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Abstract

Using rich individual level data on workers from 28 European countries, we provide the first so extensive cross-country assessment of wage response to global production links within GVC in the period 2005-2014. Unlike the other studies, we: (i) address the importance of backward linkages in globally integrated production structures (capturing imports of goods and services needed *in any* stage of the production of the final product); (ii) measure occupational task profile of workers with country specific indices of routinisation; (iii) compare the impact of global production links on wages between workers from Western, Central-Eastern and Southern Europe; employed in manufacturing and non-manufacturing sectors; (iv) account for direct and indirect dependence on GVC imports from developing and high income countries. We take into account the potential endogeneity issues. Our results suggest that global import intensity of production exhibits negative pressure on wages in Europe. This effect concerns mainly workers from Western Europe employed in manufacturing and is driven by production links with non-high income countries but our counterfactual estimates suggest that the effect is economically small.

JEL: F14, F16, J31

Keywords: wages, global value chains, global import intensity of production, tasks, EU

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1. Introduction

The labour market effects of production relocation are still being debated. Offshoring, understood as ‘the process of changing the geographic assignment of the mix of tasks needed to produce a single final good or service’ (Hummels et al., 2018: 983) has traditionally been seen as a threat to domestic workers (job losses, declining wages, heightened inequality). The topic has become a media phenomenon, an issue in the political debate and one of the main themes in current economic literature. The theoretical literature on the distributional consequences of offshoring and global value chains (GVCs), recently reviewed by Frassen (2019), is abundant but ambiguous, particularly when it comes to predicting the combined effect of the various, often conflicting mechanisms at play.¹ In the empirical literature as well, despite the impressive development of measurements and methods the debate on the labour market consequences of importing foreign inputs is still unresolved, due to the gap between concepts and what can be feasibly demonstrated given the data (Hummels et al., 2018).

This paper uses rich individual-level data on workers in 28 European countries in the period from 2005 to 2014 to produce a multidimensional cross-country evaluation of the factors that determine wages in labour markets characterised by strong links to GVCs and task-related specificity of jobs. The core of our empirical analysis relates to the way we quantify dependence on foreign inputs and the role of cross-border production relations in generating labour market outcomes. The standard measures of fragmentation are based on the ratio of imported intermediates in a given industry to its output or value added (Feenstra and Hanson, 1999). That is, the focus is on the last stage of production only, as if the use of foreign inputs were independent from the previous stages (whether performed domestically or abroad). Instead we employ the latest release of the WIOD input-output data² and methodology proposed by Timmer et al. (2016), proxying fragmentation by a newly devised index of global import intensity of production (*GII*), which counts imports of goods and services required *in any stage* of production, including trade with third countries.³ *GII* measures the extent to which a given industry depends on imported intermediates to attain its total production value (direct exposure) and previous international and cross-industry links (indirect exposure). Our approach is thus closer to the framework of sequential production and national interdependence driven by vertical specialisation and GVCs (Antràs and Chor, 2013; Kohler, 2004; Costinot et al., 2013) than to the

¹ For instance, see Frassen (2019: 3, Table 1) for a summary of conflicting theoretical predictions of the effects of GVCs on the relative demand for skilled labour present in the alternative models. In their review, Hummels et al. (2018: 1021) observe that ‘the effects for workers depend on the model at hand’.

² World Input Output Database, November 2016 release (see Timmer et al., 2015 for details). See Feenstra (2017) for a discussion of the classic measures of offshoring and ‘second-generation statistics’ on fragmentation based on input–output data.

³ The R code to compute *GII* (Szymczak et al. 2019) is available – see Section 3.1.

‘classic’ offshoring literature, which considers the last tier only (see Hummels et al., 2018, Section 2 for a review).

To illustrate this point, we refer to the statistics on GVC involvement (Table 1). Between 2000 and 2014 the import intensity of European production (ratio to total output) increased from 15.9% to 20.2%.⁴ According to the monetary interpretation of GII proposed by Timmer et al. (2016), this means that in 2014 one dollar of goods and services finished in Europe generated about 20 cents worth of imports worldwide. Conventionally measured offshoring – the inputs used in the last stage of production – accounts for a bit less than half the increase that occurred over this period. The rest of the imported intermediates were used in earlier tiers and can be traced back in the GVC framework. The United States is less dependent on imported intermediates, but there was an increase in GII there as well (from 7.9% in 2000 to 8.8 % in 2014). Worldwide, the ratio of GVC imports (i.e. imports by the country where the last stage of production occurred and by all other countries involved in earlier stages of production) to the output of the final products was approximately 16% in 2014 (12% in 2000)⁵. And only a third of it can be ascribed to the final stage of production, so proper measurement of dependence on foreign inputs in earlier stages is essential. To date, however, the literature on the labour market effects of production fragmentation has neglected this aspect.

[Table 1 about here]

The studies of the effects of fragmentation on the European labour market that have considered the task content of jobs suffer another severe limitation, namely limited coverage: these inquiries have involved only a few Western European countries,⁶ not the other, less highly developed economies of Southern or Central and Eastern Europe (CEECS).⁷ Furthermore, often only the impact on manufacturing workers is analysed (as in Geishecker et al., 2010; Baumgarten et al., 2013; Hummels et al., 2014; Geishecker and Görg, 2013).⁸ The dependence on foreign

⁴ Based on the GII index computed with WIOD data (release 2016). See Section 3.1 for details.

⁵ These values differ from those of Timmer et al. (2016) because of the different level at which the measurement is made and because of the weighting scheme adopted. Our unweighted averages for the ‘World’ are much closer to the values reported by Timmer et al. (2016: 33).

⁶ Empirical evidence has been compiled for: Germany (Baumgarten, 2015; Baumgarten et al., 2013; Becker et al., 2013; Becker and Muendler, 2015), Denmark (Hummels et al., 2014), the United Kingdom (Geishecker and Görg, 2013), or these three countries together (Geishecker et al., 2010).

⁷ So far, analysis of the labour market impact of trade or offshoring in relation to the CEECS markets has been from the perspective of the potential threat to Western European workers (Abraham and Konings, 1999; Geishecker, 2006; Dauth et al., 2014) or the effects observed within the CEECS (Egger and Egger, 2002). The task literature has shown that in most CEECS countries, unlike Western European economies, in intensity of routine cognitive tasks grew (Hardy et al., 2018).

⁸ Additionally, Baumgarten (2015) studied the impact of material and business offshoring on occupational instability among German workers. Becker et al. (2013) considered workers in German manufacturing and service sectors. Other studies on offshoring in non-manufacturing sectors include Amiti et al. (2005), Crino (2010), and Geishecker and Görg (2013).

production is sector-specific and non-negligible in non-manufacturing activities (Geishecker and Görg, 2013),⁹ so we do not limit our study to manufacturing alone.

Our central question is thus: are wages in Europe affected by globally measured dependence on foreign inputs, including direct and indirect exposure, given all the other dimensions of the wage determination process?¹⁰ To answer, we construct a rich dataset: individual-level information on wages, occupational task profiles, personal and job characteristics on 1.3 million workers in 28 European countries over the period 2005–2014. We match our microdata with input–output measures of sectoral dependence on foreign inputs, other sector characteristics, and information on national labour market institutions and wage bargaining schemes. In addition to considering *all* the pre-final tiers of production, we compare the effects of dependence on foreign inputs measured globally, regardless of country of origin, with the effects of dependence on inputs from less developed countries only. Further, given our cross-country approach, we consider the task profiles of workers, which are occupation- and country-specific (Lewandowski et al., 2019).

The paper is structured as follows. Section 2 briefly describes the theoretical background and some essential contributions on production fragmentation and wages in Europe, which our paper expands on. Section 3 presents the data and methodology and the measurement of global dependence on foreign inputs and of wages in Europe. The empirical strategy and the results of the estimations for various subsamples are presented in Section 4. The last section concludes. Numerous robustness checks are included in the additional material and available in the appendix.

2. The literature

2.1 Theoretical background

On the theoretical plane our paper is at the crossroads between the literature on the effects of offshoring on domestic workers and that on sequential production, which can be adopted to GVC analysis.¹¹ As recently described by Franssen (2019), the theoretical literature on the distributional effects of GVC is abundant but ambiguous, and ‘the hypothesized effects are

⁹ Timmer et al. (2016, p.25-26) detected appreciable variation in the intensity of foreign inputs in goods production and service production: many services are obviously produced locally (e.g. public services, education, recreation), but construction, for instance, is just as heavily dependent on foreign inputs as some manufacturing industries. Johnson and Noguera (2017) documented that over time (1970–2009), the ratio of value added to gross exports decreased in manufacturing (by 20 p.p.) but increased in agriculture and services.

¹⁰ Dealing with many countries in the analysis, we limit the study to the effects on wages, treating the employment and labour demand effects of fragmentation as issues requiring separate inquiry. See Ebenstein et al. (2014) for a joint micro-level analysis of the impact of production fragmentation on wages and employment shifts in the U.S.

¹¹ GVCs and value-added trade have been described, among others, by Antràs and Chor, 2013; Costinot et al., 2013; Johnson & Noguera, 2012; Johnson & Noguera, 2017; Koopman et al., 2014; Los, Timmer & Vries, 2015; Los et al., 2015; Timmer et al., 2015; Timmer et al., 2016; Baldwin and Lopez-Gonzalez, 2015. Some of the papers (e.g. Amador and Cabral, 2015) have referred to GVCs but, in reality, they describe labour market effects of offshoring.

highly dependent on the microeconomic foundations of the model chosen' (Feenstra, 2010, p. 3).

The conceptualisation of offshoring through trade-in-tasks has become a widely accepted reference point in the literature on production fragmentation. Theoretical models have addressed the ambiguity of the effects on domestic labour by studying how the overall outcome (wage loss or wage gain, say) is generated by the interplay of the contrasting forces in play in offshoring. According to Grossman and Rossi-Hansberg (2008), the wage impact of the growing dependence on foreign inputs due to falling offshoring costs operates indirectly through three main channels: the influence on relative productivity, the price effect and the labour supply effect.¹² Paradoxically, if the productivity gains from production relocation are sufficiently large, when tasks are offshored the ultimate result may actually be a wage gain that includes workers performing less demanding tasks.¹³ However, other models suggest that offshoring may engender wage decline because of the pressure on domestic workers to accept lower wages for fear of job offshoring (Jeon and Kwon, 2019) or the reallocation of workers from high- to low-productivity firms, with lower wages (Egger et al., 2015). A whole range of wage effects is possible, depending on the global engagement of firms (Amiti and Davis, 2011): a decrease in output tariffs lowers wages in import-competing firms and raises them in exporting firms; a decrease in input tariffs, by contrast, will raise wages at import-using firms relative to those paid by firms that rely on local inputs.

Models of sequential, multistage production and the theories of interdependence driven by vertical specialisation (Costinot et al., 2012; Costinot et al., 2013; Antràs and Chor, 2013; Kohler, 2004;) have also produced ambiguous theoretical predictions on how the production chain will affect factor prices (including, especially, wages). But they also confirm that in a world of globally integrated production, the outcomes (wages, say) observed at any one stage (e.g. final) should not be analysed separately from what happens at the previous stages. Kohler (2004) argued that the ambiguity of the response of wages to production fragmentation is deepened by cross-industry links in a multistage production setting. Costinot et al. (2013) developed a simple theory of trade with sequential production to show how global supply chains affect international

¹² In short, the final effect is the resultant of these three mechanisms. Tasks vary in their offshoring cost and low-skilled tasks can be offshored. The relative-price effect occurs when a fall in offshoring costs changes a large country's terms of trade. Price movements are mirrored by movements in relative costs, which typically exerts downward pressure on low-skill wage via the Stolper and Samuelson mechanism. The labour-supply effect derives from the reabsorption of the workers who used to do the offshored tasks: this may (but also may not) contribute to a decline in their wages. Finally, the productivity effect that Grossman and Rossi-Hansberg (2008) predict may seem counterintuitive, in that it implies that workers whose jobs are being relocated may actually *benefit* from a decrease in offshoring costs: the resulting cost savings for firms increases productivity, which in turn boosts firms' demand for low-skilled labour and pushes their wages up.

¹³ The possibility that wages might rise as a result of relocation was predicted earlier by Markusen (1989) in his model of trade in differentiated intermediate inputs: upstream production stages can be complementary to downstream tasks, resulting in higher wages from value added trade in the industry.

interdependence and Costinot et al. (2012) provide a multifactor version to study the implications for wage inequality. In such a model, with sequential production, wages respond to changes in the prices of the intermediate goods used in the industry. Hence, efficiency gains thanks to cheaper foreign inputs upstream can affect downstream productivity indirectly, and with it the wages of the workers. This is the perspective that motivates our empirical approach: earlier production tiers, performed offshore, can affect the wages of workers employed domestically in the later stages of GVC, closer to final demand.

2.2. Production fragmentation, GVC, and wages in Europe – the empirical evidence

The recent empirical literature on the fragmentation–wage nexus generally follows the influential theoretical models of trade-in-tasks (Grossman and Rossi-Hansberg, 2008; Grossman and Rossi-Hansberg, 2012; Baldwin and Robert-Nicoud, 2014). This literature consists of several different strands: the sets of studies using respectively industry-level data, firm-level data, worker-level data, and matched worker-firm data (see Hummels et al., 2018 for an excellent review). The crude division of workers into skilled and unskilled in a cross-section of industries that marked the first wave of studies on the labour market consequences of production fragmentation for different workers is no longer sufficient. In particular, tasks clearly differ from skills, especially when the objective is to gauge the potential offshorability of certain occupations (Blinder, 2006; Blinder and Krueger, 2013).¹⁴ Consequently, to evaluate the consequences of globalisation for heterogeneous groups of workers, empirical research on international trade has adopted the task setting, originally developed to analyse variation in skill requirements within occupations and the changing task composition of labour markets owing to technological progress (among others: Spitz-Oener, 2006; Autor et al., 2003; Acemoglu and Autor, 2011; Autor and Handel, 2013).

Much of the task-based work on the labour market implications of production fragmentation (offshoring) refers to the United States (Acemoglu and Autor, 2011; Ebenstein et al., 2014; Autor et al., 2014). And a good share of this literature focuses on the so-called ‘China syndrome’ or ‘China shock’ (among others: Autor et al., 2014; Shen and Silva, 2018, Feenstra and Sasahara, 2018).¹⁵

¹⁴ Baumgarten et al. (2013), in their assessment of the cross-industry effects of offshoring on wages in German manufacturing, demonstrated the substantial heterogeneity between skills and tasks.

