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RESEARCH ARTICLE

Global Value Chains and Wages: Multi-Country Evidence from Linked Worker-Industry Data

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Abstract
This paper uses a multi-country microeconomic setting to contribute to the literature on the nexus between production fragmentation and wages. Exploiting a rich dataset on over 110,000 workers from nine Eastern and Western European countries and the United States, we study the relationship between individual workers' wages and industry ties into global value chains (GVCs). We find an inverse (but weak) relationship between the degree of industries' involvement in GVCs and wages. Workers employed in routine occupations clearly earn less, but it is difficult to attribute it to the role played by the involvement of their countries and industries in global value chains.

Keywords Wage · Global value chains · Foreign value added

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1 Introduction

This paper analyses the relationship between the wages of individual workers and their industries' ties into global value chains in a broad international microeconomic

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framework with data on more than 110,000 workers in 34 manufacturing and service industries in nine European Union (EU) countries and the United States.[1] To the best of our knowledge, this is the first attempt to address this issue in a multi-country framework and a microeconomic setting (not based on average industry-level wage data).

We contribute to the literature that analyses the labour market response to global production sharing[2] which has recently become one of the main research themes in labour economics and international economics (see Acemoglu and Autor 2011 Radlo 2016 or Van Reenen 2011 for a review and Ehrenberg and Smith 2016, chapter 16: 559–586 for a description of mechanisms). Increasing cross-country industrial interdependence due to offshoring and production networks has even been dubbed "the next industrial revolution" (Blinder 2006), while today's geographically dispersed production and trade can be described as a "Factory World" (Los et al. 2015a). Unsurprisingly, labour market research has focused on potential cross-border job substitution and the employment outcomes of production sharing (Acemoglu et al. 2016; Harrison and McMillan 2011; Michel and Rycx 2012) or the impact of production fragmentation on earnings and wages (Baumgarten et al. 2013; Crinò 2010; Ebenstein et al. 2014; Geishecker and Görg 2013; Geishecker et al. 2010, Hummels et al. 2014; Parteka and Wolszczak-Derlacz 2015; Wolszczak-Derlacz and Parteka 2018).[3]

This paper ties most directly into the latter aspect: the influence of cross-border production sharing and the resulting production links on domestic workers' wages. However, we deviate from the "classic" analysis of the offshoring-wages nexus (Feenstra and Hanson 1996; Feenstra and Hanson 1999 or, more recently, Baumgarten et al. 2013) by focusing more closely on the role played by the involvement of countries and industries in global production networks and global value chains (GVCs). Models of sequential, multistage production as well as the theories of nations' interdependence driven by vertical specialisation (Antràs and Chor 2013; Kohler 2004; Costinot et al. 2013) yield ambiguous theoretical predictions of the response of factor prices to participation in GVCs (see section 2.1). Accordingly, this is an important empirical question to be addressed with the data.

To measure the strength of GVC ties, we rely on what Feenstra (2017) calls "second generation" measures of production fragmentation – indices developed within a global input-output framework (Hummels et al. 2001; Johnson 2014; Johnson and Noguera 2012; Koopman et al. 2014; Los et al. 2016). In particular, we use the foreign value added (FVA)

[1] A global value chain (GVC) "describes the full range of activities undertaken to bring a product or service from its conception to its end use and how these activities are distributed over geographic space and across international borders" (Amador and di Mauro 2015, p.14; adopted from the GVC Initiative at Duke University).

[2] There are a number of terms to describe the phenomenon of shifting some parts of the production process abroad and using foreign inputs. Among the most popular are "global production sharing," "offshoring" and "international production fragmentation." Related terms (though they do not refer to the exactly the same phenomenon) include "global value chains," "global production networks" and "global supply networks."

[3] Needless to say the employment and wage effects of import competition are related (see Kang 2017).

embodied in exports,[4] which indicates "the extent to which countries are tied into global value chains" (Feenstra 2017: 2). The measurement of an industry's involvement in cross-border production chains through FVA content dispenses with the dubious "proportionality assumption" typically used in indices based on the share of imported inputs in production (where the ratio of imports to domestic inputs is assumed to be the same in every industry; see Winkler and Milberg 2012). Moreover, measuring the relative size of different components of export decomposition (among them FVA) across countries and industries is "a way to gauge the differences in the role that countries play in global production networks" (Koopman et al. 2014: 489). The advanced economies tend to occupy upstream positions in the value chain (which is reflected in relatively little FVA in their exports), while the less developed tend to be downstream (Mattoo et al. 2013: 62; Koopman et al. 2010). Using such data for different countries, then, we can interpret our findings as a gauge of the way their relative position in GVC affects factor prices.

Los et al. (2015b) document that the share of value added outside the country of completion has increased in almost all product chains since 1995.[5] However, despite the abundant recent literature on GVCs (see, among many, Amador and Cabral 2016; Amador and di Mauro 2015; Baldwin et al. 2012; Johnson 2014; Johnson and Noguera 2012; Los et al. 2015a; Mattoo et al. 2013), as far as we know there have been no explicit assessments of the FVA-wage nexus, especially in a micro-level setting allowing for a broader cross-country and cross-industry comparative perspective. Our paper seeks to fill this gap, investigating the micro-level dimension of wage determination (Mincer 1974) augmented by measures of industries' involvement in GVCs, and, importantly, going beyond country-specific studies of the wage effects of production fragmentation (such as Geishecker and Görg 2008; Baumgarten et al. 2013; Ebenstein et al. 2014; Hummels et al. 2014). We have constructed a unique dataset matching micro-level and industry-level data for a number of economies (ten countries: nine in Europe plus the U.S.). Following the task-focused approach to labour market analysis (Baumgarten et al. 2013; Autor 2015; Becker et al. 2013; Becker and Muendler 2015), we do not only categorise workers according to education[6] but additionally explore workers'

[4] This is linked to the notion of value added exports and the value-added/export (VAX) ratio, defined as a "measure of the value added content of trade" (Johnson and Noguera 2012: 226). FVA in exports is the counterpart of the domestic content of trade. Note the difference from the share of FVA in production, which consists in "the part of the value of final output of an industry that is contributed by industries in other countries" (Amador and di Mauro 2015: 37). Hence, foreign inputs contained in the output of a domestic industry (whether or not this output is exported) differ from FVA embodied in exports. Based on WIOD data we have calculated the correlation between those different measures of fragmentation (exported FVA and imported inputs in relation to industry output); it ranges from 0.51 to 0.91 depending whether we use narrow, broad or differential measures of imported inputs (Hijzen et al. 2005).

[5] Timmer et al. (2016) document, with new WIOD data, that trade within GVCs contracted with the crisis of 2008–2009 and stagnated after 2011. However, the global import intensity of production, measured across different GVCs, is considerable, equal to about 30% in 2014, 5 percentage points more than in 2000 (Timmer et al. 2016: 5). Note that the values given in Los et al. (2015b) and Timmer et al. (2016) are not directly comparable, as they use different base years and different measures of GVC performance.

