The Impact of Global Value Chain Participation on Income Inequality

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(post-print version)
Published in *International Economics* 2022

There is a considerable amount of discussion over the effect of global value chain (GVC) participation on the increasing levels of income inequality in developed and developing countries. This paper aims to contribute to a better understanding of the interlink between income inequality and GVC participation. For this purpose, a panel data analysis is conducted with recent GVC data from the UNCTAD-Eora database. The results from panel data estimations for a sample of 39 countries over the period 1995-2016 suggest that offshoring has a significant inequality reducing effect for developing economies in the long run. Although the estimation results also indicate that some negative distributional effects of GVC related trade emerge in the short run, these seem to be mainly short run reactions of the economy, which might be offset in the long run through the adjustment of the labor market towards a new long run equilibrium.

JEL: C33, D63, F12, F14,
Key Words: Global Value Chain, Offshoring, Inequality, Gini, Correlated Random Effects, Eora

1. Introduction

World economies have become increasingly integrated and dependent on each other, with rising fragmentation of production processes on a global scale. The fall of trade barriers, opening of new markets, and information and communications technology (ICT) revolution have changed the form of trade from a simple exchange of finished goods to a constant transaction of investments, technologies, human capital, manufacturing inputs and services (Escaith, Lindenberg and Miroudot, 2010). The global production networks, in other words, global value chains (GVCs), are called the "central nervous system" and the "backbone" of the world economy, in which intermediate inputs cross borders several times before the final product reaches the customer.

The economic crisis of 2008-09 has illustrated the rising influence of GVCs on the transmission of economic shocks between countries (Cattaneo, Gereffi, and Staritz, 2010). For instance, an increase in the demand for computer and cell phone imports in the US concurrently causes an increase in the US exports of semiconductors and other components, because computer and cell phone assemblies in China and other developing countries are executed with components manufactured in the US (Cattaneo et al., 2010; Ferrantino, Michael, and Larsen, 2009).

GVCs provide new opportunities for countries to increase their participation in global trade and diversify their exports, by specializing in specific parts of the value chain (Hollweg, 2019). The existing literature finds support for a productivity increasing effect of GVC participation through learning and technology spillovers (Del Prete, Giovannetti, and Marvasi, 2017; Montalbano, Nenci, and Pietrobelli 2018; Timmer, Erumban, Los, Stehrer, and de Vries, 2014). Participating in GVCs is also found to increase income per capita growth and employment opportunities (Hollweg, 2019; Ignatenko, Raei, and Mircheva, 2019). However, at the macro level the conclusions are more attenuated as found by Lopez Villavicencio, Camarero and Tamarit (2021). The authors find that while backward participation is linked to better economic performance, forward participation could lead to declining domestic output and a rise in unemployment in some European Union countries.

However, the aggregate economic gains from GVC participation might not be distributed equally among the population (see Shepherd, 2013, for a review of the effects of GVC participation on employment). The increasing levels of inequality coinciding with growing GVC trade in developed and developing countries, has led to a debate on the distributional effects of GVC participation with two opposing views. On the one hand, it is argued that GVC participation creates winners and losers, increasing the income gap between the poor and the rich within countries (Shepherd, 2013). On the other hand, the second view claims that GVC trade leads to rising levels of income for all (IMF, 2007). Moreover, according to Grossman and Rossi-Hansberg (2008), the productivity effect of GVC participation could lead to a reduction in the wage gap, assuming that low-skilled workers are able to switch towards more productive activities. Nevertheless, the assumption of an easy mobility between the low-skilled sector to the high sector is not very realistic in OECD countries.[1]

Empirical literature finds that on average, the whole population benefits from higher integration into the world GVC trade in developing countries that are deeply engaged in GVC activities. However, in developed countries, growth in GVC participation benefits mostly the highly skilled labor and capital owners, increasing the income gap within the population further (Dollar, 2017). In developing countries, Shepherd (2013) finds that the labour market effects of GVC participation are likely to be broadly positive, but case specific.

This paper aims to contribute to a better understanding of the impact of GVC participation on income inequality. The main novelty consists in re-examining the work of (Lopez-Gonzalez, Kowalski, and Achard, 2015) using alternative data sources and extending the sample to more recent years, in order to cover the protectionist trends that emerged in the early 2010s.[2] Methodologically, we estimate a correlated random effects panel data model that allows us to disentangle short-run and long-run effects, using a sample of 39 countries over the period from 1995 to 2016.

After splitting GVC participation into its buying and selling components[3], the results suggest that a higher degree of backward participation increases the level of inequality in the short run, while it is associated with lower degrees of income inequality in the long run for developing countries. This finding indicates that one should take the long run adjustment of the economy into account, when analysing the effect of GVC participation on the within-country income distribution.

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[1] We thank an anonymous referee for pointing this out.

[2] This study uses the UNCTAD-Eora GVC dataset instead of the World Input-Output dataset (WIOD) used in the work of (Lopez-Gonzalez, Kowalski, and Achard, 2015). The Eora dataset has been selected because the updated version of the Eora includes GVC indicators until 2018 inclusive, whereas the latest data available in the WIOD dataset is up to 2014.

[3] The existing literature on GVC trade distinguishes between the buying and selling linkages of GVC participation, namely the backward and forward participation. Backward participation, measured as the foreign value added in gross exports, is also expressed as offshoring of intermediate inputs in the literature. Therefore, the definitions backward participation and offshoring are used interchangeably in this paper.

The paper is organized as follows. In the next section, we present the existing theoretical and empirical literature on the distributional effects of GVC participation on the country-level aggregate economy. Section 3 presents the empirical strategy in three subsections that describe the data, illustrate some stylized facts and outline the model specification and estimation method. Section 4 presents the main results and a number of robustness checks and Section 5 discusses the main findings, offer some policy implications and concludes.

2. Literature Review

The nature of international trade has experienced drastic changes in recent decades. With the fall in transportation costs, advancements in ICT and the emergence of trade liberalization agreements, production processes have become internationally fragmented. Unlike in the past, when trade mainly consisted of the exchange of completed goods, global trade today entails international production networks of firms, trading inputs and outputs across borders in GVCs of different degrees of complexity (UNCTAD, 2013).[4] GVC activities can be performed within the same firm or spread among several firms.

Both the classical and neoclassical trade theories were based on the notion of comparative advantage to explain the gains of trade due to specialization according to technological differences (Ricardian theories) or relative factor endowments (Hekscher-Ohlin-Samuelson (HOS)). After the 1980s, with the emergence of the "New Trade Theory" pioneered by (Helpman and Krugman, 1985), the focus on trade in final goods started to shift to trade in intermediate goods. This theory additionally acknowledged increasing returns to scale and love of variety. Thus, it provided an explanation of the existence of intra-industry trade between countries with similar technology and resource endowments.

In contrast to conventional trade models in which a complete production process takes place in one location, in GVCs, each production stage materializes in the location which has a comparative advantage for producing one particular stage. GVC activities are created by value added production across borders (Dollar, 2017). The complexity of a GVC depends on how many times intermediate inputs travel across borders during the production process until the final good is produced. With the growth of GVCs and increased international fragmentation of production, it became more difficult to trace back where the value of a final product has been added.

Nowadays, traditional trade statistics based on gross exports are argued to give a misleading picture of trade integration, and the role of countries in international trade (Johnson, 2014; Aslam, Novta, and Rodrigues-Bastos, 2017).[5] Gross trade measures are subject to the double counting of

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[4] (Cattaneo, Gereffi, and Staritz, 2010) describes GVCs as "The full range of activities that are required to bring a good or service from conception, through the different phases of production- provision of raw materials; the input of various components, sub-assemblies, and producer services, the assembly of finished goods- to delivery to final consumers, as well as disposal after use." (Cattaneo, Gereffi, and Staritz, 2010). International trade literature uses various definitions for GVCs, including the terms "production fragmentation", "vertical specialisation" (Hummels, Ishii, and Yi 2001), "offshoring"(Shelbourne, 2004), "trade in tasks"(Grossman and Rossi-Hansberg, 2008) and "global production sharing"(Feenstra and Hanson, 2001).

[5] For instance, according to the conventional trade statistics based on gross values, Korea might seem to export a lot to China. However, the majority of this trade is of components, which are ultimately destined for Europe and the US (Dollar, 2017). Similarly, attributing German intermediate inputs used in Polish exports, to Poland, would overstate Poland's economic contribution to gross trade flows (Kaplan, Kohl, and Martínez-Zarsoso, 2017).

the value of intermediate goods, which cross international borders more than once, and overestimate bilateral trade imbalances (Koopman, Wang, and Wei, 2014). [6]

With the rise in the fragmentation of international production and complexity of GVCs, value-added trade measures gained more importance over gross exports. As a consequence, value added databases have been recently built and made available, which led to the emergence of empirical literature on trade in value added. The use of input-output tables enabled recording the value added generation process for every product, in every country, at each production stage, and made it possible to identify the vertical structure of international production sharing (Inomata 2017). [7]

As one of the pioneers of empirical research on vertical specialization, (Hummels, Ishii, and Yi, 2001) use the OECD input-output database, which provides data on imported inputs, gross output and exports at the industry-level. With these data, they calculate the imported intermediate input content of exports, referred to as vertical specialization (VS), and propose a measure for the share of exports that are used by another country in the production of its own exports to a third country (VS1). They find that vertical specialization accounted for 21 percent of the world exports, and grew by almost 30 percent between 1970 and 1990 (Hummels, Ishii, and Yi 2001).

By combining input-output and bilateral trade data for many countries, (Johnson and Noguera, 2012) calculate the bilateral ratio of domestic value added to exports. Their measure of value added in exports (VAX) accounts additionally for the domestic content in intermediate exports that finally return home (Aslam, Novta, and Rodrigues-Bastos 2017). [8] They find that the world VAX ratio has fallen from around 85 percent, to around 70-75 percent, between the years 1970 and 2009. [9] Meanwhile, (Timmer, Los, Stehrer, and Vries, 2012) report that the share of foreign value added has increased 85 percent between 1995 and 2008, which underscores the growth of international fragmentation of production.

Ignatenko, Raei, and Mircheva (2019) report that the share of exports involved in GVC trade rose from 60 to 70 percent in Europe between the years 2000 and 2013. Similarly, Lopez-Gonzalez et al. (2015) find that GVC participation rose for most of the countries during the period between 1995 and 2009. Dollar (2017) reports that all trade types, including traditional trade, complex and simple GVCs have increased their shares of GDP since 1995. Although this trend was disrupted in 2008-2009, it picked up again in 2010 (Timmer et al., 2012) and the growth of GVCs stagnated since 2015, after returning to its pre-crisis levels.

Beneficial aggregate economic outcomes of GVC participation entail, amongst others, productivity growth, more sophisticated export bundles and higher trade diversification (Del Prete

[6] China- US trade imbalance becomes around 40% smaller, when measured in value added terms (Kummritz 2015). According to the World Trade Organization, in 2010, 28 percent of gross trade was double counted, which amounts to 5 trillion US dollars of 19 trillion US dollar trade in that year (UNCTAD 2013).

[7] A multi-country input-output table provides a map of the international transaction of goods and services in a dataset, which combines the national input-output tables of various countries at a given point in time. The major datasets, which break down trade according to the origin of its value added are, World Input-Output Database (WIOD), OECD Input-Output Tables, OECD's Trade in Value Added Database (TiVA) and UNCTAD-Eora GVC database (Casella et al. 2019)

[8] VAX is a quasi-inverse of the VS measure (Kummritz 2015). So, a falling VAX indicates growing vertical specialization, as countries import intermediate goods, instead of adding that value domestically.

[9] Most of this decrease in domestic value added occured after 1990, and coincided with a period of trade liberalizations of emerging economies, the growth of the European Union, new trade agreements and the ICT revolution.

et al., 2017; Montalbano et al., 2018; Timmer et al., 2014; Lopez-Gonzalez et al. 2015; among others). Participation in GVCs allows countries to benefit from learning effects and technology spillovers (Beaton, Cebotari, and Komaromi, 2017). Kummritz (2015) reports that GVC participation, including both backward (buying) and forward (selling) linkages, increases domestic value added, if certain conditions are met. According to his study, GVC participation enhances productivity through cost savings in middle- and high-income countries. However, he finds little support for the technology upgrading and spillover effects of GVCs, regarding low-and middle-income countries. This indicates that a sufficient level of absorptive capacity is necessary for an economy to benefit from the knowledge and technology spillovers generated through GVC participation.

