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GVC and wage dispersion. Firm-level evidence from employee–employer database

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Keywords: *wage inequalities; Global Value Chains; ineqrbd; regression-based decomposition*

Abstract

Research background: Wage inequalities are still part of an interesting policy-oriented research area. Given the developments in international trade models (heterogeneity of firms) and increasing availability of micro-level data, more and more attention is paid to wage differences observed within and be-tween firms.
Purpose of the article: The aim of the paper is to address the research gap concerning limited cross-country evidence on a nexus of wage inequality–global value chains (GVCs), analysed from the perspective of wage inequality components within and between firms.
Methods: This paper uses a large employee–employer database derived from the European Structure of Earnings Survey (SES), combined with sector-level indicators of GVC involvement based on the World Input-Output Database (WIOD). As a result, a rich database covering more than 7.5 million observations is created. The regression-based decomposition modelling technique developed by Fiorio and Jenkins (2010) is used to identify the contributions of different factors to wage inequalities, focusing on the components within and between firms.
Findings & value added: The analysis presented in this paper aimed to show the contribution of GVC involvement, among various other factors, to the observed inequality of wages. Due to the

use of a rich database that merges employer and employee data, the effects materialised with respect to different types of wages could be analysed separately, in particular components between and within firms. The general conclusion from the regression-based decomposition in log wages is that GVCs contribute marginally to the observed wage inequality in the European sample analysed in this paper. Some differences confronting the components within and between firms (the latter dominates) are observed; there is also certain intra sample heterogeneity in the estimated results (e.g. due to sector type or country group), but the general result is robust.

Introduction

Wage inequalities are still part of an interesting policy-oriented research area and may be analysed from different perspectives. Besides analysing the pure gender wage disproportions perceived as wage discrimination due to gender (Blau & Kahn, 2017), economic research offers its alternative explanations. Among other factors, the role played by international trade (Bøler *et al.*, 2015; Coniglio & Hoxhaj, 2018; Juhn *et al.*, 2014; Robertso *et al.*, 2020) and globalisation (Coniglio & Hoxhaj, 2018) cannot be neglected, shaping gender inequalities observed in labour markets. A significant part of the literature is devoted to the association between wage dispersion and international trade involvement in the context of Global Value Chains[1] – GVCs (see, among others,: Amiti & Davis, 2011; Sampson, 2014; Coşar *et al.*, 2016; Burstein & Vogel, 2017). The effect of GVCs on wage inequalities may be diversified due to the skill level of workers (Baumgarten *et al.*, 2013), occupation type (Ebenstein *et al.,* 2014), or employment sector (Parteka & Wolszczak-Derlacz, 2019).

Given international trade models based on the heterogeneity of firms (Melitz, 2003), more and more attention is paid to wage differences occurring between workers employed in the same sector, but in different firms (Helpman *et al.*, 2017). Empirical research indicates that the rise of GVCs may provoke both an increase in wage inequalities between workers from different firms (Helpman *et al.*, 2017), as well as between those employed in the same firm (Ge *et al.*, 2019). However, the existing evidence on the magnitude and determinants of inequalities existing among workers in the same and in different firms is rather limited and country-specific. Studies combining wage differences within and between firms with the role played

[1] The concept of GVCs covers "the full range of activities that firms and workers perform to bring a product from its conception to end use and beyond. This includes activities such as research and development (R&D), design, production, marketing, distribution and support to the final consumer. The activities that comprise a value chain can be contained within a single firm or divided among different firms." (Gereffi & Fernandez-Stark, 2016, p. 7).

in them by international trade (Ge *et al*., 2019; Helpman *et al*., 2017) are even scarcer.

This paper aims to bridge the existing research gap by using a rich cross-country dataset to examine wage differences at the firm and worker level in an international context. Particular emphasis is placed on the comparison between wage inequalities within and between firms and their association with the international trade involvement of firms. To this end, employee–employer data from the European Structure of Earnings Survey (SES) are used to provide detailed characteristics of individual workers and attributes of firms. To assess the relationship between wages and international trade, the SES dataset is merged with sectoral measures on GVC involvement based on the World Input-Output Database (WIOD). Regression-based decomposition modelling is applied to estimate linkages between different dimensions of wage inequalities and the production fragmentation process.

