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The Role of Global Value Chains for Worker Tasks and Wage Inequality

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Abstract

This paper studies the relationship between participation in global value chains, worker routine task intensity, and within-country wage inequality. It uses unique survey data from 47 countries across the development spectrum to calculate worker-level, country-specific routine task intensity and combines them with sectoral measures of backward and forward global value chains participation. Higher global value chains participation is associated with more routine-intensive work, specifically among offshorable occupations, especially in countries at lower development levels. The results by broad sectors contrast sharply: higher global value chains participation is linked to a higher routine task intensity in offshorable occupations in the industry but a lower routine task intensity in non-offshorable occupations in business services. Higher worker-level routine task intensity is strongly associated with lower wages, so global value chains participation indirectly widens the within-country wage inequality through this routine task intensity channel. At the same time, global value chains participation directly contributes to reduced wage inequality, except for the richest countries. Overall, this analysis finds that global value chains participation reduces wage inequality in most low- and middle-income countries that receive offshored jobs but widens wage inequality in high-income countries that offshore jobs.

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The Role of Global Value Chains for Worker Tasks and Wage Inequality[•]

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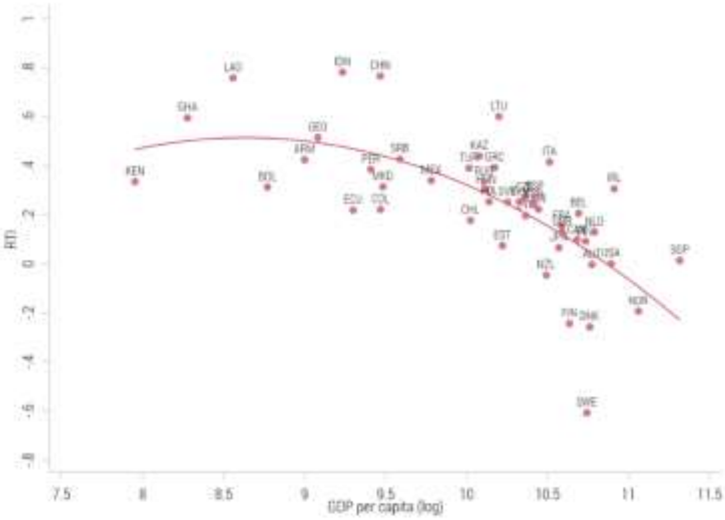
1. Introduction

Traditional trade theory predicted that countries' specialization in trade affects the international division of labor. Wealthier countries which tend to be relatively more endowed with skilled labor and technology have had a comparative advantage in the exports of skill- and technology-intensive goods and services. In contrast, developing nations have been relatively more abundant in low-wage labor and natural resources, thus specializing in labor- and resource-intensive goods exports. Both types of countries exported the goods and services that use their relatively abundant factors more intensively. Recently, however, countries specialize in the exports of tasks they have a comparative advantage in (Grossman & Rossi-Hansberg, 2008) rather than final goods and services. Technological change and trade liberalization have fostered the possibility of trading tasks, offering opportunities to developing countries to participate and upgrade in global value chains (GVCs) (Taglioni & Winkler, 2016). The "second unbundling" of corporate tasks has intensified this division of labor (Baldwin, 2014), as routine tasks are easier to offshore (Blinder & Krueger, 2013), especially in manufacturing (Rodrik, 2013). The decline in routine jobs in the United States, European Union, and some emerging countries since the late 1980s contributed to the polarization of job opportunities within countries (Autor & Dorn, 2013; Cortes et al., 2017; Goos et al., 2014; Jensen & Kletzer, 2010; Michaels et al., 2014; Reijnders & de Vries, 2018; Spitz-Oener, 2006).

A GVC consists of a series of value-adding tasks, from inception to selling a product or service for final consumption (World Bank, 2020). Richer countries perform more non-routine tasks that require creativity, data analytics, or guiding people. In contrast, poorer countries specialize in routine-intensive tasks that are often repetitive, well-structured, and require being exact and accurate rather than creative (Figure 1). What is the role of GVCs in explaining the division of worker tasks across countries? What is the GVCs' contribution to within-country differences in job tasks, and as higher routine task intensity is strongly associated with lower earnings (Autor & Handel, 2013; de la Rica et al., 2020), to wage inequality? Do various forms of GVC participation differ in this regard?

Figure 1. The average routine task intensity (RTI), by countries' development level (GDP per capita), accounts for cross-country occupational task differences.



Note: for each task content, the 0 is set at the United States average value, and 1 corresponds to one standard deviation of RTI in the United States. GDP per capita in PPP, current international $, country averages for 2011–2016.
Source: Lewandowski et al. (2022).

Drawing on a unique survey dataset, this study examines the existence and nature of linkages between GVC participation and the routine task intensity (RTI) of workers across 47 countries at all developmental stages. Specifically, this paper systematically assesses how the nature of GVCs mediates this relationship, accounting for differences across sectors and types of occupations, particularly offshorable and non-offshorable occupations. Moreover, we evaluate how GVCs contribute to the task structures in the domestic labor markets, and to within-country wage inequality, as measured by the Gini coefficient. We distinguish between the direct – through wages – and indirect – through RTI – contribution of GVC participation to wage inequality.

The relationship between GVC participation and RTI is depends on a country's factor endowments which determine its type of task specialization in GVCs. In developing countries such as Indonesia, a higher backward GVC participation, i.e., the share of imported inputs used in export production, may be associated with a higher worker-level RTI. Such countries tend to have abundant low-wage labor and specialize in the production tasks of basic manufacturing GVCs, typically the final assembly stage. Thus, they rely strongly on imported inputs which they process for their semi-final or final exports. However, high backward GVC integration also characterizes countries specializing in more advanced manufacturing and services GVCs. Such countries are endowed with skilled labor and perform some routine tasks (e.g. customer service or accounting) and some non-routine tasks (e.g., IT support) (World Bank, 2020). Examples include Central Eastern European countries (Czechia, Hungary, Poland).[1]

The type of GVC participation in East Asian and Central Eastern European countries contrasts sharply with that of many Sub-Saharan African or Latin American countries specializing in commodities – agriculture and mining (Hanson, 2017). These countries show low backward GVC participation as they predominantly export upstream GVC tasks with low reliance on imported inputs and fewer opportunities to innovate and upgrade (Fernandez-Stark et al., 2011; Taglioni & Winkler, 2016; World Bank, 2020). They typically exhibit high forward GVC participation, namely a high share of domestic value added embodied in their direct partner countries' exports (Borin & Mancini, 2015, 2019). As a result, higher forward GVC participation in commodity-exporting countries may be associated with a higher RTI, as upstream tasks in agricultural or small-scale mining GVCs are more likely to be routine-intensive.[2] High forward GVC participation is also a feature of countries specialized in innovative GVC tasks (World Bank, 2020), but its expected relationship with RTI contrasts that of commodity exporters. In innovative countries, high value-added upstream tasks, such as research and design services, make up a larger portion of their domestic value added that is re-exported by their bilateral trading partners. These tasks tend to be non-routine. These country examples illustrate that the relationship between GVC participation and RTI may vary across sectors and countries with different development levels and models. It may also differ between backward and forward GVC participation.

We make three key contributions. First, this study quantifies the relationship between GVC participation and worker task demand, which remains under-researched (Marcolin et al., 2016). Our PIAAC, STEP, and CULS survey data cover 47 countries at different development levels and types of integration into GVCs. We measure RTI at a worker level, applying the method proposed by Lewandowski et al. (2022). In the absence of direct

[1] For instance, some East Asian countries that initially specialized in blue-collar jobs managed to increase their workforce's skill supply, upgraded in GVCs, and shifted towards more upstream and downstream activities (de Vries et al., 2019). Similarly, some Central Eastern European countries (Czechia, Hungary, Poland, Slovenia) have been upgrading from an assembly-line specialization towards more advanced activities (Kordalska & Olczyk, 2022; Timmer et al., 2019).

[2] In agribusiness, for instance, routine tasks include seed sowing and harvesting. More downstream tasks, such as washing, chopping, packing, and applying bar codes on fruits and vegetables, are also routine. Assigning one specialized task to each worker, rather than having one worker perform a series of consecutive tasks, increases the RTI.

export measures at the task level,[3] we link sectoral measures of GVC participation to RTI at the worker level in a given sector, drawing on the methodology of Borin & Mancini (2019) based on EORA data. We also control for technology use with a country-sector share of workers who use computers at work. The country-sector level globalization and technology measures are plausibly exogenous to the decisions of individual firms and workers. The closest study to ours is Lewandowski et al. (2022), but we use much more disaggregated measures of GVC participation (especially in manufacturing) and assess the relative role of forward and backward linkages. Reijnders and de Vries (2018) also provided evidence on the role of offshoring and technological change in GVCs in explaining the increase in non-routine occupational labor demand in a sample of 37 advanced and emerging countries.[4] However, they assumed that occupations are identical globally and measured occupational task contents with American data (the Occupation Information Network – O*NET). We use worker-level RTI to account for cross-country task differences in comparable occupations. This is vital as theory suggests that offshoring leads to a global polarization of tasks within occupations (Grossman & Rossi-Hansberg, 2008) and occupational task demands indeed differ between countries (Caunedo et al., 2021; de la Rica et al., 2020; Lewandowski et al., 2022; Lo Bello et al., 2019).[5]

We find significant linkages between GVC participation and RTI. Importantly, these associations differ between backward and forward integration. Overall, backward GVC participation is not correlated with RTI, while higher forward GVC participation is associated with more routine-intensive work. Moreover, the strength of this relationship is negatively related to countries' development – it is stronger in countries with relatively low GDP per capita and weaker in countries with high GDP per capita.

Second, this study assesses how the nature of occupations and sectors mediates the relationship between GVC participation and worker-level RTI. Specifically, it investigates the role of occupations' offshorability (Blinder & Krueger, 2013). The relationship between GVC participation and RTI may be particularly pronounced among workers performing offshorable tasks in low-skilled occupations. Workers in less developed countries have a comparative advantage in performing routine tasks due to their larger endowment with low-skill workers (Grossman & Rossi-Hansberg, 2008). Indeed, Lewandowski et al. (2022) found that the relationship between backward GVC participation and worker-level RTI is the strongest among workers in low-skilled occupations.

We find a strong and significant relationship between GVC participation – both backward and forward – and RTI among workers in offshorable occupations, especially in less-developed countries. However, we find no such relationship among workers in non-offshorable occupations. In addition, acknowledging that sectoral specialization of countries matters for the global division of tasks (Hanson, 2017), this paper examines heterogeneity between sectors. Importantly, we find a contrasting relationship between GVC participation and RTI in the industrial and business services sectors. In industrial sectors, a higher GVC participation is associated with more routine-intensive work in offshorable occupations, confirming that a country's GVC participation is driven by the manufacturing sector (Fernandes et al., 2022). In sharp contrast, a higher GVC participation in business services sectors is correlated with less routine-intensive work in non-offshorable occupations.

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[3] To understand how GVCs shape the division of tasks across countries, research would ideally relate measures of task exports to data on tasks' routine intensity. GVC participation measures to date are only available at the sector or firm level for a given country. However, recent work has introduced new measures of income and job activities in exports where activity is defined as a sector-occupation pair (Kruse et al., 2023).