UNCTAD (2013) finds a positive correlation between GVC participation and GDP per capita growth. In the last 20 years, countries, which had the highest GVC participation growth experienced 2 percentage points higher GDP per capita growth than the average. Moreover, the report indicates that countries, which had growth in both GVC participation and domestic value added in exports, experienced GDP per capita growth of 3.4% on average. Countries, which had only an increase in GVC participation had a GDP per capita growth of only 2.2%. This result indicates that upgrading along the value chain, which means producing higher value goods, increases the benefits gained through GVC participation. [10] Creating the industrial capacity to produce higher value goods is essential from a policy standpoint to increase the benefits associated with GVC participation, including GDP, labor productivity and employment growth (UNCTAD 2013). Ignatenko, Raei, and Mircheva (2019) empirically show that participation in GVC trade is positively associated with productivity and income per capita growth for upper-middle and high-income countries, while the positive effects are not significant for low-income countries. (Inomata 2017) describes the gains from GVC participation by taking a development perspective. Firms in developing countries that are integrated in GVCs can specialize in a specific production task for which they have a comparative advantage, without having to build an entire production chain on their own. This allows them to become a part of the global economy much faster than it would have been possible without GVCs.

Even though in general the literature indicates that GVC participation is associated with income and productivity growth, the distributional effects of GVC integration are heterogeneous and complex (Kaplinsky 2000). The growing integration of the global economy coincided with increasing inequality within countries (Kaplinsky, 2000). With the opening up of emerging markets, such as China and India, the global supply of low skilled workers has increased, pulling down the relative wages of the less skilled labor in developed countries (Timmer et al., 2014). As a result, protectionist views started to rise in advanced economies (Beaton, Cebotari, and Komaromi, 2017).

Most of the existing literature on income inequality and trade focus on wage differences across workers with different skill levels. The wage gap between skilled and low skilled labor has been increasing in most of the developed and developing countries, since the 1980s (Pavcnik, 2011). For instance, relative wages of the low skilled labor declined in the UK, US and Australia. In most of the European countries, labor market policies and regulations managed to keep the wages more or less stable. However, increased unemployment, especially for the unskilled, has been a

[10] Higher value goods involve for instance, intangible production activities, such as R&D, design, marketing and after-sales services. Low value production activities are typically manufacturing and assembly activities (Inomata 2017).

contributing factor to the rising inequality levels (Beaton, Cebotari, and Komaromi ,2017; OECD, 2015).

Dollar (2017) shows that the benefits from GVC trade have been distributed unequally among participants. For instance, in the US, high skilled labor and multinational corporations collected most of the productivity gains through GVC participation, while in China, average workers benefited the most. Especially, concerning the ICT sector in the US, more jobs became available for high skilled workers with rising compensations, while almost no change in earnings was observed for the low skilled workers over the last 15 years (Dollar, 2017). These findings are in line with the empirical results of (Feenstra and Hanson, 2001), who find that trade in inputs has the effect of a skill-biased technical change on labor demand in US industries. They find that outsourcing accounted for 15-24 percent of the wage increase of non-production workers.

By using the WIOD, Lopez-Gonzalez et al. (2015) test the theoretical predictions of Grossman and Rossi-Hansberg (2008) regarding the effects of offshoring on productivity and factor incomes, in a trade in tasks model. Grossman and Rossi-Hansberg (2008) propose that the net effect of offshoring is the sum of three effects, a labor-supply effect, a relative price effect and a productivity effect.[11] The overall effect of offshoring on inequality depends on whether the labor-supply or productivity effect is higher.

The empirical results of Lopez-Gonzalez et al. (2015) indicate that the productivity effect dominates. By decomposing backward participation into high and low skilled tasks, they find that offshoring low skilled tasks is associated with lower levels of wage inequality, while offshoring high skilled tasks is associated with a higher level of wage inequality, for both developed and developing countries. The effect of offshoring low skilled tasks is higher. This is not surprising, since most of the tasks that are being offshored are low skilled, so that the overall effect of offshoring is wage inequality reducing. The same results hold when they use the Gini coefficient as the dependent variable.

Farole, Hollweg, and Winkler (2018) empirically investigate the changes in relative demand for skilled labor induced by GVC participation. Their data covers mainly developing countries. They measure relative demand for skilled labour as wages paid to the skilled labor relative to the unskilled, for producing exports. The wages include both direct wages paid to workers in the exporting sector and indirect wages paid to workers, who supply domestic inputs to exporters. According to their results, backward GVC participation is associated with greater returns to high skilled labor in upstream supplying sectors. By interacting dummy variables for income levels with GVC participation, they find a strong positive correlation between backward participation and relative demand for high skilled labor in low-income countries. This finding is in contrast with the predictions of the HOS model, as one would expect an increase in the relative demand for the unskilled labor in low-income economies, due to their specialization in low skilled tasks.

[11] The labor supply effect occurs for instance, when shifting low skilled tasks to developing countries increases the excess supply of domestic low skilled labor in developed countries. This pulls down the wages of the low skilled, and increases inequality within the offshoring country. At the same time, a productivity effect occurs through the cost savings generated from the already offshored tasks. When offshoring becomes cheaper, offshoring firms' profits and productivity increase. Hence, workers are freed from low skill tasks towards more productive ones. As the low skilled workers switch to higher skill tasks, the wage gap shrinks. The productivity effect will be large, if the extent of offshoring is also large (Lopez-Gonzalez et al. 2015).

In contrast, when examining a broader sample of countries, Timmer et al. (2014) find that the value added share of high skilled workers increased by 5 percentage points, while the share of low skilled workers in value added dropped by 8 percentage points in advanced economies, in line with the predictions of the HOS model. However, concerning developing countries, the predictions of the HOS do not hold. They find that the share of low skilled workers in value added declined by 6 percentage points, while that of capital increased by 3 percentage points in developing economies between 1995 and 2008.

Summarizing, empirical results from the literature do not always confirm the predictions of the HOS model, especially when it comes to developing countries. As mentioned before, there are complex patterns at work, which influence the effect of GVC trade on labor markets and income distribution, within and across countries.

3. Empirical Application: The Effect of GVC on Income Inequality

In this section we present the empirical analysis that allows us to control for confounding observed and unobserved factors to be able to infer causality. We first describe the data and variables in 3.1 and some stylized facts in 3.2. The model specification is outlined in subsection 3.3, which also discuss the main estimation method.

3.1 Data and Variable Description

The empirical analysis is conducted by using a panel dataset, covering 39 countries (see country list in Table A1 in the Appendix) and 23 years, between 1995 and 2016[12]. Country level data for the variables in the model is collected from four databases: the UNCTAD-Eora GVC database for the GVC indicators, the Standardised World Income Inequality Database (SWIID) and the WIID database, provided by UNU-WIDER, for the Gini coefficient, and the World Development Indicators (WDI) for the control variables. The 39 countries, which are mostly OECD members, are chosen according to data availability for all the variables, and for the selected time period.

The main interest is the GVC participation and its effect on income inequality measured using the Gini coefficient. The GVC participation index indicates the extent to which a country is involved in a vertically fragmented production process (Aslam, Novta, and Rodrigues-Bastos, 2017). It reflects the degree of an economy's involvement in GVCs for its foreign trade. A country's GVC participation is measured as a share of its gross exports (UNCTAD, 2013). The GVC participation of each country, for each year, is calculated with the data extracted from the UNCTAD-Eora GVC database. This dataset provides a reporting of the main GVC indicators, including value added exports (VA), foreign value added (FVA), domestic value added (DVA) and domestic value added in exports (DVX) for 189 countries, covering the years from 1990 to 2018.[13]

The GVC participation index comprises two key variables: DVX and FVA. At the country level, the FVA, also referred to as a measure of backward participation, corresponds to the value added

[12] Although in preliminary estimations the sample used was 1995-2018, the final estimations exclude the last two years of the sample, following the recommendation of two anonymous referees. The reason is that the last two datapoints were inputted (see next footnote).

[13] The estimates for the years from 2016 to 2018 are computed with an imputation procedure, which is based on the macroeconomic estimates of the IMF World Economic Outlook (WEO) (Casella et al. 2019).

of imported intermediate inputs that are used to produce output for exports (Aslam, Novta, and Rodrigues-Bastos, 2017). The DVX is a measure of forward participation, which calculates the exports of intermediate goods that are used as inputs for the production of exports in another country, to be exported to a third country. The formula used for calculating GVC participation, which is taken from (Aslam, Novta, and Rodrigues-Bastos 2017) is the following,

$$GVCParticipation = \left(\frac{FVA+DVX}{GrossExports}\right) * 100 \qquad (1)$$

Gross exports are equal to the sum of FVA and DVA (UNCTAD, 2013). Koopman, Wang, and Wei (2014) and (Aslam, Novta, and Rodrigues-Bastos 2017) consider value added exports (VA) a better measure of domestic value added than DVA, since DVA also includes domestically produced content in intermediate exports that finally returns home, and is a part of the double counting in official trade statistics (Koopman, Wang, and Wei 2014). Based on their inference, we calculate gross exports as the sum of FVA and DVA. The same methodology has been used to calculate gross exports by Ignatenko, Raei, and Mircheva (2019), who find a positive effect of GVC participation on income per capita and productivity. We therefore follow the detailed decomposition of gross exports presented in Aslam et al. (2017), according to which gross exports are decomposed into nine elements. But, in order to avoid double counting, only the first three components of DVA are taken into account for the calculation of exports, that is, disregarding domestic content on intermediate exports that finally return home.

Another important variable that is considered to have an effect on the Gini coefficient is the GVC position index, which characterizes the relative "upstreamness" of a country, in a global value chain (Koopman, Wang, and Wei, 2014). Upstream activities are high value adding pre-production activities, such as R&D, branding and design, which are capital intensive and require high skilled labor. High value added downstream activities are associated with post-production services, such as sales and marketing.

It is possible that two countries have the same GVC position index but different degrees of GVC participation. The GVC position of a country is calculated according to the following formula, extracted from Koopman, Wang, and Wei (2014).

$$GVCPosition = \left[\left(ln\frac{1+DVX}{GrossExports}\right) - \left(ln\frac{1+FVA}{GrossExports}\right)\right] * 100 \qquad (2)$$

For the empirical analysis, we use Gini coefficients for both market (gross) and disposable (net) household incomes, to check the robustness of results. While Gini disposable is influenced by government fiscal policies, taxes and benefits, Gini market gives a better view of the earnings and capital inequality. It is argued that inequality of disposable income matters more for welfare analysis, as it takes the effect of redistributive policies into account. Net income inequality is normally lower than that of gross income, as the tax system is usually progressive (Constanza, 2015).

Using income instead of wage inequality allows to capture the income effects of GVC participation on the unemployed and informal labor forces as well. The disadvantage of not using wage inequality is the lack of comparability with the existing literature, since most of the trade literature focus on the effect of trade on wage inequality.

The data for the Gini indices for each year and each country is taken from the SWIID, which is a recent database produced by Solt (2019). The SWIID provides highly comparable standardized Gini indices for disposable and market income inequality, covering 196 countries and the years 1960 to 2018 (Solt, 2019). It is mainly derived from the World Income Inequality Database (WIID), completed with data from other sources. The SWIID uses a multiple imputation model to compute missing observations, which is criticized by some authors such as Jenkins (2015), who prefers WIID over SWIID. The reliability of the SWIID Gini data depends on the validity of the imputation model, and since there is a high number of missing observations, this might lower the precision of estimates (Jenkins 2015). In order to check the robustness of the estimations, we also use the Gini data from the WIID database, provided by UNU-WIDER.