The remainder of the paper is as follows. Section 2 reviews the literature on wage inequalities, focusing on the role of international trade. Section 3 describes the data and methodology. Section 4 presents the results and robustness checks. Section 5 discusses the obtained results. Section 6 concludes.

Literature review

The existing research on the determinants of wage inequalities may be divided into two main types — analysing either macro-level or micro-level determinants of such inequalities (Magda *et al*., 2020). The macro-level research stresses the role played by trade, labour market frictions, technological advancement or migrations (Akerman *et al*., 2013; Helpman *et al*., 2017). The micro-level perspective underlines the role of individual workers' characteristics (which include education, skill level, age, and occupation type) in explaining the observed increase in wage inequality (Magda *et al*., 2020; Nikulin & Wolszczak-Derlacz, 2019).

Among the determinants of the wage dispersion observed at the microeconomic level, the role of firm-specific effects is relevant. The seminal work by Melitz (2003) introduced the model of international trade incorporating the heterogeneity of firms into analysis. Subsequent developments in trade theory boosted research on, *inter alia*, the effect of mechanisms observed at the firm level on affecting wage disparities (Helpman *et al*., 2017; Yasar & Rejesus, 2020). Improvements in micro-level data availability made it possible to expand empirical studies on wage inequalities typical of workers from the same sector, but employed in different firms (Burstein & Vogel, 2017; Coşar *et al*., 2016). A parallel view in the literature disentangles the observable wage inequalities into proportions attributable to the mechanisms within the same firm and between different firms (Barth *et al.*, 2016; Kelly *et al.*, 2017; Song *et al.*, 2019). The drivers of wage variation between firms may be related to the competitive labour market theory, stating that wage inequalities result from differences in labour force composition among firms (Sampson, 2014). Other explanations of wage inequality between firms are based on the link between workers' efforts and firm revenue (Amiti & Davis, 2011; Egger & Kreickemeier, 2009) or, alternatively, on the search and matching frictions and bargaining over surplus production (Helpman *et al*., 2010).

Most of related empirical evidence focuses on a sample of workers and firms from the same country. There are several studies arguing that the major part of wage inequality relates to the component between firms. For instance, Helpman *et al.* (2017) examined the Brazilian economy to find that wage inequalities are often observed within the same sector, but mostly among workers from different firms. A similar result is reported by Faggio *et al.* (2010), who analysed the UK labour market. Further, Card *et al.* (2013) drew on data from Germany to show that wage inequalities grew over time (1985–2009) — both within and between firms. Finally, several studies suggest the prevailing role of the component within firms. The study conducted for the United States (1978–2013) confirms that as much as two-thirds of an increase in wage inequalities is related to disparities occurring within firms (Song *et al*., 2019). Similarly, the study on Sweden (Akerman *et al*., 2013) reveals that the share of wage dispersion between firms is relatively small. To sum up, the shares of wage inequalities within and between firms appear to be country-specific.

Few studies offer an international perspective and address the case of more than one country. Regarding evidence from Europe, even half of the wage inequalities in CEE countries can be related to differences existing between firms (Kelly *et al*., 2017, pp. 169–170). Moreover, as Magda *et al*. (2020) argue, wage inequalities between firms are typical of countries with a higher level of general wage inequality.

Wage inequalities as such have been widely examined in the international economics' literature. The majority of the existing studies cover linkages between exposure to international markets and general wage inequality (see among others: Chen, 2017; Koymen-Ozer, 2020; Lee & Yi, 2018; Sampson, 2014). However, when it comes to the components of inequalities within and between firms, and their relation to international trade patterns, studies are scarcer. Ge *et al*. (2019) analysed the Chinese economy and revealed that wage differences occurring within firms are greater if the company imports intermediate goods. This may indicate that a stronger involvement in the process of international production fragmentation is associated with higher wage inequalities within firms. Further, Helpman *et al.* (2017) used employer–employee data for Brazil to find that wage dispersion occurring between firms is related to trade activity.