[6] This approach, dividing workers into two categories (high- and low-skilled) or three (high-, medium- and low-skilled) was common in the past, especially in multicounty studies relying on industry-level data on wages or labour demand structure (among others, see: Polgár and Wörz 2010; Lo Turco and Parteka 2011; Foster-McGregor et al. 2013; Foster-McGregor et al. 2016; Michaels et al. 2014; Parteka and Wolszczak-Derlacz 2015; Wolszczak-Derlacz and Parteka 2018).

heterogeneity in terms of occupations and tasks. As is thoroughly discussed in a recent OECD report on the importance of skill types in GVCs (OECD 2017), the mix of specific skills determines the degree to which workers from different countries gain or lose from participation in GVCs.

We contribute to the literature by quantifying the labour market consequences of increasingly substantial GVC ties by using microdata for workers from many countries and industries. Previous studies on the response of wages to global production sharing with large country samples (e.g. Polgár and Wörz 2010 on the EU25; Parteka and Wolszczak-Derlacz 2015 on the EU27; Wolszczak-Derlacz and Parteka 2018 on 40 countries) deal only with average industry-level wage data and thus miss the individual dimension of wage determination mechanisms. On the other hand, given the complicated nature of micro-analysis (limited access and high cost of data; problems of cross-country comparability and time consistency; computational difficulties stemming from the size of micro datasets), few studies have managed to avoid the problematic nature of aggregated data. The micro-level evidence to date (described in Section 2) is largely country-specific and limited to developed countries: the U.S. (Ebenstein et al. 2014 and Autor et al. 2014); Denmark (Hummels et al. 2014); Britain (Geishecker and Görg 2013); Germany (Geishecker and Görg 2008 and Baumgarten et al. 2013). Yet less developed economies, such as those of Central and Eastern Europe present in our dataset, are also increasingly involved in GVCs (Hagemejer 2017; Olczyk and Kordalska 2017), so the effects of cross-border production ties on their workers' wages should not be ignored.

The paper is organised as follows: Section 2 places our contribution in the context of the theoretical and empirical literature. Section 3 presents our unique linked worker-industry dataset and the crucial descriptive statistics on value added and wages. Section 4 describes our augmented micro-level wage models and presents the estimation results, and Section 5 concludes.

2 Theoretical Background and the Empirical Literature

2.1 Production Fragmentation, Value Added Trade, GVCs and Domestic Wages – Theoretical Considerations

Theoretically, the effects of production fragmentation and value added trade on wages are far from straightforward. Rather, they involve an interplay among multiple effects on factor prices. Given that "outsourcing involves a fragmentation of value added across national borders" (Kohler 2001: 50), the first theoretical reference for our study is models of offshoring. The conceptualisation of production fragmentation in terms of trade in tasks (Grossman and Rossi-Hansberg 2006; Grossman and Rossi-Hansberg 2008; Baldwin and Robert-Nicoud 2014) made possible predictions on the results of offshoring (including wage effects) differentiated according to type of task and thus type of labour.

In their canonical 2008 paper Grossman and Rossi-Hansberg (hereafter denoted GRH) studied the effects of task trade (offshoring) on factor prices in the domestic or source country. Trade in tasks has three kinds of effect: on productivity, on relative prices, and on labour supply. The latter two effects exert downward pressure on real wages for the factor that performs the offshored tasks. Importantly, and contrary to the common thesis that offshoring necessarily hurts low-skilled domestic workers, GRH argued that if productivity gains thanks to production relocation are large enough, they may actually result in wage gains for all domestic workers, including those who perform less demanding tasks. But if the other two forces (the labour supply and relative price effects) outweigh the efficiency effect, then wages are likely to fall.

Acemoglu et al. (2015) depart from GRH and endogenise the role of technical change in an analysis of the relative wage effects for skilled and unskilled workers in different economies. This is a useful framework in which to study the wage effects of fragmentation in countries that differ, as in our empirical analysis, in level of development and industrialisation (which Acemoglu et al. label "East" and "West"). They show that when technology is held constant, an increase in offshoring increases the wages of skilled workers in the West and of unskilled workers in the East, while the effect on unskilled workers' wages in the West is either negative or inverse U-shaped - conditional upon the initial values of offshoring (Acemoglu et al. 2015: 94). When technical change is endogenous, and when the initial cost of offshoring is high, greater opportunities for offshoring drive down unskilled workers' wages in the West. When it is low, the technical change induced is biased in favour of the less skilled (Acemoglu et al. 2015: 84). Again, as in GRH, the net effect of fragmentation on wages is ambiguous.

Important insights into the GVC-wage nexus are given by models of sequential production and nations' interdependence driven by vertical specialisation (Antràs and Chor 2013; Kohler 2004; Costinot et al. 2013). These models are closely related to our theme, in that they refer explicitly to multistage production networks and set forth theories of GVC and value added trade. Kohler (2004) starts from the observation that the ambiguity of the wage response to fragmentation (due to the interplay between labour demand and cost savings, as in GRH) deepens as a function of the way in which an industry is related to other sectors. Hence, he studies the nexus between fragmentation and factor prices in a multistage production setting (which, after all, is also a main feature of GVC). Production involves a continuum of stages differing in capital intensity, while the generalised factor price frontier setting serves to endogenise the reaction of foreign input use to variations in domestic factor prices. Given that GVC is also a kind of sequential production chain, this framework generates valuable predictions on how FVA at different stages of the chain can affect wages. Kohler (2004: C181) confirms the ambiguity of the effect of fragmentation on factor prices (wages) and shows that it depends on the relative factor intensities of the particular industry.[7]

Costinot et al. (2013) develop a theory of GVC in a model of a world economy with multiple countries, labour as a factor of production, and a final good whose production is sequential. Vertical specialisation shapes the interdependence of nations.[8] In such a framework, wages depend on the position in the value chain. Rich countries tend to have higher wages than poor countries because they specialise in the later production stages, characterised by higher prices of intermediate goods, whereas countries

[7] In discussing the implications of the lower costs of outsourcing, Kohler (2004: C183-C184) says that "the factor price effect is again ambiguous: outsourcing may occur at the labour-intensive margin of the multistage industry, yet domestic workers will benefit, provided overall domestic value added of the multistage industry is more labour-intensive than in the other industry."

[8] Along these lines, Caliendo and Parro (2015) design a model in which sectoral linkages and interdependency are key factors affecting wages in an input-output framework.

specialised in earlier stages have lower wages. How is trade in value added linked to wages? The portion of a country's exports accounted for by labour costs depends partly on the volume of imports required to produce one unit of exports (Costinot et al. 2013: 118). Hence, wage levels are affected by the pattern of vertical specialisation and the relative reliance on foreign value added. Greater complexity (in other words, a larger number of stages to produce a final good) lowers output in all stages, which in turn affects real wages (Costinot et al. 2013: 117).