¹⁵ Typically, these studies postulate job loss due to imports from China. However, an interesting later work (Feenstra and Sasahara, 2018), using the same WIOD input-output data we use here, discusses the job impact of U.S. exports as well as imports. Using the demand-side methodology of Los et al. (2015b), they quantify the positive effect of U.S. exports on employment. Their combined analysis shows that the expansion in U.S. merchandise exports relative to imports from China between 1995 and 2011 generated net demand for about 1.7 million jobs. Comparing the growth of U.S. merchandise exports to total merchandise imports, one finds a fall in net labour demand; but comparing total U.S. exports and imports, one finds an increase in net labour demand, thanks to the growth in service exports.

Not many papers are closely related to our research, with its focus on Europe, microdata and task-profile (we exclude the literature using industry-level data, such as Polgár and Wörz, 2010; Parteka and Wolszczak-Derlacz, 2015; Wolszczak-Derlacz and Parteka, 2019). The more detailed evidence, which considers the heterogeneity of workers in terms of individual characteristics, is strongly dependent on the availability of microdata, which is why just a handful of countries (and principally Germany) have dominated the debate.

Of the European countries, Germany is by far the most intensively studied. Becker and Muendler (2015) documented significant trade-task changes in the German economy over three decades (1979–2006): imports of intermediates grew, and the German workforce increasingly specialised in non-offshorable activities. Baumgarten et al. (2013) demonstrated an adverse effect of offshoring on wages, depending on the task profile of the occupations involved (higher non-routine content effectively protects workers from the wage repercussions of production relocation). Becker et al. (2013) used plant level data for German multinationals to examine the relationship between offshoring and the composition of skills and tasks in Germany. Their results suggested positive relationships between offshore employment and the shares of non-routine and interactive tasks in the total wage bill. But they also found that in any case the economic impact of offshoring on the composition of the labour force is modest and concluded that much of the variation in wage shares is explained by other factors.

The evidence on other countries confirms that offshoring has uneven effects on workers, depending on skill/task type. Hummels et al. (2014), on matched worker-firm data from Denmark, demonstrated that offshoring increases the wages of the skilled and decreases those of the low-skilled. However, considering that skills do not overlap perfectly with tasks, the wage effects vary according to tasks (that is, workers performing routine tasks suffer the most). Geishecker and Görg (2013) merged industry-level data on offshoring for the United Kingdom with individual-level data on wages (their setting thus resembles ours) and showed that the offshoring of services affects the wages of low- and medium-skilled workers negatively and leads to a wider earnings gap between skilled and unskilled. Finally, Geishecker et al. (2010), combined data for Germany, the United Kingdom, and Denmark to determine whether differences in labour market institutions may have produced differences in the wage impact of outsourcing. Surprisingly, they found that the estimated effects are actually quite similar across the three countries and fairly small.

In our study we also check whether the impact of *GII* on wages in Europe depends on the source of the imported inputs. The literature has confirmed that the provenance of inputs is indeed critical. Becker et al. (2013) showed that offshoring by German multinationals to low-

income countries (except Central and Eastern Europe) produces a stronger employment response in Germany. Wolszczak-Derlacz and Parteka (2018) examined a 40-country worldwide sample. Using industry-level wage data and breaking the input-output offshoring measure down according to source country, they found a negative (but small) wage impact of offshoring to low-wage countries.¹⁶

As far as task evaluation is concerned, to date most task-based labour market studies have focused on a single country for which the classification of tasks is available: the U.S. (Autor and Handel, 2013; Autor et al., 2014; Ebenstein et al., 2014) or Germany (Baumgarten, 2015; Becker et al., 2013). Alternatively, they simply assume that the task profile of workers in the countries they want to analyse is the same as in the United States (based on O*NET data), which Lewandowski et al. (2019) have shown to be a considerable simplification. For works along these lines, see Goos et al. (2014), Arias et al. (2014), Lewandowski et al. (2017), and Hardy et al. (2018), applying O*NET to LFS data in the European Union and/or OECD countries; or the World Development Report (2016), which utilises the typology of occupations developed by Autor (2014), based on U.S. data, to analyse changes in employment shares in developing countries.

Few studies have explicitly addressed the GVC-wage nexus merging industry-level data on GVC with individual data on workers' wages. Shen and Silva (2018) studied the relationship between the value added of exports from China and wages in the United States, demonstrating that the effects depend on the position of the Chinese industry in the GVC (its degree of downstreamness). Similarly, Szymczak et al. (2019) use the CEECs sample to show how the position of industries in the production chain affects wages. Parteka and Wolszczak-Derlacz (2019), constructing a cross-sectional dataset on nine European countries and the United States, is the work most resembling the present paper in terms of data and methodology. Those results suggested that growing cross-border industrial interdependence (measured as the foreign share in the industry's value added) decreases the wages of some workers, namely those who perform more routine tasks and are less well educated. But effects detected empirically are quite modest. In any event, that study did not cover the entire European labour market; it used a fairly crude classification of workers by task content of jobs; and it failed to explore the role of backward production linkages in multistage GVCs. The subsequent analysis addresses these shortcomings.

¹⁶ Importantly, the classification of low-wage countries is not based on aggregate data but on relative wage levels and varies across industries and time (available at https://static-content.springer.com/esm/art%3A10.1007%2Fs10663-016-9352-4/MediaObjects/10663_2016_9352_MOESM1_ESM.xlsx).

3. Empirical setting

In our study we consider workers from 28 European countries including Western Europe - W (AT, BE, CH, DE, DK, FI, FR, IE, IT, NL, NO, SE, UK); Southern Europe - S (CY, ES, EL, PT) and Central and Eastern Europe - CEECS (BG, CZ, EE, HU, LT, LU, LV, PL, RO, SI, SK). We match micro-level information (from EU-SILC) with sector-level statistics on countries' dependence on foreign inputs based on WIOD (release November 2016), described below.

3.1 The measurement of GII

In order to measure countries' and industries' global dependence on imported inputs we draw on Timmer et al. (2016) new accounting framework which they use to explain the global trade slowdown.¹⁷ Following them, we employ the newest available release of industry-level data from WIOD (November 2016) and use global import intensity of production' (*GII*) index¹⁸. *GII* is a backward measure which takes into account *'the imports by the country in which the last stage of production takes place, as well as imports by other countries that are involved in earlier stages of production. Moreover, it includes imports of intermediate goods as well as intermediate services (such as supporting business services).'*' (Timmer et al., 2016, p.4). It thus noticeably differs from offshoring intensity measured (in the spirit of Feenstra and Hanson, 1999) at one stage of production only as a ratio of imported inputs to the industrial output value. *GII* measures all imports of intermediates by all countries in the value chain induced by a dollar of output of a final product. Consequently, its interpretation in terms of total contribution of foreign inputs into the domestic production is also straightforward – contrary to the measures based on export decomposition (vertical specialisation, VS - domestic value added in exports: Hummels et al., 2001; Koopman et al., 2014 or the VAX ratio - value added exports: Johnson and Noguera, 2012).¹⁹

We adopt a sequential approach to measure the dependence on foreign inputs, in other words we use the information on imported inputs employed in the last stage of production and on imported inputs employed in all the previous production stages (backward movement along the

¹⁷ In particular, they argue that before the economic crisis the import intensity was increasing due to high demand for durables and to increasing international production fragmentation while after 2011 the fragmentation growth halted and the demand shifted to services.

¹⁸ The R code to compute *GII* (Szymczak et al. 2019) is available at: https://ezarzadzanie.zie.pg.gda.pl/apps/WorkingPapers/WP_GUTFME_A_53_code_accompanyingWP53_GII_56ind.R

¹⁹ The recent empirical evidence on long-run trends (four decades: 1970-2009) in value added exports is provided by Johnson and Noguera, (2017) while Baldwin and Lopez-Gonzalez (2015) present an overview of supply-chain trade developments since 1995 (from the perspective of: importing to produce; importing to export and value-added trade).

GVC). Formally, GII is computed as follows (Timmer et al., 2016, p. 10-12)²⁰. Let $a(t,j)(u,k)$ be the value of inputs from industry t in country j required by industry u in country k to produce one dollar of its gross output. Good z is finalised in (s,i) . All imports needed in each stage (tier) of production of good z are defined as:

$$h_z^{tier0} = \sum_u \sum_{k \neq i} a(u,k)(s,i)$$

$$h_z^{tier1} = \sum_t \sum_{j \neq k} \sum_u \sum_k [a(t,j)(u,k)] [a(u,k)(s,i)]$$

$h_z^{tier2} = \dots$ and so on, so the GII of z is equal to:

$$GII = h_z = h_z^{tier0} + h_z^{tier1} + h_z^{tier2} + \dots = \sum_t \sum_{j \neq k} \widehat{a}_z(t,j)(u,k) \quad (1)$$

where $\widehat{a}_z(t,j)(u,k)$ is the delivery of inputs from (t,j) to (u,k) induces by the production of good z .

The production of intermediate inputs provided by the first-tier suppliers involves intermediates from second-tier suppliers and so on, summing up to all tiers of production given by GII . GII takes the values between 0 and 1 where zero means that finalizing country does not need to import intermediates in *any* stage of production of product z while the value of 1 indicates a complete dependence on foreign inputs along the value chain.²¹

Figure 1 shows average values of GII in our sample of 28 European countries in 2014 (being the last year of input-output data in WIOD, as well as the last year of our analysis; values are weighted by the industry value added). GII (expressed as an index 0-1, where the value of 1 corresponds to a total, 100% dependence of the final production on imported inputs, calculated along all the backward stages of production) range between 13% of final output in Greece to 55% in Luxembourg. European countries are generally more dependent on foreign inputs than big economies like US or China, where GII equals to (respectively) 0.08 and 0.13 (8 and 13%). In almost all of the countries less than half of GII is driven by imports by the country in which the last stage of production took place (in black), while the other half depends on inputs imported in earlier stages of production which involve third-country trade. It means that conventionally measured offshoring (which accounts for imported intermediates employed in the last stage of

²⁰ The notation and description of GII in this section comes from the presentation of M. Timmer at HKUST Conference on International Economics, Hong Kong, June 1-2, 2017.

²¹ Empirically (using input-output tables and following Leontief), gross output related to the production of final good z is derived as: $\mathbf{Y}_z = (\mathbf{I} - \mathbf{A})^{-1} [\mathbf{Z}]$, where $\mathbf{A}$ is the matrix of intermediate input coefficients (foreign and domestic) while $\mathbf{I}$ is the identity matrix. Intermediate inputs linked to the production of good z are then given by $\widehat{\mathbf{A}}_z = \mathbf{A} \text{diag}[\mathbf{Y}_z]$. All intermediate imports related to z are given by: $h_z = \mathbf{u}'(\mathbf{T} \circ \widehat{\mathbf{A}}_z) \mathbf{u}$ where $\mathbf{T}$ is an indicator matrix (with zero's for domestic flows and $\mathbf{u}$ being a summation vector). Theoretically, GII can be bigger than 1 when imports are measured on a gross basis and double counting of value added contributions takes place – see Timmer et al., 2016: 11; Koopman et al., 2014) but we exclude such (few) observations from the sample.

production) can severely underestimate the importance of global sourcing and its indirect effects on domestic labour markets.

[Figure 1 about here]

Some of the industries are much more dependent on foreign inputs than the others - global import intensity of services production tends to be much lower than for goods (Timmer et al., 2016: 4). Table 2 reports values of GII for the whole economy (all industries) and by sectors, for comparison we show the data typical for Europe 28 and the three subgroups of European countries, split into Western (W), Southern (S) and Central and Eastern (CEECS) European countries in 2014. It is clear that GII is the highest in manufacturing industries (for instance, in Western Europe GVC imports account for 42% of final manufacturing production), but the ratio of imported intermediates to the final output is also considerable in services. In Europe, value chains finalised in CEECS countries are more dependent on imported inputs than in the case of Western or Southern European countries. This is a sign of significant involvement of CEECS into GVCs.

[Table 2 about here]

Our further input is to compute the variants of GII which measure the reliance of the value chain linked to the production of z on intermediates coming from different subgroups of countries. At every backward stage of production, we use the information on the source (country) of intermediates, and sum them over those coming from: high income countries only (GII^{HIC}) and from selected developing countries only (GII^{DEV}), encompassing China and India²². In particular, using the latter measure we will assess direct and *indirect* effects of production dependence on the South countries characterised by lower labour costs. According to the values reported in Table 3 (Panel B) GVC imports coming from these developing countries account for a small share of final output – in the word it is only 3% while in Europe even less (2%). In manufacturing it is 6%, so still not much. At the same time, values of GII^{HIC} are considerably higher than GII^{DEV} : in Europe, on average, the value of imported intermediates employed along the value chain and coming from other well developed economies accounts for 14% of final

²² Specifically, they are calculated on the basis of imports from *HIC* (or from *DEV*) in any upstream stage of production. The computation proceeds by backward movement along the value chain and identification of the source of imports in every stage. The sum is then done stepwise. This means that there are mixed backward linkages via high-income and non-high-income countries, while GII^{HIC} and GII^{DEV} isolate the parts of the chain depending on imports from *HIC* and *DEV* respectively. Consequently, the two (plus imports from RoW) add up to the total GII . *HIC* (*high income countries*)=AUS, AUT, BEL, CAN, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, JPN, KOR, LVA, LTU, LUX, MLT, NLD, NOR, POL, PRT, SVK, SVN, ESP, SWE, CHE, TWN, GBR, USA; *DEV* (*developing countries*)= BRA, BGR, CHN, IND, IDN, MEX, ROM, RUS, TUR; *RoW*=world – 43 countries present in WIOD2016 = world – *HIC* – *DEV*. The classification of countries is based on the World Bank's list of economies (July 2016).

output (31% in manufacturing).²³ It means that given the magnitude of the dependence on developing countries inputs, the negative consequences of imports coming from these countries are likely to be overvalued.

[Table 3 about here]

Cross-country variability in GII, as well as the changes over time (2005-2014, the years of our analysis) are shown in Table 4. Additionally, to show the importance of the proper backward measurement of foreign inputs, we report the values of *GII_tier1* encompassing imports from first-tier suppliers only and vertical specialization. The interpretation of the GII's values is as follows: for instance, one dollar of goods and services finalized in Germany (DE) generated around 16 dollar cent of imports worldwide in 2005 increasing to 20 dollar cent in 2014. At the same time, imported intermediates used in the last stage of production only, accounted for 7 cents in 2005 and 9 cents in 2014 per each one dollar of final German production. For most of the countries (the only exceptions are Sweden, SE and Spain, ES) the change in the measures has been positive, which is a clear sign of increasing GVC involvement. It can be either due to the imports rise in any stage of production, or due to new stages of production (with similar import requirements) added to GVC causing its lengthening.