[4] Reijnders and de Vries (2018) combine input-output data to decompose changes in occupational labor demand along the value chain, but their methodology does not allow differentiation between intensities of GVC participation.

[5] Other strands of literature relating globalization to the demand for workers in routine jobs study the effects of global trade (Autor et al., 2015), the China trade shock on local labor markets (Aghelmaleki et al., 2022; Autor et al., 2013, 2016), as well as offshoring (Autor et al., 2016; Baumgarten et al., 2013; Ebenstein et al., 2014; Goos et al., 2014; Hanson, 2017).

Third, this study assesses the relationship between GVC participation and wage inequality (the Gini coefficient of hourly wages) within countries. Globalization may widen differences in RTI between workers in offshorable occupations and those in non-offshorable occupations and thus contribute to earnings inequality, as workers performing less routine-intensive tasks tend to earn more (Autor & Handel, 2013; de la Rica et al., 2020). Our study confirms that a higher RTI is associated with lower wages. Consequently, GVC participation can influence wage inequality through two channels: (i) indirectly through its relationship with RTI, (ii) and directly through diverse wage effects among different types of workers, especially in offshorable and non-offshorable occupations.

Extensive literature studied the effects of offshoring on the relative demand for different occupations at the sectoral level, usually finding demand shifts with implications of inequality. It primarily differentiated between production and non-production workers and capturing relative demand for particular worker types with their share in the sector's wage bill. It initially focused on goods offshoring in manufacturing – see the seminal studies on the United States by Feenstra and Hanson (1999, 1996), and the broader literature review in Crinò (2009) – generally finding an increase in the relative demand for non-production workers. Focusing on services offshoring, some studies found it increased the relative demand for skills in the United States and Western Europe (Crinò, 2010, 2012), or lowered the relative demand for non-production workers in German manufacturing (Winkler, 2013). Several studies focused on worker-level adjustments to trade and offshoring found a downward pressure on wages in low-skilled occupations and upward pressure on wages in high-skilled occupations in the United Kingdom and Germany (Geishecker & Görg, 2013; Koerner, 2022). Ebenstein et al. (2014) found that offshoring negatively affects individuals' wages in the United States due to relocating workers from higher-wage manufacturing jobs to other sectors and occupations. Existing cross-country studies (Wolszczak-Derlacz & Parteka, 2018) find small negative effects of offshoring on the wages of low- and middle-skilled workers, but focus on high-income countries. In the meta-analysis of within-country studies, Cardoso et al. (2021) showed that offshoring benefits high-skilled workers and harms low-skilled workers, especially in the origin countries. However, Gonzalez et al. (2015) found that GVC participation has a relatively small impact on wage distributions and can reduce wage inequality among low-skilled segments of the labor force. Duarte et al. (2022) found that countries with medium levels of GVC participation tend to record higher income inequality than those with low or high levels of GVC participation.

Our study's novelty is quantifying labor market channels of globalization's contribution to within-country wage inequality, in a cross-country setting that covers both developed and developing countries and accounts for occupations' offshorability. The direct contribution – GVCs' wage effects on different types of workers – reduces wage inequality within countries, while the indirect contribution – through linkages with RTI – increases it. The relative strengths of these contributions differ between countries at different development levels. We show that in countries that primarily receive offshored jobs, GVC participation reduces wage inequality despite widening the gap in RTI between offshorable and non-offshorable occupations. However, in rich countries that mostly offshore jobs, it widens wage inequality as GVC participation benefits mainly workers in non-offshorable occupations in services.

This paper is structured as follows. Section 2 introduces the data, measurements, and descriptive analysis. Section 3 presents the model and regression results linking GVC participation to worker-level RTI, while section 4 focuses on the relationship between GVC participation and wage inequality. Section 5 concludes and outlines policy implications.

2. Data and descriptive evidence

a. Data and measurement

Our worker-level dataset covers 47 countries at different development levels (Table A4 in the Appendix). Most of the country coverage comes from the OECD's Programme for the International Assessment of Adult Competencies – PIAAC (2019). During three rounds of the study (2011-2012, 2014-2015, and 2017-2018), data were collected in 37 countries. The sample sizes amount to a few thousand 16-65 years old individuals. We complement PIAAC with the Skills Towards Employment and Productivity – STEP (World Bank, 2017) survey data from nine low- and middle-income countries. The STEP data were collected in 2012-2014 among urban residents aged 15-64 and covered a few thousand respondents in each country. We also use the "skill use at work" module of the third wave of the China Urban Labour Survey (CULS, 2017), which directly implemented the STEP questionnaire and ensured comparability with other countries in our sample. The survey collected data from six large cities in China (Guangzhou, Shanghai, Fuzhou, Shenyang, Xian, and Wuhan) and covered about 15,000 individuals.

Following Lewandowski et al. (2022), we create a worker-level task content measure of occupations across countries in the spirit of Acemoglu and Autor (2011). As the STEP surveys are urban surveys, for comparability we omit farmers and skilled agricultural workers (ISCO 6 from the sample in all countries. For methodological details, see Lewandowski et al. (2022). We calculate the worker-level routine task intensity according to the following formula:

$$RTI = \ln(r_{cog}) - \frac{(nr_{analytical} + nr_{personal})}{2} \tag{1}$$

where, r_{cog}, $nr_{analytical}$, $nr_{personal}$ are routine cognitive, non-routine cognitive analytical, and non-routine cognitive personal task levels. Table A1 in Appendix A enlists survey items used to construct these task measures. Particular task measures and RTI are standardized using their mean and standard deviation in the United States.

We use hourly wages in US dollars, adjusted for purchasing power parity, with a 99% winsorization. Wage data are available for 38 of the 47 countries in our sample (Table A4), we adjust the sample accordingly in the wage analysis.[6]

The country-sector level measures of GVC participation are based on the EORA database (Lenzen et al., 2012, 2013) and computed following the methodology of Borin & Mancini (2015, 2019). In particular, we use both backward and forward GVC participation measures. Both quantify value-added flows that cross at least two country borders. Backward GVC participation measures the share of imported inputs used in export production (% of total exports). Forward GVC participation captures the share of domestic value added embodied in a country's bilateral partners' exports (% of total exports).[7]

Finally, we follow Blinder & Krueger, 2013), dividing occupations into offshorable and non-offshorable. We assign occupations to groups starting at the 4-digit ISCO-08 level, depending on data availability. Most of the countries report occupations using 3- and 4-digit ISCO-08 codes. For clarity, Table A3 in Appendix A lists occupations with assigned offshorability groups (at the 2-digit ISCO level).

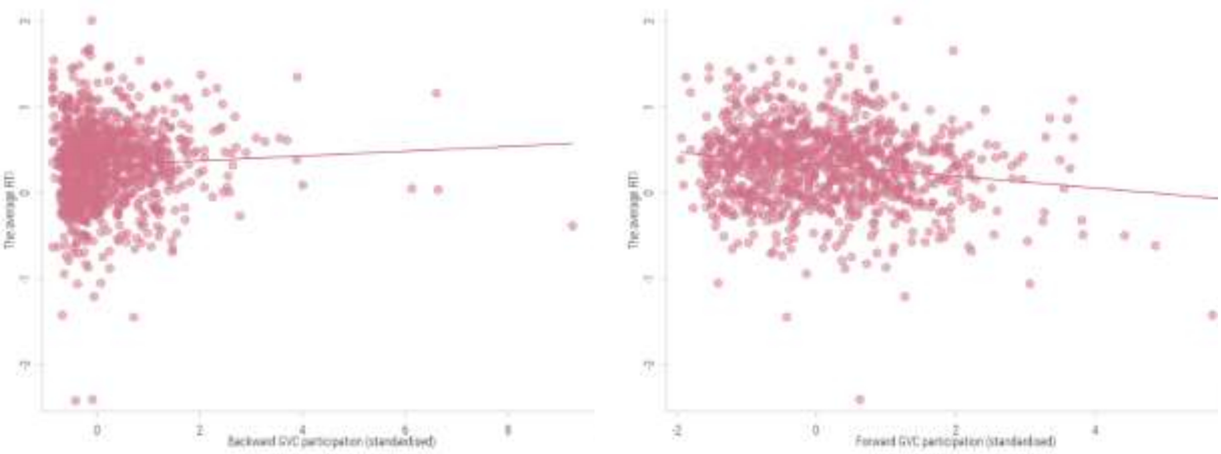
[6] We use the full sample of 47 countries in the first part of the analysis to maximize variation across countries.
[7] This measure avoids a double-counting problem prevalent in alternative measures of forward GVC participation.

b. Descriptive analysis

In the first step, we visually explore the relationship between GVC participation and RTI at the country-sector level. There is no correlation between backward GVC participation (9%, insignificant, left panel of Figure 2) and the average RTI. Similarly, the scatterplot suggests only a moderate correlation with forward GVC participation which is negative (-17%, right panel of Figure 2). The definition of GVC participation does not specify the type of value-added crossing borders – ranging from low (e.g., raw materials) to high high-value-added tasks (World Bank, 2020). These weak relationships could thus mask heterogeneity across types of countries, sectors and occupations.

Figure 2. The correlation between backward and forward GVC participation and the average routine task intensity (RTI), by country and sector.

Backward GVC participation | Forward GVC participation



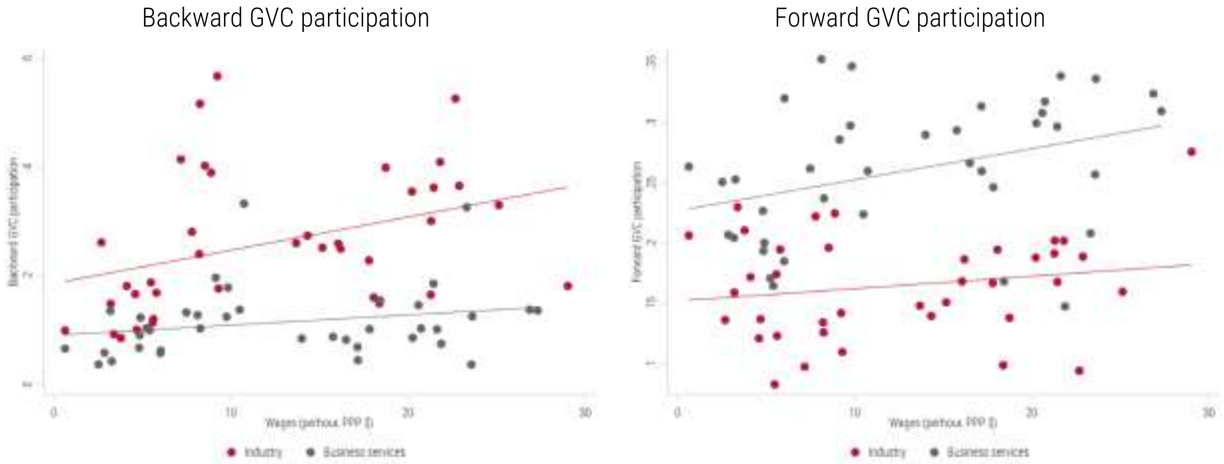
Note: for each task content, the 0 is set at the United States average value and 1 corresponds to one standard deviation of this particular task content value in the United States. GDP per capita in PPP, current international $, country averages for 2011–2016. Source: Authors' calculations based PIAAC, STEP, CULS (tasks), World Bank (GDP), and EORA (GVC) data.