2.2 The Literature on Global Value Chains

Empirically, our study builds upon the burgeoning literature on GVCs, which describes the complex structure of present-day production systems (Los et al. 2015b) and the so-called "trade in value added" (see Mattoo et al. 2013; Amador and di Mauro 2015 or OECD 2017 for a review). This GVC literature follows the first wave of research on interindustry linkages measured using input-output data (Cella 1984; Dietzenbacher 1992) and the strand of work on the global fragmentation of production and international outsourcing (Feenstra and Hanson 1996; Feenstra and Hanson 1999; Hijzen et al. 2005).

"Second-generation" statistics computed with input-output data and FVA information then began to replace the conventional ("first-generation") measures of offshoring based on the share of costs accounted for by imported intermediate inputs (see a recent comparison in Feenstra 2017). Building on the notion of vertical specialisation (Hummels et al. 2001)[9] and the foreign content of a country's exports, a number of efforts have been made to measure dependence on inputs produced abroad precisely. Hummels et al. (2001) proposed a method to decompose a country's exports into domestic and foreign value added[10] shares based on its input-output table. Johnson and Noguera (2012) combined input-output and bilateral trade data to compute the value added content of bilateral trade. However, these methods all assumed that import intensity is the same in production for export as in production for domestic sale. In the case of processing exports, this assumption is violated. Koopman et al. (2012) introduced a generalized formula to compute the share of domestic value added in a country's gross exports when the processing trade is prevalent.

The computation of input-output tables for various economies within the WIOD[11] project (Dietzenbacher et al. 2013; Timmer et al. 2015) facilitated further empirical work on GVC. Using WIOD data, Koopman et al. (2014) proposed a more detailed decomposition of gross exports, integrating the previous measures of vertical specialisation and value added trade into a unified framework; in particular, they identified double-counted terms in the official trade statistics. But sector level applications were still missing. Wang, Wei and Zhu (subsequently referred to as WWZ; Wang et al. 2013) elaborated on the accounting framework at country level proposed by Koopman et al. (2014) to devise one

[9] Hummels et al. (2001) defined vertical specialisation as "the use of imported inputs in producing goods that are exported."

[10] Following Koopman et al. (2012) we use the terms "domestic value added" and "domestic content" interchangeably; and analogously for "foreign value added" and "foreign content".

[11] World Input Output Database (www.wiod.org). Another common source of international input-output tables is TiVA (Trade in Value Added) developed by the OECD.

that decomposes gross trade flows at sector, bilateral, or bilateral- sector level (Wang et al. 2013). Importantly, the WWZ method can be used to gauge the position of an industry in an international production chain that varies by country, taking into account both offshoring and domestic production sharing. Empirically, we apply the WWZ method to measure the extent to which industries are tied into GVCs.

2.3 Empirical Evidence on the Labour Market Response to Cross-Border Production Ties

The empirical literature on the consequences for domestic workers of transferring some production processes abroad reflects common political concerns over domestic job losses or declining wages due to offshoring (Blinder 2006). These worries are not always supported by the empirical data,[12] but the offshorability of jobs[13] has undeniably become a "hot" topic.

Unsurprisingly, much of the attention has gone to the visible outcomes for the US labour market of offshoring to developing countries, notably Mexico (as addressed in Sethupathy 2013). Recent U.S.-focused research appears to be especially concerned with the effects of labour market exposure to import competition from China (Autor et al. 2013 called it "the China syndrome" – also analysed by Autor et al. 2015 and Acemoglu et al. 2016) and the general impact of offshoring on wages and job displacement (Crinò 2010; Ebenstein et al. 2014). Similar analyses have assessed the response of labour markets in single advanced Western European countries to offshoring (e.g. Michel and Rycx 2012 on employment in Belgium, Hummels et al. 2014 on wages in Denmark, and Baumgarten et al. 2013 on wages in Germany). Another important recent topic is labour market polarisation – rising employment in the best and the worst paid occupations, observed in the U.S. (Autor and Dorn 2013) and in Europe (Goos et al. 2009; Goos et al. 2014) – which is ascribed, at least in part, to offshoring and import competition.

In the first wave of empirical literature, low-skilled workers were presumed to be more exposed to wage cuts and job losses, owing above all to declining demand for unskilled labour in the developed countries (Feenstra and Hanson 1996; Feenstra and Hanson 1999; Geishecker and Görg 2008; Hijzen 2007). But more recent work underscores the necessity for proper distinction between skills and tasks (Autor 2015) and the crucial role of the specific skills of the workers employed in GVCs (OECD 2017). Hummels et al. (2014), on matched Danish worker-firm data, find that offshoring tends to increase high-skilled wages and decrease low-skilled wages but that the effects vary according to task (routine tasks suffer the most). And this is confirmed in a study on German workers (Baumgarten et al. 2013), which finds that a higher degree of interactivity, and especially non-routine content, effectively shelters workers from the wage repercussions of productive relocation.

[12] For instance, Mankiw and Swagel (2006) show that "increased employment in the overseas affiliates of US multinationals is associated with more employment in the US parent rather than less." Harrison and McMillan (2011) conclude that "offshoring by U.S.-based multinationals is associated with a quantitatively small decline in manufacturing employment."

[13] The offshorability of jobs can be understood as "the ability to perform one's work duties from abroad with little loss of quality" and may concern up to a quarter of American workers (Blinder and Krueger 2013).

There are a few micro-level studies of the consequences of cross-border production ties on labour markets in more than one country. Geishecker et al. (2010) study the impact of outsourcing on individual wages in three European countries with different labour market institutions: Germany, the UK and Denmark. Like Baumgarten et al. (2013), they adopt a setting similar to ours, matching micro-level wage data with industry-specific measures of participation in global production fragmentation. They find that low-skilled workers may suffer wage losses due to outsourcing, but that notwithstanding national differences in labour market institutions the effects in the three countries are similar and in fact fairly small. The study by Goos et al. (2014) most resembles ours in terms of country coverage (but not specific topic, as that study does not refer explicitly to the relationship between wages and the value added structure of global production). They link microdata for 16 European countries in 1993–2010 to describe the process of job polarisation, arguing that technology can replace human labour in routine tasks. They find some support for the hypothesis that it is primarily routine jobs that are offshored and show that the resulting job polarisation is not specific to certain countries but is pervasive through all the advanced economies.

As far as we know there are no micro-level studies explicitly that match the data on industry involvement in GVC with wages of workers in multiple countries, as we do.[14] In a very recent paper Shen and Silva (2018) study the role of value added exports from China in explaining changes in local labour markets in the United States. In addition to the employment effects, they estimate how value-added trade affects wages, finding a weak relationship between the two (conditional upon the relative position of the exports along the upstream/downstream continuum).