The next sections address the research gap concerning limited cross-country evidence on a nexus of wage inequality–GVCs analysed from the perspective of wage inequality components both within and between firms.

Data and research methodology

In this paper we use a large employee–employer database derived from the European Structure of Earnings Survey (SES). The SES is a cross-country, 4-yearly survey conducted in the Member States of the European Union, candidate countries, and countries belonging to the European Free Trade Association (EFTA)[2]. The main aim of the SES database is to deliver detailed information on earnings of workers from the EU Member States, along with characteristics of employees and employers. Access to micro data is available upon individual request[3].

The newest available data from 2014 are used. Considering data availability, the final sample includes workers from 19 countries[4], employed both in manufacturing as well as in services. The main objective of this paper is to find a relationship between wage inequalities and international trade involvement. To do so, the SES database is merged with sectoral statistics from the World Input-Output Database (WIOD), 2016 release (Timmer *et al.*, 2015). As a result, an extensive database covering more than 7.5 million observations is created.

GVC involvement may affect wage inequality due to its heterogeneous impact on different categories of workers (differentiated by skill level, education, or task content of occupation) and firms (varying in productivity, size, or position in the value chain with respect to their upstreamness). Given the state of the art and actual research feasibility (data availability), the following main research hypotheses are formulated:

[2] A detailed description of the SES is provided on the Eurostat website at https://ec.europa.eu/eurostat/web/microdata/structure-of-earnings-survey, date of access: 15 October 2020.

[3] Data access was granted pursuant to research proposal no. 225/2016-EU-SILC-SES.

[4] BE, BG, CZ, DE, EE, ES, FR, HU, IT, LT, LV, NL, NO, PL, PT, RO, SE, SK, UK.

H1: *Greater involvement in GVC boosts wage inequalities between workers.*

H2: *The relationship between international trade involvement and wage inequalities mainly explains wage disparities occurring between firms.*

The first hypothesis is more general, while the other divides wage disparities into two components — within firms and between firms. To verify the hypotheses, a set of econometric modelling techniques is employed.

As regards the key variable of interest, i.e. wage, hourly wage of individual worker i in relation to country mean $\overline{w_c}$ is expressed as $\widehat{w_i} = (w_i/\overline{w_c})$ (see, e.g., Magda *et al.*, 2020, for a similar approach). Given particular interest in wage inequalities between and within firms, $\widehat{w_i}$ is expressed as the product of two components: individual wage to average firm wage ($\frac{w_i}{\overline{w_f}}$) – within firm component; and average firm's wage to the country mean ($\frac{\overline{w_f}}{\overline{w_c}}$) – between firm component:

$$\left(\frac{w_i}{\overline{w_c}}\right) = \left(\frac{w_i}{\overline{w_f}}\right) \times \left(\frac{\overline{w_f}}{\overline{w_c}}\right) \tag{1}$$

Then, the regression-based decomposition modelling technique developed by Fiorio and Jenkins (2010) is applied to identify the contributions of different factors to wage inequalities[5]. The technique includes two steps.

In the first step, the wage regression model is used:

$$\begin{gathered} lnw_{ijfct} = \alpha + \beta_1 Ind_i + \beta_2 Firm_f + \beta_3 Sector_j + \\ + \beta_4 FVA_{jt-1} + D_j + + D_c + \epsilon_{ijc} \end{gathered} \tag{2}$$

where: w is one of the three types of wages (resulting from equation (1)) of worker i employed in sector j in firm f and country c at time t; *Ind* corresponds to individual characteristics of workers, such as: sex, age[6], education[7]; *Firm* denotes firm/job characteristics: full/part-time employment, categories of skills based on occupation[8], enterprise size[9]; *Sector* includes

[5] Specifically, the command *ineqrbd* in STATA is used.