[Table 4 about here]

3.2 Microdata and descriptive statistics on wages

The micro-level data for our empirical analysis comes from EU-SILC database (Statistics on Income and Living Conditions) obtainable from Eurostat²⁴. The EU-SILC provides comparable cross-sectional and longitudinal multidimensional microdata on income, poverty, social exclusion and living conditions, and is thus suitable for cross-country comparisons²⁵. In this study we use cross-sectional type of data provided by EU-SILC (optionally, longitudinal data is available but it lacks some crucial variables needed in our empirical analysis, such as the sector of employment used to merge micro-data with sector-level data on GII). Data are gathered in two types of files depending on the level of response: individual and household ones. We combine individual files (personal data and personal register) with household information (household data and household

²³ Like *GII*, *GII_tier1* can also be divided into three groups of source countries. The average value of *GII_tier1* (for all countries/sectors/years in the sample together) is 0.12 and most is from high-income countries (mean value of *GII_tier1_HIC*=0.09, *GII_tier1_DEV*=0.017 and *GII_tier1_RoW*=0.016).

²⁴ The access to EU-SILC and other microdata from Eurostat is granted to researchers on the bases of respecting rules of the confidentiality. This study is based on data from Eurostat, EU-SILC, *EUSILC UDB 2015 – version 1 of August 2016* - the access has been granted by the Eurostat under the grant agreement 64/2013-LFS-EU-SILCSES. The responsibility for all conclusions drawn from the data lies entirely with the authors.

²⁵ The documentation of EU-SILC can be found at: <http://ec.europa.eu/eurostat/web/microdata/european-union-statistics-on-income-and-living-conditions>. To transform original csv files into the Stata format we have used the routines from Gesis (prepared by Heike Wirth, <http://www.gesis.org/en/missy/materials/EU-SILC/setups>).

register) on the basis of the following matching variables: year, country, individual id and household id. Our analysis is performed on the pooled waves of EU-SILC data covering the years 2005–2014²⁶ and 28 European countries²⁷.

The key variable of interest (our dependent variable) - hourly wage - is computed on the basis of variables from EU-SILC data files. Using the information on gross annual employee income²⁸, the number of months worked during the income reference year and the average number of hours worked per week we are able to calculate hourly earnings (gross hourly wages) with the assumption of the average number of 4.2 weeks per one worked month.²⁹ Alternatively (we will use this variable for the robustness checks), we have run additional estimations using another way of calculating the dependent variable. Instead of hourly wages we used total annual income, i.e. employees' gross cash or quasi-cash income (monetary compensation of employees in cash payable by the employer).³⁰ Wages are expressed in EUR with the use of conversion rate provided in EU-SILC. Additionally, we use HICP from Eurostat to report wages in real terms (HICP 2015 = 100).

For the purpose of our analysis we employ other micro-level variables from EU-SILC which are important for the determination of wages. The set of individual characteristics consist of: sex, age, marital status, education (based on the highest ISCED level attained and reclassified into groups with high education: ISCED level 6, 7 and 8 or less than high education: ISCED from 0 to 4),³¹ Labour characteristics include: the information on the size of the company an employee is working for (micro firm if less than 11 persons are employed, medium - 11-49 employees and big - 50 or more employees), the type of contract (permanent versus temporal, including work contract of limited duration), managerial position (if the work includes supervisory

²⁶ Theoretically the data for the 2015 is also present, however for the limited number of countries. There are some differences between data collected under different waves. The documentation we rely on is provided (along with the data files) in EC (2016).

²⁷ Out of 32 countries covered by EU-SILC, two are not reported in WIOD (Iceland and Serbia), while for Malta and Croatia the number of missing information referring to hourly wages and specific aggregation of other variables do not allow us to include them in the final sample.

²⁸ We take into account gross employee cash or near cash income which refers to the monetary compensation of employees in cash payable by an employer to an employee. Among others it includes: wages and salaries paid in cash for time worked or work done, holiday payments, payments for overtime, additional payments e.g.: thirteenth month payment, payment based on one's productivity, commissions, tips and gratuities. Gross means that neither taxes nor social contributions have been deducted.

²⁹ The assumption of an average of 4.2 weeks worked per month reflects minimum yearly holidays. However, we have run an additional robustness check assuming $52/12=4.33$ weeks per month instead of 4.2. The results, which do not differ substantially from the benchmark, are reported in Table 2A in Appendix.

³⁰ This includes: wages and salaries for time worked or work done, holiday pay, overtime, and additional payments such as "thirteenth month," productivity pay, commissions, tips and gratuities. The results taking annual income as dependent variable are reported in Table 2A in Appendix.

³¹ Unfortunately, the data on experience (the number of years spent in paid work) is missing for: DK, EL (years 2005 – 2009), FI, HU, NO, SE, UK (years 2005 – 2009) so we do not include this variable in our wage regression. However, the correlation between age and experience is high (0.9), so age should be a good proxy for work experience as well.

responsibilities), the sector of employment (NACE Rev 1.1 for 2004-2007 and NACE Rev.2 for 2008 onwards) and occupation (following 2 digit ISCO-88 classification till 2011 and ISCO-08 afterwards)³².

We restrict our sample to full time workers within working age population 18-65 for whom we have the data allowing us to compute wage measure as well as the information about their occupation and sector of employment. Additionally, we do not take into account armed force occupations. In order to eliminate outlier values in our sample, we correct top and bottom distribution of wages. At the bottom we trim the distribution at the 1/100 of country-specific mean and at the bottom wages greater than ten times the national median are set to ten times the national median. The trimming is performed for each year and each country separately³³. In Table 1A in the appendix we report summary statistics of all the micro-level variables. Average worker in our sample is 41 years old with 19 years of work experience and earns 14 euro per hour; 60% of workers are males and 32% have tertiary education; 56% are married, almost half of the workers are employed in a big firm, 89% have permanent contract while 11% work with a temporary job contract, 28% hold managerial position which includes formal responsibility for supervising a group of other employees also only during some times and doing some of the work

³⁴

An important feature of our data is that we are able to quantify the routine content of jobs of particular workers. For this purpose we use country-specific routine task intensity indices (RTIs) which not only reflect the differences in routinisation between particular occupations, but also between countries (Lewandowski et al., 2019)³⁵. RTI is based on survey data from OECD's PIAAC, the World Bank's Skills Toward Employment and Productivity (STEP), plus the China Urban Labor Survey (CULS), which closely mirrors the occupational task measurements in Acemoglu and Autor (2011) based on the U.S. O*NET data. Lewandowski et al. (2019) document that the relative importance of various tasks differs between countries for workers

³² Our concordance between sectors and occupations takes into account the changes in classifications over time. For the period of time when the old classification existed we match data of individual workers from EUSILC with other variables e.g. sectoral ones based on that old classification, after the classification changed we use the most recent schemes.

³³ Alternatively, we considered to trim the distribution at the bottom at 1st percentile and at the top at the 99th percentile of country and year specific wages. This does not change the results effectively.

³⁴ The comparison of these values with data reported by Eurostat proves that our sample reflects quite well the European labour market. For instance, according to the official statistics 34.2 % of the 25-54 olds in the EU-28 had completed tertiary education (source: Eurostat, edat_lfs_9903, 2017); the proportion of employees aged 15-74 in the EU-28 with a contract of limited duration (fixed-term employment) was 14.2 % (source: Eurostat, lfsa_esegt, 2016), lower employment rates are observed for women than men (gender employment gap equals to 11.5p.p., source: Eurostat, lfsa_ergan, 2017).

³⁵ We would like to thank Piotr Lewandowski from IBS Warsaw for sharing their country-specific indices of routinisation (see Hardy et al., 2018a for methodological details on their computation). The set of indices is available for 42 countries that participated in PIAAC, STEP and CULS surveys. For some of the countries we attribute the values of the most similar country (in terms of economic development, location and size).

performing seemingly similar jobs. Given that they find substantial cross-country differences in the content of work, also within occupations, we use RTIs that are country-occupation-specific and accordingly measure differences in routinisation between countries and between occupations.³⁶

Given that we are primarily interested in the evolution of wages, in Figure 2 we show boxplots of wages by task quartile and, additionally, by skill group. For this purpose, we compute country-specific quartiles of RTI indices which allows us to divide workers into four categories where the bottom category contains workers with the lowest degree of job routinisation (1st quartile of RTI) while the top category refers to workers with the highest degree of job routinisation (4th quartile of RTI). Importantly, thanks to the use of country-specific routinisation indices, the job routinisation of each worker is assessed here with respect to the national distribution of tasks. Skill groups (1-4 where 1 is the lowest and 4 the highest) are defined on the basis of ILO (2012) methodology mapping major ISCO groups to skill levels. Unsurprisingly, higher wages are paid to workers performing occupations which require high skills and are less routine. The box plots³⁷ also show noticeable dispersion of wages within each category.

[Figure 2 about here]

There are of course noticeable cross-country differences in wages. In Table 5 we show average wages, by RTI quartile, in the three groups of European countries (in Table 11A in the Appendix we show analogous country-specific values). Unsurprisingly, the highest wages are reported for those performing low routine occupations, meaning the first quartile of RTI (e.g. in Western Europe the average wage in such occupations equals almost 24 euro per hour, while in CEECS only 5 euro). Workers employed in the most routine intensive jobs earn considerably less. This tendency is stable across countries.

[Table 5 about here]

Is this a sign that major GII is among significant determinants of wages, once all the other factors influencing wage determination process are accounted for? We will address this question in the next section.

³⁶ Having country- and occupation-specific RTI, the differences in wage distribution by RTI quartiles in the countries examined are likely to be due to the differences in the composition of occupations across countries and to the differences in the routinisation measure of occupations. The importance of country heterogeneity in measuring task contents has recently been pointed out by other authors as well – for instance, de Arcangelis and Mariani (2019) document that multi-country variability of PIAAC-based task indexes for European countries is non-negligible and recommend these measures for multi-country analysis (as in our paper).

³⁷ The line inside each box corresponds to the median wage value, box edges show 25th and 75th percentile while the lines extending from the box indicate the variability outside the upper and lower quartiles.

4. Empirical model and estimation results

4.1 The results

Our empirical strategy is based on the estimation of individual wage regression augmented with the measure of the dependence of domestic production on foreign inputs – *GII* - typical for sector in which a given person is employed. Similar approach has been adopted (among others) by Baumgarten et al. (2013), Geishecker et al. (2010) and Ebenstein et al. (2014) who merged micro-level data on labor market outcomes with sectoral observation on offshoring intensity or Parteka and Wolszczak-Derlacz (2019) who combined individual wage data with statistics on sectoral foreign value added share.

First, we estimate the following model:

$$\ln wage_{ijoct} = \alpha + \beta X_{it} + \gamma Job_{it} + \delta RTI_{oc} + \theta GII_{jct} + \mu \ln Prod_{jct} + D_t + D_j + D_c + \varepsilon_{ijoct} \quad (2)$$

where i denotes a worker employed in sector j in occupation o in country c at time t . We regress the log of the gross hourly wage ($\ln wage$) on a set of personal characteristics X (sex, age, age², marital status, education), job characteristics Job (firm size, type of the contract, managerial position) and information on the routine content of occupation RTI (routine task intensity index). We augment the model with the information on global import intensity (GII where $GII = [0 - 1]$) so coefficient θ represents the elasticity of wages with respect to globally measured dependence on foreign inputs. As more productive sectors are likely to pay higher wages, in some specifications we also include productivity ($Prod$), measured as the ratio of real sectoral value added to the total number of hours worked by employees, as an additional industry-level control. Additionally we include time effects D_t (controlling for time specific economic fluctuations, e.g. 2008/2009 crisis), industry dummies D_j (allowing for all the remaining industry-specific characteristics or wage regulations) and country dummies D_c (picking up all country-specific conditions, including labour market institutions and wage-setting mechanisms).³⁸

Eq. (2) is estimated with the use of weighted regression (with normalized weights based on original personal weights provided by EU-SILC and normalized by the number of observations per country to sum up to 10,000 within each country) and robust standard errors which are clustered at the country-industry level. Given the potential endogeneity between the use of foreign inputs (and thus offshoring activity) and wages, we adopt instrumental variables

³⁸ In the robustness section we will add to the estimation more information about the characteristics of labour market institutions which vary across countries. The results are reported in Table 4A. Additionally, we have considered the estimations including a dummy for occupations but as our *RTI* measure is country- and occupation-specific, we find the specification with country and occupation dummies to be overly restrictive. The results are reported in Table R3.

estimation.³⁹ We instrument the global import intensity of a country by the contemporaneous composition of global imports of other countries related to the lagged value of their final product, which is close in spirit to the approach of Autor et al. (2013). Indeed, we find that instruments are correlated with *GII* and orthogonal to changes of individual workers' wages. The choice of the instruments is confirmed by under- and weak identification tests.

[Table 6 about here]

The first two columns of Table 6 present estimation results of the basic specification (eq.2) based on pooled OLS, they differ in a set of explanatory variables (information on contract type and managerial position are not available for all workers). In columns 3 and 4 we report analogous IV estimations. On average, male, older, married workers with higher education earn more. Additionally, higher wages are characteristic for employees working in medium and big companies (in relation to small firms), having a permanent contract and holding managerial position which requires supervisory responsibilities (columns 2 and 4). Hence, in all specifications, the obtained coefficients concerning workers' individual and job characteristic are in line with the microeconomic theory of wage determination (the Mincerian model) - to save space, in the subsequent tables we will not report them. Unsurprisingly, the degree of routinisation, measured by *RTI*, is a significant and negative determinant of wage level.