3 The Data and Descriptive Statistics

3.1 Matched Worker-Industry Data and Comparative Data on Wages

We constructed a cross-sectional database matching WIOD industry-level data[15] with personal data from the Luxembourg Income Study (LIS wave 8, reference year 2010). The main problem in building such a dataset is matching the data on the industry of employment of individuals present in the LIS database with the industries covered by WIOD. We computed correspondence tables on a

[14] There are some recent studies on the relationship between GVC status and firms' productivity (among others, see Baldwin and Yan 2014; Hagemejer 2015). A good review of the literature on the effects of GVC on employment, wages and productivity (as well as on trade and FDI) is Amador and Cabral (2015). Lopez Gonzalez et al. (2015) analyse the link between GVC and aggregate wage inequality while Marcolin et al. (2016) focus on the routine intensity of occupations and trade in value-added (TiVA) patterns.

[15] WIOD's industry-level labour data has been used to analyse such topics as the skill structure of labour demand (Foster-McGregor et al. 2013), the effects of production fragmentation on incomes and jobs (Timmer et al. 2013), wage convergence patterns (Parteka and Wolszczak-Derlacz 2015) and the wage effects of offshoring (Wolszczak-Derlacz and Parteka 2018). In particular, these studies have found evidence of shrinking demand for medium-skill workers (Foster-McGregor et al. 2013), growing European specialisation in service and more highly-skilled jobs (Timmer et al. 2013), very slow conditional wage equalisation among EU countries (Parteka and Wolszczak-Derlacz 2015), and a moderate negative impact of offshoring on the wages of domestic low- and medium-skilled workers (Wolszczak-Derlacz and Parteka 2018).

country-by-country basis,[16] ultimately producing a set of 34 manufacturing and service industries (the list is given in the Appendix, Table 11). Our sample is restricted to non-military workers aged 24–65.[17] Table 12 in the Appendix reports summary statistics of the main characteristics of the sample workers (overall and by country).

The basic dependent variable in our wage regression is the worker's gross basic hourly wage for the main job (*gross1*).[18] This data is available for ten countries (LIS wave 8): nine in the EU (CZE, DEU, ESP, EST, FIN, GRC, IRL, LUX and SVK) plus the U.S. In order to explore cross-country heterogeneity we consider the European countries (E9) separately and split them into two groups: old EU member states (OMS), i.e. DEU, ESP, FIN, GRC, IRL and LUX; and new member states (NMS), i.e. CZE, EST, SVK).

As an alternative robustness check we devised crude proxies for hourly earnings, namely total paid employment income (*pile*)[19] or paid monetary employment income *(pmile)* divided by number of hours worked, designated *hw1* and *hw2* in our tables.[20] To eliminate extreme observations and potential outliers we corrected all the alternative hourly wage measures (*gross1*, *hw1*, *hw2*). At the bottom, we trimmed the distribution by defining as "missing" observations with negative or zero hourly wages; at the top, we adjusted wages more than ten times the national median down to ten times the median.[21] Values in national currencies are all converted into dollars using the Penn World Table (PWT) bilateral exchange rates. As a robustness check, we use wages corrected for purchasing power (PPP too is taken from PWT).

Table 1 reports the average hourly wage in the ten sample countries. A comparison of the benchmark hourly wage data (*gross1*) and its proxies (*hw1, hw2*) shows they can serve for a reasonable sensitivity analysis. But wages clearly differ greatly across countries. Focusing on *gross1*, in our sample the average hourly wage in US manufacturing (in 2010) is \$24.80. The European average is \$15.20, but with a range from just \$5.40 in the Slovak Republic to \$32.90 in Luxembourg. There are significant differences between old and new EU member states (the gross hourly wage in manufacturing is some 4 times higher in OMS than in NMS), and similar differentials are found in services as well.

Moreover, within these two broad categories of activity there is also considerable variability between industries (see Fig. 1). In a first step we use micro-level wage data

[16] This exercise had to be performed separately for every country, since the variable ind1_c (from LIS) was not standardized, given that national classification categories differ. For instance, NACE rev 2.1 is used in CZE, EST, ESP, FIN, GRC, LUX and SVK; NACE rev 1.1 in DEU and IRL; Census 2002 Industry Code in the U.S., while the WIOD classification has 35 categories based on the CPA and NACE rev. 1 (ISIC rev 2) classifications. Correspondence tables are available on request.

[17] We exclude industry P (Private Households with Employed Persons). As a robustness check we further restrict industry and/or worker coverage, excluding agricultural, forestry and fishery workers, employees in industry 23 (coke, refined petroleum and nuclear fuel) and workers with more than one job.

[18] This excludes overtime payments, bonuses and gratuities, family allowances and other social security payments by employers, as well as ex gratia payments in kind supplementary to normal wage rates.

[19] Monetary payments and the value of non-monetary goods and services received from regular and irregular payroll employment.

[20] The missing values of hours worked (*hours* variable) were imputed using the Gaussian normal regression method (around 5% of missing values were imputed).

[21] All these steps were performed during a visit to the LIS premises. We trim the distribution at the top because we are not interested in top income shares (Atkinson et al. 2011; Burkhauser et al. 2012) so much as in the possible changes to wage determination due to GVC ties that affect "normal" workers. Alternatively, we considered excluding the top percentile of wages; this does not alter the final conclusions.

Table 1 Comparison of hourly wages (alternative measures) across countries and types of activity

	mean gross hourly wage, in US$ - manufacturing			mean gross hourly wage, in US$ - services		
	gross1	*hw1*	*hw2*	*gross1*	*hw1*	*hw2*
Czech Republic (CZE)	6.5	6.7	6.5	6.9	7.1	6.8
Estonia (EST)	5.5	5.8	5.6	6.2	6.4	6.2
Finland (FIN)	27.0	27.4	27.0	24.5	25.3	25.0
Germany (DEU)	24.9	26.9	26.9	22.4	22.9	22.9
Greece (GRC)	10.5	12.7	12.6	12.4	14.3	14.2
Ireland (IRL)	25.2	28.8	28.6	28.4	29.5	29.4
Luxemburg (LUX)	32.9	33.9	33.7	33.8	34.9	34.7
Slovak Republic (SVK)	5.4	5.5	5.4	5.4	5.6	5.4
Spain (ESP)	14.1	14.2	14.0	15.2	15.2	15.1
USA	24.8	25.2	25.2	23.6	24.4	24.4
Europe (E9)	15.2	16.2	16.0	18.3	18.8	18.6
OMS	23.8	24.7	24.5	24.4	24.3	24.2
NMS	5.8	6.1	5.8	6.1	6.3	6.1
All countries (10)	15.9	16.8	16.6	19.0	19.4	19.2

