, Peru, Vietnam, Russia, Thailand, Belarus, Bulgaria, India, Chile, Colombia, Costa Rica, Mexico, and Turkey are middle-income countries. The GINI coefficient was used to represent within-country income inequality, which is used as the dependent variable in the study. GINI coefficients range between 0 and 1 and were collected from Solt's Standardised World Income Inequality Database (SWIID) (Solt, 2020). This coefficient indicates that as it increases, income inequality rises, and conversely, as it decreases, income inequality decreases. The main Global Value Chain (GVC) indicators used in the study are GVC forward linkages (DVX), GVC backward linkages (FVA), and the GVC participation index. GVC backward linkages refer to the foreign value added embodied in a country's exports. Therefore, the higher a country's backward linkages, the more downstream it is along global production lines. On the other hand, GVC forward linkages (DVX) are a country's exports of inputs and intermediate goods used by another country for export production. It is expressed as the domestic value added present in each country's exports that is subsequently re-exported by other importing countries (Carpa et al., 2022, p. 273). The larger a country's forward linkages, the more upstream the country is located along the global production line. These indicators were first proposed by Koopman et al. (2010), and the GVC participation index was calculated using a combination of these two indicators (Koopman et al., 2010, p. 21):

$$GVC\ Participation\ Index = \frac{GVC\ forward\ (DVX) + GVC\ backward\ (FVA)}{GrossExports}$$

The data on these indicators used in calculating the GVC participation index were obtained from the TiVA (Trade in Value-Added) database. Developments in the GVC decomposition method have enabled the creation of databases related to GVC, which have enabled more detailed analysis of GVC variables. OECD TiVA is one of the leading databases created. In addition to GVC indicators, other independent variables used in the analysis are per capita income, net foreign direct investment inflow, labour force participation rate, and fixed capital investments. The data for these variables were obtained from the World Bank database. Per capita income was taken at current prices and is in dollars. Net foreign direct investment inflow was included in the analysis in dollars. The study used Labor force participation as a rate; fixed capital investments were expressed as a ratio to gross domestic product (GDP).

[2] Methodology

This study aims to analyse the effect of participation in the global value chain on the Gini coefficient. In the analysis, the GVC participation index (GVC), GDP per capita (GDPpc), net foreign direct investment inflow (FDI), ratio of fixed capital investment to GDP (GCF), and labour force participation rate (LFP) were used as independent variables. The relationship of variables is given in equation (1). The econometric representation of equation (1) is in equation (2).

$$GINI = f(GVC, GDPpc, FDI, GCF, LFP) \tag{1}$$

$$lnGINI_{i,t} = lnGVC_{i,t} + lnGDPpc_{i,t} + lnFDI_{i,t} + lnGCF_{i,t} + lnLFP_{i,t} + \varepsilon_{i,t} \tag{2}$$