When it comes to industry-level characteristics, employment in more productive sectors is associated with higher wages while sectors with more intensive process of international production fragmentation (higher *GII*) offer lower wages. Additionally, in Table 7 (and in the subsequent tables) we present the regression with plain *GII* and *RTI* and also with the interaction between *GII* and *RTI*. In the augmented specifications (with interaction) the marginal effect of a change in *GII* on wages also depends on the value of *RTI*. Thus the interaction could help to clarify whether the negative relationship between *GII* and log wage is attenuated or magnified in countries and industries where occupations are typically more routine. The results suggest that in general the degree of routinisation is a highly robust determinant of wages (clearly the more routine the job, the lower the wage). The interaction between *GII* and *RTI* is not statistically significant, so we conclude that wages are determined by a set of microlevel variables (Mincerian framework), the type of tasks performed on the job, and *GII* (independent of routinisation). As reported in Table 7, the negative relationships between hourly wage and job routines and between *GII* and wages are not sensitive to the set of other control variables included into the model as wage determinants. The magnitude of the wage effect of *GII* is higher when the

³⁹ Although we try to take the endogeneity problem into account, causal interpretation should be made with caution. Our empirical analysis is based on pooled waves of EU-SILC data for 2005-2014, which is not a panel where individuals are observed over time.

endogeneity is taken into account, from now on we will concentrate on IV estimations. To save space, we will report coefficients for *GII*, the routinisation and interaction *GII*×*RTI* only, but all the models include personal and employment controls, industry characteristics (productivity), time, country and industry dummies.⁴⁰

[Table 7 about here]

The basic specification was estimated on the full sample of countries, sectors and *GII* independently of the source country of imports. In order to understand what drives the effect of *GII* on wages we re-run the estimations taking into account *GII* computed on the base of information of inputs employed in the value chain and coming exclusively from high income countries (*HIC*), from developing countries (*DEV*) included in WIOD and from the *RoW* (in fact including mainly the aggregate for the developing world – see the note under Table 3). According to the results reported in Table 8, the negative impact of import intensity on wages is much higher when inputs employed along the production chain come from the developing countries and/or *RoW* (columns 4 and 6), than when *GII* is measured with GVC imports from high income countries (columns 1 and 2). Such a result indicates that the process of transferring production to low income (thus low wage) countries, which are characterised by lower cost of production, and then importing inputs from them along the sequential production chain force native workers to accept lower wages. Such a result is much weaker when we consider only GVC imports coming from less competitive high income countries (columns 1 and 2).

[Table 8 about here]

Given that our sample consists of workers from different countries and sectors, we also explore these sources of results' heterogeneity (these results are reported in appendix B). According to the estimations of eq.2 conducted on sample splits, the negative and statistically significant effect of *GII* on wages concerns mainly workers from Western and Southern European countries (Table 1B in appendix B) and the effect is much more pronounced for workers employed in manufacturing than in services (Table 2B in appendix B). Additionally, in a model focusing on workers in Western Europe, the interaction between *GII* and *RTI* is negative and statistically significant, which indicates that *GII* is connected with a sharper decline in the wages of workers doing more routine labour (the opposite is true for workers from Central and Eastern Europe

⁴⁰ We have also run the estimations (with interaction term) for the four *RTI* quartiles - the coefficient for *GII* is the highest for the 4th quartile (the most routine). Additionally, in line with Baumgarten et al. (2013), we rerun the estimations including interactions between specific skill groups and either *GII*, *RTI* or both: the marginal effects of *GII* and *RTI* are skill-specific and the strongest (negative) correlation is for the lowest-skilled workers. Next, we included the interactions between *GII*/*RTI* and specific occupations grouped by ISCO-08 1-digit classification, finding the heterogeneity of marginal effects of *GII*/*RTI* across occupations with stronger (negative) effects for elementary occupations and weaker effects for professionals and managers. The results are reported in Table R4, Table R5 and Table R6 in appendix, respectively.

(Table 1B in appendix B). It is plausible, that this is the effect of offshoring between Western and Eastern Europe, as routine tasks are ‘moved’ to Eastern Europe, where the demand for workers performing them increases. Further, we simultaneously consider diverse sources of heterogeneity. Table 3B reports the results for workers from Western European countries and when *GII* is differentiated according to the source of inputs along the value chain. The negative association between *GII* and wages is confirmed for workers from Western Europe and its magnitude is the highest when GVC inputs are imported from developing countries. Additionally, as reported in Table 4B, this negative effect is felt by Western European workers employed in manufacturing.

As our study seems to be the first to employ *GII* to measure global dependence on foreign inputs, it is thus interesting to compare our results to the ones obtained with conventional measures of value added trade and offshoring (Johnson and Noguera, 2012; Koopman et al., 2014; Wang et al., 2013; Feenstra and Hanson, 1999), as they may differ. To do so, we have computed: OFF- imports of intermediate inputs in proportion to the value added of a given sector (traditional offshoring measure as in Feenstra and Hanson, 1999); FVA/EXP- foreign value added in exports (derived from export decomposition following Wang et al. (2013); FVA_FIN/EXP – foreign value added used in final goods exports (Wang et al. 2013); FVA_INT/EXP - foreign value added used in intermediate exports over total exports (Wang et al. (2013); VS/EXP – vertical specialisation measured as the ratio of foreign value added (FVA) and pure double counting from foreign sources (FDC) to exports (Koopman et al., 2014); VS1/EXP – vertical specialisation measured as the ratio of foreign value added (FVA) plus total pure double counting (PDC) to exports (Wang et al., 2013).

As expected, our measure (*GII*) is closely correlated with the other measures of value added trade/offshoring (high pairwise correlation coefficients, reported in Table R2⁴¹). To show how alternative measures of value added trade and offshoring work in the framework of Mincer regressions, Table 9 reports the results where these alternative measures have been included in the set of regressors, instead of *GII*. Additionally, in column 2 we report the results taking into account only import intensity of production measured at the last stage (*GII_tier1*) while *GII_except_tier1* (column 3) takes into account previous cross-country and cross-industry links along the entire production sequence but except the last stage (indirect exposure). The coefficients are always negative and statistically significant. In order to assess the relative strength

⁴¹ The country rankings and trends based on *GII* and different measures of vertical specialization (*FVA/EXP*, *FVA_FIN/EXP*, *FVA_INT/EXP*, *VS/EXP*, *VS1/EXP*) and the traditional measure of offshoring (OFF) are similar, in keeping with strong correlation between those measures of production fragmentation (reported in Table R2 in appendix). The various methods of measuring fragmentation lead to the conclusion that the country-sectors that rely heavily on imported inputs are also those with high proportions of exported FVA.

of each of the different measures of GVC, we provide standardized regression coefficients that show the effect on wages of a one-standard-deviation increase in any given GVC measure. Comparing the results obtained with *GII*, *GII_tier1* and *GII_except_tier1*, the strongest effect is for total *GII* while the weakest for direct exposure (*GII_tier1*). The differences in the magnitudes of standardised coefficients for the last stage of production and all stages except the last are not as significant, which could be due to the nature of sequential production and the interplay between various stages of the chain. However, the coefficients should be put in the perspective of the actual value of *GII* measures (see Table 4): the value of imported inputs used in the last stage (*GII_tier1*) is less than when all the backward stages of production are taken into account (*GII*).

[Table 9 about here]

4.2 Economic significance of the results

Based on the above results, one would conclude that the involvement of domestic industries into production fragmentation, measured globally along all the chain of production, impacts negatively mainly wages of Western European workers (once all other - individual, job, country and sectoral characteristics are controlled for).

How strong are the estimated effects in economic terms? In other words, how much wages in Europe changed due to increased *GII*? First of all, let's remind that *GII* index ranges between 0 and 1. Hence, the estimates of log-linear model (2) indicate that an increase in *GII* by one unit (hence by 1, which is equivalent to a rise of *GII* by 100%) is associated with a change in hourly wage by $\theta\%$. Taking into account the results for all sample (Europe28) the biggest estimated coefficient θ is equal to -0.316 (Table 7, column 4). We shall put it in the perspective of registered rise in GVC imports and data on wages in Europe. Table 10 shows the economic significance of the results (based on statistically significant estimates only reported in Table 7, Table 8 and Table 3B in appendix B) where we compare the results, split by the source of imports along the GVC, for all the sample and for Western European workers only, typically perceived in the literature as negatively exposed to the effects of production fragmentation.

According to our data, over the sample period *GII* (averaged over all industries) in the whole EU28 sample rose from 0.166 (=16.6% of final output) in 2005 to 0.202 (=20.2%) in 2014, hence *GII* rose by 0.0354 (=3.54p.p.). Combining it with the coefficient estimate from Table 7 (column 4) and with the data on average hourly wage in the initial year (15.75 eur per hour), we find that the change in GVC imports in the period 2005-2014 resulted in average cumulated wage decrease by only 0.176 eur [=3.54/100*(-0.316)*15.75 eur]. Assuming 1564 of working hours per year (source: EUKLEMS, 2018, EU28_output_17ii) this is equivalent to an annual earnings 'loss' of 30.6 euro. In other words, if the use of inputs along the GVC had

remained unchanged with respect to year 2005, hourly wage of European workers would have been higher by 18 cents in 2014. This effect is not large. As reported in Table 10, the magnitude of the effect estimated for Europe 28 is, however, almost twice higher if we consider the impact of GVC imports coming from developing countries.

The picture changes a bit if we consider only workers from Western Europe and developments in GII therein. The counterfactual calculations for Western European workers result in cumulative hourly wage ‘decline’ by 0.16 euro which is equivalent to 27.45 euro less of annual earning. This effect is higher when we take into account stronger effect exhibited by GVC imports from developing countries (and measured by GII^{DEV}). If the use of inputs along the GVC coming from developing countries had remained unchanged with respect to year 2005, hourly wage of European workers in 2014 would have been higher by 0.7 euro (annual loss of 122 euro). Hence, the effect of global import intensity of production on wages in Western Europe is economically small.

[Table 10 about here]

4.3 Extensions and robustness checks

We considered numerous robustness checks and extensions of the basic model estimated for workers from 28 European countries. The general result of the negative effect of GII on wages of all European workers is robust to: the way we measure our dependent variable (Table 2A in the appendix) and changes in the weighting scheme adopted in the regression (Table 3A in the appendix). None of these changes alters in a considerable way our main result: negative influence of global import intensity of production on wages of European workers.

Then, even though our model incorporates sector and country specific fixed effects, and thus should capture all the other wage determinants not explicitly included into the model, we considered the extended estimations including additional control variables. Following Geishecker et al. (2010) and Schäfer and Gottschall (2015) we considered differences in labour market institutions and country-specific wage bargaining schemes (Table 4A in appendix A). We also included variables related to country-level and industry-level trade openness (Table 5A in appendix A). Confirming other studies (e.g. Hummels et al, 2014), sectors which are more export oriented (with higher share of export to value added) are characterised by higher wages. In line with the literature on the role of technology in wage determination process (Autor et al., 2003; Acemoglu and Autor, 2011; Goos et al., 2014), we also took into account the potential role played by technology and R&D (we employed industry-level variables on computing, communications and R&D equipment, expressed either as capital formation or stock – Table 6A in the appendix). The inclusion of additional country-specific or sector specific variables do not

change our main results and interestingly those additional variables are hardly statistical significant. Finally, our results are also not driven by any specific country or industry (we checked it by eliminating, one-by-one, countries or industries from the sample – the results over such limited subsamples showing mean, minimum and maximum coefficients are reported in Table 7A and Table 8A in appendix A). We also split time of our analysis into pre and post crises; respectively we run regressions for two time periods: 2005 – 2008 and 2009 – 2014. As indicated in Table 9A, indeed in the years before the crisis, when the growth of GII was more intensive then afterwards, the effect on wages was two times higher than in the years after 2009 when the slowdown of GII growth was observed (Timmer et al., 2016).

Finally, to check the average industry position in GVCs we introduced in our regression the upstreamness measure (*UP*) developed by Fally (2011) and Antràs et al. (2012). The index is based on forward linkages and measures an industry’s average distance from the final stage of production.⁴² The results of an augmented estimation of the wage model are reported in Table R1: neither *UP* nor its interaction with *GII* is statistically significant. The other explanatory variables (microlevel Mincerian determinants of wages, routinisation of occupation, degree of GVC dependency measured by *GII*) explain up to three quarters of wage variability in our sample.

5. Conclusions

In this paper we have attempted to contribute to the empirical literature on microeconomic consequences of cross-border production links for European workers. We have addressed several limits of single-country studies on offshoring/production fragmentation and wages. We have used comparable worker-level data from 28 European countries matched with industrial statistics in a methodologically uniform and generally accepted (Mincerian) framework, which should provide a robust set of facts concerning the effects of GVC on wages in Europe. We considered differences in countries level of development or labour market institutions, sectoral specificity, the heterogeneity of foreign inputs according to source countries’ characteristics; we took into account country-specific task content of jobs affecting wage levels. The way we measured fragmentation within GVCs (global import intensity of production computed with newest 2016 World Input-Output Database) allowed us to trace back the involvement of sectors into the global structure of production. This measure, contrary to conventional measures of offshoring,

⁴² Fally (2011) notices that within manufacturing, upstreamness is positively correlated with physical capital intensity and negatively correlated with skill intensity. We have additionally verified the relationship between per capita income (*GDPpc*) and a country’s GVC position. The correlation coefficient between *UP* and *GDPpc* in our sample is -0.0166. This is in line with the previous findings: ‘We verify that the bivariate correlation between country upstreamness and log real GDP per capita is not statistically significant.’ (Antràs et al., 2012: p.416).

captures imports of goods and services needed in any backward stage of the production of the final product and involves third-country trade. Such a view is more coherent with the key feature of GVC seen as cross-country multistage production network which results in cross-country industrial interdependence. Consequently, we believe it is the broadest European perspective adopted so far to the study of wage response to global production links and our conclusions are not country specific as in many related papers.

Our empirical analysis in the whole sample of 28 European countries shows a negative correlation between the wages of domestic labour and involvement in GVCs (importantly, not only when GVCs are measured by *GII* but also by other measures).⁴³ However, we find significant heterogeneity with respect to subsamples of European countries and with respect to the source of imports along the value chain. The downward pressure on wages concerns mainly workers in Western Europe and is driven by production links with developing countries.

Our results also confirm that the degree of occupation routinisation is a particularly robust determinant of wages (the more routine the job, the lower the wage), regardless of GVC participation. Additionally, in a model focusing on workers employed in Western European countries, *GII* is connected with the lower wages of workers doing more routine tasks. Hence, in line with our empirical data, Western European workers with more routine jobs may feel more threatened, especially when they have to compete with cheap labor in developing countries (or with the product of their labour, e.g. intermediate inputs produced by routine workers in developing countries), while their counterparts in Central and Eastern Europe may benefit from involvement in GVCs, thanks to greater demand for their labour (owing to the shift of more routine tasks to low-wage countries). Still, this negative wage effect of *GII* is rather modest and not strong in economic terms.