In the following, control variables which are considered to be important determinants of income inequality are described. Piketty (2014) characterizes skill biased technical change and education as the two main determinants of income inequality in the long run. While an increase in the overall education level raises the supply of skilled labor in an economy, technological advancements increase its demand (Piketty 2014). We use the ratio of school enrollment in tertiary education over gross enrollment as a proxy for education.

According to the (OECD, 2011) inequality report, technological progress in both manufacturing and service industries has benefited high skilled labor, increasing the earnings gap between low and high skilled workers further. IMF (2007) reports that new technologies automate low skill jobs and increase the skill premium, both in developed and developing economies. For instance, technological progress measured by the share of ICT to capital is found to be one of the main drivers of the rising inequality. The literature suggests that technological innovations occur mainly through R&D investments. Following Lopez-Gonzalez et al. (2015), technology is proxied by the log of R&D expenditure as a share of GDP. The usage of R&D as an indicator of technological change is supported by Di Pietro (2002), given that it is measured consistently across countries and over the years.

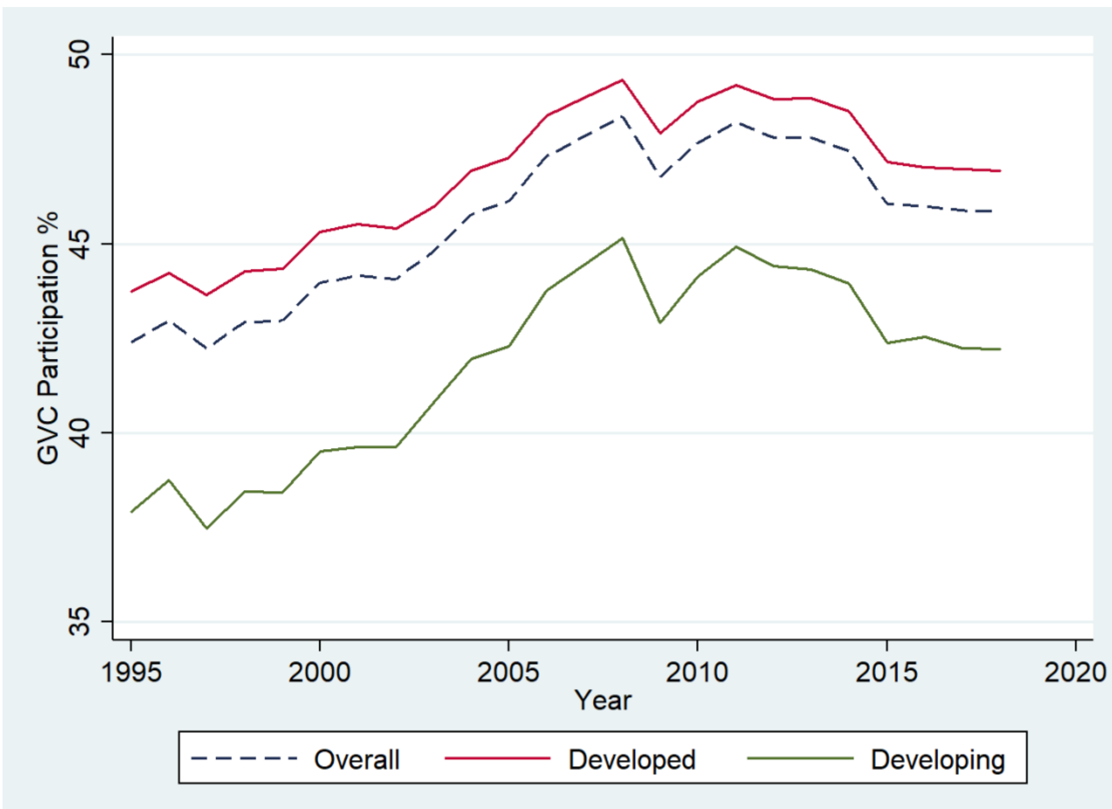
To account for the effect of economic development and the Kuznets effect, log of GDP per capita at constant PPP 2011 prices and its squared, are included as explanatory variables in the regression. Another important explanatory variable is the net inflows of foreign direct investments (FDI). Kinoshita (2000) describes FDI inflows as a source of advanced knowledge from foreign firms. Previous literature suggests that inward FDI may contribute to higher earnings inequality, particularly in developing countries, by raising the relative earnings of the skilled workers. On the other hand, rising inflows of FDI in developing countries is a source of know-how diffusion (OECD, 2008). By conducting a panel data analysis, Figini and Görg (2006) find that the effect of FDI on wage inequality is different for developed and developing economies. For instance, in developing countries, wage inequality increases with inward stocks of FDI. However, this effect disappears with further FDIs, indicating a non-linear effect. For developed countries, they find a negative relationship between higher FDI inward stock and wage inequality. For this reason, we will also distinguish in our estimations between developed and developing countries in the sample. The natural log of net inflows of FDI as a share of GDP is added to the model to control for the potential effect of FDI on inequality.

We also control for the potential effects of unemployment and female labor force participation. Lopez-Gonzalez, Kowalski, and Achard (2015) surprisingly find a negative relationship between unemployment and inequality, which indicates that higher levels of unemployment are associated with lower levels of inequality. However, given that their first measure of inequality is based on wages, unemployment in their model might be absorbing workers that have very low-skills, and would increase inequality if they were employed. We add unemployment as the share of total labor force into the model, and expect it to have a positive effect on income inequality. Lastly, we expect higher female labor force participation in an economy to have a negative effect on the level of inequality, as higher female employment would increase household incomes. A list of variables, definitions and summary statistics can be found in Table A2 in the Appendix.

3.2 Stylized Facts

Figure 1 illustrates the evolution over time of GVC participation as a share of exports for a sample of 39 developed and developing countries between the years 1995 and 2018.

Figure 1. Evolution over Time of GVC Participation in Developed and Developing Countries



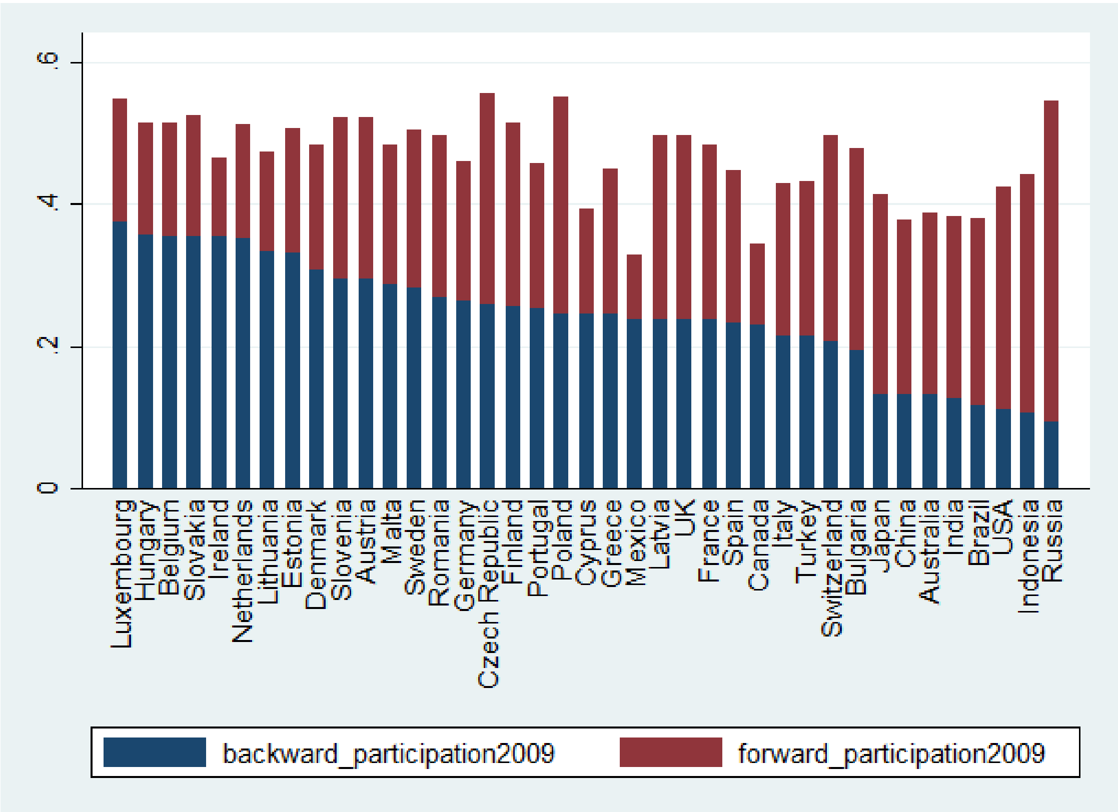
Source: Authors' elaboration using UNCTAD-Eora data.

The average GVC participation rate has increased from 42 percent to around 48 percent of exports from 1995 until 2008 for all the countries. There was a short decline in 1997, possibly related to the Asian financial crisis, but it recovered afterwards. The sharp increase after 2001 coincides with China's WTO accession, and suggests that the growing GVC participation in this period is attributed to China's rising integration into the world trade in intermediate goods.

The next drop in GVC trade came in the year 2009, again for both developed and developing economies. This global drop in GVC trade, following the 2008-09 economic crisis reflects the extent of the interdependence and integration of world economies. Domestic and regional shocks are transmitted globally, since production processes of many industries are scattered around the world. The effect of adverse shocks on firms do not occur only through their sales of final goods, given that disruptions in the buying and selling linkages of GVCs can cause fluctuations in the supply and demand of intermediate inputs (Cattaneo, Gereffi, and Staritz 2010).

It took around two years for the GVC trade to return to its pre-crisis levels, until 2011. Since then, GVC trade has been declining to its 2005 levels and stagnating. This decline and lack of further growth since 2015 may also reflect the effect of protectionist interventions of governments, such as raising barriers on intermediate goods trade, in order to protect their domestic industries.

Figure 2. GVC Participation by Country in 2009

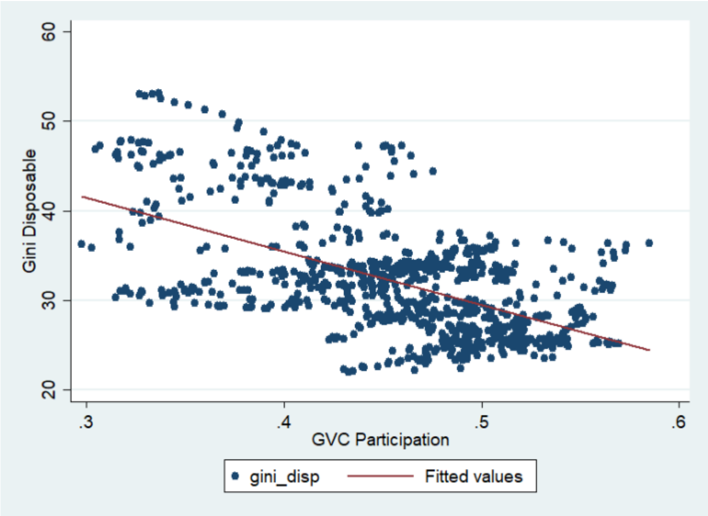


Source: Authors' elaboration using Eora GVC data.

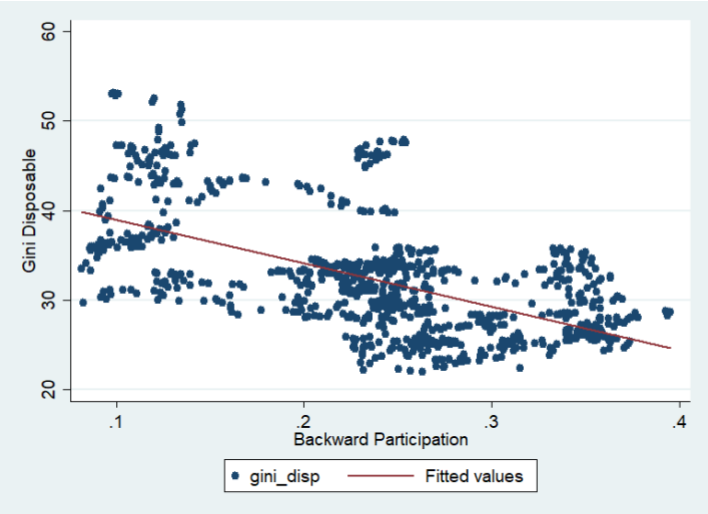
Figure 2 displays GVC participation of countries in year 2009 in percentages, decomposed into backward and forward participation linkages. It can be observed that, while large countries such as Russia, USA and Brazil are more engaged on the selling side of the value chain (forward linkages), small countries such as Luxembourg, Belgium and Ireland show a higher engagement in the buying side, that is, backward participation shares in GVCs are higher. This could be explained by the fact that small countries have relative scarcity in resources. Large countries in contrast are usually relatively well endowed with raw materials, capital and human capital. As a result, small countries depend on the supply of factors from larger countries for their production of goods, which they sell or consume later.