[6] Three age categories: *ageyoung* (below 30), *ageaverage* (30-49), and *ageold* (50 and more).

[7] Three education categories: *loweduc* (less than primary, primary, lower secondary), *mededuc* (upper secondary and post-secondary*),* and *higheduc (*tertiary education and above*)*.

[8] Four skill categories according to mapping of ISCO major groups to skill levels (ILO,

sector characteristics such as productivity; and *FVA* is a foreign value-added to export ratio. The *FVA* is the measure of GVC involvement[10] and was obtained as a result of export decomposition as described by Koopman *et al*. (2014). Additional controls include sector and country dummies — D_j and D_c — respectively. To take possible endogeneity issues into account, the lagged GVC measure, namely the FVA from 2013, is employed. In the estimation procedure, weights based on the recalculated grossing-up factor[11] provided by SES[12] are used to ensure that observations from different countries are equally represented. Table 1 provides the descriptive statistics of the variables and Table 2 presents partial correlations between them.

In the second step, the estimated coefficients (corresponding to various explanatory variables) are applied to obtain the share of the log variance of wage attributable to each factor (Fields, 2003):

$$s_k(lnw) = \left(\beta_k \delta(X_k) \times cor(X_k, lnw)\right)/\delta(lnw) \tag{3}$$

In equation (3), X_k is the set of regressors (together with the error) from equation (2), whereas β_k denotes the estimated coefficients. The share of the residual stands for all other determinants of wages not included in the model.

Results

Wage inequalities are analysed taking into account three different types of wage measures (equation (1)): individual wage related to the country mean, individual wage to the firm mean, and average firm wage to the country mean. The key results, corresponding to the second stage of regression-based decomposition[13], are presented in Table 3.

2012).

[9] Small (<50 employees), medium (50–249 employees), and large (>249 employees).

[10] Due to data availability, GVC involvement is measured not at the firm level but at the sectoral level. In other words, it is assumed that companies operating in more GVC-intensive sectors have a higher probability of being involved in cross-border production fragmentation.

[11] The grossing-up factor for employees is calculated as (*Number of local units in the population) / (Number of local units in the sample) × (Number of employees in the local unit / Number of employees in the sample).* See *the Structure of Earnings Survey 2014.*

[12] The weights are brought to the common scale so that in each country they sum up to 10,000.

[13] The first stage results are not reported due to space constraints. However, the coefficients of all individual and firm-level characteristics are statistically significant and have

The first column of Table 3 includes the contribution of factor *f* to total inequality (s_f=rho_f×sd(f)/sd(lnw)), where rho_f is the correlation between factor *f* and log wage. The next columns show: S_f = s_f*CV(lnw), where CV(lnw) is the coefficient of variation of lnw, the relative mean of a given factor (m_f/m), coefficient of variation of a given factor (CV_f = sd(f)/m_f), and the CV of factor *f* to the CV of the total (lnw).

Apart from the residual that corresponds to a large part of wage/country inequality, workers' skills are the largest contributor to wage inequality (e.g. skill 1 contributes to 13% and skill 2 to almost 14% of wage variation, whereas education variables correspond to 3.7 and 3.6% of wage variation respectively). The key variable of our interest, the FVA, is responsible for only 0.03% of relative individual/country inequality. When individual wage to firm average (Panel B in Table 3) is considered, the contribution of GVCs to inequalities within firms is also negligible (0.001%). Finally, Panel C shows that GVC contribution to wage inequality between firms represents 0.07 % of total inequality.

To check the sensitivity of the results, certain extensions and robustness checks are performed. The results showing the contribution of GVCs to wage inequality in alternative model specifications are shown in Tables 4–7. Firstly, additional explanatory variables referring to characteristics of firms are included (such as the length of service in the enterprise, form of economic and financial control: public versus private enterprises, and the type of collective pay agreement: national, industry, enterprise, or no agreement) – see Table 4.