On the theoretical plane the relationship between wages and GVC involvement is far from straightforward, with insights from various models. The empirical results should be thus interpreted taking into account the intertwined relationship between *GII*, the level of surpluses, productivity, and wages in industries. Our general results (the negative correlation between GVC and wages) have at least a threefold explanation. One interpretation highlights the pressure on domestic workers to accept lower wages in fear of job displacement; the recent paper of Jeon and Kwon (2019), for instance, develops a theoretical model to show that the *threat* of offshoring can impact on wages even when there is no *actual* offshoring. The first interpretation can also be seen

⁴³ This is in line with the literature, as the negative correlation between GVC (offshoring) and wages of domestic workers (or some types of workers, i.e. low skilled and/or performing routine tasks) has been shown in previous studies: among others, Amiti and Davis (2011), Baumgarten et al. (2013), Geishecker and Görg (2013), Parteka and Wolszczak-Derlacz (2019), Ebenstein et al. (2014).

as a situation in which the fear of displacement offsets the potential productivity gains from involvement in GVC. Another explanation could be that country-industries with low surpluses, hence low wages, and that share it under bargaining, tend to use more *GII* in order to increase their surplus. Finally, our results might represent the effect of reallocation of labour between firms/sectors of differing productivity as in equilibrium model by Egger et al. (2015) in which offshoring, unlike international trade in final goods, may reallocate production workers from high- to low-productivity firms. The mechanism is quite simple: falling trade costs, starting from an excessively high level, cause international production fragmentation among the more productive firms, which frees some domestic labour and drives down wages.

An interesting extension of our work could be to separate, for each European downstream country, the parts of GVCs that fall into upstream European countries in the sample. For those GVCs, one could then relate upstream GVCs to downstream wages but also downstream wages to upstream wages in a separate Mincer regression.

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TABLES AND FIGURES – REVISED (This version: 27 April, 2020)

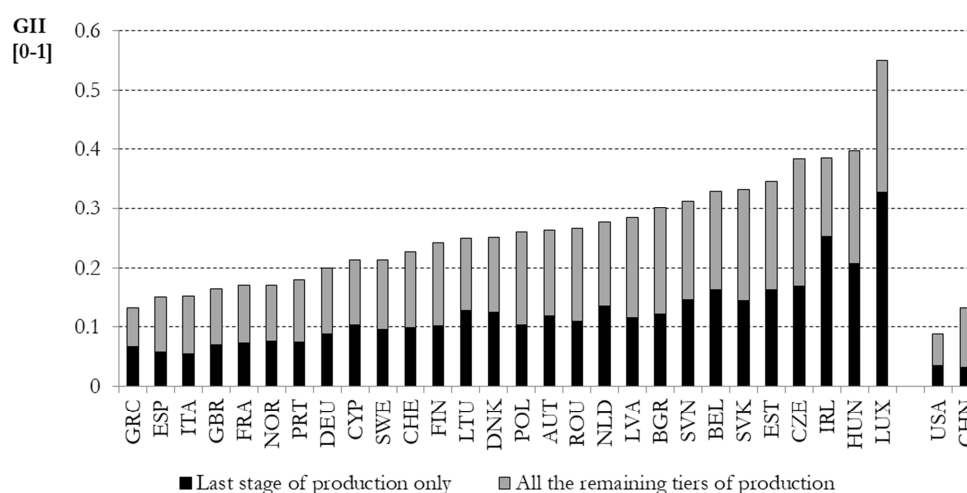
Table 1. Global import intensity of production, as % of final output (World, Europe, USA)

	Last stage of production			All tiers of production (<i>GII</i>)		
	World	Europe(28)	USA	World	Europe (28)	USA
2000	5.2	7.4	2.8	11.8	15.9	7.9
2014	6.3	8.8	3.5	15.8	20.2	8.8

Notes: average values calculated across countries and 56 industries and weighted by industrial value added (VA_{ijt}). *GII* calculated as in eq. 1, *GII* reflects the ratio of GVC imports to the output of the final products and ranges here between 0 and 100%. Europe (28) consists of: *W* - Western Europe (AT, BE, CH, DE, DK, FI, FR, IE, IT, NL, NO, SE, UK); *S*- Southern Europe (CY, ES, EL, PT); *CEE*- Central and Eastern Europe (BG, CZ, EE, HU, LT, LU, LV, PL, RO, SI, SK).

Source: own calculations based on WIOD (release Nov 2016) and Timmer et al. (2016) methodology.

Figure 1. Global import intensity of production (*GII*, index 0-1) – 28 European countries versus the U.S. and China



Notes: average values calculated across 56 industries and weighted by industrial value added (VA_{ijt}). *GII* calculated as in eq. 1. *GII* is a sum of the values for the last stage of production only and of all the remaining tiers of production. 28 European countries (Europe 28) included in the sample: *W* - Western Europe (AT, BE, CH, DE, DK, FI, FR, IE, IT, NL, NO, SE, UK); *S*- Southern Europe (CY, ES, EL, PT); *CEECs*- Central and Eastern European Countries (BG, CZ, EE, HU, LT, LU, LV, PL, RO, SI, SK).

Source: own calculations based on WIOD (release Nov 2016) and Timmer et al. (2016) methodology.

Table 2. Global import intensity of production (*GII*, index 0-1), 2014 – by sectors

Country sample:	all industries	manufacturing	services
World	0.16	0.29	0.11
Europe28	0.20	0.42	0.13
Western Europe (<i>W</i>)	0.20	0.41	0.14
Southern Europe (<i>S</i>)	0.15	0.40	0.09
<i>CEECs</i>	0.30	0.54	0.19

Notes: *average values weighted by industrial value added (VA_{ijt}). *GII* calculated as in eq. 1. Country groups: *W* - Western Europe (AT, BE, CH, DE, DK, FI, FR, IE, IT, NL, NO, SE, UK); *S*- Southern Europe (CY, ES, EL, PT); *CEECs*- Central and Eastern European Countries (BG, CZ, EE, HU, LT, LU, LV, PL, RO, SI, SK).

Source: own calculations based on WIOD (release Nov 2016) and Timmer et al. (2016) methodology

Table 3. Global import intensity of production (GII), 2014 – split by the source of intermediate inputs along the value chain (GII^{HIC} and GII^{DEV})

Panel A.	GII^{HIC}		
Country sample:	all industries	manufacturing	services
World	0.09	0.16	0.06
Europe28	0.14	0.31	0.10
Western Europe (W)	0.14	0.30	0.10
Southern Europe (S)	0.09	0.25	0.06
CEECs	0.21	0.37	0.14
Panel B.	GII^{DEV}		
Country sample:	all industries	manufacturing	services
world	0.03	0.06	0.02
Europe28	0.02	0.06	0.02
Western Europe (W)	0.02	0.05	0.02
Southern Europe (S)	0.02	0.06	0.01
CEECs	0.04	0.09	0.03
Panel C.	GII^{RoW}		
Country sample:	all industries	manufacturing	services
world	0.03	0.07	0.02
Europe28	0.03	0.06	0.02
Western Europe (W)	0.04	0.05	0.02
Southern Europe (S)	0.03	0.10	0.02
CEECs	0.04	0.07	0.03

Notes: as under Table 1. HIC (*high income countries*)=AUS, AUT, BEL, CAN, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, JPN, KOR, LVA, LTU, LUX, MLT, NLD, NOR, POL, PRT, SVK, SVN, ESP, SWE, CHE, TWN, GBR, USA; DEV (*developing countries*)= BRA, BGR, CHN, IND, IDN, MEX, ROM, RUS, TUR; RoW =world – 43 countries present in WIOD2016 = world – HIC – DEV .

Source: own calculations based on WIOD (release Nov 2016) and Timmer et al. (2016) methodology.

Table 4. Import intensity of production based on first tier imports only (*GII_tier1*) and including all imports in the GVC (*GII*), vertical specialization – by country (Europe28)

	<i>GII</i>		<i>GII_tier1</i>		<i>VS/Exp</i>		<i>Change 2005-2014 [in %]</i>		
Country	2005	2014	2005	2014	2005	2014	<i>GII</i>	<i>GII_tier1</i>	<i>VS/Exp</i>
Western Europe (W)									
AT	0.23	0.26	0.11	0.12	0.17	0.19	14.3	5.7	8.4
BE	0.26	0.33	0.13	0.16	0.19	0.24	28.1	27.3	25.1
CH	0.21	0.23	0.09	0.10	0.16	0.16	7.8	5.4	4.4
DE	0.16	0.20	0.07	0.09	0.11	0.13	27.6	25.9	21.5
DK	0.22	0.25	0.11	0.12	0.17	0.18	13.6	10.6	9.9
FI	0.22	0.24	0.09	0.10	0.17	0.18	10.5	8.6	7.1
FR	0.14	0.17	0.06	0.07	0.10	0.12	25.4	22.1	15.2
UK	0.14	0.16	0.07	0.07	0.11	0.12	17.6	3.8	11.7
IE	0.31	0.39	0.18	0.25	0.26	0.30	23.7	39.7	17.4
IT	0.13	0.15	0.05	0.06	0.10	0.11	17.8	11.1	10.5
LU	0.47	0.55	0.28	0.33	0.39	0.46	17.6	16.8	17.2
NL	0.21	0.28	0.11	0.14	0.16	0.20	33.4	23.6	25.2
NO	0.14	0.17	0.06	0.08	0.10	0.12	25.1	21.5	21.4
SE	0.21	0.21	0.10	0.10	0.16	0.15	2.2	-0.5	-1.7
Southern Europe (S)									
CY	0.20	0.21	0.10	0.10	0.15	0.15	9.0	1.3	2.1
ES	0.16	0.15	0.06	0.06	0.13	0.11	-8.1	-9.9	-11.5
EL	0.12	0.13	0.06	0.07	0.09	0.10	12.9	12.8	6.4
PT	0.17	0.18	0.07	0.07	0.13	0.13	8.8	8.6	2.4
Central&Eastern Europe (CEECs)									
BG	0.27	0.30	0.11	0.12	0.21	0.22	10.2	7.6	2.7
CZ	0.29	0.38	0.12	0.17	0.22	0.27	30.8	36.1	23.2
EE	0.31	0.35	0.15	0.16	0.23	0.24	10.7	10.2	3.0
HU	0.30	0.40	0.15	0.21	0.23	0.28	30.5	35.4	22.7
LT	0.22	0.25	0.11	0.13	0.17	0.18	15.3	12.0	8.1
LV	0.25	0.28	0.11	0.12	0.19	0.20	13.2	2.6	7.1
PL	0.21	0.26	0.09	0.10	0.15	0.18	26.3	16.6	18.6
RO	0.24	0.27	0.11	0.11	0.18	0.19	8.8	-0.1	4.8
SI	0.27	0.31	0.12	0.15	0.23	0.23	8.1	2.5	-0.3
SK	0.31	0.33	0.14	0.15	0.19	0.22	18.2	15.9	13.1

Notes: *average values weighted by industrial value added (VA_{ijt}). *GII* (Timmer et al., 2016) calculated as in eq. 1. *VS/EXP* - vertical specialisation measured as the ratio of foreign value added (*FVA*) and pure double counting from foreign sources in export (Koopman et al., 2014)

Source: own calculations based on WIOD (release Nov 2016)

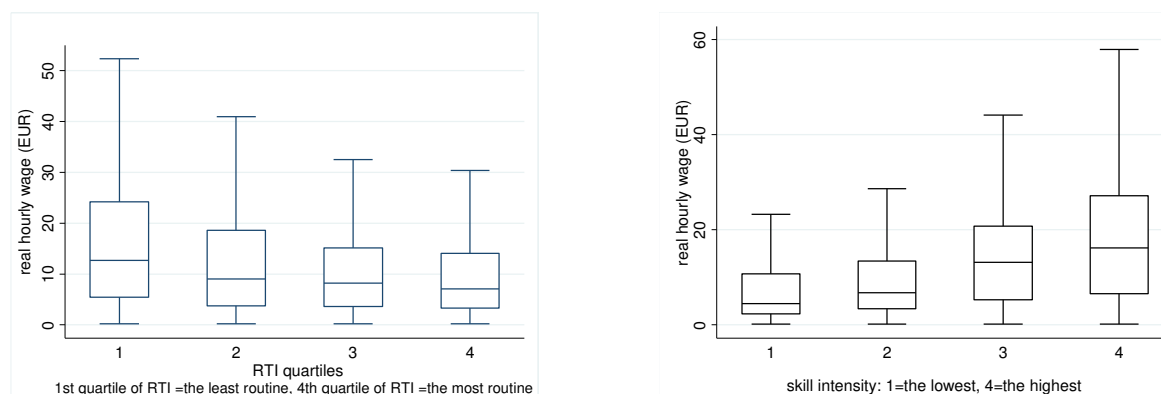


Figure 2. Wages by job routinisation intensity and by skill intensity (Europe 28, 2014)

Source: own calculations based on EU-SILC. RTI quartiles based on country-specific indices of job routinisation from Lewandowski et al. (2019), skill categories based on mapping main ISCO groups into skill groups according to ILO (2012).

Table 5. Wages by job routinisation intensity (Western Europe, Southern Europe and CEECs, 2014)

Country sample:	RTI quartile 1 (=the least routine)	RTI quartile 2	RTI quartile 3	RTI quartile 4 (=the most routine)
Western Europe (W)	23.87	18.92	14.74	14.20
Southern Europe (S)	14.98	10.51	9.10	7.74
CEECs	5.13	3.20	3.25	3.04

Note: RTI quartiles based on country-specific indices of routine task intensity of occupations from Lewandowski et al. (2019).

Source: own calculations based on EU-SILC.