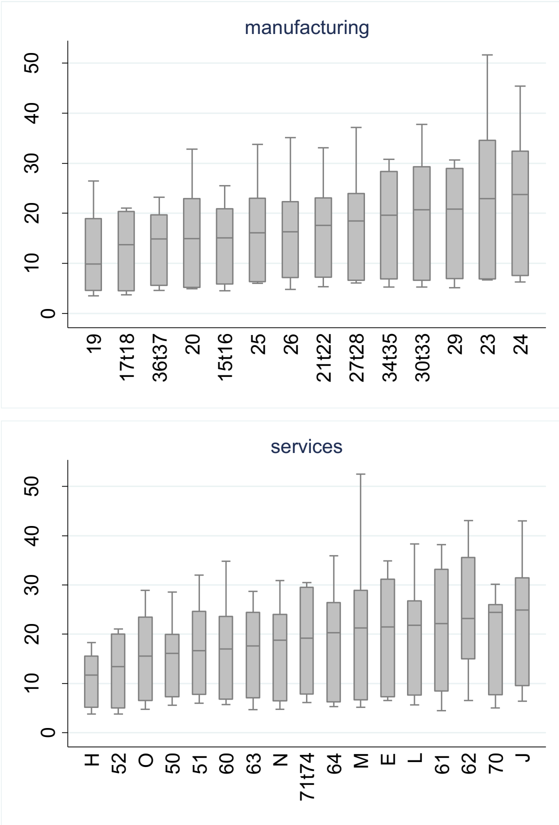
gross1 gross hourly wage (benchmark variable directly obtainable from LIS, *hw1* hourly wage obtained on the basis of paid income data, *hw2* hourly wage obtained on the basis of paid monetary income data; missing values imputed using the Gaussian normal regression imputation method). Normalised weights used. OMS: old EU member states: DEU, ESP, GRC, IRL and LUX; NMS: new EU member states of the EU: CZE, EST, SVK

Source: own compilation based on LIS data (wave 8–2010)

to calculate the average hourly wages paid in the ten countries in every sector, then use boxplots of the cross-country wage variation within each industry. Gauged by the median, the highest wages in manufacturing are in industry 24 (chemicals), the lowest in industry 19 (leather and footwear). The lowest manufacturing wages are paid in Central and East European countries: Estonia (industries 15, −16, 17, 18, 19, 24, 36, 37), the Czech Republic (industries 20, 25) and the Slovak Republic (industries 21,22, 23, 26, 27, 28, 29, 30–35). The highest are found in Luxembourg for all sectors except 29, 30–33, 36 and 37 (where Finland was the leader). In services, the median wage is lowest in hotels and restaurants, highest in financial intermediation. However, here too earnings differ considerably across countries: the lowest are again in the Slovak Republic and Estonia, while the highest are registered in Luxembourg, Finland, Germany and Ireland. The U.S. appears to pay the highest salary of all ten countries in only one industry, namely industry 70, real estate activities.

In our dataset, workers are classified by education (low, medium or high[22]) and by main tasks performed. Based on original country-specific information in the LIS database (2-digit ISCO code), we assign each occupation to one of three categories: *AbsServ* (low in routine, high in abstractness and service task importance), *Serv* (low in

[22] Classed by the highest level completed. "High" means a university degree (ISCED level 5 or 6), "medium" signifies a secondary diploma (ISCED level 3 or 4), and "low" less than that (never attended, no completed education or education completed at ISCED level 0, 1 or 2).



15t16: Food, Beverages and Tobacco
17t18: Textiles and Textile Products
19: Leather, Leather and Footwear
20: Wood and Products of Wood and Cork
21t22: Pulp, Paper, Paper, Printing and Publishing
23: Coke, Refined Petroleum and Nuclear Fuel
24: Chemicals and Chemical Products
25: Rubber and Plastics
26: Other Non-Metallic Mineral
27t28: Basic Metals and Fabricated Metal
29: Machinery, Nec
30t33: Electrical and Optical Equipment
34t35: Transport Equipment
36t37: Manufacturing, Nec; Recycling

E: Electricity, Gas and Water Supply,
50: Sale, Maintenance and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
51: Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles
52: Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods
H: Hotels and Restaurants
60: Inland Transport
61: Water Transport
62: Air Transport
63: Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies
64: Post and Telecommunications
J: Financial Intermediation
70: Real Estate Activities
71t74: Renting of M&Eq and Other Business Activities
L: Public Admin and Defense, Compulsory Social Security
M: Education
N: Health and Social Work
O: Other Community, Social and Personal Services

Fig. 1 Comparison of hourly wages* across industries: variation among countries. Note: **gross1* – gross hourly wage (variable directly obtainable from LIS). In the first step average values across workers employed in a given industry in a given country were calculated. The line in the box corresponds to the median wage calculated across countries; lower (upper) adjacent lines correspond to countries paying min (max) wages in a given industry. Sample: workers from 10 countries (listed in Table 1). Source: own compilation based on LIS data (wave 8–2010)

routine and abstractness, high in service task importance) and *Rout* (highly routine, low in abstractness and service task importance) – see Table 13 in the Appendix.[23] As Table 2 shows, wages differ by educational attainment (highly educated workers naturally earn the most, but the differences between medium and low educational attainment are not so pronounced). In terms of tasks, non-routine occupations have the highest salaries (*AbsServ*, which covers such workers as managers, professionals, technicians and associate professionals). In manufacturing, these workers earn approximately twice as much as workers performing mainly routine or simple service tasks.

[23] We draw on Goos et al. (2014), who use the approach of Autor and Dorn (2013) and Autor et al. (2015), to compute a Routine Task Intensity index for occupations at the 2-digit ISCO level, to conform with our level of occupational detail. Specifically, we use additional material accompanying Goos et al. (2014) (task.dta file available at https://www.aeaweb.org/articles?id=10.1257/aer.104.8.2509) to divide workers into the three main categories listed in Table 13. We are obliged to use relatively highly aggregated data on occupations because most of the European countries reporting to LIS use 2-digit ISCO codes, and very few provide more detailed data (the LIS database classifies workers in the U.S. into 526 occupations, those in Germany into 288).

Table 2 Comparison of hourly wages* (in US$) across occupational task categories and educational groups

task	manufacturing					services				
	all countries	E9	OMS	NMS	USA	all countries	E9	OMS	NMS	USA
AbsServ	30.0	24.2	33.8	7.8	35.1	27.1	22.9	30.2	7.2	29.1
Rout	14.4	11.6	18.1	5.1	17.7	15.4	12.7	16.4	5.1	17.2
Serv	15.7	13.8	18.3	5.6	18.0	15.1	13.6	17.5	4.6	15.9
education	manufacturing					services				
	all countries	E9	OMS	NMS	USA	all countries	E9	OMS	NMS	USA
high	31.8	27.9	34.4	8.7	34.0	27.9	24.3	29.8	7.7	29.4
medium	15.3	12.3	21.3	5.5	19.4	16.2	14.1	20.5	5.4	17.6
low	13.4	13.3	15.6	4.5	13.5	13.9	14.8	16.0	4.0	12.8

**gross1* – gross hourly wage (variable directly obtainable from LIS). Average values across workers within industries. Sample: workers from 10 countries (listed in Table 1). OMS: old EU member states: DEU, ESP, GRC, IRL and LUX; NMS: new EU member states of the EU: CZE, EST, SVK

Source: own compilation based on LIS data (wave 8–2010)

The international differences are pronounced (*AbsServ* workers average $33.80 an hour in OMS, $35.10 in the U.S. and only $7.80 in NMS); the multiple-country perspective is accordingly mandatory.