Then, instead of GVC measured as the FVA to export ratio, the traditional offshoring measure is employed: intermediate inputs to the output of the domestic industry (Feenstra & Hanson, 1999) — Table 5. These two modifications hardly affect the results[14], and the general conclusion still holds. Finally, several aspects of intrasample heterogeneity are considered. The analysis is performed separately for manufacturing and services (Table 6), as well as for two subsamples of European countries ('old' and 'new' Member States: OMS and NMS respectively — Table 7). Interestingly, some differences can be observed in this case. GVCs seem to be positively correlated with wage inequalities typical of workers employed in manufacturing, while in services it has an equalising effect, e.g. GVCs contribute to

expected signs. Specifically, male and older workers with higher education obtain bigger remuneration. The FVA is positively correlated with wages expressed in relation to the country mean and with between-firm component, while it is not statistically correlated with wages relative to within-firm mean.

[14] When regression with more RHVs is considered, GVCs have an equalising effect on wage inequalities within firms; however, the extent of this effect is negligible (-0.003%).

1% lower wage inequality in the case of between firm component. There are also several noteworthy differences between workers from old and new Member States (note that country dummies are still included). In the case of the OMS, the de-equalising effect of GVCs is stronger, except for the between firm component. For the NMS, GVCs contribute solely to higher wage inequality between firms. Firms operating in sectors diversified by GVC involvement (but having other characteristics in common) differ in wages. Still, the general conclusion holds: the contribution of GVC involvement to different dimensions of wage inequalities in Europe is very small.

Discussion

The results make it possible to verify the initial research hypothesis. GVC involvement turns out to explain a marginal part of the observed wage inequality. Bearing in mind that individual, firm, and sectoral characteristics are controlled for, this result can be interpreted in the following way — if workers of the same characteristics were considered, the variation of their wages stemming from the differences in GVC involvement of their employment sectors would be negligible. The results hold for general wage inequality, as well as for inequality within and between firms. Additionally, even if there is any effect of GVCs, it is materialised in wage inequality between firms. However, other factors such as education level, skills, and firm characteristics are much more important in explaining wage variation at the micro level.

In general, the findings of this paper are in line with the existing evidence (including Faggio *et al*., 2010, and Helpman *et al*., 2017) asserting the expansion of wage inequalities between firms. The findings match those of Helpman *et al.* (2017), who found considerable wage dispersion within sectors, and a contribution of trade to wage inequalities between firms.

The majority of previous studies focused on the effects of trade and international production sharing on skilled–unskilled wage inequalities or gender wage differences (see, i.a., Magda *et al*., 2020; Nikulin & Wolszczak-Derlacz, 2019; Wang *et al.*, 2021). This study is believed to fill the research gap concerning limited cross-country evidence on a nexus of wage inequality–GVCs analysed from the perspective of components within and between firms.

Conclusions

The analysis presented in this paper was aimed to show the contribution of GVC involvement, among various other factors, to the observed inequality of wages in Europe. Due to the use of a rich database that merges employer and employee data, the effects materialised with respect to different types of wages could be analysed separately, in particular components between and within firms.

Taking into account the sign of coefficients' estimates (regression-based decomposition), GVCs appear to contribute positively to wage inequality, mainly through the intercorporate component. However, when the proportion of inequality explained by that factor is considered, the degree of the GVC effect is marginal. Some degree of heterogeneity is observed across sectors and country groups: the equalising effect of GVCs is found in services, while in the NMS, GVCs contribute solely to wage inequalities between firms.

This study has some limitations. The measure of GVCs applied in this paper is sector-specific (rather than firm-specific), and, additionally, the SES dataset made it possible to analyse European countries only (so the sample used in the study consists of developed economies). Further research may focus on the comparison of the approach taken in this paper with the results obtained via alternative methods of wage inequality decomposition. In addition, an interesting research idea may include conducting a similar analysis for both developed and developing countries to see wage effect differences (including components within and between firms) for countries with strongly diversified GVC involvement.