Equation (2) shows the natural logarithm of GVC, GDPpc, FDI, GCF, LFP, and GINI. Therefore, the variables in the equation are lnGVC, lnGDPpc, lnFDI, lnGCF, lnLFP, and lnGINI. This study first analysed the variables' unit root tests. In panel data analysis, unit root tests of variables are divided into first and second generations. While first-generation tests do not consider cross-sectional dependence, second-generation tests consider this dependence. Therefore, it is necessary to perform a cross-sectional dependence test to determine the appropriate unit root test for the variables. The cross-sectional dependence tests the simultaneous dependency relationship between units. If cross-sectional dependence is detected, there is a correlation between units, and unit root tests that consider the presence of inter-unit correlation should be preferred. One of the most widely used methods in the literature to measure cross-sectional dependence is the method proposed by Pesaran (2004). This method includes the Pesaran scaled LM test and the Pesaran CD test. The Pesaran scaled LM test, developed based on Breusch and Pagan's (1980) LM test, aims to measure cross-sectional dependence by calculating the correlation coefficient from the error terms of the model. This test is derived from the proposal of Im et al. (2003) and is called CIPS. The CIPS method solves the cross-sectional dependence problem with an asymptotic approach. Regressions obtained by estimating the model are used as a tool in the analysis. T-statistics are obtained using cross-sectional averages calculated with the lags and first differences of variables, and the CIPS statistic is estimated. In panel data analysis, slope homogeneity is as essential as cross-sectional dependence. Determining whether the slope coefficients are homogeneous allows for a healthier analysis of the long-term relationships between variables. Ignoring slope homogeneity can weaken the reliability of estimates. Therefore, this situation must be considered in the studies performed. For this purpose, the Pesaran and Yamagata (2008) method, widely used in the literature, is frequently applied to test slope homogeneity. Pesaran and Yamagata (2008) developed an approach based on the least squares method. In this method, a weighted fixed effect pooled estimator (WFE) is used, and deviations of variables from the mean are considered. In other words, this approach presents a test procedure that includes WFE estimates, ordinary least squares (OLS) estimates, and deviations from the mean. After determining slope homogeneity in panel data analysis, long-term relationships between variables should be examined. If problems such as cross-sectional dependence or slope homogeneity are detected in the model, it becomes critical to prefer appropriate methods. The literature has proposed different tests to analyse the cointegration relationship between variables. The Westerlund (2005) test has an error correction mechanism sensitive to cross-sectional dependence. Before estimating the long-term coefficients of the variables, Westerlund (2005) is very useful for determining the cointegration relationship of the variables. Ordinary least squares (OLS), fixed effects (FE), and fully modified ordinary least squares (FMOLS) methods are used to determine long-term effects. It is a significant disadvantage that long-term coefficient estimators are not sensitive to problems such as cross-sectional dependence and slope homogeneity. Therefore, the study's panel quantile regression (PQR) method is essential. The PQR method allows for analysing the relationships between variables, not with a single coefficient, but with coefficients estimated in different distribution segments. Thus, the effects of variables on the dependent variable can be revealed more clearly under different income levels or economic conditions.

The PQR method allows for variability of the error term and is not based on a specific variance assumption. Additionally, it can capture the extremes that multiple linear regression might miss when considering extreme values. For example, income distribution analyses can more accurately determine the effects of the highest or lowest income groups. Koenker (2004) proposes a fixed effects model where unobservable heterogeneity is controlled through fixed effects. This model is represented by equation (3), and the term α_i represents unobservable heterogeneity at the individual level. The study in question aims to analyse causality and estimate the effects of independent variables on the dependent variable within the framework of specific quantiles. In this context, Koenker (2004) demonstrates that causal relationships can be examined more thoroughly using a quantile regression approach (Koenker, 2004, pp. 76-77). Koenker (2004) proposes a model where the term αi represents unobservable heterogeneity, and the role of unit effects is determinative. Within the equation (3) framework, (τ) represents the τth quantile of the dependent variable. Here, Y_{it} denotes the dependent variable, while x'_{it} shows the vector of independent variables. The parameter τ indicates which amount of the conditional distribution is being examined and has a value between 0 and 1. The constant term αi in the model represents the fixed effects of individuals and is independent of τ. In contrast, the impact of the x'_{it} vector can vary depending on τ; therefore, the effects on the conditional quantiles of the dependent variable may also differ according to the quantile (Koenker, 2004, p. 77).

$$Q_{Y_{it}}(\tau|x_{it}) = \alpha_i + x'_{it}\,\beta + u_{it} \qquad i: 1, 2....N \qquad t: 1, 2 ...... T \tag{3}$$

The method proposed by Koenker (2004) focuses on estimating the fixed effects vector α_i and aims to determine unit effects along with the coefficient vector containing the impact of independent variables. This framework estimates the α_i vector using penalised quantile regression (PQR) estimators. The penalty term based on the ℓ_1 norm in equation (4) reduces the deviation in parameter α, ensuring that fixed effects converge to standard values. Equation (5) represents the PQR model containing this penalty term. The term $(u) = u\,(\ -1\ (u<0))$ used here is based on the Koenker and Bassett (1978) approach. The weight term w_j plays a critical role in the correct estimation of individual effects and control of the sensitivity of the penalty term. This method enables more reliable estimates by reducing parameter bias in cases where the panel dimension increases (Koenker, 2004, p. 78).

$$\mathbf{P}(\boldsymbol{\alpha}) = \sum_{i=1}^{N}|\boldsymbol{\alpha}_i| \tag{4}$$

$$\min_{\alpha,\beta} \sum_{j=1}^{J}\sum_{i=1}^{N}\sum_{t=1}^{T} w_j\,\rho_{\tau_j}\,(Y_{it} - \alpha_i - x'_{it}\,\beta(\tau_j)) + \lambda\sum_{i=1}^{N}|\alpha_i| \tag{5}$$