In the second step, we relate GVC participation to average wages at the country-sector level, differentiating between the industrial and business services sectors. Overall, backward and forward GVCs participation measures positively correlate with average hourly wages at the country-sector level (Figure 3), suggesting positive productivity spillovers from firms participating in GVCs for workers. In the case of backward GVC participation, the correlation with wages in the industrial sector (37%) is stronger relative to the business services sector[8] (23%, Figure 3, left panel). It is in line with the intuition that high backward GVC participation in the industrial sector (driven mainly by manufacturing sectors) is associated with assembly tasks of specialized sectors where hourly wages can be expected to be higher (think of, e.g., technicians in the automotive sector). There is, however, high dispersion, because high backward GVC participation can characterize low-wage countries specialized in limited manufacturing GVCs, but also richer countries specialized in more sophisticated GVCs

In the case of forward GVC participation, the opposite finding holds. The correlation with average hourly wages in the business services sector (36%) is higher than in the industrial sector (18%, Figure 3, right panel). High forward GVC participation in business services is associated with high-value-added tasks such as product design or R&D, which earn higher hourly wages. The high dispersion again suggests that high forward GVC participation is associated with lower-wage commodity exporters and innovative countries.

[8] Retail and wholesale trade, accommodation, food service, transportation, storage, information and communication, financial, real estate, professional and administrative service activities (G-N ISIC rev. 4 sections).

Figure 3. The correlation between backward and forward GVC participation and hourly wages, by country and broad sector.



Note: Hourly wages are in PPP US $, top 1% of earners are excluded. Average wages are weighted with sectors' output.
Source: Authors' calculations based PIAAC, STEP and EORA (GVC) data.

3. Global value chain participation and routine task intensity

a. Econometric model

The econometric model quantifies the relationship between GVC participation and the average RTI of workers and exploits variation between countries within sectors (especially within manufacturing). It broadly follows the specification of Lewandowski et al. (2022). In particular, we estimate pooled OLS regressions of the following form:

$$RTI_{ijsc} = \beta_0 + \beta_1 G_{sc} + \beta_2 Z_{sc} + \beta_3 X_{ijsc} + \lambda_s + \epsilon_{ijsc} \quad (2)$$

where RTI_{ijsc} is the RTI of individual i in occupation j in sector s in country c; G_{sc} measures GVC participation in sector s in country c; Z_{sc} captures technology in sector s in country c; X_{ijsc} are individual skills of worker i in occupation j in sector s in country c; and λ_s are sector fixed effects.

We use measures of backward and forward GVC participation in sector s and country c. The measures are standardized within the sample to allow for interpretation regarding their relative economic magnitudes. Importantly, these measures vary between narrowly defined sub-sectors within manufacturing. Additionally, we control for foreign direct investment (FDI) as a share of GDP to capture globalization more broadly.

To capture technology, we use the share of workers in sector s and country c who use computers at work. These measures are based on the PIAAC and STEP survey questions about a worker's personal computer use. We aggregate this worker-level information to the sector level to address potential endogeneity concerns, as the performance of particular tasks may require computers. We include a quadratic term, allowing for possible non-linear linkages between computer use and the RTI. We also include sector-level fixed effects (18 sectors of 1-digit International Standard Industrial Classification, ISIC rev. 4) and their interactions with a country's GDP per capita (log, demeaned) to control for structural differences between countries.

To control for individual characteristics and skill levels, we include variables for age (10-year age groups), gender, education level (primary, secondary, tertiary), and a test-based measure of literacy skills (four proficiency levels). The literacy test comprehensively quantifies individuals' skills to understand, evaluate, use, and engage with written texts in personal, work-related, societal, and educational contexts (PIAAC Literacy Expert Group, 2009).

We estimate the regression for all workers, and two main subsamples: workers in offshorable and non-offshorable occupations. We apply the allocation proposed by Blinder and Krueger (2013), see Table A3 in Appendix A for details. In all worker-level regressions, standard errors are clustered at the country-sector level.

b. Pooled sample regression results

We start by regressing worker-level RTI against backward and forward GVC participation at the country-sector level and a set of controls (see econometric model, 2) in the pooled sample of 47 countries. Overall, we find no correlation between backward GVC participation and the average RTI, while a higher forward GVC participation is associated with a higher RTI of workers. The latter correlation decreases with rising development levels, as indicated by the negative interaction term between GVC participation and GDP per capita (Table 1, column 1). These findings confirm our intuition: workers in higher-income countries perform fewer routine-intensive tasks. Hence, a higher forward GVC participation in such country settings captures higher value-added tasks such as R&D rather than repetitive upstream tasks as would be the case in commodity-exporting countries.

However, the relationship between GVC participation and the RTI of workers may differ between types of occupations. To shed light on this hypothesis, we divide the sample into offshorable and non-offshorable occupations, using the preferred classification proposed by Blinder and Krueger (2013). In line with our assumption, the correlation between these occupational groups differs. We find no correlation between GVC participation and RTI among workers performing non-offshorable occupations (Table 1, column 2). However, among workers in occupations classified as offshorable, higher backward and forward GVC participation is linked with a higher average RTI (Table 1, Columns 2 and 3).

As backward and forward GVC participation measures are standardized within the sample, the larger (in absolute terms) coefficient of backward GVC participation suggests this variable's relatively greater importance relative to forward GVC participation.[9] The worker-level RTI is standardized with the United States mean and standard deviation, to provide a reference point and comparability with the widely used (Acemoglu & Autor, 2011) RTI measure based on the US O*NET data. The interpretation would be the following. An increase in backward (forward, resp.) GVC participation by one standard deviation is associated with a rise in worker-level RTI by 0.079 (0.053, resp.) the US standard deviations.

The negative interaction terms with GDP per capita for both GVC measures imply that the relationship between GVC participation and RTI weakens with countries' development levels. We provided the rationale for this finding in the case of forward GVC participation under the overall findings in the previous paragraph. Similarly, higher backward GVC participation in high-income countries captures more high-value added worker tasks – even in the assembly stage – while in lower-income countries, those tasks tend to be more repetitive (think of technician operating machines in the former versus assembly line workers in the latter). For example, in Ecuador (relatively low GDP per capita, about 1 log point below the sample average), one standard deviation higher backward GVC participation among workers performing offshorable occupations is associated with RTI higher by 0.133. In contrast, in Canada (relatively high GDP per capita, about 1 log point above the sample average), it is associated with RTI higher by only 0.025. Considering that backward GVC participation in both countries is

[9] As a robustness check, we run models for backward and forward GVC participation measures separately, rather than combining them in one joint regression, and obtain similar results (Table 1A, Panel A in Appendix A).

at a similar level (12-14%), the positive association between backward GVC participation and the RTI is stronger in Ecuador, due to the interaction term with GDP per capita.

Table 1. The relationship between GVC participation and RTI, total and by occupation type, standardized

Dependent variable: worker level RTI	(1) All workers	(2) Non-offshorable	(3) Offshorable
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.004	-0.016	0.079***
	(0.019)	(0.020)	(0.024)
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.017	0.027	-0.054*
	(0.029)	(0.030)	(0.032)
Forward Global Value Chain participation (GVCF) share in exports (std.)	0.019*	0.011	0.053***
	(0.010)	(0.011)	(0.014)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.060***	-0.059***	-0.074***
	(0.012)	(0.013)	(0.017)
Ln(GDP per capita) –mean(Ln(GDP per capita))	0.033	0.041	-0.014
	(0.038)	(0.038)	(0.060)
Observations	167,034	144,914	22,120

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The standard errors are clustered at a sector × country level. Measures for GVCB share and GVCF share are standardized. All regressions include controls for technology (computer use, computer use squared), FDI, skills, education, age, gender, sector FE, and sector FE interacted with GDP per capita.
Source: Authors' calculations based on PIAAC, STEP, CULS (tasks), World Bank (GDP), EORA data and Borin and Mancini (2015, 2019) (GVC participation measures).

c. Sector-specific regression results

Next, we study differences between broad sectors by estimating regressions for specific subsamples. We distinguish three broad sectors – industry (B-F ISIC rev. 4 sections), business services (G-N ISIC rev. 4 sections), and other services (O-S ISIC rev. 4 sections). For details, see Table A2 in Appendix A.

For the industrial sector, we find no correlation between backward GVC participation and RTI. In contrast, a higher forward GVC participation is linked to more routine tasks, although decreasing with development level (Table 2, Panel A, column 1). We also find no correlation between backward and forward GVC participation and the RTI among non-offshorable occupations (Table 2, Panel A, column 2). Both these patterns are consistent with the overall results for all sectors (Table 1). However, in the case of offshorable occupations, the higher the backward GVC participation is in a country and sector, the higher the workers' RTI (Table 2, Panel A, Column 3). We also find a positive association between forward GVC participation and RTI among workers in offshorable occupations (Table 2, panel B, column 3), again confirming the pooled sample's results (Table 1).

However, a negative interaction term of GVC participation with GDP per capita in industrial sectors suggests that the development level counterbalances this relationship. In contrast to the overall results (Table 1), this interaction term is insignificant for backward GVC participation. Hence, workers in industrial sectors and countries specialized in smaller segments of GVC (e.g., assemblers of final products) tend to perform more routine-intensive tasks. For forward GVC participation, the interaction term with GDP per capita is negative and significant, in line with the overall results (Table 1). In countries with GDP per capita twice the average in our sample (comparable to the United States), the interaction term offsets the coefficient of forward GVC participation, so the overall association with RTI is 0.[10] Our findings align with the literature: manufacturing of

[10] We obtain similar results for manufacturing (ISIC rev. 4 section C) rather than industry – results are available upon request.

low-value-added, basic intermediates that require more routine-intensive work tends to be outsourced to less developed countries (factory economies), while the production of non-routine tasks remains in countries at higher development levels (Baldwin, 2013).