Being rich in natural resources is also associated with a higher share of forward participation. For instance, as one of the main oil exporters in the world, Russia has the highest forward participation rate in the sample. The simple correlations, shown in Figure 3 indicate that overall, a higher involvement in GVC trade is negatively correlated with the Gini coefficient.

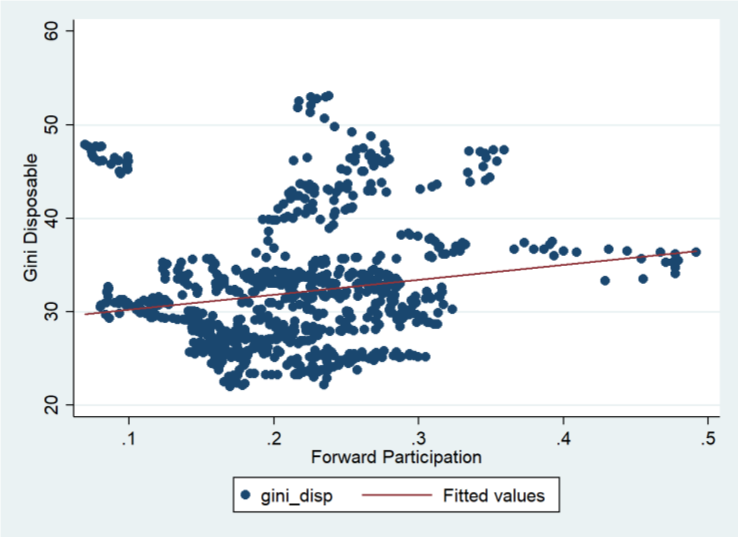
Figure 3. Scatter Plots: Income Inequality and GVC Participation Variables



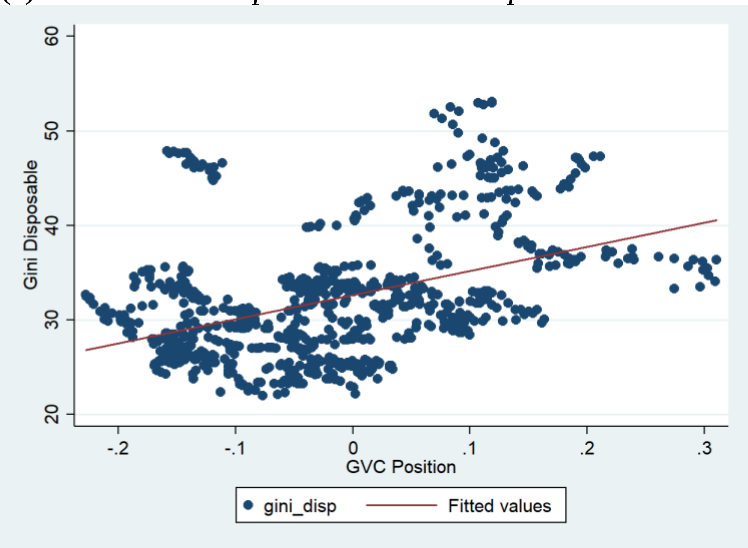
(a)GVC Participation and Gini Disposable



(b)Backward Participation and Gini Disposable



(c) *Forward Participation and Gini Disposable*



(d) GVC Position and Gini Disposable

Source: Authors' elaboration using Eora GVC data.

While countries with high backward participation rates tend to have lower levels of income inequality, higher forward participation is associated with higher levels of inequality. The correlation in Figure 3a suggests that the effect of backward participation dominates the effect of forward participation. This indicates that most of the GVC trade in our sample occurs through the buying side. This is not surprising, since the sample of this paper covers mainly developed and new industrialized countries, which mostly have higher backward participation shares.

Figure 3d illustrates that being more upstream in the value chain is positively correlated with inequality, reflecting the higher relative demand for skilled labor in upstream production activities, such as research and development (R&D) and design. However, simple correlation results do not mean causality. There might be other confounding factors, which influence both income inequality and GVC participation, and they should be taken into account.

Table A3 in the Appendix shows the growth rate of GVC participation for each country in the sample, between the years 1995 and 2018. The country, which experienced the highest participation growth with a growth rate of 30 percent is unsurprisingly China. China is followed by Indonesia, with 20 percent of GVC participation growth.

While the USA has the third place with a GVC participation growth of almost 16 percent, Russia is the fourth with 13 percent. The results confirm the increasing role of China in simple GVCs, concerning both supply and demand linkages, especially after its WTO accession in 2001, while USA continues to be one of the most important countries in complex GVCs (Dollar, 2017). A closer look at the within-country variation in GVC participation indicates that, for most countries, participation increased steadily until 2008 and stagnated thereafter. Figure A1 shows the trend for each country in the sample.

Figure A2 displays the trend of Gini disposable between the years 1995 and 2018. The average Gini disposable had a modest upward trend for all countries from 1995 until 2012, rising slightly from around 31-32 percent. After 2015, a sharp increase of Gini around 5 percent is visible for most countries.

Figure A3 plots the distribution of the average country Gini coefficients for the period between 1995 and 2018 by using Box-Plots. The line across the box, which is the median country Gini, shows that Denmark and Sweden are among the most equal countries in terms of income distribution. Brazil has the highest median and maximum Gini disposable reported, followed by India, Indonesia and China. This indicates that growth in GVC participation does not automatically translate into distributional benefits, and the aggregate gains from trade in intermediate goods are distributed unequally.

3.3. Methodology and Empirical Model

The empirical analysis is conducted by using an unbalanced panel dataset with a maximum of 897=39*21 observations. The key variable of interest is the GVC participation rate, which is then decomposed into backward and forward participation. Control variables for the position in the value chain, the level of economic development, foreign investment flows, technology and unemployment, as well as proxies for education level and female labor market participation are included in the model. The baseline specification for the estimations is given by,

$$Gini_{it}=\beta_1\, GVCParticipation_{it}+ \beta_2\, GVCPosition_{it}+ \beta_3\, logGDPpc_{it}+ \beta_4\, (logGDPpc)^2_{it}+ \beta_5\, logFDInetInflows_{it}+ \beta_6\, logR\&D_{it}+ \beta_7\, Enrollment_{it}+ \beta_8\, Unemployment_{it}+ \beta_9\, FemaleLabor_{it}+\theta_t +\alpha_i +\epsilon_{it} \quad (3)$$

where the outcome variable, the Gini coefficient and the independent variables are observed for each country *i* and year *t*. θ_t represents time fixed effects, whereas α_i denotes country unobserved heterogeneity that can be treated as fixed or as random, in this latter case being the time-invariant component of the error term. ϵ_{it} is the idiosyncratic error term. The model includes year fixed effects, θ_t , in order to control for the influence of time-variant factors that affect all countries. Panel regressions, which do not control for these factors, might be picking up the influence of common time trends that have nothing to do with causal relationships. For instance, a concurrent increase of income inequality and a decrease of GVC participation over a certain time period do not have to be causally related to each other. They might be driven by global economic shocks, such as the 2008-09 economic crisis or other business cycle fluctuations. According to the result of the joint test for time fixed effects, the null hypothesis that the coefficients for all years are jointly equal to zero is rejected. Therefore, this justifies the inclusion of time fixed effects in the model.

A second specification uses the above-mentioned decomposition into backward and forward participation and given that the former is highly correlated with GVC position, this control variable is no longer included in the model. The model is thus given by,

$$Gini_{it}=\beta_1\ GVC\_Backward_{it}+\beta_2\ GVC\_Forward_{it}+\beta_3\ logGDPpc_{it}+\beta_4\ (logGDPpc)^2_{it}+\beta_5\ logFDInetInflows_{it}+\beta_6\ logR\&D_{it}+\beta_7\ Enrollment_{it}+\beta_8\ Unemployment_{it}+\beta_9\ FemaleLabor_{it}+\theta_t+\alpha_i+\epsilon_{it} \quad (4)$$

A method based on (Mundlak 1978), named correlated random effects (CRE) by Wooldridge (2010), which includes within and between effects in a single empirical model, is used for the main estimations. The model is estimated using robust standard errors, to correct for heterokedasticity. The reasons for this choice, explained in detail below, are mostly related to the fact that most of the variation in our data come from cross-country differences in inequality, rather than from within-country variations and we are willing to retain both (Andress, Golsch, and Schmidt, 2013). Moreover, countries in a panel dataset systematically differ from each other in unobserved ways, which might affect the estimation outcome (Mummolo and Peterson, 2018).

Lopez-Gonzalez et al. (2015) also argue that OLS estimates, in which cross-sectional variation dominates, are more likely to capture long run equilibrium effects, while the within estimates are more likely to represent short run adjustments. Due to the fact that the cross-sectional variation in our data set is higher than the across-time variation, the OLS estimates possibly represent the results of the between estimator. However, if the signs of the coefficients differ substantially for the between and within estimates, the OLS estimates might be reflecting only one side of the story.

The usual approach to control for unobserved heterogeneity in a panel data framework is the use of a fixed effects model that retains only the within-country variation of the variables and eliminates the between-country variation (Wooldrige 2010). Given the fact that including country fixed effects in a panel data model, time-invariant heterogeneity is eliminated, there is no need to include in the model country characteristics that do not vary over time, such as the geographical location, the institutional quality etc., in order to reduce the amount of possible omitted-variable bias in the estimations. For instance, according to (Dollar and Kidder, 2017), all else equal, countries with stronger property rights and rule of law tend to participate more in GVCs, given that complex value chains involve contract enforcement between many firms, in which each firm faces a risk of contract failure. At the same time, countries with better rule of law tend to have more equal income distributions, given that they have more effective tax collection and redistribution policies. Not including country fixed effects would lead to an overestimation of the effect of GVC participation on inequality in this case.

It is standard to use the Hausman test to decide whether the time-invariant unobserved heterogeneity should be treated as fixed or random. The null hypothesis estates that the country-level unobserved heterogeneity, α_i, is uncorrelated with the regressors, whereas the alternative indicates that the country time-invariant heterogeneity is correlated with the explanatory variables. In the latter case, a fixed effects estimator is preferred over a random effects one. However, this test is subject to strong underlying assumptions, such as independent and identically distributed (i.i.d.) errors, which is violated in our model.

The modern econometric literature argues that the traditional Hausman test is not always a sufficient statistic to choose between random and fixed effects estimators, given that i.i.d. errors are the exception rather than the norm (Wooldridge 2010), and that using only the within variation, by ignoring the between group variation, might not be the best approach (Dieleman and Templin, 2014). In particular, the fixed effects estimator does not allow to explore the effects of country-level characteristics, and if there is not much time variation in the data or if there are errors in the data, it might lead to less precise estimates (Andress, Golsch, and Schmidt, 2013). In the absence of correlation between the unobserved country heterogeneity and the explanatory variables, a random effects framework could provide more efficient estimates. But, in most of the cases, unobserved individual characteristics are correlated with some variables included in the estimation (Dieleman and Templin, 2014) and hence, a pure random effects framework is not suitable.

Wooldridge (2010) and Andress, Golsch, and Schmidt (2013) suggest using the Mundlak/CRE method as an alternative to choosing between fixed and random effects estimators. According to these authors, also stated by (Mundlak 1978), the random effects estimator can provide identical within-country effects as the fixed effects estimator, if the model is specified properly. By including the time averaged means of the time-variant explanatory variables as additional regressors, it is possible to obtain unbiased estimates of the within-country effects in a random effects framework, even if the unobserved effect is correlated with some of the observed time-varying regressors (Andress, Golsch, and Schmidt, 2013; Wooldrige, 2010).