Table 6. Estimation results (1) – *GII* among other determinants of wages in Europe

Dep.var: log hourly wage (gross)	OLS (1)	OLS (2)	IV (3)	IV (4)
Sex (=1 if male)	0.167*** [0.008]	0.163*** [0.008]	0.168*** [0.008]	0.163*** [0.008]
Age (years)	0.048*** [0.003]	0.041*** [0.002]	0.048*** [0.003]	0.041*** [0.002]
Age ²	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
Marital status (=1 if married)	0.032*** [0.003]	0.026*** [0.003]	0.031*** [0.003]	0.026*** [0.003]
Education (=1 if high)	0.208*** [0.007]	0.199*** [0.007]	0.208*** [0.007]	0.199*** [0.007]
Firm size (=1 if big)	0.259*** [0.010]	0.191*** [0.008]	0.259*** [0.010]	0.192*** [0.008]
Firm size (=1 if medium)	0.167*** [0.009]	0.100*** [0.007]	0.167*** [0.009]	0.101*** [0.007]
ln_Prod (VA/H)	0.106*** [0.030]	0.126*** [0.029]	0.102*** [0.030]	0.123*** [0.029]
<i>RTI</i>	-0.377*** [0.010]	-0.347*** [0.010]	-0.378*** [0.010]	-0.347*** [0.010]
<i>GII</i>	-0.153** [0.074]	-0.149* [0.077]	-0.240*** [0.075]	-0.211*** [0.078]
Job contract (=1 if permanent)		0.212*** [0.017]		0.213*** [0.018]
Job position (=1 if managerial)		0.125*** [0.004]		0.125*** [0.004]
R ²	0.76	0.8	0.76	0.8
N	1217953	1105538	1213922	1101866
Under-identification			0.00	0.00
Weak identification			472352.6	444775.6
Hansen J (p-value)			0.42	0.51

Notes: normalised weighted regression with robust standard errors (in parentheses), clustered at the country-industry level, the weights are based on personal cross-sectional weights (from EU-SILC) normalised by the number of observation per country (see main text for the details); * $p \leq .10$, ** $p \leq .05$, *** $p \leq .01$. In specification (3) and (4) *GII* is treated as an endogenous variable, see the main text for the explanation of instrument construction. The figures reported for the under-identification test are the p-values and refer to the Kleibergen-Paap rk LM test statistic, where a rejection of the null indicates that the instruments are not under-identified. The weak identification test refers to the Kleibergen-Paap Wald rk F statistic test for the presence of weak instruments. As a ‘rule of thumb’ the statistic should be at least 10 for weak identification not to be considered a problem (Staiger and Stock, 1997). The Hansen J test of overidentifying restrictions (null hypothesis is that the instruments are valid) refers to its p-value.

Source: own elaboration based on data from EU-SILC and WIOD.

Table 7. Estimation results (2) – *GII* as wage determinant in Europe (interaction with job routinisation, *RTI* and the inclusion of extended set of control variables)

Dep.var: log hourly wage (gross)	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.563*** [0.026]	-0.400*** [0.023]	-0.390*** [0.023]	-0.378*** [0.023]
<i>GII</i>	-0.299*** [0.100]	-0.279*** [0.090]	-0.301*** [0.089]	-0.316*** [0.089]
<i>GII</i> × <i>RTI</i>	0.101 [0.068]	0.055 [0.062]	0.033 [0.062]	0.093 [0.065]
Personal controls	no	yes	yes	yes
Firm controls	no	no	yes	yes
Job controls	no	no	no	yes
Time dummies p-value	0.000	0.000	0.000	0.000
Country dummies p-value	0.000	0.000	0.000	0.000
Industry dummies p-value	0.000	0.000	0.000	0.000
R ²	0.72	0.75	0.76	0.8
N	1312076	1304717	1213922	1101866
Under-identification	0.00	0.00	0.00	0.00
Weak identification	277005.8	274132.8	260375	247920.2
Hansen J (p-value)	0.6	0.33	0.36	0.48

Notes: normalised weighted regression with robust standard errors (in parentheses), clustered at the country-industry level, the weights are based on personal cross-sectional weights (from EU-SILC) normalised by the number of observation per country (see main text for the details); *p ≤ .10, **p ≤ .05, ***p ≤ .01. *Personal controls* include: age, age2, marital status, education (the default category for education are non-high (medium /low-educated workers)), *Employment controls* refer to the size of the entities: the default category are small firms, *Job controls* refer to the type of the contract (the default category is non-permanent contract) and type of the position (the default category non-managerial). *GII* is treated as an endogenous variable, see the main text for the explanation of instrument construction. In all specifications time, country and industry dummies are included, p-values for the Wald tests of hypothesis that dummies' coefficients are zero. The figures reported for the under-identification test are the p-values and refer to the Kleibergen-Paap rk LM test statistic, where a rejection of the null indicates that the instruments are not under-identified. The weak identification test refers to the Kleibergen-Paap Wald rk F statistic test for the presence of weak instruments. As a 'rule of thumb' the statistic should be at least 10 for weak identification not to be considered a problem (Staiger and Stock, 1997). The Hansen J test of overidentifying restrictions (null hypothesis is that the instruments are valid) refers to its p-value.

Source: own elaboration based on data from EU-SILC and WIOD.

Table 8. Estimation results (3) - *GII* as wage determinant in Europe, split according to the source of imports along the value chain

Dep.var: log hourly wage (gross)	<i>GII</i> – imports coming from:					
	high income countries (<i>HIC</i>)		developing countries (<i>DEV</i>)		rest of the world (<i>RoW</i>)	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.381*** [0.011]	-0.384*** [0.023]	-0.379*** [0.011]	-0.403*** [0.023]	-0.382*** [0.011]	-0.400*** [0.024]
<i>GII</i>	-0.387*** [0.120]	-0.392*** [0.124]	-1.781** [0.718]	-2.169** [0.924]	-1.905*** [0.703]	-2.122*** [0.720]
<i>GII</i> × <i>RTI</i>		0.016 [0.088]		0.606 [0.476]		0.43 [0.495]
R ²	0.77	0.77	0.76	0.76	0.76	0.76
N	1207394	1207394	1207394	1207394	1207112	1207112
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	249260.4	120640.3	14588.23	8218.53	24809.44	12125.69
Hansen J (p-value)	0.9	0.79	0.05	0.04	0.06	0.03

Notes: as under Table 7. Personal and employment controls, time, country and industry dummies included in all models. *HIC* (*high income countries*)=AUS, AUT, BEL, CAN, HRV, CYP, CZE, DNK, EST, FIN, FRA, DEU, GRC, HUN, IRL, ITA, JPN, KOR, LVA, LTU, LUX, MLT, NLD, NOR, POL, PRT, SVK, SVN, ESP, SWE, CHE, TWN, GBR, USA; *DEV* (*developing countries*)= BRA, BGR, CHN, IND, IDN, MEX, ROM, RUS, TUR; *RoW*=world – 43 countries present in WIOD2016 = world – *HIC*–*DEV*.

Source: own elaboration based on data from EU-SILC and WIOD

Table 9. Estimations with different measures of GVC/ production fragmentation – standardized coefficients

Dep.var: log hourly wage (gross)	Measure of GVC/production fragmentation								
	GII	GII_tier1	<i>GII_except_tier1</i>	OFF	FVA/EXP	FVA_FIN/EXP	FVA_INT/EXP	VS/EXP	VS1/EXP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>RTI</i>	-0.380*** [0.011]	-0.380*** [0.011]	-0.381*** [0.011]	-0.380*** [0.011]	-0.381*** [0.011]	-0.381*** [0.011]	-0.381*** [0.011]	-0.381*** [0.011]	-0.381*** [0.011]
<i>GVC</i>	-0.040*** [0.015]	-0.033** [0.013]	-0.035** [0.016]	-0.022** [0.010]	-0.044*** [0.013]	-0.022** [0.011]	-0.035*** [0.012]	-0.045*** [0.014]	-0.044*** [0.014]
<i>GVCx RTI</i>	0.006 [0.011]	0.001 [0.010]	0.014 [0.012]	0.003 [0.010]	0.005 [0.011]	0.006 [0.010]	0.004 [0.011]	0.005 [0.011]	0.005 [0.011]
R ²	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76
N	1217953	1217953	1217953	1217953	1213922	1213922	1213922	1213922	1213922

Notes: as under Table 7, time, country and industry dummies included in all models. OLS estimates.

Source: own elaboration based on data from EU-SILC and WIOD

Table 10. Economic significance calculations

Sample: workers from EU28									
	<i>GII</i>		<i>GII^{HIC}</i>		<i>GII^{DEV}</i>		<i>GII^{RoW}</i>		
Estimated coefficient <i>GII</i> *	-0.316		-0.392		-2.169		-2.122		
Change in <i>GII</i> 2005-2014 (in p.p.)	3.54		1.82		0.93		0.78		
Average hourly wage in 2005 (in eur)	15.75								
	percent	euro	percent	euro	percent	euro	percent	euro	
cumulative economic effect on hourly wage	-1.12	-0.18	-0.71	-0.11	-2.02	-0.32	-1.66	-0.26	
average annual affect on earnings		-30.62		-19.53		-55.21		-45.20	
Sample: workers from Western Europe									
	<i>GII</i>		<i>GII^{HIC}</i>		<i>GII^{DEV}</i>		<i>GII^{RoW}</i>		
Estimated coefficient <i>GII</i> **	-0.222		-0.252		-3.872		-1.835		
Change in <i>GII</i> 2005-2014 (in p.p.)	3.69		2		0.94		0.74		
Average hourly wage in 2005 (in eur)	19.28								
	percent	euro	percent	euro	percent	euro	percent	euro	
cumulative economic effect on hourly wage	-0.82	-0.16	-0.50	-0.10	-3.64	-0.70	-1.36	-0.26	
average annual affect on earnings		-27.45		-16.89		-121.95		-45.50	

Note: *results from Table 7 and Table 8; **results from Table 9 and Table 3B (Appendix B).

Source: own calculations based on EU-SILC and WIOD.

Online appendices and supplementary materials accompanying the paper:

Parteka A., Wolszczak-Derlacz J. (2020). Wage response to global production links – evidence for workers from 28 European countries (2005-2014)

Appendix A.

Table 1A. Summary statistics of micro-level variables

	variable	n	mean	st.dev.	min	max
Dependent variable – <i>gross hourly wage</i> [EUR, real]	<i>wage1</i>	546964	12.31	10.04	0.01	113.46
	<i>wage2</i>	1377903	13.95	10.93	0.08	160.36
Personal characteristics	<i>Sex</i> (male=1)	1377903	0.60	0.49	0.00	1.00
	<i>Age</i> (age, in years)	1377903	40.94	11.10	18.00	65.00
	<i>Exp</i> (experience, in years)	1013152	19.21	11.63	0.00	65.00
	<i>Mededuc</i> (medium education completed)	1370211	0.64	0.48	0.00	1.00
	<i>Hieduc</i> (high education completed)	1370211	0.32	0.47	0.00	1.00
	<i>Married</i> (family status)	1377903	0.56	0.50	0.00	1.00
Job characteristics	<i>MicroFirm</i> (company size: micro, 1-10)	1342522	0.22	0.41	0.00	1.00
	<i>SizeMed</i> (company size: medium, 11-49)	1280416	0.28	0.45	0.00	1.00
	<i>SizeBig</i> (company size: big, >=50)	1280416	0.49	0.50	0.00	1.00
	<i>Cont_Perm</i> (permanent contract)	1239555	0.89	0.31	0.00	1.00
	<i>Cont_Temp</i> (temporary contract)	1239555	0.11	0.31	0.00	1.00
	<i>Manag</i> (managerial position)	1261068	0.28	0.45	0.00	1.00

Note. *n* varies due to limited availability of some of the variables, observations weighted by personal cross-sectional weights.

Source: authors' calculations with EU-SILC data

Table 2A. Estimation results – *GII* as wage determinant in Europe, robustness with respect to the way the dependent variable is measured

Dep.var:	hourly wage*		annual income	
	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.378*** [0.011]	-0.387*** [0.023]	-0.447*** [0.011]	-0.443*** [0.021]
<i>GII</i>	-0.283*** [0.083]	-0.299*** [0.089]	-0.280*** [0.079]	-0.272*** [0.084]
<i>GII</i> $\times$ <i>RTI</i>		0.03 [0.062]		-0.014 [0.058]
R ²	0.75	0.75	0.71	0.71
N	1216142	1216142	1213922	1213922
Under-identification	0.00	0.00	0.00	0.00
Weak identification	462064.1	260434.1	461909.9	260375
Hansen J (p-value)	0.22	0.38	0.80	0.98

Notes: as under Table 7. Hourly wage* calculated on the data of the number of months worked during the income reference year, the average number of hours worked per week with the assumption of the average number of 4.33 weeks per one worked month. The annual income accounts gross employee cash or near cash income which refers to the monetary compensation of employees in cash payable by an employer to an employee, for the specific components of the income see the main text.

Source: own elaboration based on data from EU-SILC and WIOD.

Table 3A. Estimation results – *GII* as wage determinant in Europe, robustness with respect to the weighting scheme adopted in the regression

Dep.var: log hourly wage (gross)	Weight type					
	weights 1		weights 2		weights 3	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.380*** [0.011]	-0.390*** [0.023]	-0.390*** [0.010]	-0.402*** [0.022]	-0.393*** [0.010]	-0.405*** [0.021]
<i>GII</i>	-0.283*** [0.083]	-0.301*** [0.089]	-0.194** [0.082]	-0.218** [0.085]	-0.203** [0.081]	-0.227*** [0.085]
<i>GII</i> $\times$ <i>RTI</i>		0.033 [0.062]		0.04 [0.063]		0.042 [0.061]
R ²	0.76	0.76	0.74	0.74	0.74	0.74
N	1213922	1213922	1213922	1213922	1213922	1213922
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	461909.9	260375	627482.3	364617.6	479364.7	287737.2
Hansen J (p-value)	0.22	0.36	0.19	0.31	0.16	0.34

Notes: as under Table 7. Country, industry and time dummies included. Weighted regression, normalised weights with different scaling methods: weight 1 – benchmark weights: normalised personal weights, which always sums to 10 000 within each country, weights 2: normalised personal weights by number of observations according to inverse probability, as in Rabe-Hesketh and Skrondal, (2006); weights 3: personal weights normalised by country mean (mean of weights by country = 1).