Table 2. The relationship between GVC participation and RTI, total and by sector and occupation type, standardized

Dependent variable: worker-level RTI	(1)	(2)	(3)
Panel A: Industry	All workers	Non-offshorable	Offshorable
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.027	-0.007	0.092***
	(0.024)	(0.027)	(0.029)
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.004	0.018	-0.021
	(0.032)	(0.036)	(0.040)
Forward Global Value Chain participation (GVCF) share in exports (std.)	0.030**	0.008	0.062***
	(0.015)	(0.018)	(0.019)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.043***	-0.030	-0.079***
	(0.017)	(0.020)	(0.023)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.096	0.006	-0.304***
	(0.066)	(0.081)	(0.103)
Observations	38,917	28,790	10,127
Panel B: Business services			
Backward Global Value Chain participation (GVCB) share in exports (std.)	-0.055**	-0.056**	-0.002
	(0.024)	(0.027)	(0.044)
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.063*	0.083**	-0.080*
	(0.037)	(0.039)	(0.047)
Forward Global Value Chain participation (GVCF) share in exports (std.)	-0.015	-0.020	0.019
	(0.016)	(0.017)	(0.024)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.046***	-0.043**	-0.064**
	(0.017)	(0.017)	(0.029)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.027	-0.017	-0.067
	(0.049)	(0.049)	(0.078)
Observations	71,979	63,003	8,976
Panel C: Other services			
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.220***	0.206***	0.396***
	(0.079)	(0.079)	(0.152)
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.329***	-0.326***	-0.400
	(0.114)	(0.114)	(0.257)
Forward Global Value Chain participation (GVCF) share in exports (std.)	0.029	0.023	0.116**
	(0.023)	(0.023)	(0.057)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.073**	-0.077**	0.013
	(0.032)	(0.032)	(0.064)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.210***	-0.126*	-0.129
	(0.076)	(0.074)	(0.180)
Observations	50,843	48,133	2,710

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The standard errors are clustered at a sector × country level. Measures for GVCB share and GVCF share are standardized. All regressions include controls for technology (computer use, computer use squared), FDI, skills, education, age, gender, sector FE, and sector FE interacted with GDP per capita.
Source: Authors' calculations based on PIAAC, STEP, CULS (tasks), World Bank (GDP), EORA data and Borin and Mancini (2015, 2019) (GVC participation measures).

In business services, we find a negative association between backward GVC participation and workers' RTI (Table 2, Panel B, column 1). Due to the positive interaction term with GDP per capita, this effect is weaker in countries at higher development levels: it disappears in countries with GDP per capita twice the sample average, comparable to the United States, and becomes positive in countries with even higher GDP per capita (e.g., Norway). In contrast to the overall sample (Table 1), these results are driven by non-offshorable occupations, whereas the coefficients among offshorable occupations are insignificant (Table 2, Panel B, columns 2 and 3). This could reflect that services are less tradeable than manufactured goods and involve more occupations that cannot be offshored (e.g., truck drivers, see also the list of occupations by offshorability in Table A3).

In other services – much less integrated into GVCs than the other two broad sectors[11] – higher backward GVC participation correlates with higher worker-level RTI (Table 2, Panel C, column 1), contrasting the overall sample results (Table 1). The net 'effect' depends on a country's development level. Results for offshorable occupations are similar to the pooled sample: in countries with a GDP per capita lower than 170% of the average in our sample (comparable to Canada or Austria), backward GVC participation is associated with more routine intensive work, and in countries with GDP per capita above this level – with less routine intensive work (Table 2, Panel C, columns 1-2). Similarly, higher forward GVC participation is linked to higher RTI at the worker level (Table 2, Panel C, column 3).

d. Robustness check: Occupation by skill intensity

As a robustness check for differences between occupational groups, we re-estimate the regressions of Section c. We focus on occupational groups by their skill levels rather than between offshorable and non-offshorable occupations. We distinguish between by high-skilled (managers, professionals, technicians – ISCO 1-3), medium-skilled (clerical workers, sales and services workers – ISCO 4-5) and low-skilled (craft and related trades workers, plant and machine operators, elementary occupations – ISCO 7-9) occupations. This classification of occupations follows the standard typology of the International Labour Organisation, and was used by Lewandowski et al. (2022). These occupational groups perform tasks with different routine intensities. On average, workers in high-skilled occupations perform relatively non-routine tasks, workers in middle-skilled occupations moderately routine-intensive tasks, and workers in low-skilled occupations more routine-intensive tasks.

Results for high-skilled occupations somewhat resemble those for non-offshorable occupations, while results for medium- and low-skilled occupations resemble those for offshorable occupations (see Table B2 in Appendix B). Importantly, we observe almost identical patterns in correlations between GVC participation and RTI for specific sectors. It confirms that distinguishing between industries is crucial for studying the relationship between GVC participation and labor market outcomes. Our results suggest that the relationship between GVC participation and RTI differs substantially between the industrial and business services sectors. In the industrial sector, higher GVC participation is associated with more routine intensive work in offshorable occupations that usually demand low to medium levels of skills. In business services, it is associated with less routine intensive work in non-offshorable occupations, which often require higher skills.

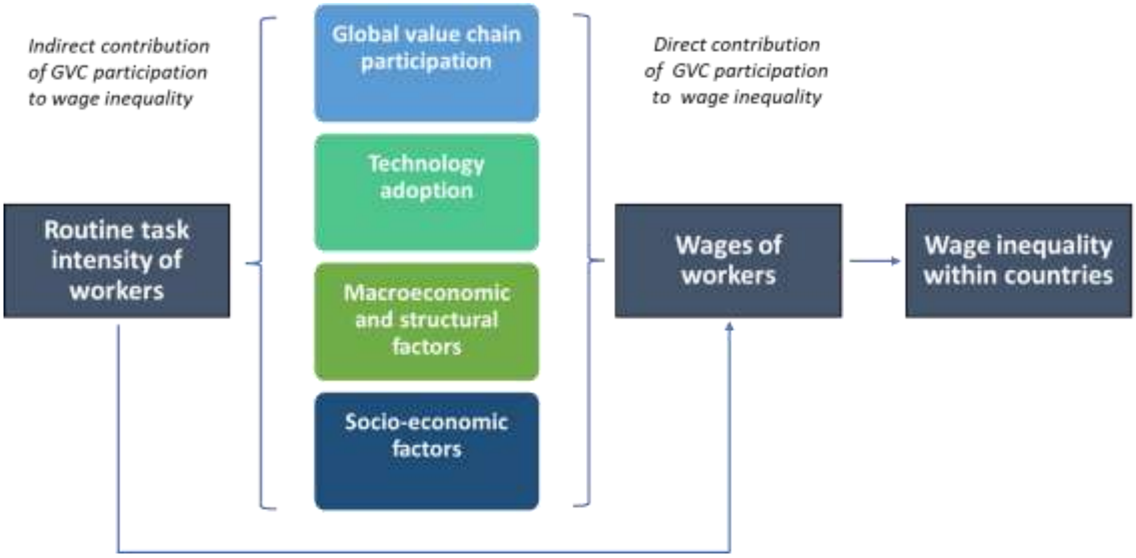
[11] On average, backward GVC participation in other services is 17.4 pp lower than in industry, and forward GVC participation is 3.3 pp lower (differences estimated as broad sector fixed effects in regressions on GVC participation measures, controlling also for country fixed effects).

4. Global value chain participation and wage inequality within countries

a. Econometric model and decomposition method

As a higher RTI is negatively correlated with earnings, both at the occupation and worker level (Autor & Handel, 2013; de la Rica et al., 2020), GVC participation may widen wage inequality between workers in offshorable occupations and those in non-offshorable occupations. In this section, we study the contribution of GVC participation to wage inequality within countries. We distinguish between two channels: (1) the direct contribution of GVC participation to individual wages, and (2) the indirect contribution of GVC participation through its relationship with workers' RTI. We calculate the Gini coefficient to quantify the relationship between GVC participation and inequality. The diagram in Figure 3 exemplifies our reasoning. Our analysis includes four steps.

Figure 4. Diagram of wage inequality analysis.



Source: Own elaboration.

In the first step, we divide our sample into six subsamples by broad sector of employment (industry, business services and other services) and occupation (offshorable and non-offshorable), as introduced in section 3. For each subsample, we estimate the following Mincerian wage regression:

$$w_{ijsc} = \beta_0 + \beta_1 G_{sc} + \beta_2 Z_{sc} + \beta_3 X_{ijsc} + \beta_3 RTI_{ijsc} + \lambda_j + \epsilon_{ijsc} \tag{3}$$

where, w_{ijsc} is the wage of individual i in occupation j in sector s in country c; while the rest of the notation follows equation (2). Our key variable of interest in the wage regression is worker-level RTI. Based on the estimated coefficients for each right-hand side variable, we predict wages for workers in each of the six subpopulations. For each country, we then calculate the Gini coefficient, our *baseline scenario*. Appendix A gives a more detailed description, including formulas for the underlying methodology, which we outline below.

In the second step, we assess the direct contribution of GVC participation to wage inequality. We assume a second *scenario of no GVC participation* and calculate predicted wages conditional on GVC participation values in equation (3) equal to zero (i.e., $G_{sc} = 0$) for each of the six subsamples. Then, we re-calculate the Gini coefficient of predicted wages for each country in this second scenario. We define the direct contribution of GVC participation to within-country wage inequality as the difference between the Gini coefficient of wages calculated in the baseline scenario and the Gini coefficient of wages obtained in the scenario of no GVC participation.

In the third step, we analyze the indirect contribution of GVC participation to wage inequality, through its relationship with workers' RTI. Specifically, we use the estimated coefficients for the six sub-samples following equation (2) to predict worker-level RTI, now assuming GVC participation values equal to zero. In other words, we compute counterfactual workers' RTI in the economy under the scenario of no GVC integration. We then use the estimated models for the six sub-samples following equation (3) to predict wages, conditional on these new counterfactual RTI values. To isolate the indirect contribution of GVC participation to wages through its relationship with workers' RTI, we use the observed values of GVC participation in this wage model (rather than setting their values to zero), which is the *counterfactual RTI scenario*. We define the indirect contribution of GVC participation to wage inequality as a difference between the Gini coefficient of wages calculated in the baseline scenario and the Gini coefficient of wages obtained in the counterfactual scenario.

In the fourth step, we calculate the *total* contribution of GVC participation to wage inequality. We set the GVC participation values in equation (3) to zero (as in the calculation of the direct contribution), and we use the counterfactual RTI conditional on no GVC participation (as in the calculation of the indirect contribution) to calculate wages using the original coefficients estimated in the six models. We identify the total contribution of GVC participation to wage inequality as the difference between the Gini coefficient of wages in the baseline scenario and the Gini coefficients of wages in this last scenario.

Importantly, we estimate equations (2) and (3) for six sub-samples for different combinations of broad sectors (industry, business services and other services) and occupation types (offshorable and non-offshorable) to capture the likely different contributions of GVC participation in these worker subgroups. The relationship between GVC participation, RTI and wages may differ between the industrial and services sectors, as products created in the industrial sector are more tradeable and easier to fragment, especially in manufacturing. Also, offshorable occupations may be more vulnerable to wage adjustments than non-offshorable occupations.

b. Sector-specific regression results

In this subsection, we explore the contribution of GVC participation to within-country wage inequality, distinguishing between its direct and indirect contributions through workers' RTI. Our approach likely provides an upper bound, as we use cross-sectional regression that describes the equilibrium allocation of tasks and wages across workers in different countries. GVC participation may be partly endogenous to comparative advantage in tasks and pre-existing wage-level differences. For this reason, we focus on the contribution of GVC participation to within-country wage inequality rather than cross-country differences in wage levels. Moreover, only a small share of cross-country differences in RTI can be attributed to globalization, as differences in technology use and skill supply play a much larger role (Lewandowski et al., 2022).