Similarly, using a hybrid model, Andress, Golsch, and Schmidt, 2013; Schunck (2013)[14] combine within and between effects estimations, and prove that, as stated by Wooldridge (2010), within effect estimates for the time-varying regressors are identical to their fixed effects estimates, while the coefficients of the means of the regressors correspond to their between estimates. Thus, both the hybrid model and the Mundlak approach enable to disentangle the within and between estimates in a single model. Moreover, according to Egger and Pfaffermayer (2004) this framework is especially suitable for unbalanced panels, when there are missing values and when the time span is not long enough, which prevents the proper specification of a dynamic model with lags and leads of the variables. In a similar line, Wooldridge (2019) also analyze the case of unbalanced panels in a CRE framework and indicates how the approach could be very useful to relax the assumption of strictly exogenous covariates in non-linear models. A new extension of the Mundlak approach, the two-way Mundlak regression, has been proposed in Wooldridge (2021). The approach is meant to be useful for intervention analysis with heterogeneous treatment.

In empirical applications, the Mundlak approach has been used by Egger and Url (2006) to estimate the effects of export credit guarantees on exports and by Martínez-Zarzoso et al. (2016) to investigate whether foreign aid promotes exports. Moreover, Ruiz (2016) suggests that when between and within estimates differ, this could be due to different long-run (structural), and short-run (cyclical) components of an explanatory variable. By decomposing the variance of the explanatory variable into its between and within variations, one can decompose it into its structural

[14] For a more detailed explanation of the model see (Andress, Golsch, and Schmidt 2013, pp.164–169) and (Schunk 2013, pp. 66-67). The hybrid model differs from the Mundlak model only in that the estimates of the between effects are directly obtained in the former, whereas in the later the coefficients of the averaged variables provide between-within effects.

and temporary components. Similarly, Bartelsman, Caballero, and Lyons (1994) suggest that including cross-sectional components in the estimation is likely to capture long run equilibrium effects, whereas the within country changes are likely to represent short run reactions of the economy.

For all these reasons, in order to explore the long- and short-run implications of GVC participation on inequality, we use the Mundlak/CRE method according to which each time-variant variable is included twice in the model, once in its original form and once averaged over time (indicated by the prefix "*avg*"). The model specification is given by,

$$Gini_{it}=\beta_1\ GVCParticipation_{it}+\ \beta_2\ GVCPosition_{it}+\ \beta_3\ logGDPpc_{it}+\ \beta_4\ (logGDPpc)^2_{it}+\ \beta_5\ logFDInetInflows_{it}+\beta_6\ logR\&D_{it}+\beta_7\ Enrollment_{it}+\beta_8\ logUnemployment_{it}+\beta_9\ FemaleLabor_{it}+\delta_1\ avg\_GVCParticipation_{i.}+\delta_2\ avg\_GVCPosition_{i.}+\delta_3\ avg\_logGDPpc_{i.}+\delta_4\ avg\_(logGDPpc)^2_{i.}+\delta_5\ avg\_logFDInetInflows_{i.}+\delta_6\ avg\_logR\&D_{i.}+\delta_7\ avg\_Enrollment_{it}+\delta_8\ avg\_logUnemployment_{i.}+\delta_9\ avg\_FemaleLabor_{i.}+\theta_t+u_{it} \quad (5)$$

where the error term has two components: $u_{it}=\alpha_i+\epsilon_{it}$

A similar model is estimated that includes forward and backward GVC participation variables, instead of GVC participation and position. Feasible Generalized Least Squares (FGLS) on model (5) obtains both the within effects (β_{FE}) and the additional between (between-within, $\delta_k=\beta_{BE}–\beta_{FE}$) effects (π, compare Mundlak 1978). With a dynamic underlying data-generating process, the former, β_{FE}, approximate short-run effects and the β_{BE} their additional long-run (δ_k=long-run–short-run) counterparts (Egger and Pfaffermayr, 2004). According to (Mundlak 1978), the heterogeneity bias will be minimal, due to the fact that the correlation between the country-pair effects and the explanatory variables is captured in the model. FGLS estimation of model (5) will provide identical estimates to the within transformation (the so-called fixed effect model) and, therefore, unbiased estimates for the target explanatory variables.

Moreover, according to Wooldridge (2010) a regression-based approach to computing a Hausman statistic consists of testing H_0: $\delta_k=0$ to determine whether the heterogeneity is correlated with the time averages of the explanatory variables. The advantage of this test is that it can be made robust to non i.i.d. errors and that can be applied for each individual regressor. Therefore, in the empirical estimations we proceed as follows: first we estimate model (5) by random effects with robust standard errors, which is asymptotically efficient, including all controls in the model, and then proceed to test for $\delta_k=(\beta_{BE}–\beta_{FE})=0$. This allows us to infer for which independent variables the between-effect differs from the within effect and dropping it from the model when the difference is not statistically significant will increase efficiency of the remaining parameter estimates by reducing multicollinearity (Wooldridge 2010, pp.332).

4. Empirical Results

In this section we first present the results obtained using the preferred empirical model and then proceed in subsection 4.2 with additional results obtained using alternative methodologies. All models have been estimated using the software Stata (version 17).

4.1. Main Results

Table 1 presents the main results from applying the Mundlak approach. The dependent variable is the Gini coefficient measured as GINI_disp and GINI_mkt in columns (1) and (2) taken from SWIID and the GINI_net from UNU-WIDER in column (3). The first part of the table presents estimates for model (1), in which the GVC participation and GVC position are included as target variables, whereas in the second part of the table, GVC participation is decomposed into its buying and selling linkages, as specified in model (2), hence including backward and forward participation variables, columns (4)-(6), where also the three Gini measures are used as dependent variables. In a preliminary analysis we estimated a model with within and between effects for all the regressors and tested the random effects assumption that the unobserved heterogeneity is uncorrelated with the regressors, for the regressors for which we could not reject the null hypothesis, only the within effect is retained in the final specification. Table A.4 shows the results of the regression based Hausman test. The test indicates that the null hypothesis of equality between within and between effects is rejected for GVC variables in all models and for GDPs in one. According to these outcomes, the selected specification includes within effects for all regressors, but only between-within effects for the GVC variables and in one case for GDP variables, as shown in Table 1.

Concerning the results for the target variables, in the first part of Table 1, the GVC participation variable has only a significant effect on inequality in the short run, when the Gini from the UNU-WIDER is used as the dependent variable (column 3). The estimated coefficient indicates that an increase in GVC participation of 10 percentage points (pp) increases inequality by around 3.6 Gini points, whereas in the long-run, the coefficient is negative and significant in columns (1) and (3) indicating that 10 percentage points (pp) increase in GVC participation reduces inequality by around 10.5 GINI points ((-0.839-0.206)*10). On the other hand, the position in the GVC is negatively correlated with the Gini in the short-run, but only significant in column (1), indicating that a more upstream position is related to lower levels of GINI, whereas the opposite is the case in the long-run. Interestingly, when GINI after transfers and taxes is used as a dependent variable, the GVC participation is not statistically significant, the same is the case for the GVC position. Indeed, only the economic variables, that is, income per capita and the rate of unemployment are the factors explaining the GINI in this case.

In column (4), only the backward participation has a significant effect in the short-run, while being on the selling side of the GVC, by supplying inputs to other countries, does not have any statistically significant effect in the short term. Contrarily, the time mean of the backward participation variable has a significant and negative effect in column (4), suggesting that offshoring is associated with lower levels of inequality in the long run. For instance, column (4) indicates that a 1 pp increase in the share of foreign value added in gross exports is associated with a reduction in the GINI of about 1.5 pp in the long run. The long-run estimates with the Gini net from UNU-WIDER in column (6) confirm that the significance and negative direction of the effect of backward participation is robust to the choice of data source for the GINI. Differently, the mean of forward participation is only statistically significant in column (4) when using GINI disposable from the first source and it is also showing a negative effect.

Table 1. Main Results for All Countries: Mundlak Approach

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Gini_disp**	**Gini_mkt**	**Gini_net**	**Gini_disp**	**Gini_mkt**	**Gini_net**
Independent Variables:						
gvc_participation	0.206	0.026	0.358*			
	(0.141)	(0.211)	(0.192)			
gvc_position	-0.152**	-0.129	-0.208			
	(0.074)	–(0.094)	(0.130)			
backward_p				0.342*	0.142	0.522**
				(0.180)	(0.230)	(0.231)
forward_p				0.094	-0.070	0.156
				(0.124)	(0.218)	(0.217)
log_GDP_PC	35.815***	21.605**	65.407***	35.917***	21.717**	71.539***
	(7.222)	(10.568)	(20.200)	(7.207)	(10.510)	(18.569)
log_GDP_PCsq	-1.846***	-1.001*	-3.323***	-1.851***	-1.006*	-3.588***
	(0.402)	(0.608)	(1.029)	(0.401)	(0.605)	(0.968)
RSDV_log	-1.334***	0.582	-0.576	-1.337***	0.575	-0.784
	(0.488)	(0.607)	(0.859)	(0.486)	(0.603)	(0.914)
FDI_IN_log	-0.185**	-0.133	-0.192*	-0.184**	-0.132	-0.204**
	(0.073)	(0.085)	(0.105)	(0.073)	(0.085)	(0.100)
UEM	0.049	0.181***	0.085	0.048	0.181***	0.110*
	(0.040)	(0.043)	(0.062)	(0.040)	(0.043)	(0.058)
SETER	-0.017	0.011	-0.041**	-0.017	0.011	-0.033*
	(0.015)	(0.019)	(0.019)	(0.015)	(0.019)	(0.019)
FLFP	-0.010	0.033	-0.053*	-0.009	0.033	-0.024
	(0.023)	(0.028)	(0.032)	(0.023)	(0.028)	(0.030)
avg_gvc_participation100/backward	-0.839***	-0.322	-1.069***	-1.153***	-0.475	-1.215***
	(0.244)	(0.281)	(0.329)	(0.278)	(0.329)	(0.357)
avg_gvc_position100/forward	0.375***	0.175	0.458***	-0.546**	-0.188	-0.562
	(0.095)	(0.133)	(0.161)	(0.233)	(0.271)	(0.368)
Observations	607	607	551	607	607	551
Number of country_id	38	38	37	38	38	37
year FE	Yes	Yes	Yes	Yes	Yes	Yes
country RE	Yes	Yes	Yes	Yes	Yes	Yes
R^2_within	0.402	0.516	0.273	0.403	0.517	0.282
R^2_between	0.674	0.163	0.569	0.671	0.163	0.688
R^2_overall	0.683	0.202	0.587	0.681	0.202	0.631

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients of GDPs time-averaged variables are not shown to save space. GINI_disp and GINI_mkt measure disposable and market GINI, respectively, and are taken from SWIID. GINI_net measures disposable Gini from UNU-WIDER. All models have been estimated with the Stata command *xtreg* with the *re robust* options. Variable definitions can be found in Table A.2.

In Table 2, countries are divided based on their levels of economic development according to the IMF World Economic Output Database (2018). We also employed the Mundlak estimation, in order to see whether the effect of backward participation differs by level of economic development. The first two columns illustrate the results for the developed countries, we only considered disposable GINI from the abovementioned available sources.

The results indicate that only the forward GVC participation has a significant effect on the level of inequality in developed economies in the short run (first two variables in columns 1 and 2) whereas neither forward nor backward participation seems to affect inequality in the long run (last two variables in the same columns).

For developing countries, both the within and between estimates suggest that backward participation has a significant effect on the Gini coefficient (see columns 3 and 4). This effect is positive in the short run, while it becomes negative in the long run. However, it is important to notice that the number of observations for developing countries is considerably low, and hence the results should be taken with caution. The fact that the long run effect of backward participation is consistently negative and significant, but only for developing countries suggests that participating in the GVCs as an intermediate input buyer is associated with lower levels of inequality, when the economy reaches its long run equilibrium. The magnitude of the effect of backward participation indicates that a 1 pp increase in FVA as a share of gross exports relates to about 2-3 pp lower levels of inequality.