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Annex

Table 1. Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
ln $(w\_i/\overline{w_c})$	7,810,824	-0.152	0.457	-1.604	1.653
ln $(w\_i/\overline{w_f})$	7,810,824	-0.054	0.322	-2.556	2.249
ln $(\overline{w_f}/\overline{w_c})$	7,811,048	-0.097	0.336	-1.604	1.653
sex	7,811,049	0.457	0.498	0	1
ageyoung	7,810,872	0.172	0.378	0	1
ageaverage	7,810,872	0.507	0.500	0	1
ageold	7,810,872	0.321	0.467	0	1
loweduc	7,811,049	0.131	0.337	0	1
mededuc	7,811,049	0.532	0.499	0	1
higheduc	7,811,049	0.337	0.473	0	1
FT	7,811,049	0.817	0.387	0	1
skill_1	7,742,262	0.097	0.296	0	1
skill_2	7,742,262	0.446	0.497	0	1
skill_3	7,742,262	0.172	0.378	0	1
skill_4	7,742,262	0.284	0.451	0	1
small	7,783,835	0.171	0.376	0	1
medium	7,783,835	0.212	0.408	0	1
large	7,783,835	0.618	0.486	0	1
indefinite	7,586,712	0.850	0.357	0	1
shortdur	7,811,049	0.121	0.326	0	1
meddur	7,811,049	0.287	0.452	0	1
logdur	7,811,049	0.375	0.484	0	1
vlongdur	7,811,049	0.217	0.412	0	1
public	7,550,335	0.462	0.499	0	1
nationagr	7,488,992	0.077	0.267	0	1
industagr	7,488,992	0.215	0.411	0	1
enterpagr	7,488,992	0.286	0.452	0	1
noagr	7,488,992	0.422	0.494	0	1
ln_Prod	7,808,366	3.463	0.907	0.502	7.756

Table 1. Continued

Variable	Obs	Mean	Std. Dev.	Min	Max
FVA	7,756,399	0.137	0.092	0.009	0.465
OFF	7,811,049	0.122	0.113	0.000	0.460

Notes: sex (1 if male), age: ageyoung (below 30), ageaverage (30-49), ageold (50 and more), education (loweduc (less than primary, primary, lower secondary), mededuc (upper secondary and post-secondary), higheduc (tertiary education up to 4 years and more than 4 years), FT - Full time (1 if full-time employed), skills based on recoded occupation: skill_1 (elementary occupations), skill_2 (clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators, and assemblers), skill_3 (technicians and associate professionals), skill_4 (managers and professionals), type of employment contract (permanent versus temporary), length of service in enterprise: shordur (less than 1 year), meddur (1-4 years), longdur (4 -14 years), very long duration (more than 14 years), public (1 if public company), size of enterprise: small (1-49 employees), medium (50-249), large (250 and more), type of collective agreement: nationagr (national agreement), industagr (industry agreement), enterpagr (enterprise agreement), noagr (no agreement).

Source: authors' own elaboration based on SES (2014) and WIOD (2016).

Table 2. Partial correlation between independent variables used in baseline regression

	sex	Age young	Age average	Low educ	Med educ	FT	Skill_1	Skill_2	Skill_3	ln_prod	med.	large
sex	1.00											
ageyoung	0.04	1.00										
ageaverage	-0.01	-0.46	1.00									
loweduc	0.02	0.07	-0.07	1.00								
mededuc	0.06	0.01	-0.01	-0.41	1.00							
FT	0.19	-0.06	0.07	-0.10	0.06	1.00						
skill_1	-0.03	0.00	-0.04	0.27	0.01	-0.10	1.00					
skill_2	0.11	0.12	-0.04	0.13	0.36	-0.03	-0.29	1.00				
skill_3	-0.03	-0.02	0.03	-0.12	0.06	0.06	-0.15	-0.41	1.00			
ln_Prod	0.18	0.03	-0.02	0.08	-0.04	-0.12	-0.08	0.09	0.02	1.00		
medium	-0.01	-0.03	0.00	0.03	0.00	0.03	0.06	0.00	-0.03	-0.06	1.00	
large	0.03	0.02	0.01	-0.05	0.00	0.03	-0.11	0.00	0.07	0.10	-0.66	1.00
FVA	0.24	0.03	0.04	0.01	0.23	0.24	-0.03	0.24	-0.01	0.15	0.03	0.03

Source: authors' own elaboration based on SES (2014) and WIOD (2016).