We first estimate the relationship between RTI and individual-level wages in Mincerian wage regressions (equation 3), for each of the six subpopulations by broad sector and occupation type (Table 3). The regression results consistently show a significant and negative association between workers' RTI and wages, in all types of occupations and sectors; that is, more routine intensive tasks tend to pay lower wages. The magnitude is the largest among offshorable occupations in business services, suggesting a particularly strong wage penalty for performing routine tasks in this sector (column 4). The wage penalty for more routine tasks is the second largest among offshorable occupations in industrial sectors (column 2). It is smaller in non-offshorable occupations in the industrial (column 1) and business services (column 3) sectors, but not in other services (columns 5 and 6).

Table 3. The relationship between RTI, GVC participation, and wages, by sector and occupation type, standardized

Dependent variable: worker-level wages	Industry		Business services		Other services	
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-offshorable	Offshorable	Non-offshorable	Offshorable	Non-offshorable	Offshorable
Routine Task Intensity (RTI, std)	-1.646***	-1.704***	-1.593***	-2.116***	-1.514***	-1.206***
	(0.147)	(0.206)	(0.109)	(0.238)	(0.101)	(0.247)
Backward GVC participation (GVCB) share in exports (std.)	0.134	0.141	0.394**	-0.589*	0.712	0.089
	(0.165)	(0.167)	(0.186)	(0.300)	(0.558)	(0.913)
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.084	0.045	0.127	-0.196	0.519	1.182**
	(0.059)	(0.074)	(0.080)	(0.133)	(0.391)	(0.552)
Forward GVC participation (GVCF) share in exports (std.)	0.404***	-0.146	0.761***	0.123	-0.010	0.595
	(0.147)	(0.100)	(0.140)	(0.193)	(0.371)	(0.516)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.265***	-0.002	0.338***	-0.165	-0.166	-1.109***
	(0.058)	(0.047)	(0.077)	(0.129)	(0.161)	(0.231)
Ln(GDP per capita) – mean(Ln(GDP per capita))	0.268*	0.440**	-0.017	0.446**	0.198	-0.061
	(0.157)	(0.205)	(0.106)	(0.195)	(0.668)	(0.717)
Observations	18,647	7,600	38,659	6,714	31,523	2,091

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The standard errors are clustered at a sector × country level. Measures for GVCB share and GVCF share are standardized. All regressions include controls for technology (computer use, computer use squared), skills, education, age, gender, sector FE, and country FE. The wage data for Canada, China, Hungary, Macedonia (FYROM), Peru, Serbia, Singapore, Sweden, and Türkiye are unavailable; therefore, these countries are excluded from the sample.
Source: Authors' calculations based on PIAAC, STEP, CULS (tasks), World Bank (GDP), EORA data, and Borin and Mancini (2015, 2019) (GVC participation measures).

At the same time, the relationship between GVC participation and wages is significant only in some types of occupations and sectors. First, higher forward GVC participation is associated with higher wages among workers in non-offshorable occupations in the industrial and business services sectors. This could indicate high value-added tasks such as R&D upstream in GVCs which are more difficult to offshore and thus pay high wages. Second, more backward GVC participation is associated with higher wages only in business services – positively in non-offshorable occupations, and negatively in offshorable occupations.

Due to the unavailability of wage data, we had to exclude Canada, China, Hungary, Macedonia (FYROM), Peru, Serbia, Singapore, Sweden and Türkiye from the previous analysis. Table 4 thus replicates the results of Table 2 for the reduced country sample when assessing the relationship between GVC participation and RTI. The estimated coefficients shown in Tables 2 and 4 differ slightly. Still, the findings are the same: more backward and forward GVC participation are associated with higher RTI among workers in offshorable occupations in the industrial sector, especially for countries at the average development level in our sample, but with a lower RTI among workers in non-offshorable occupations in business services (Table 4).

Table 4. The relationship between GVC participation and RTI, by sector and occupation type, standardized

Dependent variable: worker-level RTI	Industry		Business services		Other services	
	(1)	(2)	(3)	(4)	(5)	(6)
	Non-offshorable	Offshorable	Non-offshorable	Offshorable	Non-offshorable	Offshorable
Backward GVC participation (GVCB) share in exports (std.)	-0.004	0.074***	-0.038*	0.041	0.204***	0.353***
	(0.025)	(0.024)	(0.021)	(0.032)	(0.049)	(0.099)
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.009	-0.014	0.078***	-0.030	-0.221***	-0.259
	(0.030)	(0.031)	(0.026)	(0.031)	(0.080)	(0.199)
Forward GVC participation (GVCF) share in exports (std.)	-0.002	0.092***	-0.015	0.044*	-0.057*	0.107
	(0.019)	(0.018)	(0.018)	(0.024)	(0.032)	(0.071)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.026	-0.080***	-0.039**	-0.083***	0.039	0.074
	(0.020)	(0.021)	(0.017)	(0.028)	(0.039)	(0.079)
Ln(GDP per capita) − mean(Ln(GDP per capita))	-0.124**	-0.139	0.017	-0.010	-0.037	-0.065
	(0.060)	(0.125)	(0.052)	(0.075)	(0.096)	(0.138)
Observations	21,023	8,364	44,351	7,578	34,540	2,326

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The standard errors are clustered at a sector × country level. Measures for GVCB share and GVCF share are standardized. All regressions include controls for technology (computer use, computer use squared), FDI, skills, education, age, gender, sector FE, and sector FE interacted with GDP per capita. The specification follows that in Table 2, but for consistency with Table 3, Canada, China, Hungary, Macedonia (FYROM), Peru, Serbia, Singapore, Sweden, and Türkiye (for which wage data are not available) are excluded.
Source: Authors' calculations based on PIAAC, STEP, CULS (tasks), World Bank (GDP), EORA data. and Borin and Mancini (2015, 2019) (GVC participation measures).

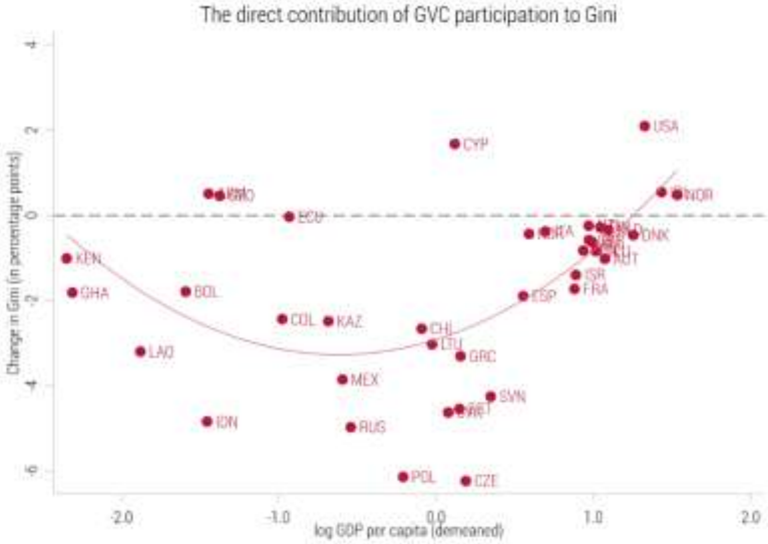
c. Quantifying the direct and indirect contribution of GVC participation to wage inequality

In this subsection, we use the estimated models to quantify the contribution of GVC participation to wage inequality in the reduced country sample of 38 countries, both directly and indirectly. We find that the direct contribution of GVC participation to wage inequality is negative in most countries (Figure 5a). In other words, higher GVC participation is linked to reduced wage inequality within countries. Some notable exceptions include the US and small countries intensively integrated into GVC, such as Ireland (high backward GVC participation) or Norway (high forward GVC participation). The results suggest a U-shaped relationship between GDP per capita and the direct contribution of GVC participation to wage inequality (Figure 5a). That is, the reduction in wage inequality is the strongest in upper-middle-income and bottom-high-income countries, but the smallest in low-income countries (which are weakly integrated into GVCs) and high-income countries. The Mincerian wage regressions suggest that the direct contribution reflects the positive role of forward GVCs for workers' wages in non-offshorable occupations in the industrial and business services sectors (Table 3).

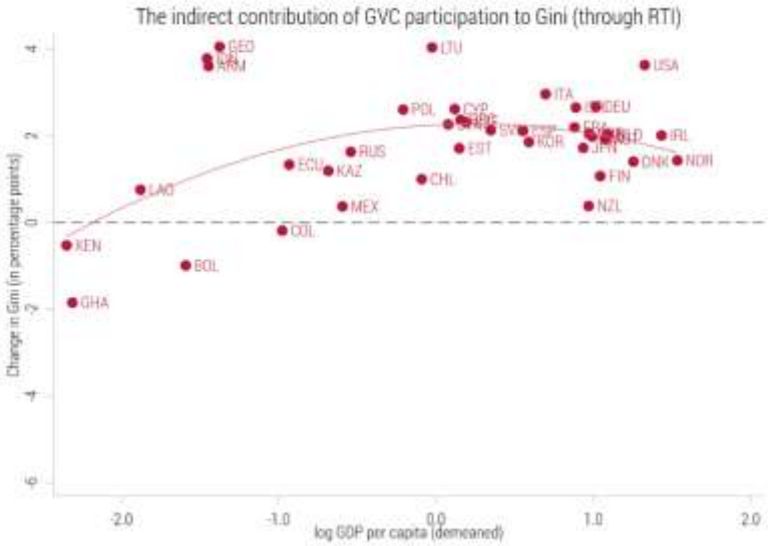
In sharp contrast, the indirect contribution of GVC participation to wages through its link with workers' RTI widens wage inequality in most countries (Figure 5b). Contrasting relationships between GVC participation and RTI among different groups of workers drive this pattern. The Mincerian wage regressions suggest a negative relationship between the RTI of workers and individual wages in all sectors and occupation types (Table 3). So, a higher GVC integration is associated with wider within-country wage inequality through larger RTI gaps between workers in offshorable and non-offshorable occupations in different sectors. In most countries, the indirect contribution is smaller in absolute terms than the direct contribution.

Figure 4. The contribution of GVC participation to within-country wage inequality

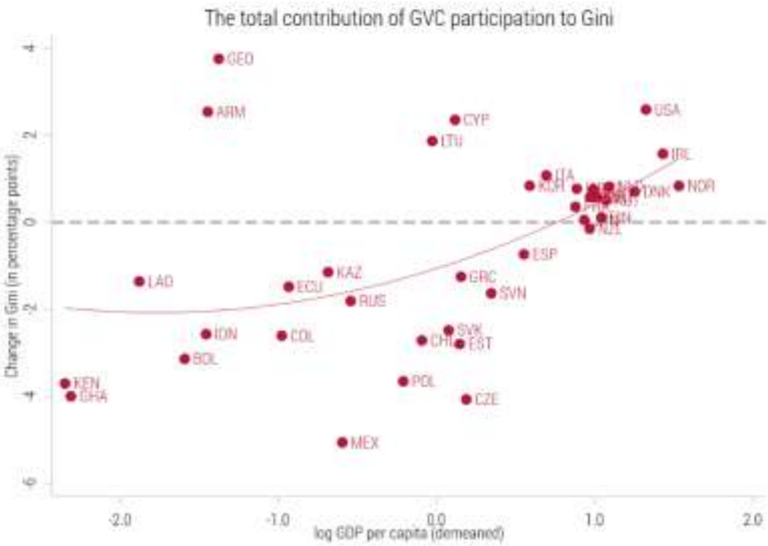
a)



b)



c)



Source: Authors' calculations based on PIAAC, STEP, CULS (tasks), EORA data and Borin and Mancini (2015, 2019) (GVC participation measures).