The effect of R&D is negative and significant for developed countries, whereas increasing shares of FDI inflows, better education and higher female labour force participation significantly reduce inequality for developing countries. Concerning the effect of GDP per capita, the Kuznets curve appears valid only for developing countries when using Gini from WIDER, whereas for developed countries a U-shaped curve seems to indicate that Gini decreases with income in the short run and then increases again. According to the results in column (1) the turning point of income per capita is 30253 USD, meaning that for countries such as the US or the UK increases in GDP per capita are linked to more inequality in the short run, whereas for Portugal the opposite is the case. As for countries classified as developing, the turning point is 18363 USD, according to column (4), indicating that for countries below this threshold, like India and Indonesia, an increase in GDP per capita lead to more inequality, whereas in countries above the turning point, such as Bulgaria, an increase in GDP per capita is linked to less inequality.

Table 2. Estimation Results for Developed and Developing Countries

Dependent Variable:	**(1) Gini_disp**	**(2) Gini_net**	**(3) Gini_disp**	**(4) Gini_net**
Countries:	**Developed**		**Developing**	
Independent Variables:				
backward_p	-0.315	-0.095	0.694***	1.037***
	(0.336)	(0.348)	(0.137)	(0.313)
forward_p	-0.675**	-0.515	0.092	-0.133
	(0.287)	(0.346)	(0.109)	(0.175)
log_GDP_PC	-58.644*	-81.208**	12.278	126.732***
	(30.763)	(32.200)	(17.068)	(30.749)

log_GDP_PCsq	2.842*	3.940**	-0.382	-6.454***
	(1.485)	(1.560)	(0.961)	(1.719)
RSDV_log	-2.570**	-3.277***	-1.931***	-3.797
	(1.009)	(1.017)	(0.573)	(2.434)
FDI_IN_log	0.028	0.101	-1.523***	-1.761***
	(0.255)	(0.269)	(0.357)	(0.651)
UEM	0.036	0.046	0.016	-0.220
	(0.092)	(0.105)	(0.105)	(0.237)
SETER	0.053**	0.062*	-0.069**	-0.093**
	(0.026)	(0.032)	(0.033)	(0.046)
FLFP	-0.021	0.011	-0.091***	-0.185**
	(0.039)	(0.039)	(0.014)	(0.083)
avg_backward	-0.133	-0.385	-2.124***	-2.887***
	(0.376)	(0.402)	(0.162)	(0.404)
avg_forward	0.418	0.243	-0.873***	-0.646***
	(0.333)	(0.386)	(0.138)	(0.225)
Observations	456	439	151	112
Number of countries	29	29	9	8
year FE	Yes	Yes	Yes	Yes
country RE	Yes	Yes	Yes	Yes
R^2_within	0.0413	0.0307	0.684	0.625
R^2_between	0.547	0.484	0.992	0.935
R^2_overall	0.479	0.466	0.964	0.884

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GINI_disp measures disposable GINI, and is taken from SWIID. GINI_net measures disposable Gini from UNU-WIDER. All models have been estimated with the Stata command *xtreg* with the *re robust* options.

4.2. Robustness

In this section three sets of robustness checks are presented. First, we estimated the model accounting for the potential endogeneity of the globalization variables. For this we used a Hausman and Taylor (1981) instrumental variables approach. The Hausman-Taylor estimator uses the individual means of the strictly exogenous regressors as instruments for the time invariant regressors that are correlated with the individual effects and allows some of the explanatory variables to be correlated with individual effects (Baltagi et al., 2003).

The results presented in Table 3 confirm the estimates in Table 1 and also show significance of the globalization variables for the Gini market, at the 10 percent level in column (2) for GVC participation and at the 5 percent level in column (5) for backward participation.

Table 3. Determinants of Inequality for All Countries: Instrumental Variables Approach

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	**Gini_disp**	**Gini_mkt**	**Gini_net**	**Gini_disp**	**Gini_mkt**	**Gini_net**
Independent Variables:						
gvc_participation	0.199***	0.025	0.323***			
	(0.054)	(0.067)	(0.110)			
gvc_position	-0.155***	-0.129***	-0.218***			
	(0.024)	(0.029)	(0.048)			
backward_p				0.338***	0.142*	0.524***
				(0.059)	(0.073)	(0.120)
forward_p				0.084	-0.071	0.157
				(0.056)	(0.069)	(0.113)
log_GDP_PC	37.453***	21.976***	72.942***	37.590***	22.090***	72.616***
	(4.189)	(5.166)	(9.976)	(4.184)	(5.161)	(9.918)
log_GDP_PCsq	-1.900***	-1.018***	-3.666***	-1.906***	-1.023***	-3.647***
	(0.229)	(0.282)	(0.537)	(0.228)	(0.282)	(0.534)
RSDV_log	-1.285***	0.571*	-0.724	-1.292***	0.564*	-0.729
	(0.266)	(0.328)	(0.535)	(0.265)	(0.327)	(0.534)
FDI_IN_log	-0.191***	-0.135**	-0.210**	-0.190***	-0.134**	-0.209**
	(0.049)	(0.061)	(0.095)	(0.049)	(0.061)	(0.095)
UEM	0.064***	0.182***	0.109***	0.064***	0.182***	0.109***
	(0.019)	(0.024)	(0.037)	(0.019)	(0.024)	(0.037)
FLFP	-0.011*	0.012	-0.030**	-0.011*	0.012	-0.030**
	(0.006)	(0.008)	(0.012)	(0.006)	(0.008)	(0.012)
SETER	0.013	0.036**	-0.016	0.014	0.036**	-0.016
	(0.013)	(0.017)	(0.026)	(0.013)	(0.017)	(0.026)
avg_gvc_participation	-0.749***	-0.359*	-0.879***			
	(0.154)	(0.198)	(0.219)			
avg_gvc_position	0.343***	0.214*	0.458***			
	(0.086)	(0.111)	(0.108)			
avg_backward_p				-1.037***	-0.544**	-1.279***
				(0.181)	(0.233)	(0.245)
avg_forward_p				-0.482***	-0.197	-0.522**
				(0.156)	(0.201)	(0.226)
Observations	607	607	551	607	607	551
Number of countries	38	38	37	38	38	37
year FE	Yes	Yes	Yes	Yes	Yes	Yes

country RE	Yes	Yes	Yes	Yes	Yes	Yes
F-test first-stage	11.94	15.48	6.525	11.98	15.53	6.577

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Coefficients of other time-averaged variables are not shown to save space. GINI_disp and GINI_mkt measure disposable and market GINI, respectively, and are taken from SWIID. GINI_net measures disposable Gini from UNU-WIDER. All models have been estimated with the Stata command *xthtaylor* and specifying the GVC variables as endogenous. Variable definitions can be found in Table A.2.

Second, we also estimated a dynamic panel data model adding the lagged dependent variable in a generalized method of moments (GMM) framework, see Arellano and Bond (1991) and Blundell and Bond (1998).

The results presented in Table 4 indicate that although we confirm the negative coefficient in the backward participation variables, it is only statistically significant in column (4) when using GINI from UNU-WIDER, while the lagged dependent variable is only significant in two of the four models estimated. Moreover, most of the control variables are imprecisely estimated, which is surely due to the fact that the models rely mostly on the within variation and errors in the data are usually magnified in these models. Therefore, we prefer the former approach that was used to obtain the main results.

Table 4. Determinant of Inequality for All Countries: Difference- and System-GMM Estimation Results

	(1)	**(2)**	**(3)**	**(4)**
Dependent variable:	**Gini_disp**	**Gini_disp**	**Gini_net**	**Gini_net**
Independent Variables:	**Diff-GMM**	**Sys-GMM**	**Diff-GMM**	**Sys-GMM**
Gini_t-1	1.239*	0.889***	-0.172	-0.027
	(0.679)	(0.080)	(0.607)	(0.376)
backward_p	-0.082	-0.064	0.723	-0.604**
	(0.116)	(0.061)	(0.524)	(0.255)
forward_p	-0.048	-0.036	0.659	-0.421
	(0.094)	(0.037)	(0.515)	(0.260)
log_GDP_PC	66.743	-12.439	228.838	11.420
	(61.095)	(7.791)	(239.443)	(175.553)
log_GDP_PCsq	-3.476	0.624	-11.741	-0.801
	(3.160)	(0.409)	(11.962)	(8.691)
RSDV_log	-0.410	-0.443	6.054	-2.119
	(0.405)	(0.316)	(4.537)	(3.814)
FDI_IN_log	0.011	-0.038	-0.026	-0.009
	(0.033)	(0.030)	(0.071)	(0.250)
UEM	-0.025	0.024	-0.104	0.017
	(0.043)	(0.016)	(0.084)	(0.243)

SETER	0.015	0.002	0.022	0.009
	(0.010)	(0.008)	(0.025)	(0.097)
FLFP	0.036	-0.001	0.150***	0.022
	(0.027)	(0.006)	(0.053)	(0.091)
Observations	513	607	418	512
Number of countries	35	38	34	37
year FE	Yes	Yes	Yes	Yes
Diff-GMM	Yes		Yes	
Sys-GMM		Yes		Yes
AR1 (p-value)	0.618	0.0282	0.684	0.249
AR2 (p-value)	0.443	0.143	0.646	0.378
Hansen (p-value)	0.985	0.922	0.991	0.992

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. All models have been estimated with the Stata command *xabond2* with the options *robust twostep small h(2) nolevel* in columns (1) and (3) and excluding the *nolevel* option in columns (2) and (4). The results of the AR1 and AR2 tests indicates that there is not autocorrelation of order 2 in the residuals. And the Hansen test cannot reject the null of validity of the instruments. Variable definitions can be found in Table A.2.

Finally, we also estimate the model using the classical random effect versus fixed effect approaches and present as well results for the model using Discroll and Kraay (1998) standard errors that are robust to cross-correlations between panel units (Table A5). The main results remain unchanged with the only exception of positive and significant effects in the short run for developed countries when SE are robust to cross-sectional correlations.

5. Discussion, Policy Implications and Conclusions

The goal of this study is to explore the impact of GVC participation on income inequality in developed and developing countries, in order to get a better understanding of the distributional consequences of participating in global value chains.

The main finding according to the Mundlak estimates is that the direction of changes in the level of income inequality with respect to GVC participation is different depending upon whether a short- or long-run interpretation is used. While the results are mixed and non-significant in some cases for forward participation, the effect of backward participation on the level of inequality measured in developing countries is consistently significant. The effect of offshoring on both Gini disposable and Gini market is positive in the short run, while it becomes negative, associated with lower levels of inequality, in the long run. For developed countries there are no statistically significant changes in inequality related to backward participation according to our main results. The Hausman Taylor estimator confirm the robustness of our Mundlak estimations and hence, our results suggest that overall, the significant effect of GVC participation on inequality is driven by backward participation.

Our estimations do not generally support a statistically significant effect of backward participation on inequality in developed countries, which could be linked to the fact that labour market rigidities predominate in those countries. For instance, GVC participation might affect inequality through two channels: changes in unemployment and changes in wages. The HOS model assumes perfectly competitive labor markets, in which no changes in unemployment occur in the long run. Thus, workers who lose their jobs due to offshoring in the contracting sector will be allocated to new jobs in the expanding sector, when the economy reaches its new long run equilibrium. Krugman (1993) describes this phenomenon as the natural rate of unemployment, which stays constant in the long run. Based on the assumption that changes in unemployment are only short run responses due to adjustment costs, such as job search and transaction costs, transportation and removal costs etc., most of the trade literature focuses on the wage effects of trade (Görg 2011).