Table 3. Regression-based decomposition of inequality in log wages

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV (total)
Panel A: Dependent variable: ln $(w\_i/\overline{w_c})$					
residual	54.185	-1.474	0.000	2.62e+17	-9.62e+16
sex	1.638	-0.045	-29.798	1.082	-0.398
ageyoung	3.005	-0.082	19.182	-2.242	0.824
ageaverage	-0.328	0.009	13.185	-0.992	0.365
loweduc	3.731	-0.102	19.000	-2.298	0.845
mededuc	3.633	-0.099	36.953	-1.067	0.392
FT	0.265	-0.007	-10.906	0.516	-0.190
skill_1	12.810	-0.348	39.607	-2.834	1.042
skill_2	14.269	-0.388	112.564	-1.105	0.406
skill_3	-1.444	0.039	20.663	-2.412	0.886
ln_Prod	1.612	-0.044	-95.397	0.280	-0.103
large	4.060	-0.111	-59.899	0.943	-0.347
medium	-0.416	0.011	-17.383	1.704	-0.626
FVA	**0.032**	**-0.001**	**-25.829**	**0.655**	**-0.241**
Total	100	-2.721	100	-2.721	1.000
Panel B: Dependent variable: ln $(w\_i/\overline{w_f})$					
residual	75.096	-4.360	0.000	1.77e+16	-3.05e+15
sex	1.092	-0.063	-60.309	1.082	-0.186
ageyoung	2.736	-0.159	45.889	-2.242	0.386
ageaverage	-0.293	0.017	34.363	-0.992	0.171
loweduc	1.365	-0.079	26.912	-2.298	0.396
mededuc	2.162	-0.126	62.260	-1.067	0.184
FT	-0.058	0.003	54.312	-0.516	0.089
skill_1	7.550	-0.438	77.134	-2.834	0.488
skill_2	9.331	-0.542	232.983	-1.105	0.190
skill_3	0.108	-0.006	52.585	-2.412	0.415
ln_Prod	-0.175	0.010	140.604	-0.280	0.048
large	0.014	-0.001	35.349	-0.943	0.163
medium	0.039	-0.002	8.373	-1.704	0.293
FVA	**0.001**	**-0.000**	**6.821**	**-0.655**	**0.113**
Total	100	-5.805	100	-5.805	1.000
Panel C: Dependent variable: ln $(\overline{w_f}/\overline{w_c})$					
residual	63.942	-1.968	0.000	9.45e+15	-3.07e+15
sex	0.509	-0.016	-15.484	1.082	-0.351
ageyoung	0.534	-0.016	6.652	-2.242	0.728
ageaverage	-0.047	0.001	3.250	-0.992	0.322
loweduc	2.152	-0.066	15.288	-2.298	0.746
mededuc	1.377	-0.042	25.081	-1.067	0.346
FT	1.084	-0.033	-41.505	0.516	-0.168
skill_1	4.574	-0.141	22.001	-2.834	0.921
skill_2	4.411	-0.136	56.069	-1.105	0.359
skill_3	-0.475	0.015	5.686	-2.412	0.783
ln_Prod	3.570	-0.110	-206.121	0.280	-0.091
large	8.204	-0.253	-104.589	0.943	-0.306
medium	-0.581	0.018	-29.467	1.704	-0.553
FVA_NewExp	**0.072**	**-0.002**	**-41.148**	**0.655**	**-0.213**
Total	100	-3.079	100	-3.079	1.000

Notes: The rows of the first column in the panels do not sum to 100 due to the sector and country dummies included in the regression – not presented here for illustrative purposes. The regression is weighted using the country-specific grossing up factor – see the main text for explanation. Omitted variables: *ageold*, *higheduc, part time, skill_4,* and *small.*

Source: authors' own elaboration based on data from SES (2014) and WIOD (2016).