3.2 Trends in GVC Participation and Foreign Value Added

To measure the extent to which domestic industries are tied into GVCs, we rely on the decomposition of WIOD data by Wang et al. (2013).[24] First we break gross exports down into four principal components: domestic added value absorbed abroad (DVA),[25] added value exported initially but eventually returning home (RDV), foreign value added (FVA) and pure double-counted terms (PDC).[26] FVA, reflecting vertical specialisation (Hummels et al. 2001), is a good proxy for degree of involvement in global production structures,[27] overcoming the methodological weaknesses of the first generation of offshoring measures (Feenstra 2017: 21).[28]

[24] We use the *decompr* package in R (Quast and Kummritz 2015).
[25] Domestic value added in a country's exports and value-added exports are quite different concepts. "This concept [domestic value-added in a country's exports] only looks at where the value added is originated, regardless of where it is ultimately absorbed. In comparison, a country's 'value-added exports' refers to a subset of 'domestic value added in a country's exports' that is ultimately absorbed abroad (Mattoo et al. 2013, p.10)
[26] For a detailed derivation of the breakdown, see the Appendix of Wang et al. (2013).
[27] Theoretically, FVA contained in exports could be equal to zero even if imported inputs are used in production (because the industry does not export). No such situation is confirmed in our data: all the sectors in our sample report positive exports and positive foreign value added. It could be possible, of course, at a more detailed level of decomposition (in line with Melitz's "new-new" trade theory that not all the firms export). We thank an anonymous referee for pointing this out.
[28] Before the decomposition of Koopman et al. (2014) and Wang et al. (2013) became popular, simplified measures of offshoring based on WIOD input-output tables were standard. For instance, Parteka and Wolszczak-Derlacz (2015). Foster-McGregor et al. (2013) and Wolszczak-Derlacz and Parteka (2018) use the ratio of imported intermediate inputs to value added of the domestic sector.

Table 3 shows the effects of the basic WWZ decomposition. The United States, where FVA accounted for 11.9% of manufacturing exports and 3.8% of service exports in 2010, is less closely involved in GVCs than the European countries (11% and 26% respectively). Unsurprisingly, manufacturing is generally more heavily involved in GVCs than service activities. It is worth noting that economies broadly seen as offshoring hosts, such as our NMS countries (the Czech Republic, the Slovak Republic and Estonia), also rely heavily on FVA, which accords with Olczyk and Kordalska (2017). Table 3 also reports average annual growth rates of the monetary value of FVA. Generally (counting all industries), all the countries in our sample registered an increase, at an average annual pace of 7.2% in Europe and 5.5% in the U.S. This indicates a deepening of GVC ties.

4 The Impact of GVC Ties on Wages – Econometric Analysis

4.1 Augmented Micro-Level Wage Model(s)

Our project is to run an empirical test of whether the degree to which industries are tied into GVCs is a significant factor in domestic workers' wages, once all the other wage determinants are taken into account. We estimate an augmented

Table 3 GVC ties in the light of foreign value added export share (by country)

	FVA in 2010 [%]*			annual growth rate of monetary value of *FVA* (1995–2010) [%]**		
	FVA all industries	FVA manufacturing	FVA services	FVA all industries	FVA manufacturing	FVA services
Czech Republic	19.2	32.7	13.0	5.1	8.4	2.6
Estonia	16.2	26.2	11.2	9.2	7.6	10.6
Finland	12.5	21.9	10.0	7.5	5.1	9.5
Germany	10.0	20.5	6.3	4.3	4.4	4.8
Greece	9.9	17.8	7.3	5.5	3.9	6.8
Ireland	21.8	39.2	19.0	6.3	1.4	10.2
Luxembourg	23.8	32.2	21.9	15.3	2.9	26.8
Slovak Republic	16.9	31.9	12.1	5.7	2.6	8.5
Spain	9.5	19.3	7.5	6.0	8.7	4.5
United States	5.3	11.9	3.8	5.5	4.1	6.5
Europe(E9)	14.4	26.0	11.03	7.2	5.1	9.4
OMS	13.0	22.3	10.6	8.3	4.0	12.0
NMS	17.7	31.1	12.2	5.1	7.1	4.0
All countries (10)	9.3	19.7	6.8	7.1	4.9	9.0

* as % of exports (result of WWZ decomposition); **real average annual growth rate of the monetary value of FVA, deflated with GDP deflator (2005 = 100) from PWT. OMS: old EU member states: DEU, ESP, GRC, IRL and LUX; NMS: new EU member states of the EU: CZE, EST, SVK

Source: own elaboration based on WWZ methodology and WIOD data micro-level wage model using our unique matching dataset of individual and industry data for ten countries. Our empirical strategy is similar to Baumgarten et al. (2013) and Geishecker et al. (2010); like them, we merge micro-level data on labour market outcomes (here, wages) with an industry-level metric of cross-border production ties (here, GVC).

We consider three alternative specifications, the first being:

$$ln\text{wage}_{ijct} = \alpha + \beta X_{it} + \textstyle\sum_{e-1}\gamma_e Educ_{eit} + \sum_{n-1}\delta_n Task_{nit} + \theta GVC_{jct-1} + D_j + D_c + D_{jc} + \varepsilon_{ijct} \quad (1)$$

The dependent variable is the log of the gross hourly wage: ln*wage,* where *wage* = *{gross1, hw1, hw2}* is the wage of worker i in industry j country c at time t (here t = 2010). X denotes a set of individual characteristics typically present in the Mincer equation (*sex,*[29] *age*, *age²*, marital and family status,[30] occupation, part-time employment[31]). The information on educational level is denoted as *Educ* = {*high*, *medium*, *low*}, where "low" is the omitted e category. Additionally, we include the nature of the worker's task: *Task* = {*AbsServ*, *Serv*, *Rout*}, where the reference category n is *Rout*. For our analysis, the crucial information is given in the GVC variable (FVA expressed as a share of the industry's value added)[32] which reflects the magnitude of the GVC ties of the worker's industry. Following Ebenstein et al. (2014), we lag GVC in order to allow for the time required for wage adjustment. Further, we add a full set of dummies: D_j is an industry dummy (capturing all the remaining industry-specific characteristics or wage regulations); D_c is the country dummy (capturing all country-specific labour market conditions and wage-setting mechanisms[33]) and, finally, D_{jc} is a two-dimensional dummy capturing any other unobserved industry-country effects.