4. Results and discussion

Table 1 presents the descriptive statistics of the variables used in the study, while Table 2 presents the cross-sectional dependence estimates of these variables. The Pesaran CD, Breusch-Pagan LM, and Pesaran scaled LM estimates of lnGVC, lnGDPpc, lnFDI, lnLFP, and lnGCF are given in detail in Table 2. The statistics of all variables are significant, as estimated by the three methods. This indicates that lnGVC, lnGDPpc, lnFDI, lnLFP, and lnGCF have cross-sectional dependence. Considering this, the CIPS method, which is a decision based on the cross-sectional dependence of variables, was chosen to estimate unit root tests in the analysis.

Table 1. Descriptive Statistics

	Mean	Median	Maximum	Minimum	Std.dev.	Observations
lnGINI	3.5051	3.4843	3.9945	3.0864	0.2139	1352
lnGVC	3.7138	3.7352	4.2046	2.9014	0.2373	1352
lnGDPpc	9.4456	9.7101	11.5478	5.6622	1.2748	1352
lnFDI	3.4037	3.3592	4.6051	0.0000	0.1859	1352
lnGCF	3.1676	3.1589	3.9836	0.1460	0.2331	1352
lnLFP	4.2650	4.2746	4.4909	3.9015	0.0985	1352

Source: Authors ‘own creation.

Table 2. Cross-Sectional Dependence Estimates

	Pesaran CD	Breusch-Pagan LM	Pesaran scaled LM
lnGINI	8.6439 (0.0000)	12711.43 (0.0000)	221.0867 (0.0000)
lnGVC	130.0714 (0.0000)	19981.49 (0.0000)	362.2596 (0.0000)
lnGDPpc	162.2311 (0.0000)	26937.79 (0.0000)	497.3397 (0.0000)
lnFDI	49.4188 (0.0000)	5422.03 (0.0000)	79.5383 (0.0000)
lnGCF	15.1328 (0.0000)	5602.43 (0.0000)	83.0415 (0.0000)
lnLFP	53.1312 (0.0000)	14778.72 (0.0000)	261.2303 (0.0000)

Note: * p<0.01. Values in parentheses are p-estimations.

Source: Authors 'own creation.

Table 3 shows the unit root test estimates for lnGVC, lnGDPpc, lnFDI, lnLFP, and lnGCF. The first column in Table 3 includes the estimates for the variables at levels without constant, with constant, and with continuous and trend.

Table 3. CIPS Estimates

	Level I(0)			First Difference I(1)		
	no constant	**constant**	**constant + trend**	**no constant**	**constant**	**constant + trend**
lnGINI	0.365	-2.071***	-2.234	-2.492*	-2.899*	-2.968*
lnGVC	-1.679**	-1.767	-2.451	-4.046*	-4.414*	-4.610*
lnGDPpc	-0.351	-2.312*	-2.286	-3.614*	-3.948*	-4.035*
lnFDI	-0.490	-1.940	-3.139*	-6.091*	-5.361*	-5.393*
lnGCF	-1.472***	-1.695	-2.265	-4.361*	-4.442*	-4.527*
lnLFP	-1.383	-1.936	-2.062	-3.824*	-4.000*	-4.332*

Note: * p<0.01, ** p<0.05, *** p<0.10

Source: Authors 'own creation.

The second column provides the first difference estimates. According to the first column of Table 3, while lnGVC is significant at the 5% level and lnGCF at the 10 percent level, other variables are insignificant. Accordingly, lnGVC is stationary at the 5% level and lnGCF at the 10& level, while other variables do not have stationarity. In the level estimates, lnGVC, lnGCF, lnLFP, and lnFDI are insignificant. Therefore, lnGVC, lnGCF, and lnLFP are not stationary. The lnGINI estimate is significant at the 10% level, and the lnGVCback estimate is at the 5% level. When examining the constant+trend estimates of variables at the level, it was determined that lnGINI, lnGVC, lnGDPpc, lnGCF, and lnLFP are not stationary. The second column of Table 3 provides the first difference estimates of the variables. Accordingly, when all variables' first differences are taken, constant and constant+trend estimates are stationary. Table 4 shows the possible slope homogeneity estimates in the panels. According to Table 4, the Δ and Δ_{adj} statistics are significant. Therefore, slope heterogeneity exists for the units that comprise the panels. For this reason, choosing a method sensitive to slope heterogeneity for cointegration estimates of variables is essential.