Source: own elaboration based on data from EU-SILC and WIOD

Table 4A. Estimation results – *GII* as wage determinant in Europe, specification with additional country-level variables describing wage bargaining and labour market institutions

	<i>Wage bargaining / labour market institutions measure:</i>														
	<i>coord</i>	<i>nms</i>	<i>nmw</i>	<i>sector</i>	<i>type</i>	<i>ud</i>	<i>unagr</i>	<i>wage</i>	<i>wage_max</i>	<i>wage_proc</i>	<i>wc</i>	<i>negot</i>	<i>rights</i>	<i>hrs</i>	<i>unempl</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
<i>RTI</i>	-0.389***	-0.389***	-0.389***	-0.391***	-0.389***	-0.379***	-0.391***	-0.388***	-0.388***	-0.388***	-0.391***	-0.390***	-0.390***	-0.388***	-0.389***
	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]	[0.023]
<i>GII</i>	-0.293***	-0.298***	-0.300***	-0.304***	-0.285***	-0.317***	-0.304***	-0.299***	-0.298***	-0.299***	-0.302***	-0.300***	-0.302***	-0.299***	-0.307***
	[0.089]	[0.090]	[0.090]	[0.091]	[0.090]	[0.096]	[0.091]	[0.090]	[0.090]	[0.090]	[0.091]	[0.091]	[0.091]	[0.090]	[0.089]
<i>GII × RTI</i>	0.033	0.032	0.032	0.036	0.031	0.028	0.035	0.032	0.032	0.032	0.034	0.033	0.034	0.032	0.032
	[0.062]	[0.063]	[0.063]	[0.063]	[0.064]	[0.066]	[0.063]	[0.063]	[0.063]	[0.063]	[0.062]	[0.062]	[0.062]	[0.063]	[0.062]
<i>Wage Bargaining</i>	0.019***	0.004	-0.036**	0.036**	0.005	-0.005**	0.062**	-0.012	0.013***	0.006	0.103***	0.003	0.033***	0.005	-0.007***
	[0.005]	[0.006]	[0.015]	[0.015]	[0.004]	[0.002]	[0.026]	[0.010]	[0.005]	[0.009]	[0.023]	[0.012]	[0.011]	[0.015]	[0.001]
R ²	0.76	0.76	0.76	0.76	0.75	0.74	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76	0.76
N	1213922	1202974	1202974	1197623	1184789	960956	1197623	1200152	1200152	1200152	1199149	1199149	1199149	1200152	1213922
Under	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Weak	261311.1	250362.7	250747.3	249983.8	257132	193620.4	250027.9	251155.3	251148.9	251714.9	251681.3	250374.1	251734.9	250804	260139.3
Hansen	0.35	0.38	0.37	0.46	0.32	0.93	0.47	0.38	0.37	0.37	0.43	0.44	0.41	0.38	0.41

Notes: as under Table 7. Country, industry and time dummies included.

Wage bargaining, source Visser (2016) ICTWSS Database version 5.1: *coord* - coordination of wage-setting; *nms* - Minimum Wage Setting; *nmw* - National Minimum Wage; *sector* - Sectoral organization of employment relations; *type* - type of coordination of wage setting; *ud* - union density rate, net union membership as a proportion of wage earners in employment; *unagr* - union (affiliate) role in wage bargaining; *wage* - pact or agreement is about wage issues; *wage_max* - pact or agreement contains a norm or ceiling regarding maximum wage rise; *wage_proc* - pact or agreement is about procedure for wage setting; *wc* - status of works council; *negot* - involvement of works councils (or similar structures) in wage negotiations; *rights* - rights of works councils; *hrs* - pact or agreement contains, and/or is predicated on, concessions regarding working hours. *unempl* - unemployment, % of total labor force, source: WDI.

Source: own elaboration based on data from EU-SILC and WIOD

Table 5A. Estimation results – *GII* as wage determinant in Europe, specification with additional country or sector-level variables describing openness

Dep.var: log hourly wage (gross)	Openness measure:					
	<i>Export_GDP</i>		<i>Import_GDP</i>		<i>Export_Sector</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.380*** [0.011]	-0.297*** [0.090]	-0.380*** [0.011]	-0.286*** [0.090]	-0.380*** [0.011]	-0.580*** [0.129]
<i>GII</i>	-0.279*** [0.083]	-0.390*** [0.023]	-0.268*** [0.084]	-0.390*** [0.023]	-0.552*** [0.120]	-0.395*** [0.023]
<i>GII</i> × <i>RTI</i>		0.033 [0.062]		0.033 [0.062]		0.051 [0.063]
<i>Openness</i>	-0.001 [0.001]	-0.001 [0.001]	-0.002*** [0.001]	-0.002*** [0.001]	0.070*** [0.022]	0.070*** [0.022]
R ²	0.76	0.76	0.76	0.76	0.76	0.76
N	1213922	1213922	1213922	1213922	1213922	1213922
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	460948.2	260316	454660.5	256640.5	199865.5	103080.3
Hansen J (p-value)	0.21	0.36	0.21	0.37	0.13	0.23

Notes: as under Table 7 Country, industry and time dummies included.

Openness measures: *Export_GDP* - Exports of goods and services (% of GDP), source: WDI, *Import_GDP* - Imports of goods and services (% of GDP), source: WDI, *Export_Sector* – export to value added of a given sector, calculation from WIOD (2016)

Source: own elaboration based on data from EU-SILC and WIOD

Table 6A. Estimation results – *GII* as wage determinant in Europe, specification with additional technological variables describing technology and R&D

	Technology and R&D measures								
	<i>I_IT</i>	<i>I_CT</i>	<i>I_RD</i>	<i>K_IT</i>	<i>K_CT</i>	<i>K_RD</i>	<i>Kq_IT</i>	<i>Kq_CT</i>	<i>Kq_RD</i>
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
<i>RTI</i>	-0.406*** [0.025]	-0.406*** [0.025]	-0.411*** [0.025]	-0.406*** [0.025]	-0.406*** [0.025]	-0.406*** [0.025]	-0.406*** [0.025]	-0.406*** [0.025]	-0.406*** [0.025]
<i>GII</i>	-0.327*** [0.096]	-0.326*** [0.096]	-0.328*** [0.098]	-0.333*** [0.097]	-0.326*** [0.096]	-0.327*** [0.096]	-0.330*** [0.097]	-0.325*** [0.096]	-0.327*** [0.096]
<i>GII</i> × <i>RTI</i>	0.034 [0.065]	0.036 [0.065]	0.052 [0.064]	0.034 [0.065]	0.034 [0.065]	0.037 [0.065]	0.034 [0.065]	0.035 [0.065]	0.036 [0.065]
<i>Techn</i>	-0.071 [1.337]	0.482 [0.882]	0.398 [0.355]	0.382 [0.512]	0.02 [0.107]	0.013 [0.079]	0.305** [0.150]	0.051 [0.114]	0.009 [0.079]
R ²	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72	0.72
N	1073018	1073018	1073018	1073018	1073018	1073018	1073018	1073018	1073018
Under	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak	215616.7	214923.1	209378.4	215881.4	214910.5	210412.5	215595.2	214754.9	210467.8
Hansen	0.17	0.16	0.15	0.16	0.17	0.17	0.17	0.17	0.17

Notes: as under Table 7. Country, industry and time dummies included. Data on *Techn* from EUKLEMS expressed as *Techn/VA*: *I_IT*: Computing equipment, gross fixed capital formation; *I_CT*: Communications equip., gross fixed capital formation; *I_RD*: R&D, gross fixed capital formation; *K_IT*: Computing equipment, nominal capital stock; *K_CT*: Communications equip., nominal capital stock; *K_RD*: R&D, nominal capital stock; *Kq_IT*: Computing equipment, real fixed capital stock; *Kq_CT*: Communications equipment, real fixed capital stock; *Kq_RD*: R&D, real fixed capital stock.

Table 7A. Estimation results – *GII* as wage determinant in Europe, robustness: elimination industry by industry

Dep.var: log hourly wage (gross)	Elimination industry by industry					
	Mean coefficient		Min coefficient		Max coefficient	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.380*** [0.762]	-0.391*** [0.024]	-0.385*** [0.750]	-0.427*** [0.021]	-0.368*** [0.77]	-0.351*** [0.029]
<i>GII</i>	-0.286*** [0.087]	-0.307*** [0.094]	-0.314*** [0.073]	-0.396*** [0.077]	-0.218*** [0.106]	-0.186*** [0.123]
<i>GII</i> $\times$ <i>RTI</i>		0.042 [0.067]		-0.055 [0.057]		0.196 [0.115]
R ²	0.76	0.76	0.75	0.75	0.77	0.77
N	1112762	1112762	921692	921692	1183087	1183087
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	453390	248666	334288	196641	696757	337714
Hansen J (p-value)	0.24	0.32	0.14	0.08	0.39	0.47

Notes: as under Table 7. Mean/Min/Max coefficients – average/min/max values of coefficients of specifications in which one by one industry are excluded. R², N, Under-identification, Weak identification also reported as mean/min and maximum value of the statistics.

Source: own elaboration based on data from EU-SILC and WIOD

Table 8A. Estimation results – *GII* as wage determinant in Europe, robustness: elimination country by country

Dep.var: log hourly wage (gross)	Elimination country by country					
	Mean coefficient		Min coefficient		Max coefficient	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.380*** [0.011]	-0.390*** [0.023]	-0.387*** [0.009]	-0.409*** [0.02]	-0.368*** [0.011]	-0.368*** [0.024]
<i>GII</i>	-0.283*** [0.084]	-0.301*** [0.091]	-0.319*** [0.082]	-0.334*** [0.088]	-0.237*** [0.088]	-0.252*** [0.096]
<i>GII</i> $\times$ <i>RTI</i>		0.033 [0.064]		0.000 [0.06]		0.085 [0.065]
R ²	0.76	0.76	0.75	0.75	0.77	0.77
N	1170568	1170568	1122674	1122674	1193676	1193676
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	459265	257917.9	372850	218596.1	712073	372355.3
Hansen J (p-value)	0.23	0.37	0.13	0.04	0.35	0.62

Notes: as under Table 7. Mean/Min/Max coefficients – average/min/max values of coefficients of specifications in which one by one industry are excluded. R², N, Under-identification, Weak identification also reported as mean/min and maximum value of the statistics.

Source: own elaboration based on data from EU-SILC and WIOD

Table 9A Estimation results – different time periods of the analysis

Different periods of the analysis				
Dep.var: log hourly wage (gross)	2004 - 2008		2009 -2014	
	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.377*** [0.012]	-0.374*** [0.026]	-0.382*** [0.011]	-0.400*** [0.023]
<i>GII</i>	-0.333*** [0.103]	-0.328*** [0.111]	-0.217*** [0.078]	-0.249*** [0.084]
<i>GII</i> $\times$ <i>RTI</i>		-0.012 [0.080]		0.059 [0.059]
R ²	0.77	0.77	0.76	0.76
N	439970	439970	773952	773952
Under-identification	0.00	0.00	0.00	0.00
Weak identification	169423.2	105202.4	327345.3	177844.6
Hansen J (p-value)	0.88	0.85	0.6	0.34

Notes: as under Table 7.

Source: own elaboration based on data from EU-SILC and WIOD

Table 10A. Wages by RTI quartile and by country, 2014

	quartile 1 (the least routine)	quartile 2	quartile 3	quartile 4 (the most routine)
AT	24.25	17.08	16.11	16.40
BE	25.63	22.96	19.21	17.02
BG	2.91	1.77	1.99	1.82
CH	43.79	36.25	27.00	24.11
CY	17.75	11.90	8.93	6.52
CZ	6.73	4.56	4.77	4.14
DE	23.68	19.41	14.62	13.71
DK	32.40	31.42	25.70	23.40
EE	7.96	5.11	5.59	4.35
EL	11.62	8.55	6.97	6.41
ES	16.74	11.81	10.43	8.81
FI	26.48	20.37	15.54	16.42
FR	20.28	15.72	12.53	13.58
HU	4.89	3.16	3.17	2.91
IE	31.30	24.75	17.64	18.19
IT	18.60	13.82	12.71	11.27
LT	5.12	3.75	2.99	2.96
LU	39.48	28.55	20.68	17.26
LV	5.98	4.39	3.25	3.47
MT	14.16	9.93	8.24	8.21
NL	32.01	27.30	22.73	21.25
NO	40.53	36.24	30.99	28.09
PL	6.19	3.58	3.63	3.64
PT	10.77	6.15	5.22	4.68
RO	2.70	1.76	1.72	1.63
SE	24.11	21.85	17.60	17.11
SI	7.57	7.66	7.64	6.27
SK	5.43	4.09	3.93	4.04
UK	25.33	19.36	14.44	12.74

Appendix B

Table 1B. Estimation results (4) - *GII* as wage determinant in Europe, cross-country heterogeneity

Dep.var: log hourly wage (gross)	Sample: workers employed in:					
	Western Europe		Central and Eastern Europe		Southern Europe	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.309*** [0.010]	-0.273*** [0.022]	-0.427*** [0.013]	-0.482*** [0.031]	-0.588*** [0.051]	-0.685*** [0.076]
<i>GII</i>	-0.279** [0.114]	-0.222** [0.106]	0.021 [0.094]	-0.104 [0.096]	-0.402* [0.236]	-0.680** [0.286]
<i>GII</i> $\times$ <i>RTI</i>		-0.130* [0.077]		0.167** [0.079]		0.465 [0.284]
R ²	0.38	0.38	0.54	0.54	0.5	0.5
N	529542	529542	529836	529836	154544	154544
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	276542.4	145274.2	919420.7	458940.6	73916.41	37039.23
Hansen J (p-value)	0.96	0.9	0.3	0.61	0.16	0.03

Notes: as under Table 7. Personal and employment controls, industry characteristics (productivity), time, country and industry dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD.

Table 2B. Estimation results (5) - *GII* as wage determinant in Europe, manufacturing versus services

Dep.var: log hourly wage (gross)	Workers employed in:			
	manufacturing		services	
	(5)	(6)	(7)	(8)
<i>RTI</i>	-0.357*** [0.072]	-0.301*** [0.015]	-0.406*** [0.032]	-0.428*** [0.033]
<i>GII</i>	-0.595** [0.286]	-0.531* [0.287]	-0.053 [0.105]	-0.095 [0.124]
<i>GII</i> $\times$ <i>RTI</i>		-0.108 [0.141]		0.108 [0.133]
R ²	0.81	0.81	0.75	0.75
N	292230	292230	795143	795143
Under-identification	0.00	0.00	0.00	0.00
Weak identification	212.42	114.61	1980379	639235.1

Notes: as under Table 7. Personal and employment controls, industry characteristics (productivity), time and country dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD.