Eq. 1 is a basic model for estimating the general effect of GVC ties on the wage determination process within a given industry. Our second specification adds the interaction term (*Task*GVC)*, which captures the heterogeneity of the GVC effect specific to the task profiles:

$$\begin{aligned} ln\text{wage}_{ijct} &= \alpha + \beta X_{it} + \textstyle\sum_{e-1}\gamma_e Educ_{eit} + \sum_{n-1}\delta_n Task_{nit} + \theta GVC_{jct-1} \\ &\quad + \textstyle\sum_{n-1}\vartheta_n Task_{nit} \times GVC_{jct-1} + D_j + D_c + D_{jc} + \varepsilon_{ijct}. \end{aligned} \quad (2)$$

Given that *Rout* is defined as the benchmark task category, the coefficient θ in eq. 2 measures the GVC elasticity of the wages of workers doing routine tasks, while ($\theta + \vartheta_n$) are the elasticities of the wages of workers belonging to a given (n) task category.

29 *sex* = 1 if male.

30 Whether a person lives with or without children (*children* = 1 if living with children); *partner* = 1 if living with a partner, *marital status* = 1 if married.

31 As a robustness check, we add more information about job characteristics (one job or more than one, size and ownership of company, work experience, supervisory tasks). However, these additional variables are not available for all ten countries.

32 For the econometric analysis we first multiply the export share of FVA (resulting from the WWZ decomposition) by the industry's gross exports by value (from WIOD) to obtain the monetary value of FVA (in US dollars and deflated with the GDP deflator) in each industry. Value added scaling eliminates the problem of industry size and controls for potentially greater FVA in larger industries and/or larger countries. As a robustness check, we consider the specification in which FVA is as share of exports.

33 In the section on robustness checks we add more information on national labour market institutions.

Finally, the third specification,

$$\begin{aligned} ln\text{wage}_{ijct} = \alpha + \beta X_{it} + \textstyle\sum_{e-1}\gamma_e Educ_{eit} + \sum_{n-1}\delta_n Task_{nit} + \theta GVC_{jct-1} \\ + \textstyle\sum_{e-1}\vartheta_e Educ_{eit} \times GVC_{jct-1} + D_j + D_c + D_{jc} + \varepsilon_{ijct}, \end{aligned} \tag{3}$$

focuses on the heterogeneity of GVC effects according to the worker's educational attainment (*Educ*). Here, low-educated workers serve as the benchmark, so the interaction terms (*Educ×GVC*) enable us to assess the role of GVC in determining the wages of workers with medium or high education, in relation to the low-educated. In other words, by comparing the estimation results of models (2) and (3) we can determine the importance of the occupational task profile relative to the educational level of workers in industries that differ in the extent of their GVC ties.

Our estimation uses weighted regressions[34] with cluster-robust standard errors, where the clusters refer to country-industry pairs.

4.2 The Basic Estimation Results

Table 4 reports the estimation results for our basic specification (1), in which the Mincerian model factors in the different tasks that workers perform and is augmented by the GVC involvement metric. Separate columns give the estimates resulting from alternative wage measures as dependent variable – first our preferred gauge (*gross1*) and then those with imputed earnings data (*hw1*, *hw2*). All the key personal characteristics variables have the expected sign: older, male, better educated workers living with a partner and/or children and working full time earn more. Further, the wages of workers whose tasks are less routine in content (*AbsServ* and *Serv*) are significantly higher than the reference group of workers engaged in highly routine tasks. And even controlling for many aspects of personal heterogeneity, the task effect remains significant, in perfect accordance with the relevant "task" literature (Baumgarten et al. 2013; Autor 2015; Becker et al. 2013; Becker and Muendler 2015). Finally, the estimate of the coefficient θ, associated with the GVC variable, is negative and statistically significant. Hence, there is an inverse (albeit weak) correlation between industries' involvement in GVCs and wages.

Now, the question is whether and how this effect varies among workers, given task profile and level of education. We address this issue using the interaction terms. Table 5 reports the results for eq. (2) with the (*GVC×Task*) interaction. Workers in routine occupations serve as reference group. The estimates suggest that generally (and unsurprisingly) these workers earn less than those who perform non-routine tasks (the coefficients for *AbsServ* and *Serv* are positive at 0.5 and 0.15, respectively). What

[34] We use normalized person weights based on the individual-level cross-sectional weights (provided by LIS), which make the sample representative of the total national population or the total population covered (for more on the rules, practices and definitions applied during the harmonisation process to ensure consistency over the LIS datasets together with sample-selection and weighting procedures, see the LIS guidelines at: http://www.lisdatacenter.org/wp-content/uploads/our-lis-documentation-harmonisation-guidelines.pdf). The individual weights are normalized to 10,000 by country. As a result, in our multi-country analysis workers from each country are assigned the same weight, so the results are not driven by countries with large numbers of observations.

Table 4 Estimation results (eq.1) – basic specification

	Dep: var.: ln*wage*$_{ijct}$ (log of gross hourly wage)		
	gross1	*hw1*	*hw2*
age_i	0.031***	0.033***	0.033***
	[0.003]	[0.003]	[0.003]
age_i^2	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]
sex_i	0.185***	0.195***	0.190***
[=1 if male]	[0.008]	[0.009]	[0.008]
marital status$_i$	0.000	−0.002	−0.003
[=1 if married]	[0.009]	[0.010]	[0.010]
$partner_i$	0.055***	0.065***	0.066***
[=1 if living with a partner]	[0.009]	[0.009]	[0.009]
$children_i$	0.041***	0.042***	0.042***
[=1 if living with children]	[0.006]	[0.007]	[0.007]
part-time$_i$	−0.045**	−0.02	−0.021
[=1 if working part-time]	[0.019]	[0.019]	[0.019]
$hieduc_i$	0.267***	0.270***	0.269***
[=1 if having high education]	[0.017]	[0.018]	[0.018]
$mededuc_i$	0.102***	0.099***	0.098***
[=1 if having medium education]	[0.014]	[0.013]	[0.014]
$AbsServ_i$	0.510***	0.564***	0.529***
[=1 if low in routine, high in abstractness & service task]	[0.031]	[0.027]	[0.046]
$Serv_i$	0.157***	0.157***	0.133***
[=1 if low in routine & abstractness, high in service task]	[0.028]	[0.017]	[0.044]
GVC_{jct-1}	−0.060***	−0.064***	−0.064***
	[0.022]	[0.024]	[0.024]
R^2	0.757	0.692	0.699
N	113,932	120,724	120,702

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance. Sample: workers from 10 countries, $t = 2010$

Source: own elaboration with data from LIS and WIOD

is more, where workers performing routine tasks are employed in industries characterised by stronger GVC involvement, there is added downward pressure on their wages (the estimated coefficient θ equals −0.06), while the other two task categories do not show any statistically significant difference in this respect.