Dutt, Mitra, and Ranjan (2009) find that trade liberalization is associated with an immediate increase in unemployment in the short run, while this effect is reversed in the medium to long run. Hence, employment is higher in the new long run equilibrium. The coefficients of backward participation, obtained in the estimations for developing countries, could be reflecting a similar transmissions channel through changes in employment. In the short run, importing intermediate goods might cause the displacement of domestic workers employed in the production processes of the imported goods. However, this effect might be offset in the long run. Sectors, which use the cheaper imported intermediate goods can reduce their costs and decrease their prices, expanding their sales. The additional profits, generated through increased sales and lower cost of production can be invested into new projects, creating new jobs in the market. As these investments will not be materialized immediately, the employment increasing effect of offshoring is expected to come into effect in the long run. Nevertheless, it is important to notice that perfect inter-sectoral mobility is not guaranteed in many OECD countries.

At the same time, the productivity of the remaining sectors might increase, as the economy specializes in the production of more productive tasks. In competitive labor markets, workers that are displaced from the contracting sector could be switching to more productive tasks in the expanding sector. This mechanism implies that countries with more flexible labor markets and easier mobility of labor would gain more from backward participation over the long run, as each worker can be allocated to the task for which she is the most productive.

The second channel, through which backward participation might reduce inequality in the long run could be related to changes in wages across workers with different skill endowments. This is the most commonly used channel in the empirical literature on trade and inequality. If wages are the main transmission channel of the effect of GVC participation on inequality, the between estimates in Table 2 would imply that higher backward participation lowers the skill premium in developing countries over the long run. However, several studies have found that offshoring is associated with higher skill premiums in both advanced and emerging economies (Görg 2011).

One possible explanation for the rise in the skill premiums related to offshoring in developing countries could be that developing countries might also import low skill intensive goods from other less developed economies. This would lower the relative demand and the relative wages for the low skilled labor in the short run. It is also possible that the imported intermediate goods from abroad are used for the production of skill intensive final goods. This would increase the relative demand for skilled labor and the skill premium in the developing offshoring countries. However, as argued above, the increase in skill premium might be only a short-term reaction of the economy and can be offset through the cost savings and increased specialization in more productive tasks over the longer period.

To explore how offshoring tasks with different skill levels affects the skill premium in the offshoring countries, Lopez-Gonzalez, Kowalski, and Achard (2015) decompose backward participation into its low and high skill components. They find that foreign high skilled value added is associated with higher levels of wage inequality, while the reverse is observed for offshoring low and medium skilled tasks. The coefficient for the low skilled backward participation is larger than that of high skilled participation in their pooled OLS estimates, such that the overall effect of offshoring is inequality reducing. Their results are robust to using the Gini coefficient as the measure of inequality. As we are unable to decompose backward participation into its skill components due to lack of data (the WIOD decomposition was not updated and Eora does not contain such decomposition), our results possibly reflect the overall effect of backward participation, dominated by the effect of the low skilled component. This is consistent with the findings of Lopez-Gonzalez, Kowalski, and Achard (2015).

Finally, according to our main results, other controls, such as FDI inflows and R&D appear to have reducing effects on inequality in the short-run, but we cannot find evidence of long-run effects on income inequality, in contrast to what is expected according to the trade and inequality literature (IMF 2007). Our results do not support the hypothesis that skill biased technological change is the main driver of increasing levels of inequality. It is possible that GVC participation has additional effects on the distribution of income through changes in unemployment and wages, which are not captured by FDI and R&D.

The between estimates in our model suggest that backward participation is associated with a reduction of inequality in the long run for developing economies whereas no significant effect has been found for developed countries. The negative distributional consequences appear to be only a short term reaction of the economy to GVC trade. It is possible that the aggregate benefits of GVC participation, including increases in productivity and specialization, are distributed more equally over the long run, when labor and wages adjust towards their new equilibrium.

OECD (2013) suggests that the labor adjustment process towards the new long run equilibrium can be mitigated with the right policy instruments, such as effective re-employment services and training programs. Investment in the skills of the labor force through education and training are essential to benefit from GVC participation, concerning economic development. Increasing productivity and skill-upgrading of the labor force through training, automation and introduction of new technologies is crucial to benefit from participating in GVCs, especially for developing countries (OECD, 2013).

It is important to notice that the countries selected for the analysis mainly include developed countries and a fewer number of less advanced countries. Comparative purposes and a high number of missing observations for some of the control variables, especially for the least developed countries were reasons to restrict the country coverage of the sample. Given that our sample is strongly biased towards developed countries, the results for the developing countries have to be taken with caution. The effect of GVC participation might be different for least developed countries, which is not discussed in this paper. Future research should cover a larger number of countries to improve the external validity of this study. Likewise, since GVC participation does not change randomly in each country, and firms decide to participate or to extend their GVC participation according to a number of factors, we would like to emphasize the need for future work that explores potential factors and the implications concerning unobserved variables that could affect the empirical results.

The usage of the Gini coefficient as the measurement of inequality has its advantages and disadvantages. The main advantage is that it is available for a broad number of countries and years. One of the drawbacks of the Gini is related to its computation by using income information from household surveys. Surveys are subject to several measurement issues related to the design of the survey and biases in responses, such as underreporting of top incomes in the distribution. The quality of the Gini data might differ across countries and years, making its comparability difficult. To minimize the issues related to the comparability of Gini indices, the SWIID database is used. Concerns related to the imputation of missing values is addressed by using the WIID Gini disposable from UNU-WIDER in order to cross-check the robustness of estimates. Finally, the Gini is more sensitive to changes in the middle of the distribution compared to other measures of inequality, such as the Atkinson index and the Theil index, not allowing to capture whether inequality is driven at the top or bottom of the distribution. The latter information could be important for policy implications, especially if one is interested in differences in changes in inequality across different parts of the income distribution.

Finally, research should try to distinguish between the skill levels of the offshored tasks involved in GVCs, this will give further insights related to how GVC participation influences inequality, depending on the skill type of the traded intermediate task, as suggested by the related literature.

Appendix

Table A1. List of Countries Included in the Sample

Developed	**Developing**
Australia	Bulgaria
Austria	Brazil
Belgium	China
Canada	India
Cyprus	Indonesia
Czech Rep.	Mexico
Denmark	Poland
Estonia	Romania
Finland	Russia
France	Turkey
Germany	
Greece	
Hungary	
Ireland	
Italy	
Japan	
Latvia	
Lithuania	
Luxembourg	
Malta	
Netherlands	
Portugal	
Slovakia	
Slovenia	
Spain	
Sweden	
Switzerland	
UK	
USA	

Source: IMF World Economic Outlook Database, Oct 2018.

Table A2. Variable Definitions, Sources and Descriptive Statistics

Variable	Definition and Source	Obs	Mean	Std. Dev.	Min	Max
Gini_disp	Disposable Gini after transfer and taxes (1-100), SWIID	856	32.1	6.423	22	53.1
Gini_mkt	Market Gini before transfers and taxes (0-100), SWIID	856	45.9	4.619	32.5	59.9
Gini_net	Disposable Gini after transfer and taxes (1-100), UN-WIDER					
Gvc_partic.	Global Value Change Participation Index, Eq. (1)	936	45.644	6.072	29.761	58.523
Gvc_position	Global Value Change Position, Eq. (2)	936	-2.023	10.867	-22.751	31.051
Backward_p	Backwards Global Value Change Participation Index, EORA	936	24.094	7.829	8.163	39.502
Forward_p	Forwards Global Value Change Participation Index, EORA	936	21.55	6.806	6.972	49.17
Log_GDP_PC	Gross-Domestic Product per capita, WDI	934	10.143	.641	7.702	11.491
RSDV_log	Research &Development Expenditure/GDP (%), WDI	744	.156	.688	-3.046	1.365
FDI_IN_log	Inwards Foreign Direct Investment/GDP, WDI	869	1.053	1.344	-7.234	6.113
SETER	School enrolment, tertiary (% gross), WTO	750	52.689	22.584	4.479	126.383
LFPFEM	Labor force participation rate for ages 15-24, female (%), ILO	936	42.329	14.25	12.773	75.444
UEM	Unemployment Rate (%), WDI	936	7.871	4.088	1.805	27.466

Note: The gvc_ partic. measure is the sum of backward and forward participation rates expressed as a share of gross exports. Data includes observations for 39 countries between the years 1995-2016. Log denotes variables are in natural logarithms.

Table A3. GVC Changes between 1995-2018

Country id	Country	1995	2018	Change	% Change
1	Australia	33.83	36.01	2.18	6.44
2	Austria	46.49	51.84	5.34	11.49
3	Belgium	48.5	50.57	2.07	4.27
4	Brazil	33.35	35.49	2.14	6.4
5	Bulgaria	43.12	47.35	4.23	9.8
6	Canada	34.45	34.71	0.26	0.75
7	China	30.29	39.49	9.2	30.38
8	Cyprus	36.18	39.09	2.91	8.05
9	Czech Republic	48.89	54.09	5.21	10.65
10	Denmark	43.24	47.83	4.59	10.6
11	Estonia	48.22	50.02	1.8	3.73
12	Finland	46.63	49.82	3.18	6.83
13	France	44.29	47.69	3.4	7.69
14	Germany	42.47	44.29	1.82	4.29
15	Greece	41.26	46.18	4.92	11.93
16	Hungary	47.54	49.95	2.4	5.06
17	India	33.24	36.26	3.03	9.1

18	Indonesia	37.42	45.04	7.62	20.37
19	Ireland	44.86	45.96	1.1	2.44
20	Italy	37.94	41.94	4	10.54
21	Japan	35.48	39.59	4.11	11.6
22	Latvia	45.24	48.33	3.09	6.84
23	Lithuania	45.11	46.25	1.13	2.51
24	Luxembourg	53.53	54.8	1.27	2.37
25	Malta	44.37	48.87	4.5	10.15
26	Mexico	32.89	32.2	-0.69	-2.1
27	Netherlands	48	50.72	2.71	5.65
28	Poland	48.3	51.02	2.73	5.65
29	Portugal	42.48	44.98	2.5	5.89
30	Romania	44.47	46.9	2.43	5.46
31	Russia	47.91	54.15	6.23	13.01
32	Slovakia	48.95	51.56	2.61	5.32
33	Slovenia	46.74	50.92	4.18	8.93
34	Spain	41.07	43.95	2.88	7.02
35	Sweden	45.79	49.78	4	8.73
36	Switzerland	42.05	46.01	3.96	9.42
37	Turkey	38.56	43.02	4.46	11.57
38	UK	44.92	50.14	5.23	11.64
39	USA	35.75	41.35	5.6	15.66

Source: UNCTAD-Eora Global Value Chain Database.

Table A4. Regression based Hausman Test. Results for Models in Table 1

Tests of the random effects assumption in column (4)	p-value
_b[B_backward_p100] = _b[W_backward_p100]	**0.000**
_b[B_forward_p100] = _b[W_forward_p100]	**0.0002**
_b[B_log_GDP_PC] = _b[W_log_GDP_PC]	0.1703
_b[B_log_GDP_PCsq] = _b[W_log_GDP_PCsq]	0.2112
_b[B_RSDV_log] = _b[W_RSDV_log]	0.9063
_b[B_FDI_IN_log] = _b[W_FDI_IN_log]	0.9498
_b[B_UEM] = _b[W_UEM]	0.9772
_b[B_SETER] = _b[W_SETER]	0.2405
_b[B_LFPFEM] = _b[W_LFPFEM]	0.3243
Tests of the random effects assumption in column (5)	
_b[B_backward_p100] = _b[W_backward_p100]	**0.0001**
_b[B_forward_p100] = _b[W_forward_p100]	**0.0182**

_b[B_log_GDP_PC] = _b[W_log_GDP_PC]	0.9591
_b[B_log_GDP_PCsq] = _b[W_log_GDP_PCsq]	0.9329
_b[B_RSDV_log] = _b[W_RSDV_log]	0.4855
_b[B_FDI_IN_log] = _b[W_FDI_IN_log]	0.5247
_b[B_UEM] = _b[W_UEM]	0.7755
_b[B_SETER] = _b[W_SETER]	0.4134
_b[B_LFPFEM] = _b[W_LFPFEM]	0.4657
Tests of the random effects assumption in column (6)	
_b[B_backward_p100] = _b[W_backward_p100]	**0.000**
_b[B_forward_p100] = _b[W_forward_p100]	**0.0379**
_b[B_log_GDP_PC] = _b[W_log_GDP_PC]	**0.0103**
_b[B_log_GDP_PCsq] = _b[W_log_GDP_PCsq]	**0.0149**
_b[B_RSDV_log] = _b[W_RSDV_log]	0.9282
_b[B_FDI_IN_log] = _b[W_FDI_IN_log]	0.7713
_b[B_UEM] = _b[W_UEM]	0.6743
_b[B_SETER] = _b[W_SETER]	0.6613
_b[B_LFPFEM] = _b[W_LFPFEM]	0.6219