Table 4. Slope Homogeneity

	Δ	**Δ_{adj}**
Delta	32.296*	37.780*
p-value	0.0000	0.0000

Note: * p<0.01, ** p<0.05, *** p<0.10.

Source: Authors ‘own creation.

Table 5 shows the Westerlund cointegration estimates. According to Table 5, the Westerlund cointegration test statistic is significant. According to this result, it was determined that there was a cointegration relationship between the variables.

Table 5. Westerlund Cointegration Test

	Statistic	**p-value**
Variance ratio	2.5854*	0.0049

Note: * p<0.01.

Source: Authors ‘own creation.

Table 6 presents the OLS, FE, and FMOLS estimates. Table 6 demonstrates that in all three methods, lnGVC has a negative and significant effect on lnGINI. It is observed that increased participation in global value chains positively affects income inequality. The lnGDPpc variable also negatively and significantly affects lnGINI. The lnFDI variable exhibits a positive and significant relationship with lnGINI across all three methods. Accordingly, foreign direct investment has a deteriorating effect on income distribution. When examining the pooled OLS and FE methods, a negative and significant relationship is found between the lnGCF and lnLFP variables and lnGINI; however, according to the FMOLS method, a positive and significant relationship is observed.

Table 6. OLS, FE, and FMOLS Estimates

		Pooled	**FE**	**FMOLS**
lnGVC	Coefficient	-0.2627*	-0.3640*	-0.1807*
	Std. error.	0.0208	0.0209	0.0035
	p-value	0.0000	0.0000	0.0000
lnGDPpc	Coefficient	-0.0649*	-0.0781*	-0.0975*
	Std. error.	0.0042	0.0040	0.0006
	p-value	0.0000	0.0000	0.0000
lnFDI	Coefficient	0.1343*	0.0996*	0.3561*
	Std. error.	0.0254	0.0243	0.0039
	p-value	0.0000	0.0000	0.0000
lnGCF	Coefficient	-0.0354***	-0.0381***	0.0466*
	Std. error.	0.0206	0.0196	0.0034
	p-value	0.0859	0.0524	0.0000
lnLFP	Coefficient	-0.2833*	-0.2624*	0.8762*
	Std. error.	0.0526	0.0496	0.0048
	p-value	0.0000	0.0000	0.0000

Note: * $p<0.01$, ** $p<0.05$, *** $p<0.10$

Source: Authors ‘own creation.

In this study, the effect of GVC variables on the Gini coefficient was analysed using the PQR method. Table 7 shows the PQR estimates. Additionally, this analysis is shown in Figure 1. In Table 7, the effect of independent variables on lnGINI was analysed with nine quantiles. When examined generally, the effect of lnGVC, which represents the GVC participation index, on lnGINI is negative and significant in every quantile. This result indicates that participation in GVCs has an effect that improves income distribution in every income distribution group. Therefore, the global value chain increase contributes to a more equitable income distribution.