Finally, we combine the direct and indirect channels to assess the total (net) contribution of GVC participation to wage inequality within countries (Figure 5c).[12] We find that GVC participation is linked to higher wage inequality in the top high-income countries, such as the US and Ireland, which in most cases is driven by the indirect contribution of GVCs through its links with worker RTI. At the same time, GVC participation is associated with reduced wage inequality in most low- and middle-income countries (in particular Kenya and Ghana, but also Mexico), as well as the bottom high-income countries (Central Eastern and Southern Europe, in particular, Czechia and Poland) where the direct reduction in wage inequality is stronger than the indirect contribution.

The findings can be interpreted as follows. Our results suggest that in countries that mostly receive offshored jobs, GVC participation reduces wage inequality, despite widening the gap in the RTI of work between offshorable and non-offshorable occupations. However, in rich countries that mostly offshore jobs, GVC participation widens wage inequality as it benefits mainly workers in non-offshorable occupations in services.[13]

5. Conclusions and policy implications

In this paper, we investigated the relationship between GVC participation and the RTI of workers and its contribution to within-country wage inequality. We used a unique dataset combining worker-level, country-specific RTI measures based on a pooled sample of survey data for 47 (38, resp.) countries at all development levels, applying the methodology of Lewandowski et al. (2022), with measures of backward and forward GVC participation at the country-sector level based on the method of Borin and Mancini (2019, 2015). We find that the relationship between GVC participation and the RTI of workers is complex and depends on the nature of GVCs, occupations and sectors. This study also finds that GVC participation contributes to wage inequality within countries directly and indirectly through its relationship with workers' RTI.

First, we found that the relationship between GVC participation and RTI differs between types of GVC participation: higher forward GVC participation correlates with more RTI of workers, while higher backward GVC participation does not. Importantly, these associations differ across occupational groups. In countries and sectors with higher GVC participation of either type, workers in offshorable occupations perform more routine-intensive work, with weaker associations for higher-income countries. At the same time, we find no such results among workers in non-offshorable occupations.

Second, the industrial sector, which produces primarily tradable goods, follows this general pattern, whereas business services, which are tradable to a lesser extent, do not. Higher backward GVC participation is associated with less routine-intensive tasks in business services, especially among workers in non-offshorable

[12] As the Gini coefficient is a non-linear measure, the sum of Gini coefficients with two separate shocks (direct and indirect effect) does not necessarily equal the Gini coefficient simulated with the same two shocks jointly (total effect). The residual, however, is relatively small compared to the total contribution (see Figure B1 in Appendix A).

[13] Our approach may raise the question if the RTI and wage regressions can be estimated separately. We use seemingly unrelated regression (SUR) to test the validity of our results. We find that separate estimation is correct. First, we find no correlation between the residuals from RTI and wage models, suggesting that they are unrelated. Additionally, we confirm that error terms have fairly symmetric distributions required for the estimator to be unbiased in small samples. Second, the point estimates are consistent with those obtained from separate estimations. Minor differences occur due to slight differences in the estimation sample. Some individuals do not report their wages, resulting in slightly smaller sample sizes than RTI models (see Tables 3 and 4). The SUR approach requires samples of both models to be equal, so the RTI sample must be reduced to a wage sample. The SUR estimates are available upon request.

occupations, but with more routine-intensive tasks in other services. Focusing on the skill content of occupations as a robustness check shows that results for high-skilled occupations somewhat resemble those for non-offshorable occupations. In contrast, results for medium- and low-skilled occupations resemble those for offshorable occupations.

Third, we studied the contribution of GVC participation to within-country wage inequality: direct and indirect through its relationship with the workers' RTI. GVC participation is associated with larger wage inequality in most high-income countries, but with reduced wage inequality in most low- and middle-income countries. Its indirect contribution to wage inequality – widening the gap between the RTI of workers in offshorable occupations in the industrial sector and workers in non-offshorable occupations in business services sectors – is a crucial mechanism.

Understanding the differences in the RTI of workers across the development spectrum and its relationship with fundamental factors – technology adoption, skill supply, and globalization – has important policy implications. The transition from routine to non-routine work has been a key dimension of structural change in labor markets, increasing worker productivity and earnings. Jobs with a higher non-routine content involve higher levels of technology, require higher skill levels, and offer higher earnings between and within occupations (Autor & Handel, 2013; de la Rica et al., 2020). Diverging effects of globalization on the RTI of different types of workers can thus contribute to wage inequality within countries.

At the same time, cross-country differences in RTI, especially between high- versus low- and middle-income countries, are larger than implied by mere cross-country differences in skills supply, as they can be mainly attributed to differences in technology use (Lewandowski et al., 2022). Investments in education and skills in developing and emerging economies are frequently cited as necessary conditions to foster shared prosperity (World Bank, 2019). They are also often highlighted to counter the adverse labor market effects of increased technology adoption in developing countries. The mediating role of worker skills becomes even more urgent amid rapid advances in artificial intelligence, such as recent developments of Chat-GPT and GPT-4. While they are most likely required to achieve these goals, they are unlikely to be sufficient, given that differences in job task content are largely related to differences in technology use and participation in GVCs. In any case, policies to increase technology use and approaches to facilitate upgrading in GVCs should complement investments in skills, especially since technological change within GVCs tends to increase the relative demand for non-routine work (Reijnders & de Vries, 2018).

Our study has limitations. First, it does not claim to have determined a causal effect. Since the survey data were collected once per country, only cross-sectional analysis is possible. The analysis therefore cannot capture wage changes over time or cases where GVC participation created new labor market segments that did not exist before. In the future, the second round of PIAAC data collection will allow running a quasi-panel study to study the relationship between changes in GVC participation, technology use, and the supply of skills, with the RTI of particular occupations in various countries. Second, the survey data do not distinguish between domestic and foreign-owned firms, so it is unclear if FDI correlates with RTI differences within sectors. Lewandowski et al. (2022) showed that FDI is not a significant factor behind RTI differences between sectors, but there may be a relationship within sectors. Third, adult skill surveys have greatly improved our understanding of skills supply and the quality of education worldwide. It is possible, though, that literacy or numeracy measures are insufficient to fully understand factors behind differences in the nature of work, task content of jobs, and productivity. Differences in managerial and interpersonal skills may also contribute to differences in organizing and performing work. These skills are unfortunately not measured in the same survey data that capture worker tasks. Finally, the estimated contribution of technology adoption to worker-level RTI may likely increase in the future. Advances in artificial intelligence may more strongly affect business services tasks, the extent of offshoring, and thus the relationship between GVC participation and RTI.

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Appendix A – Methodological details

a. Measurements and classifications

Table A1. The task items selected to calculate task content measures with the US PIAAC data

Task content	Non-routine cognitive analytical	Non-routine cognitive interpersonal	Routine cognitive	Manual
Task items	Solving problems Reading news (at least once a month) Reading professional journals (at least once a month) Programming (any frequency)	Supervising others Making speeches or giving presentations (any frequency)	Changing order of tasks - reversed (not able) Filling out forms (at least once a month) Making speeches or giving presentations - reversed (never)	Physical tasks
Correlation with O*NET-based measures	0.77	0.72	0.55	0.74

Note: The cut-offs for the "yes" dummy in brackets. For the full wording of questions and definitions of cutoff see Lewandowski et al. (2022). O*NET-based measures are based on Acemoglu and Autor (2011).
Source: Lewandowski et al. (2022).

Table A2. Wide sectors aggregation, ISIC rev. 4/ NACE rev. 2

Section	Tittle	Wide sector
B	Mining and quarrying	Industry
C	Manufacturing:	Industry
	-Food and Beverages	Industry
	-Textiles and Wearing Apparel	Industry
	-Wood and Paper	Industry
	-Petroleum, Chemical and Non-Metallic Mineral Products	Industry
	-Metal Products	Industry
	-Electrical and Machinery	Industry
	-Transport Equipment	Industry
	-Other Manufacturing	Industry
D	Electricity, gas, steam and air conditioning supply	Industry
E	Water supply, sewerage, waste management and remediation activities	Industry
F	Construction	Industry
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	Business services
I	Accommodation and food service activities	Business services
H	Transportation and storage	Business services
J	Information and communication	Business services
K	Financial and insurance activities	Business services
L	Real estate activities	Business services
M	Professional, scientific and technical activities	Business services
N	Administrative and support service activities	Business services
O	Public administration and defense; compulsory social security	Other services
P	Education	Other services
Q	Human health and social work activities	Other services
R	Arts, entertainment and recreation	Other services
S	Other service activities	Other services

Source: Authors' elaboration.

Table A3. Offshorability and task groups allocation by occupations, ISCO08 2-digit

ISCO 08 code	Offshorability	Task group	Title
11	not offshorable	NRCP	Chief Executives, Senior Officials and Legislators
12	not offshorable	NRCP	Administrative and Commercial Managers
13	not offshorable	NRCP	Production and Specialized Services Managers
14	not offshorable	NRCP	Hospitality, Retail and Other Services Managers
21	not offshorable	NRCA	Science and Engineering Professionals
22	not offshorable	NRCA	Health Professionals
23	not offshorable	NRCP	Teaching Professionals
24	not offshorable	NRCA	Business and Administration Professionals
25	offshorable	NRCA	Information and Communications Technology Professionals
26	not offshorable	NRCA	Legal, Social and Cultural Professionals
31	not offshorable	NRCA	Science and Engineering Associate Professionals
32	not offshorable	NRCP	Health Associate Professionals
33	not offshorable	RC	Business and Administration Associate Professionals
34	not offshorable	RC	Legal, Social, Cultural and Related Associate Professionals
35	not offshorable	NRCA	Information and Communications Technicians
41	offshorable	RC	General and Keyboard Clerks
42	not offshorable	RC	Customer Services Clerks
43	offshorable	RC	Numerical and Material Recording Clerks
44	not offshorable	RC	Other Clerical Support Workers
51	not offshorable	NRM	Personal Services Workers
52	not offshorable	RC	Sales Workers
53	not offshorable	NRM	Personal Care Workers
54	not offshorable	NRM	Protective Services Workers
61	not offshorable	NRM	Market-oriented Skilled Agricultural Workers
62	not offshorable	NRM	Market-oriented Skilled Forestry, Fishery and Hunting Workers
63	not offshorable	NRM	Subsistence Farmers, Fishers, Hunters and Gatherers
71	not offshorable	NRM	Building and Related Trades Workers (excluding Electricians)
72	not offshorable	RM	Metal, Machinery and Related Trades Workers
73	offshorable	RM	Handicraft and Printing Workers
74	not offshorable	NRM	Electrical and Electronic Trades Workers
75	not offshorable	RM	Food Processing, Woodworking, Garment and Other Craft and Related Trades Workers
81	offshorable	RM	Stationary Plant and Machine Operators
82	offshorable	RM	Assemblers
83	not offshorable	NRM	Drivers and Mobile Plant Operators
91	not offshorable	NRM	Cleaners and Helpers
92	not offshorable	NRM	Agricultural, Forestry and Fishery Laborers
93	not offshorable	NRM	Laborers in Mining, Construction, Manufacturing and Transport
94	not offshorable	RM	Food Preparation Assistants
95	not offshorable	NRM	Street and Related Sales and Services Workers
96	not offshorable	NRM	Refuse Workers and Other Elementary Workers

Note: NRCA- Non-Routine Cognitive Analytical, NRCP- Non-Routine Cognitive Personal, RC- Routine Cognitive, RM- Routine Manual, NRM- Non-Routine Manual.