Note: Test of the equality of the between (B_) and Within (W_) coefficients. Rejections of the null at the 1 or 5% significant level in **Bold.** Similar tests were run for models in columns (1)-(3) of Table 1 to choose the specification. The tests were done using the command *xthybrid* with the option *test.*

Table A5. Random-Effects and Fixed Effects results for developed and developing countries

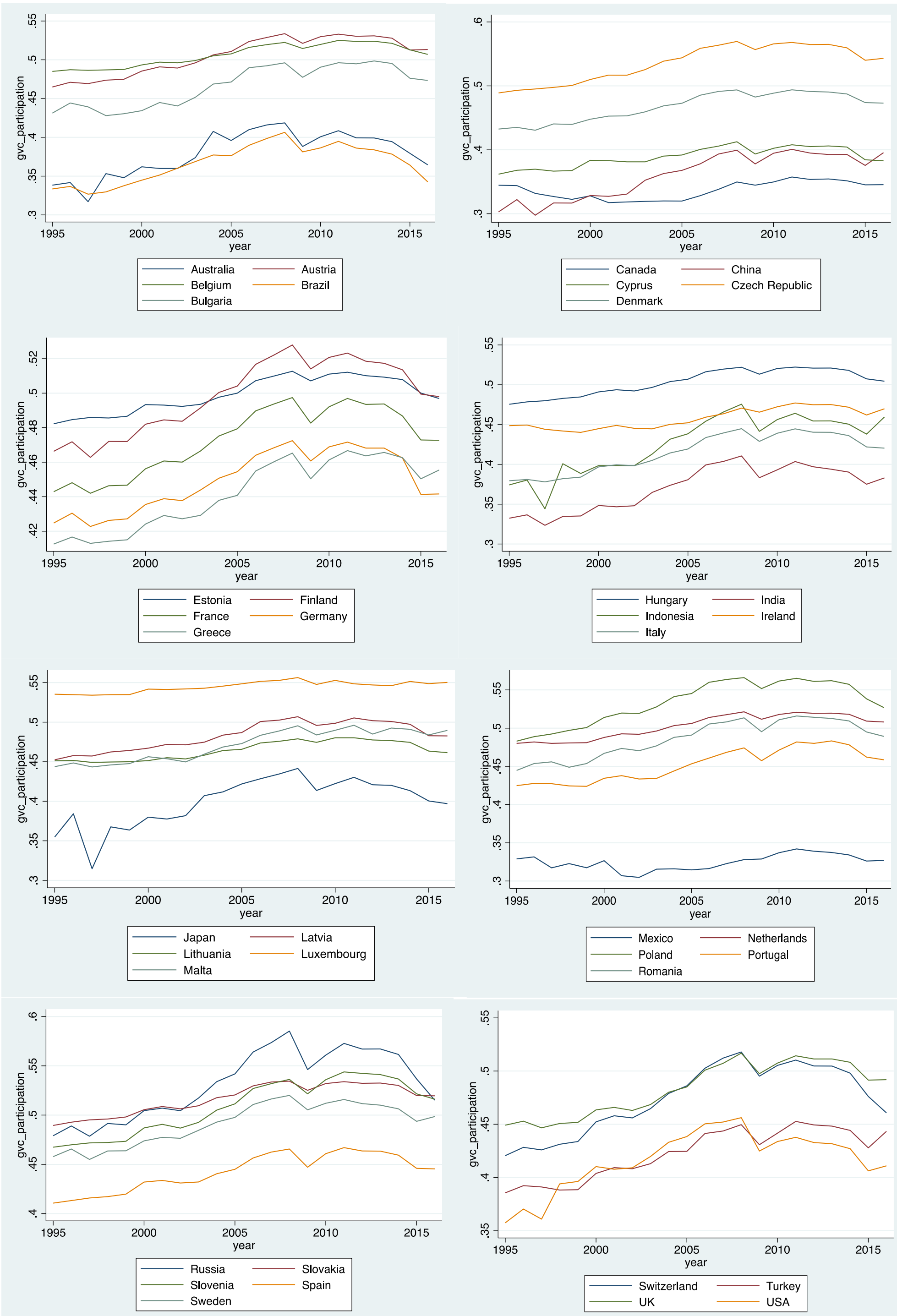
Short-Run Estimates	Developed	Developing	Developed	Developing	Developed	Developing
DEP.VAR: Gini_disp	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Method	**RE**	**RE**	**FE**	**FE**	**FE & Cross-sectional-correlation**	
EXPL. VARIABLES						
backward_p	-0.440***	-1.296***	0.176	0.700**	0.176**	0.700***
	(0.120)	(0.068)	(0.154)	(0.218)	(0.077)	(0.222)
forward_p	-0.268**	-0.791***	0.071	0.240	0.071	0.240*
	(0.124)	(0.070)	(0.161)	(0.167)	(0.069)	(0.130)
log_GDP_PC	-56.050*	44.012	66.022***	33.961	66.022***	33.961
	(29.736)	(27.077)	(19.245)	(26.018)	(13.680)	(20.317)
log_GDP_PCsq	2.723*	-2.183	-3.364***	-1.780	-3.364***	-1.780
	(1.440)	(1.532)	(0.958)	(1.436)	(0.719)	(1.123)
RSDV_log	-2.546**	-0.395	-1.348**	-2.730*	-1.348***	-2.730*
	(1.010)	(0.906)	(0.570)	(1.407)	(0.200)	(1.364)
FDI_IN_log	0.020	-1.597**	-0.086**	-1.010**	-0.086***	-1.010***
	(0.254)	(0.669)	(0.039)	(0.356)	(0.024)	(0.242)
UEM	0.025	-0.108	0.022	-0.053	0.022	-0.053
	(0.094)	(0.196)	(0.034)	(0.087)	(0.032)	(0.050)

SETER	0.054**	-0.022	0.010	-0.028	0.010	-0.028
	(0.027)	(0.060)	(0.013)	(0.035)	(0.007)	(0.027)
FLFP	-0.025	-0.101***	0.051**	-0.160	0.051***	-0.160***
	(0.040)	(0.035)	(0.022)	(0.091)	(0.009)	(0.029)
Observations	456	151	456	151	456	151
Number of countries	29	9	29	9	29	9
year FE	Yes	Yes	Yes	Yes	Yes	Yes
country RE	Yes	Yes				
country FE			Yes	Yes	Yes	Yes
Standard Errors	robust	robust	robust	robust	Discroll-Kraay	Discroll-Kraay
R-squared within			0.394	0.727		
Hausmann Test	Chi2 (8)=112.53	Chi2 (8)=121.90				
Probability	Prob=0.000	Prob=0.000				

Notes: Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Variable definitions can be found in Table A.2.

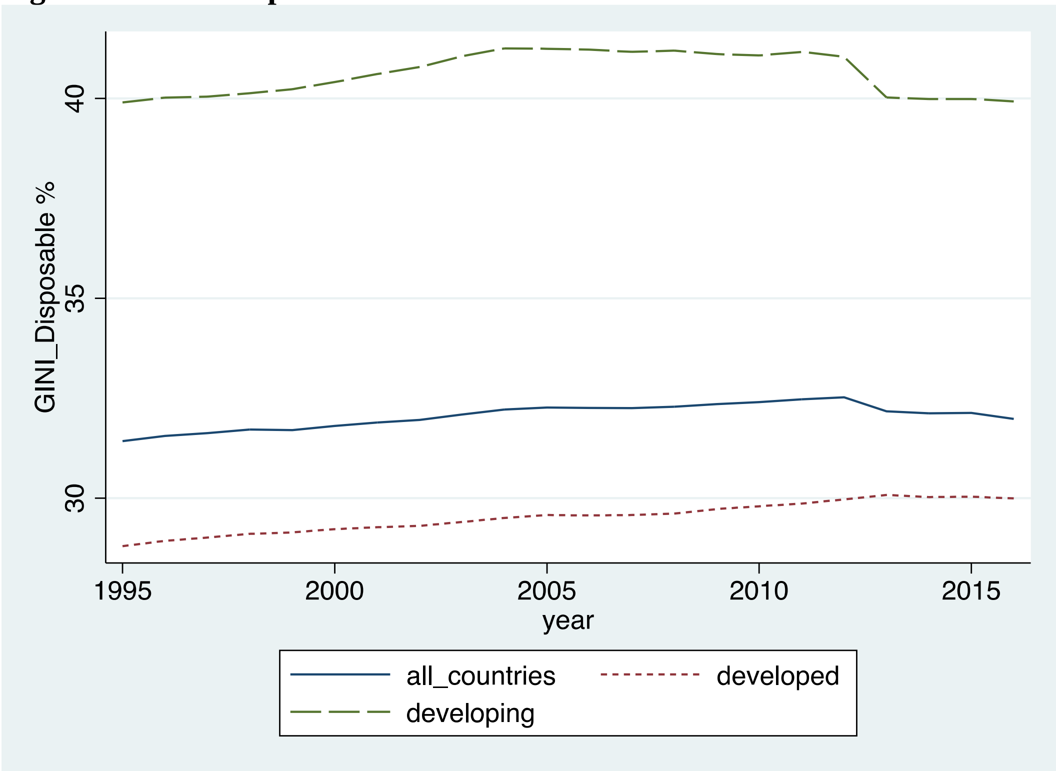
Figures

Figure A1. GVC Participation by country



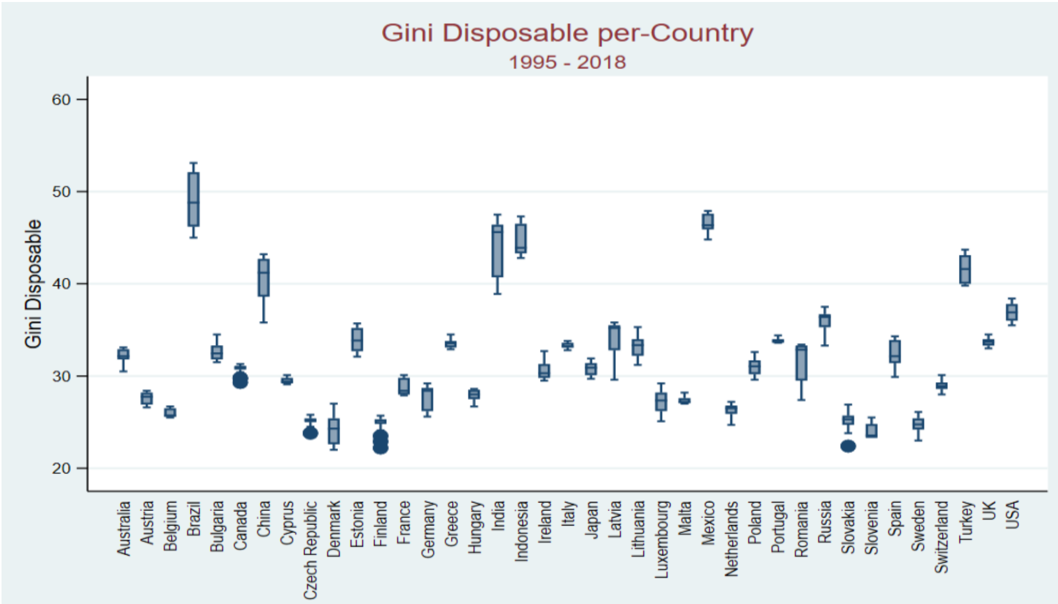
Source: Authors' elaboration using UNCTAD-Eora Global Value Chain Database.

Figure A2. Gini Disposable. Evolution over Time



Source: Authors' calculations from SWIID data.

Figure A3. Average Gini Disposable per Country



Source: Authors' calculations from SWIID data.

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