Table 7. PQR Estimates

Variables		.10	.20	.30	.40	.50	.60	.70	.80	.90
lnGVC	Coefficient	-0.2898*	-0.3432*	-0.3536*	-0.3186*	-0.2726*	-0.2457*	-0.2581*	-0.2522*	-0.1132**
	Std. error.	0.0268	0.0174	0.0164	0.0234	0.0295	0.0296	0.0322	0.0423	0.0487
	p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0202
lnGDPpc	Coefficient	-0.0061	-0.0319*	-0.0513*	-0.0614*	-0.0760*	-0.0880*	-0.0969*	-0.1117*	-0.1152*
	Std. error.	0.0061	0.0079	0.0061	0.0056	0.0062	0.0058	0.0070	0.0072	0.0071
	p-value	0.3222	0.0001	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
lnFDI	Coefficient	0.1407*	0.1857*	0.2368*	0.2194*	0.2077*	0.2129*	0.1486*	0.1093*	0.0975*
	Std. error.	0.0469	0.0089	0.0407	0.0412	0.0388	0.0350	0.0373	0.0366	0.0248
	p-value	0.0028	0.0017	0.0000	0.0000	0.0000	0.0000	0.0001	0.0029	0.0001
lnLFP	Coefficient	-0.3755*	-0.2367*	-0.2942*	-0.3732*	-0.3253*	-0.2559*	-0.2309*	-0.4304**	-0.6475*
	Std. error.	0.878	0.0643	0.0613	0.0486	0.0595	0.0559	0.0559	0.1741	0.1022
	p-value	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0000	0.0136	0.0000
lnGCF	Coefficient	-0.0355**	-0.0334	-0.0303	-0.0222	-0.0131	-0.0256	-0.0117	-0.0441	-0.1096*
	Std. error.	0.0164	0.0435	0.0506	0.0366	0.0245	0.0195	0.0229	0.0328	0.0297
	p-value	0.0306	0.4427	0.5493	0.5449	0.5918	0.1901	0.6072	0.1791	0.0002

Note: * p<0.01, ** p<0.05.

Source: Authors ‘own creation.

However, the impact of GVC participation on lnGINI differs between quantiles. It is observed that this effect weakens in high quantiles compared to those in low quantiles.

This shows that the improving effect of GVC participation on income distribution is more substantial in groups where income distribution is most balanced. In groups with a distorted income distribution, the income distribution-improving effect of GVC participation decreases. In other words, groups with balanced income distribution benefit more from the inequality-reducing effects obtained from GVC integration. The effect of lnGDPpc on lnGINI is negative and significant in all quantiles, except the ten percent quantile. Furthermore, this effect increases in every quantile. Again, lnLFP negatively and significantly affects lnGINI in every quantile. Accordingly, labour force participation has a strong improving effect on the income distribution. It is observed that lnFDI has a positive and significant effect on lnGINI for every quantile. The fact that foreign direct investments show a disruptive effect on income distribution in the analysis is a situation that needs to be considered. Finally, lnGCF significantly and negatively affects lnGINI in the tenth and ninetieth quantiles.

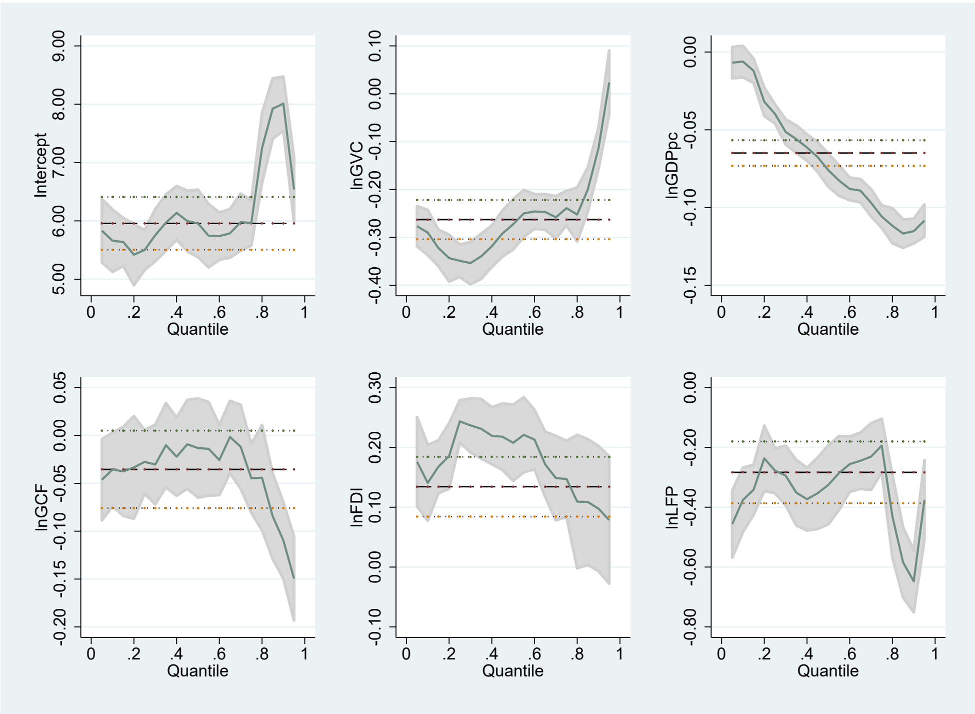

Figure 1. PQR estimation graph for Model-I. lnGVC, LnGDPpc, lnFDI, lnLFP, and lnGCF are on the Y-axis. lnGINI is given on the X-axis. PQR estimates are lines within the grey area. The confidence interval of PQR estimates is 95%. OLS estimates are dashed black lines. Confidence intervals of OLS estimates are red scattered lines. The confidence intervals of OLS estimates are 95%.