Source: own elaboration based on (Acemoglu & Autor, 2011; Blinder & Krueger, 2013).

Table A4. List of countries used in the study

Country name	Country ISO3	Source	Survey year	RTI sample	Wage sample
Armenia	ARM	STEP	2013	yes	yes
Austria	AUT	PIAAC	2012	yes	yes
Belgium	BEL	PIAAC	2012	yes	yes
Bolivia	BOL	STEP	2012	yes	yes
Canada	CAN	PIAAC	2012	yes	no
Chile	CHL	PIAAC	2015	yes	yes
China	CHN	CULS	2016	yes	no
Colombia	COL	STEP	2012	yes	yes
Cyprus	CYP	PIAAC	2012	yes	yes
Czechia	CZE	PIAAC	2012	yes	yes
Denmark	DNK	PIAAC	2012	yes	yes
Ecuador	ECU	PIAAC	2017	yes	yes
Estonia	EST	PIAAC	2012	yes	yes
Finland	FIN	PIAAC	2012	yes	yes
France	FRA	PIAAC	2012	yes	yes
Georgia	GEO	STEP	2013	yes	yes
Germany	DEU	PIAAC	2012	yes	yes
Ghana	GHA	STEP	2013	yes	yes
Greece	GRC	PIAAC	2015	yes	yes
Hungary	HUN	PIAAC	2017	yes	no
Indonesia	IDN	PIAAC	2015	yes	yes
Ireland	IRL	PIAAC	2012	yes	yes
Israel	ISR	PIAAC	2015	yes	yes
Italy	ITA	PIAAC	2012	yes	yes
Japan	JPN	PIAAC	2012	yes	yes
Kazakhstan	KAZ	PIAAC	2017	yes	yes
Kenya	KEN	STEP	2013	yes	yes
Korea, Rep.	KOR	PIAAC	2012	yes	yes
Lao PDR	LAO	STEP	2012	yes	yes
Lithuania	LTU	PIAAC	2015	yes	yes
Macedonia, FYR	MKD	STEP	2013	yes	no
Mexico	MEX	PIAAC	2017	yes	yes
Netherlands	NLD	PIAAC	2012	yes	yes
New Zealand	NZL	PIAAC	2015	yes	yes
Norway	NOR	PIAAC	2012	yes	yes
Peru	PER	PIAAC	2017	yes	no
Poland	POL	PIAAC	2012	yes	yes
Russian Federation	RUS	PIAAC	2012	yes	yes
Serbia	SRB	STEP	2016	yes	no
Singapore	SGP	PIAAC	2015	yes	no
Slovak Republic	SVK	PIAAC	2012	yes	yes
Slovenia	SVN	PIAAC	2015	yes	yes
Spain	ESP	PIAAC	2012	yes	yes
Sweden	SWE	PIAAC	2012	yes	no
Türkiye	TUR	PIAAC	2015	yes	no
United Kingdom	GBR	PIAAC	2012	yes	yes
United States	USA	PIAAC	2012	yes	yes

Source: own elaboration.

b. Wage inequality analysis

Baseline scenario

In a first step, we divide the full sample into six groups by broad sector (industry, business, and other services) and type of occupation (offshorable and non-offshorable) and for each group estimate Mincerian wage regressions of the following form:[14]

$$w_{ijsc} = \beta_0 + \beta_1 RTI_{ijsc} + \beta_2 GVC_{sc}^B + \beta_3 GVC_{sc}^F + \beta_4 GVC_{sc}^B * OUT_{sc} + \beta_5 GVC_{sc}^F * OUT_{sc} + \beta_6 Z_{sc} + \beta_7 X_{ijsc} + \lambda_s + \rho_c + \epsilon_{ijsc} \quad (1)$$

where w_{ijsc} stands for hourly wages of individual i, in occupation j, in sector s, and in country c; GVC_{sc}^B is backward and GVC_{sc}^B forward GVC participation in sector s and in country c; OUT_{sc} is output in sector s and in country c; Z_{sc} measures technology in sector s and in country c; X_{ijsc} are individual skills of worker i, in occupation j, in sector s and in country c; λ_s and ρ_c are, respectively, sector and country fixed effects.

Based on the estimated coefficients from equation (1) and actual values for each right-hand side variables, we can predict wages ($\widehat{w}_{ijsc}^{base}$) for each individual in the six groups. Formally:

$$\widehat{w}_{ijsc}^{base} = \beta_0 + \beta_1 RTI_{ijsc} + \beta_2 GVC_{sc}^B + \beta_3 GVC_{sc}^F + \beta_4 GVC_{sc}^B * OUT_{sc} + \beta_5 GVC_{sc}^F * OUT_{sc} + \beta_6 Z_{sc} + \beta_7 X_{ijsc} + \lambda_s + \rho_c \quad (2)$$

For each country, we then calculate the Gini coefficient (ρ_c^{base}) of predicted wages:

$$\rho_c^{base} = gini(\widehat{w}_{ijsc}^{base}) \quad (3)$$

This is our baseline scenario.

Scenario of no GVC participation

In the second step, we assess the direct contribution of GVC participation to wage inequality (E^{direct}). This is based on the estimated models from equation (1), but based on predicted wages conditional on GVC participation values equal to zero ($\widehat{w}_{ijsc}^{direct}$). Formally:

$$\widehat{w}_{ijsc}^{direct} = \beta_0 + \beta_1 RTI_{ijsc} + \beta_2 * 0 + \beta_3 * 0 + \beta_4 * 0 * OUT_{sc} + \beta_5 * 0 * OUT_{sc} + \beta_6 Z_{sc} + \beta_7 X_{ijsc} + \lambda_s + \rho_c \quad (4)$$

For each country, we then calculate the Gini coefficient (ρ_c^{direct}) under the assumption of no integration into GVCs:

$$\rho_c^{direct} = gini(\widehat{w}_{ijsc}^{direct}) \quad (5)$$

We describe the direct contribution of GVC participation to wage inequality (E^{direct}) as the difference between the Gini coefficients of wages calculated in the baseline scenario and in the scenario of no GVC participation:

$$E^{direct} = \rho_c^{base} - \rho_c^{direct} \quad (6)$$

[14] This model is equivalent to equation (3) in the main body of the paper. However, for simplicity reasons the expression $GVC_{sc}^B + GVC_{sc}^F + GVC_{sc}^B * OUT_{sc} + GVC_{sc}^F * OUT_{sc}$ is noted as G_{sc}.

Counterfactual RTI scenario

In a third step, we analyze how GVC participation indirectly contributes to wage inequality through its relationship with workers' RTI ($E^{indirect}$). Specifically, we estimate the model of workers' RTI and then calculate counterfactual worker-level RTI, assuming GVC participation values equal to zero ($\widehat{RTI}_{ijsc}^{indirect}$).[15] Formally:

$$RTI_{ijsc} = \beta_0 + \beta_1 GVC_{sc}^B + \beta_2 GVC_{sc}^F + \beta_3 GVC_{sc}^B * GDP_c^{PC} + \beta_4 GVC_{sc}^F * GDP_c^{PC} + \beta_5 Z_{sc} + \beta_6 X_{ijsc} + \lambda_s + \epsilon_{ijsc} \quad (7)$$

$$\widehat{RTI}_{ijsc}^{indirect} = \beta_0 + \beta_1 * 0 + \beta_2 * 0 + \beta_3 * 0 * GDP_c^{PC} + \beta_4 * 0 * GDP_c^{PC} + \beta_5 Z_{sc} + \beta_6 X_{ijsc} + \lambda_s + \epsilon_{ijsc} \quad (8)$$

We then use the estimated models from equation (1) to predict wages $\widehat{w}_{ijsc}^{indirect}$ conditional on $\widehat{RTI}_{ijsc}^{indirect}$. To isolate the indirect contribution of GVC participation to wage inequality through RTI, we use the observed values of GVC participation in the wage model:

$$\widehat{w}_{ijsc}^{indirect} = \beta_0 + \beta_1 \widehat{RTI}_{ijsc}^{indirect} + \beta_2 GVC_{sc}^B + \beta_3 GVC_{sc}^F + \beta_4 GVC_{sc}^B * OUT_{sc} + \beta_5 GVC_{sc}^F * OUT_{sc} + \beta_6 Z_{sc} + \beta_7 X_{ijsc} + \lambda_s + \rho_c \quad (9)$$

We describe the indirect contribution of GVCs participation to wage inequality ($E^{indirect}$) as the difference between the Gini coefficients of wages calculated in the baseline scenario (ρ_c^{base}) and the Gini coefficients of wages in the counterfactual RTI scenario ($\rho_c^{indirect}$).

$$\rho_c^{indirect} = gini(\widehat{w}_{ijsc}^{indirect}) \quad (10)$$

$$E^{indirect} = \rho_c^{base} - \rho_c^{indirect} \quad (11)$$

Total contribution of GVC participation

In a fourth step, we calculate the total contribution of GVC participation to wage inequality (E^{total}). We set the GVC participation values to zero (as in the calculation of the direct contribution), and we use the counterfactual RTI conditional on zero GVC participation ($\widehat{RTI}_{ijsc}^{indirect}$, as in the calculation of the indirect contribution) to predict wages using the estimated coefficients in the models from equation (1).

$$\widehat{w}_{ijsc}^{total} = \beta_0 + \beta_1 \widehat{RTI}_{ijsc}^{indirect} + \beta_2 * 0 + \beta_3 * 0 + \beta_4 * 0 * OUT_{sc} + \beta_5 * 0 * OUT_{sc} + \beta_6 Z_{sc} + \beta_7 X_{ijsc} + \lambda_s + \rho_c \quad (12)$$

We define the total contribution of GVC participation to wage inequality (E^{total}) as the difference between the Gini coefficient of wages in the baseline scenario (ρ_c^{base}) and the Gini coefficient of wages in this last scenario (ρ_c^{total}).

$$\rho_c^{total} = gini(\widehat{w}_{ijsc}^{total}) \quad (13)$$

$$E^{total} = \rho_c^{base} - \rho_c^{total} \quad (14)$$

[15] Equation (7) is equivalent to equation (2) in the main body of the paper.