Table 3B. Estimation results (6) - *GII* as wage determinant in Western European countries, accounting for the source of imports along the value chain

Dep.var: log hourly wage (gross)	GII – imports coming from:					
	high income countries (<i>HIC</i>)		developing countries (<i>DEV</i>)		rest of the world (<i>RoW</i>)	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.310*** [0.010]	-0.276*** [0.021]	-0.309*** [0.010]	-0.275*** [0.022]	-0.311*** [0.010]	-0.274*** [0.025]
<i>GII</i>	-0.318** [0.145]	-0.252* [0.134]	-4.552** [1.959]	-3.872** [1.930]	-2.327*** [0.899]	-1.835** [0.850]
<i>GII</i> $\times$ <i>RTI</i>		-0.159 [0.098]		-1.22 [0.768]		-0.948 [0.655]
R ²	0.38	0.38	0.38	0.38	0.38	0.38
N	523719	523719	523719	523719	526119	526119
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	243304.8	123123	5800.82	2956.9	12119.4	5531.59
Hansen J (p-value)	0.52	0.79	0.07	0.2	0.37	0.58

Notes: as under Table 7. Personal and employment controls, industry characteristics (productivity), time, country and industry dummies included in all models. Sample: workers employed in Western Europe countries

Source: own elaboration based on data from EU-SILC and WIOD

Table 4B. Estimation results (7) - *GII* as wage determinant in different country subgroups, manufacturing versus services

Dep.var: log hourly wage (gross)	Workers employed in:			
	manufacturing		services	
Workers employed in Western Europe	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.303*** [0.017]	-0.263*** [0.076]	-0.337*** [0.013]	-0.292*** [0.030]
<i>GII</i>	-0.627** [0.268]	-0.586** [0.266]	-0.012 [0.135]	0.061 [0.129]
<i>GII</i> $\times$ <i>RTI</i>		-0.083 [0.164]		-0.217 [0.141]
R ²	0.43	0.43	0.37	0.37
N	111425	111425	369177	369177
Under-identification	0.07	0.11	0.00	0.00
Weak identification	235.43	126.5	1479903	556228.2
Workers employed in CEECs	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.414*** [0.023]	-0.517*** [0.114]	-0.440*** [0.018]	-0.565*** [0.059]
<i>GII</i>	0.173 [0.620]	0.055 [0.581]	0.176 [0.174]	-0.165 [0.245]
<i>GII</i> $\times$ <i>RTI</i>		0.177 [0.211]		0.620** [0.258]
R ²	0.58	0.58	0.53	0.53
N	153705	153705	315824	315824
Under-identification	0.02	0.04	0.00	0.00
Weak identification	109.74	80.22	1247547	512746.4
Workers employed in Southern Europe	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.430*** [0.071]	0.122 [0.243]	-0.716*** [0.081]	-0.731*** [0.100]
<i>GII</i>	-0.669 [0.642]	0.247 [0.768]	-0.346 [0.324]	-0.382 [0.532]
<i>GII</i> $\times$ <i>RTI</i>		-1.278** [0.641]		0.108 [0.903]
R ²	0.49	0.49	0.48	0.48
N	27100	27100	110142	110142
Under-identification	0.03	0.03	0.00	0.00
Weak identification	1852.29	2742.65	71419.2	23376.28

Notes: as under Table 7. Personal and employment controls, industry characteristics (productivity), time and country dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD.

SUPPLEMENTARY MATERIAL

Table R1. Upstreamness (*UP*) as additional control variable: plain and interacted with *GII*

Dep.var: log hourly wage (gross)	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.533*** [0.013]	-0.533*** [0.013]	-0.383*** [0.011]	-0.383*** [0.011]	-0.380*** [0.011]	-0.380*** [0.011]
<i>GII</i>	-0.245*** [0.087]	-0.624** [0.269]	-0.252*** [0.083]	-0.549** [0.266]	-0.286*** [0.082]	-0.486* [0.270]
<i>UP</i>	0.023 [0.030]	-0.026 [0.043]	0.019 [0.029]	-0.02 [0.042]	0.023 [0.029]	-0.003 [0.041]
<i>GII</i> $\times$ <i>UP</i>		0.155 [0.104]		0.122 [0.103]		0.083 [0.105]
Personal controls	no	no	yes	yes	yes	yes
Firm controls	no	no	no	no	yes	yes
R ²	0.72	0.72	0.75	0.75	0.76	0.76
N	1312076	1312076	1304717	1304717	1213922	1213922
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	458977.6	309808.3	454439.8	323768.1	432326.3	302800.7
Hansen J (p-value)	0.4	0.48	0.24	0.39	0.25	0.39

Notes: as under Table 7, time, country and industry dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD

Table R2. Partial correlation between different measures of GVC/production fragmentation

	<i>GII</i>	<i>tier1</i>	<i>OFF</i>	<i>FVA/EXP</i>	<i>FVA_FIN/EXP</i>	<i>FVA_INT/EXP</i>	<i>VS/EXP</i>	<i>VS1/EXP</i>
<i>GII</i>	1							
<i>tier1</i>	0.976	1						
<i>OFF</i>	0.952	0.966	1					
<i>FVA/Exp</i>	0.983	0.968	0.941	1				
<i>FVA_FIN/EXP</i>	0.88	0.885	0.877	0.899	1			
<i>FVA_INT/EXP</i>	0.861	0.829	0.787	0.873	0.572	1		
<i>VS/EXP</i>	0.996	0.981	0.955	0.99	0.877	0.878	1	
<i>VS1/EXP</i>	0.996	0.981	0.955	0.989	0.878	0.877	0.99	1

Notes:

OFF- import of intermediate inputs to the value added of a given sector (traditional offshoring measure as in Feenstra and Hanson, 1999);

FVA/EXP- foreign value added in export (derived from export decomposition following Wang et al. (2013)

FVA_FIN/EXP – foreign value added used in final goods in export (Wang et al., 2013)

FVA_INT/EXP - foreign value added used in intermediate exports to total export (Wang et al., 2013)

VS/EXP – vertical specialisation measured as the ratio of foreign value added (FVA) and pure double counting from foreign sources (FDC) in export (Koopman, Wang and Wei, 2014)

VS1/EXP – vertical specialisation measured as the ratio of foreign value added (FVA) plus total pure double counting (PDC) in export (Wang et al., 2013).

Table R3. Estimation results – the inclusion of occupation dummies

Dep.var: log hourly wage (gross)	(1)	(2)	(3)	(4)
<i>RTI</i>	-0.023 [0.029]	-0.027 [0.027]	-0.021 [0.027]	-0.024 [0.027]
<i>GII</i>	-0.165* [0.090]	-0.220** [0.087]	-0.250*** [0.086]	-0.255*** [0.085]
<i>GII × RTI</i>	-0.122** [0.062]	-0.044 [0.058]	-0.051 [0.059]	-0.006 [0.061]
Personal controls	no	yes	yes	yes
Firm controls	no	no	yes	yes
Job controls	no	no	no	yes
R ²	0.73	0.76	0.77	0.81
N	1312076	1304717	1213922	1101866
Under-identification	0.00	0.00	0.00	0.00
Weak identification	277134.7	274207.6	260485.1	247974.5
Hansen J (p-value)	0.16	0.18	0.21	0.28

Notes: as under Table 7, time, country, industry and occupation dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD

Table R4. Estimation results across the four RTI quartiles

Dep.var: log hourly wage (gross)	RTI quartiles:							
	1st	2nd		3rd	4th			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
<i>RTI</i>	-0.332*** [0.028]	-0.263*** [0.046]	-0.517*** [0.045]	-0.475*** [0.058]	-0.323*** [0.069]	-0.251*** [0.078]	-0.161*** [0.037]	-0.230*** [0.064]
<i>GII</i>	-0.395*** [0.109]	-0.380*** [0.108]	-0.365*** [0.083]	-0.293*** [0.100]	-0.233** [0.113]	-0.003 [0.199]	-0.181** [0.074]	-0.408** [0.175]
<i>GII × RTI</i>		-0.259* [0.134]		-0.153 [0.128]		-0.268 [0.170]		0.213 [0.135]
R ²	0.74	0.74	0.8	0.8	0.74	0.74	0.77	0.77
N	356119	356119	298212	298212	298675	298675	260916	260916
Under-identification	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Weak identification	159048.7	86992.03	137195	76952.48	134905.5	71553.98	104557	51211.26
Hansen J (p-value)	0.03	0.06	0.39	0.54	0.19	0.29	0.29	0.29

Notes: as under Table 7. Personal and employment controls, time and country dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD.

Table R5. Estimation results, interaction with skill groups, 1-lowest, 4-highest

Dep.var: log hourly wage (gross)	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.315*** [0.018]		-0.393*** [0.022]	-0.309*** [0.018]		-0.392*** [0.022]
<i>GII</i>		-0.200** [0.078]	-0.272*** [0.084]		-0.272*** [0.080]	-0.342*** [0.091]
<i>Skill1</i> $\times$ <i>GII</i>	-0.522*** [0.096]			-0.622*** [0.100]		
<i>Skill2</i> $\times$ <i>GII</i>	-0.255*** [0.086]			-0.337*** [0.087]		
<i>Skill3</i> $\times$ <i>GII</i>	-0.140* [0.080]			-0.212*** [0.080]		
<i>Skill4</i> $\times$ <i>GII</i>	-0.094 [0.080]			-0.159** [0.080]		
<i>Skill1</i> $\times$ <i>RTI</i>		-0.473*** [0.020]			-0.474*** [0.020]	
<i>Skill2</i> $\times$ <i>RTI</i>		-0.365*** [0.009]			-0.365*** [0.009]	
<i>Skill3</i> $\times$ <i>RTI</i>		-0.245*** [0.018]			-0.245*** [0.018]	
<i>Skill4</i> $\times$ <i>RTI</i>		-0.070*** [0.025]			-0.072*** [0.025]	
<i>Skill1</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			-0.143** [0.062]			-0.158** [0.064]
<i>Skill2</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			0.087 [0.066]			0.084 [0.066]
<i>Skill3</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			0.408*** [0.092]			0.418*** [0.094]
<i>Skill4</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			0.695*** [0.111]			0.729*** [0.115]
R ²	0.76	0.76	0.76	0.76	0.77	0.76
N	1217953	1217953	1217953	1213922	1213922	1213922
Under-identification				0.00	0.00	0.00
Weak identification				127882.5	462026.3	110276.8
Hansen J (p-value)				0.15	0.23	0.14

Notes: as under Table 7. Personal and employment controls, time and country dummies included in all models.

Source: own elaboration based on data from EU-SILC and WIOD.

Table R6. Estimation results, interactions with different occupations

Dep.var: log hourly wage (gross)	OLS			IV		
	(1)	(2)	(3)	(4)	(5)	(6)
<i>RTI</i>	-0.338*** [0.020]		-0.394*** [0.023]	-0.333*** [0.019]		-0.395*** [0.023]
<i>GII</i>		-0.191** [0.076]	-0.272*** [0.084]		-0.262*** [0.078]	-0.353*** [0.088]
<i>Occ1</i> $\times$ <i>GII</i>	-0.167* [0.086]			-0.238*** [0.089]		
<i>Occ2</i> $\times$ <i>GII</i>	-0.103 [0.084]			-0.165** [0.083]		
<i>Occ3</i> $\times$ <i>GII</i>	-0.144* [0.079]			-0.218*** [0.079]		
<i>Occ4</i> $\times$ <i>GII</i>	-0.111 [0.084]			-0.185** [0.084]		
<i>Occ5</i> $\times$ <i>GII</i>	-0.402*** [0.090]			-0.485*** [0.090]		
<i>Occ6</i> $\times$ <i>GII</i>	-1.124*** [0.209]			-1.316*** [0.222]		
<i>Occ7</i> $\times$ <i>GII</i>	-0.288*** [0.086]			-0.372*** [0.086]		
<i>Occ8</i> $\times$ <i>GII</i>	-0.159* [0.088]			-0.244*** [0.087]		
<i>Occ9</i> $\times$ <i>GII</i>	-0.520*** [0.096]			-0.620*** [0.099]		
<i>Occ1</i> $\times$ <i>RTI</i>		-0.252*** [0.030]			-0.258*** [0.030]	
<i>Occ2</i> $\times$ <i>RTI</i>		0.089** [0.039]			0.087** [0.039]	
<i>Occ3</i> $\times$ <i>RTI</i>		-0.243*** [0.019]			-0.242*** [0.019]	
<i>Occ4</i> $\times$ <i>RTI</i>		-0.286*** [0.013]			-0.287*** [0.013]	
<i>Occ5</i> $\times$ <i>RTI</i>		-0.426*** [0.015]			-0.427*** [0.015]	
<i>Occ6</i> $\times$ <i>RTI</i>		-0.784*** [0.058]			-0.784*** [0.058]	
<i>Occ7</i> $\times$ <i>RTI</i>		-0.402*** [0.013]			-0.403*** [0.013]	
<i>Occ8</i> $\times$ <i>RTI</i>		-0.329*** [0.011]			-0.329*** [0.011]	
<i>Occ9</i> $\times$ <i>RTI</i>		-0.482*** [0.020]			-0.483*** [0.020]	
<i>Occ1</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			0.288** [0.112]			0.313*** [0.113]
<i>Occ2</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			1.400*** [0.201]			1.484*** [0.213]
<i>Occ3</i> $\times$ <i>GII</i> $\times$ <i>RTI</i>			0.402*** [0.099]			0.422*** [0.102]

<i>Occ4 × GII × RTI</i>			0.275***			0.290***
			[0.079]			[0.080]
<i>Occ5 × GII × RTI</i>			-0.11			-0.103
			[0.090]			[0.091]
<i>Occ6 × GII × RTI</i>			-0.901***			-1.044***
			[0.185]			[0.197]
<i>Occ7 × GII × RTI</i>			0.006			0.009
			[0.076]			[0.077]
<i>Occ8 × GII × RTI</i>			0.155**			0.158**
			[0.069]			[0.069]
<i>Occ9 × GII × RTI</i>			-0.160**			-0.169**
			[0.066]			[0.069]
R ²	0.76	0.77	0.76	0.76	0.77	0.77
N	1217953	1217953	1217953	1213922	1213922	1213922
Under-identification				0	0	0
Weak identification				65522.18	460494.6	59027.3
Hansen J (p-value)				0.08	0.17	0.02

Notes: as under Table 7. Personal and employment controls, time and country dummies included in all models. Occupations according to ISCO-08 1 digit classification:

- 1- Managers
- 2- Professionals
- 3- Technicians and Associate Professionals
- 4- Clerical Support Workers
- 5- Services and Sales Workers
- 6- Skilled Agricultural, Forestry and Fishery Workers
- 7- Craft and Related Trades Workers
- 8- Plant and Machine Operators, and Assemblers
- 9- Elementary Occupations

Source: own elaboration based on data from EU-SILC and WIOD.

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