Source: Authors ‘own creation.

5. Conclusions

This study examines the heterogeneous effects of participation in the global value chain on income inequality. For this purpose, the study used data from 52 countries, including 33 high-income and 19 middle-income countries, for the period 1995-2020. The study primarily focused on long-term relationship analysis; in this context, cointegration tests were applied to determine the cointegration relationship between variables. After selecting a cointegration relationship, long-term coefficients were estimated using pooled OLS, fixed effects, and FMOLS. In addition to these methods, this study uses panel quantile regression (PQR) to estimate long-term coefficients between variables. Using the PQR method, the effects of the global value chain on income distribution at different quantiles are observed in detail.

The findings reveal that participation in the global value chain improves the income distribution in all quantiles, reducing income inequality. This situation demonstrates that with greater integration into the global value chain, all segments of society benefit from greater economic income. The observation of heterogeneous effects across quantiles indicates that the focus should be on the quantitative status of participation in global value chains and the quality of the involvement. First, participation in Global Value Chains (GVCs) facilitates countries' access to external markets, thereby expanding export volumes and stimulating aggregate production and employment. The resulting increase in labour demand broadens the income base by integrating a larger share of the workforce into productive activities, thereby reducing inequality. Moreover, GVC integration promotes productivity gains across firms. Enhanced access to a wider variety of intermediate inputs, improved technological diffusion, and more efficient production organisation collectively foster these productivity improvements.

Such gains, particularly in developing economies, contribute to a more balanced wage structure and a more equitable distribution of income. Furthermore, empirical evidence indicates that FDI is associated with increased income inequality. The returns generated through FDI flows are predominantly appropriated by multinational enterprises and domestic capital holders, with limited transmission to the labour segment of the economy. Such an asymmetric distribution of factor returns ultimately widens the divergence between capital income and labour income. In line with this study's findings, integration into the global value chain is vital in improving income distribution. It is possible to develop various policy recommendations focusing on the quantity and quality of the global value chain. First, the findings show that participation in global value chains and the quality of that participation are essential. The fact that the inequality-reducing effect of global value chains is more pronounced, especially in countries with more balanced income distribution, indicates that countries need to integrate into global value chains in high-value-added, knowledge, and technology-intensive production areas. In this regard, countries with distorted income distributions should examine participation quantitatively and aim to ensure higher-quality, sustainable integration. The findings reveal that the effect of involvement in the global value chain on reducing income inequality is more limited in countries with a distorted income distribution. This situation requires the development of inclusive policies to ensure that all segments of society share the economic gains from global value chains. In particular, social transfer programmes, skill development and education policies, and support mechanisms to increase access to the labour market should be established to enable low-income groups to benefit more from the opportunities provided by global value chains.

Additionally, the study found that backward linkages improve income distribution across all quantiles. The estimates of this study support the view that, despite the use of foreign value added, a more effective integration of local producers into global value chains reduces income inequality. Therefore, it is essential to encourage SME participation in global value chains, especially by supporting policies that enhance international cooperation, such as knowledge transfer and technology transfer. The study's finding that the effect of value chains on reducing income inequality is more pronounced in the long term suggests that sustainable development and industrial policies should support the integration process. Beyond short-term economic gains, it is essential to make global value chain integration permanent and inclusive through long-term industrial, technology, R&D, and education policies. Finally, heterogeneous effects across quantiles may indicate regional and sectoral differences within countries. Therefore, policies towards value chain integration must be designed not as one-size-fits-all but with a differentiated approach sensitive to regional and sectoral dynamics.

Acknowledgements: *This article is derived from İsmail TAMBOĞA's doctoral thesis entitled "The Impact of Global Value Chains on Income Distribution," submitted to the Social Sciences Institute of Karamanoğlu Mehmetbey University.*

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