Table 4. Contribution of GVC to wage inequality (results based on regression-based decomposition of inequality with additional variables: length of service in the enterprise, form of economic and financial control of enterprise: public versus private, and type of collective pay agreement)

Decomp.	**100*s_f**	**S_f**	**100*m_f/m**	**CV_f**	**CV_f/CV (total)**
ln $(w\_i/\overline{w_c})$	0.036	-0.001	-17.676	0.647	-0.248
ln $(w\_i/\overline{w_f})$	-0.003	0.000	17.234	-0.647	0.114
ln $(\overline{w_f}/\overline{w_c})$	0.069	-0.002	-33.579	0.647	-0.221

Notes: as for Table 3

Source: authors' own elaboration based on data from SES (2014) and WIOD (2016).

Table 5. Contribution of GVC to wage inequality: GVC measured by offshoring indices

Decomp.	**100*s_f**	**S_f**	**100*m_f/m**	**CV_f**	**CV_f/CV (total)**
ln $(w\_i/\overline{w_c})$	0.030	-0.001	-18.958	0.921	-0.252
ln $(w\_i/\overline{w_f})$	0.006	-0.000	-12.344	0.921	-0.160
ln $(\overline{w_f}/\overline{w_c})$	0.024	-0.001	-23.794	0.921	-0.185

Notes: regression-based decomposition, individual- and firm-level characteristics, and other variables included as in Table 3.

Source: authors' own elaboration based on data from SES (2014) and WIOD (2016).

Table 6. Contribution of GVC to wage inequality: manufacturing versus services

Decomp.	**100*s_f**	**S_f**	**100*m_f/m**	**CV_f**	**CV_f/CV (total)**
			manufacturing		
ln $(w\_i/\overline{w_c})$	0.134	-0.004	-30.314	0.205	-0.067
ln $(w\_i/\overline{w_f})$	0.008	-0.000	40.225	-0.205	0.036
ln $(\overline{w_f}/\overline{w_c})$	0.357	-0.014	-71.923	0.205	-0.055
			services		
ln $(w\_i/\overline{w_c})$	-0.886	0.021	-32.061	0.455	-0.189
ln $(w\_i/\overline{w_f})$	-0.006	0.000	-30.275	0.455	-0.078
ln $(\overline{w_f}/\overline{w_c})$	-1.094	0.028	-32.778	0.455	-0.176

Notes: regression-based decomposition, individual- and firm-level characteristics, and other variables included as in Table 3.

Source: authors' own elaboration based on data from SES (2014) and WIOD (2016).

Table 7. Contribution of GVC to wage inequality: old Member States (OMS) versus new Member States (NMS)

Decomp.	100*s_f	S_f	100*m_f/m	CV_f	CV_f/CV (total)
			OMS		
ln $(w\_i/\overline{w_c})$	0.306	-0.009	-26.279	0.716	-0.250
ln $(w\_i/\overline{w_f})$	0.007	-0.001	-24.990	0.716	-0.111
ln $(\overline{w_f}/\overline{w_c})$	0.336	-0.011	-26.805	0.716	-0.223
			NMS		
ln $(w\_i/\overline{w_c})$	0.002	0.000	-36.878	0.572	-0.225
ln $(w\_i/\overline{w_f})$	0.000	0.000	-0.025	0.572	-0.110
ln $(\overline{w_f}/\overline{w_c})$	0.454	0.005	87.640	0.000	0.444

Notes: regression-based decomposition, individual- and firm-level characteristics, and other variables included as in Table 3.

Source: authors' own elaboration based on data from SES (2014) and WIOD (2016).