Appendix B – Additional results

Table B1. The Correlates of Routine Task Intensity (RTI) at the Worker Level, in the pooled sample, and by broad sectors, standardized (backward and forward GVC)

Panel A: Pooled	(1) All workers	(2) Non-offshorable	(3) Offshorable	(4) All workers	(5) Non- offshorable	(6) Offshorable
Backward Global Value Chain participation (GVCB) share in exports (std.)	-0.000	-0.007	0.046**			
	(0.010)	(0.010)	(0.019)			
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	-0.011	-0.013	0.015			
	(0.007)	(0.008)	(0.014)			
Forward Global Value Chain participation (GVCF) share in exports (std.)				0.019*	0.013	0.039***
				(0.011)	(0.012)	(0.015)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]				0.036	0.049	-0.038
				(0.028)	(0.031)	(0.033)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.016	-0.006	-0.075	-0.006	0.006	-0.072
	(0.038)	(0.039)	(0.060)	(0.036)	(0.036)	(0.059)
Observations	167,253	145,122	22,131	167,034	144,914	22,120
Panel B: Industry						
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.019	-0.011	0.077**			
	(0.024)	(0.026)	(0.030)			
GVCB share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]	0.015	0.026	0.005			
	(0.030)	(0.032)	(0.043)			
Forward Global Value Chain participation (GVCF) share in exports (std.)				0.029*	0.011	0.048**
				(0.015)	(0.018)	(0.020)
GVCF share (std.) * [Ln(GDP pc) –mean(Ln(GDP pc)]				0.024	0.029	0.009
				(0.031)	(0.034)	(0.046)
Ln(GDP per capita) –mean(Ln(GDP per capita))	-0.112	-0.091	-0.364***	-0.089	-0.032	-0.334***
	(0.070)	(0.074)	(0.110)	(0.067)	(0.075)	(0.109)
Observations	38,949	28,816	10,133	38,917	28,790	10,127

Panel C: Business services						
Backward Global Value Chain participation (GVCB) share in exports (std.)	-0.086***	-0.093***	-0.014			
	(0.018)	(0.020)	(0.034)			
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.048**	0.058***	-0.054*			
	(0.019)	(0.020)	(0.031)			
Forward Global Value Chain participation (GVCF) share in exports (std.)				-0.021	-0.024	-0.001
				(0.015)	(0.016)	(0.023)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]				0.101***	0.121***	-0.052
				(0.031)	(0.033)	(0.039)
Ln(GDP per capita) −mean(Ln(GDP per capita))	-0.065	-0.051	-0.136*	-0.051	-0.038	-0.132*
	(0.044)	(0.045)	(0.075)	(0.044)	(0.045)	(0.075)
Observations	72,153	63,173	8,980	71,979	63,003	8,976
Panel D: Other services						
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.265***	0.249***	0.436***			
	(0.075)	(0.076)	(0.149)			
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.371***	-0.363***	-0.478*			
	(0.113)	(0.114)	(0.256)			
Forward Global Value Chain participation (GVCF) share in exports (std.)				0.075***	0.070***	0.133***
				(0.025)	(0.026)	(0.044)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]				-0.234**	-0.235**	-0.236
				(0.104)	(0.103)	(0.224)
Ln(GDP per capita) −mean(Ln(GDP per capita))	-0.199***	-0.199***	-0.292**	-0.130**	-0.134*	-0.176
	(0.070)	(0.073)	(0.135)	(0.066)	(0.069)	(0.128)
Observations	50,843	48,133	2,710	50,843	48,133	2,710

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The standard errors are clustered at a sector × country level. Measures for Computer Use, GVCB share and FDI/GDP are standardized. All regressions include controls for technology (computer use, computer use squared), FDI, skills, education, age, gender, sector FE, and sector FE interacted with GDP per capita.

Source: Authors' calculations based on Lewandowski et al. (2022) and PIAAC, STEP, CULS (tasks), and World Bank (GDP, taxonomy groups, government education spending), EORA data and Borin and Mancini (2015, 2019) (GVC participation measures).

Table B2. Pooled regression of backward and forward and by wide sectors and occupational groups, standardized (backward and forward GVC)

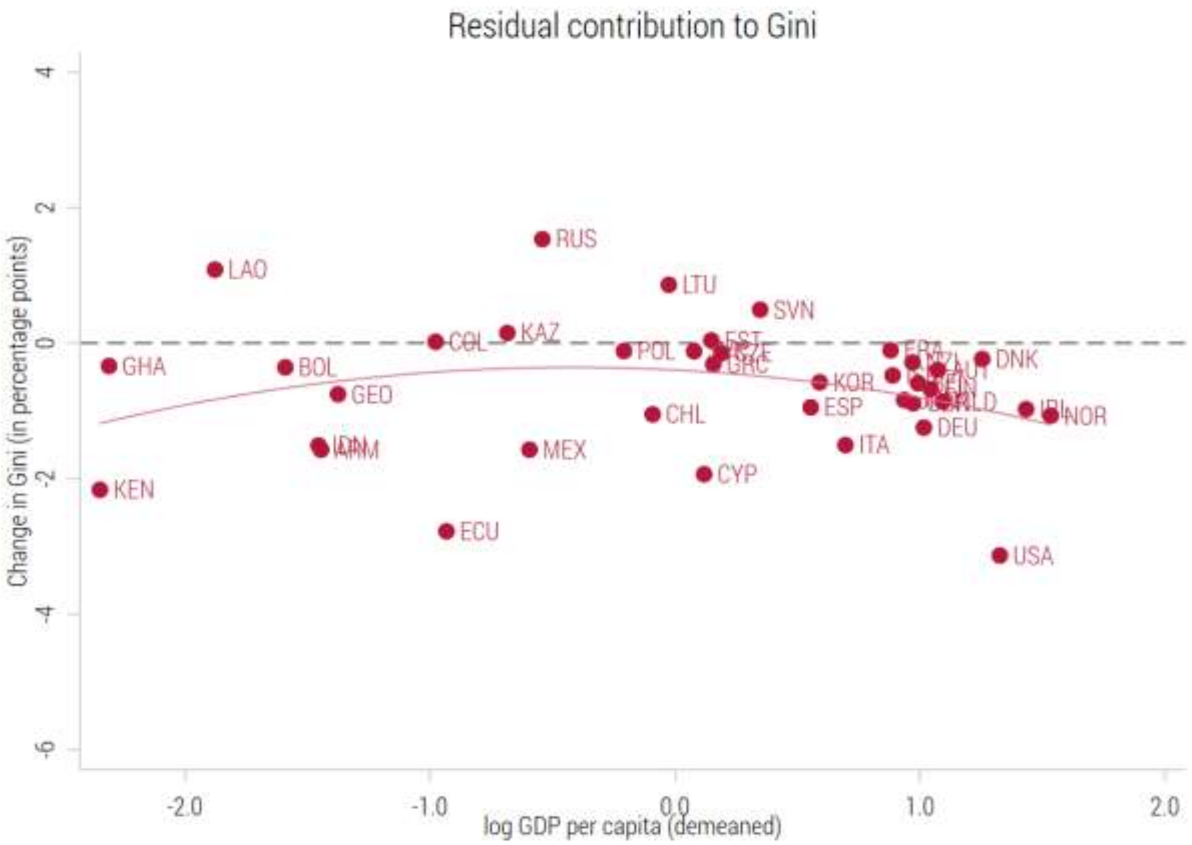
Panel A: Pooled	(1) All workers	(2) High-skilled occupations (ISCO 1-3)	(3) Middle-skilled occupations (ISCO 4-5)	(4) Low-skilled occupations (ISCO 7-9)
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.004	-0.031*	-0.059**	0.064***
	(0.019)	(0.017)	(0.025)	(0.022)
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.017	-0.035	0.085**	0.023
	(0.029)	(0.026)	(0.039)	(0.030)
Forward Global Value Chain participation (GVCF) share in exports (std.)	0.019*	0.019*	0.009	0.046***
	(0.010)	(0.011)	(0.017)	(0.011)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.060***	-0.074***	-0.042**	-0.045***
	(0.012)	(0.014)	(0.016)	(0.013)
Ln(GDP per capita) −mean(Ln(GDP per capita))	0.033	0.011	0.013	0.107**
	(0.038)	(0.037)	(0.046)	(0.050)
Observations	167,034	68,439	52,895	45,700
Panel B: Industry				
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.027	-0.051**	0.038	0.056**
	(0.024)	(0.020)	(0.036)	(0.024)
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.004	0.066**	-0.051	0.003
	(0.032)	(0.031)	(0.044)	(0.038)
Forward Global Value Chain participation (GVCF) share in exports (std.)	0.030**	0.017	-0.026	0.051***
	(0.015)	(0.018)	(0.032)	(0.016)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.043***	-0.006	-0.011	-0.060***
	(0.017)	(0.021)	(0.034)	(0.018)
Ln(GDP per capita) −mean(Ln(GDP per capita))	-0.096	-0.109	-0.237**	0.016
	(0.066)	(0.074)	(0.099)	(0.060)
Observations	38,917	11,245	4,208	23,464
Panel C: Business services				
Backward Global Value Chain participation (GVCB) share in exports (std.)	-0.055**	-0.037	-0.098**	0.030
	(0.024)	(0.028)	(0.044)	(0.032)
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	0.063*	-0.070**	0.101*	0.124***
	(0.037)	(0.035)	(0.053)	(0.043)
Forward Global Value Chain participation (GVCF) share in exports (std.)	-0.015	0.010	-0.026	0.021
	(0.016)	(0.014)	(0.020)	(0.023)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.046***	-0.089***	-0.029	0.006
	(0.017)	(0.019)	(0.018)	(0.025)
Ln(GDP per capita) −mean(Ln(GDP per capita))	-0.027	-0.008	-0.064	-0.054
	(0.049)	(0.050)	(0.059)	(0.067)
Observations	71,979	24,754	32,362	14,863

Panel D: Other services				
Backward Global Value Chain participation (GVCB) share in exports (std.)	0.220***	0.058	0.251**	0.640***
	(0.079)	(0.085)	(0.100)	(0.127)
GVCB share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.329***	-0.242**	-0.342***	-0.451***
	(0.114)	(0.123)	(0.123)	(0.145)
Forward Global Value Chain participation (GVCF) share in exports (std.)	0.029	0.030	0.038	0.073
	(0.023)	(0.027)	(0.031)	(0.047)
GVCF share (std.) * [Ln(GDP pc) −mean(Ln(GDP pc)]	-0.073**	-0.078**	-0.082**	0.049
	(0.032)	(0.034)	(0.042)	(0.055)
Ln(GDP per capita) −mean(Ln(GDP per capita))	-0.210***	-0.225***	-0.084	-0.024
	(0.076)	(0.079)	(0.108)	(0.113)
Observations	50,843	31,609	15,051	4,183

Note: ***p < 0.01, **p < 0.05, *p < 0.1. Standard errors in parentheses. Standardized weights are used that give each country equal weight. The standard errors are clustered at a sector × country level. Measures for GVCB share and GVCF share are standardized. All regressions include controls for technology (computer use, computer use squared), FDI, skills, education, age, gender, sector FE, and sector FE interacted with GDP per capita.

Source: Authors' calculations based on Lewandowski et al. (2022) and PIAAC, STEP, CULS (tasks), and World Bank (GDP), EORA data and Borin and Mancini (2015, 2019) (GVC participation measures).

Figure B1. The contribution of GVC participation to wage inequality, residual term.



Source: Authors' calculations based on Lewandowski et al. (2022) and PIAAC, STEP, CULS (tasks), EORA data and Borin and Mancini (2015, 2019) (GVC participation measures).