Table 6 reports the estimation results for model 3, where the interaction term is designed to capture education-specific heterogeneity in the GVC-wage nexus, with the less educated group as default category. Again, the positive and statistically significant estimates of the coefficients for *hieduc* and *mededuc*, as well as *AbsServ* and *Serv*, indicate

Table 5 Estimation results (eq.2) – accounting for heterogeneous wage response to GVC ties due to tasks performed

	dep. var.: ln*wage*$_{ijct}$ (log of gross hourly wage)		
	gross1	*hw1*	*hw2*
age_i	0.031***	0.033***	0.033***
	[0.003]	[0.003]	[0.003]
age_i^2	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]
sex_i	0.185***	0.194***	0.190***
[=1 if male]	[0.008]	[0.009]	[0.008]
marital status$_i$	0.00	−0.002	−0.003
[=1 if married]	[0.009]	[0.010]	[0.010]
$partner_i$	0.055***	0.065***	0.066***
[=1 if living with a partner]	[0.009]	[0.009]	[0.009]
$children_i$	0.041***	0.042***	0.042***
[=1 if living with children]	[0.006]	[0.007]	[0.007]
part-time$_i$	−0.045**	−0.02	−0.021
[=1 if working part-time]	[0.019]	[0.019]	[0.019]
$hieduc_i$	0.267***	0.270***	0.269***
[=1 if having high education]	[0.017]	[0.018]	[0.018]
$mededuc_i$	0.102***	0.099***	0.098***
[=1 if having medium education]	[0.014]	[0.013]	[0.014]
$AbsServ_i$	0.512***	0.564***	0.528***
[=1 if if low in routine, high in abstractness & service task]	[0.031]	[0.027]	[0.046]
$Serv_i$	0.153***	0.155***	0.131***
[=1 if low in routine & abstractness, high in service task]	[0.028]	[0.017]	[0.044]
GVC_{jct-1}	−0.059***	−0.069***	−0.069***
	[0.022]	[0.025]	[0.024]
$GVC_{jct-1} \times AbsServ_i$	−0.012	0.004	0.004
	[0.020]	[0.022]	[0.023]
$GVC_{jct-1} \times Serv_i$	0.034	0.027	0.027
	[0.030]	[0.032]	[0.031]
R^2	0.757	0.692	0.699
N	113,932	120,724	120,702

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance. Sample: workers from 10 countries, t = 2010

Source: own elaboration with data from LIS and WIOD

that in general better-educated workers and those performing non-routine tasks earn more. However, the extra downward pressure of GVC ties on the wages of the less educated workers is confirmed only in the estimates obtained using imputed earnings (*hw1*, *hw2*).

Table 6 Estimation results (eq.3) – accounting for heterogeneous wage response to GVC ties due to education level

	dep. var.: ln$wage_{ijct}$ (log of gross hourly wage)		
	gross1	*hw1*	*hw2*
age_i	0.031***	0.033***	0.033***
	[0.003]	[0.003]	[0.003]
age_i^2	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]
sex_i	0.185***	0.195***	0.191***
[=1 if male]	[0.008]	[0.009]	[0.008]
marital status$_i$	0	−0.002	−0.003
[=1 if married]	[0.009]	[0.010]	[0.010]
$partner_i$	0.055***	0.065***	0.066***
[=1 if living with a partner]	[0.009]	[0.009]	[0.009]
$children_i$	0.040***	0.042***	0.042***
[=1 if living with children]	[0.006]	[0.007]	[0.007]
part-time$_i$	−0.045**	−0.02	−0.021
[=1 if working part-time]	[0.019]	[0.019]	[0.019]
$hieduc_i$	0.272***	0.270***	0.269***
[=1 if having high education]	[0.019]	[0.020]	[0.020]
$mededuc_i$	0.101***	0.095***	0.095***
[=1 if having medium education]	[0.016]	[0.015]	[0.015]
$AbsServ_i$	0.511***	0.565***	0.529***
[=1 if if low in routine, high in abstractness & service task]	[0.031]	[0.027]	[0.046]
$Serv_i$	0.157***	0.157***	0.134***
[=1 if low in routine & abstractness, high in service task]	[0.028]	[0.017]	[0.044]
GVC_{jct-1}	−0.059	−0.087*	−0.084*
	[0.047]	[0.049]	[0.048]
$GVC_{jct-1} \times hieduc_i$	−0.042	−0.002	−0.004
	[0.043]	[0.041]	[0.042]
$GVC_{jct-1} \times mededuc_i$	0.01	0.031	0.028
	[0.037]	[0.038]	[0.037]
R^2	0.757	0.692	0.699
N	113,932	120,724	120,702

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance. Sample: workers from 10 countries, t = 2010

Source: own elaboration with data from LIS and WIOD

The broad conclusion implied by the estimation results for the entire sample (workers in all countries and all industries) is that the level of wages is determined primarily by workers' individual characteristics and occupations. Employment in industries with strong GVC ties appears to exert some downward pressure on wages, but in the whole sample this effect is not unambiguously related to workers' educational level or task profile.

Moreover, the magnitude of the downward wage "pressure" exerted by GVC involvement is very small indeed: the point estimates are around 0.06 (in absolute terms). The regressions consider all the main individual characteristics that play a role in wage determination, so we can interpret this effect as the wage gap between workers who differ only by industry. The magnitude of the effect indicates that, other things being equal, work in an industry with a 1% higher FVA output share means an hourly wage just 0.06% lower than that of a similar worker in another industry. How much does this amount to in monetary terms? Assuming an hourly wage of \$16.00 (the mean gross wage in manufacturing in our sample countries, see Table 1) and a working year of 1820 h (35 h a week), a 1% increase in GVC involvement would result in a decrease in annual earnings of just \$17.50 (16x1820x0.06/100). To check the long-term effect, we can match this with the recent trends in industries' involvement in GVCs in our sample countries. Between 1995 and 2010 the share of FVA embodied in exports (with respect to the industry's output)[35] rose at a pace of 4% per year in manufacturing and 5% in services. This would imply an annual wage loss of some \$70.00 (17.5 × 4.0) in manufacturing and \$87.50 in services. In short, the economic impact of the GVC effect on wages is marginal. Recalling that this is the estimate for the entire sample, let us now go on to explore the heterogeneity of effects on workers in different countries and sectors.

4.3 The Estimation Results –Cross-Country Heterogeneity

Our sample is composed of 10 countries, and we replicate our estimations for selected subgroups of countries. Eq.2 (Table 7) and eq.3 (Table 8) are crucial,[36] so we compare the results for workers in Europe generally (E9), new EU member states (NMS), old EU member states (OMS) and, for comparison, the United States.

As Table 7 reports, in all the subgroups workers in occupations low in routine and high in abstractness and service tasks earn more (the coefficient for *AbsServ* is positive and statistically significant). The correlation is stronger in Europe than in the U.S. As to the importance of GVC ties in wage determination, Table 7 reveals some interesting variations, in particular the differences between Europe and the United States in general and between subsets of European countries. The coefficient for the GVC variable is negative and statistically significant only for the OMS subgroup (where the interaction terms are insignificant). For the NMS subsample no effect emerges. On the contrary, in the U.S. wages in occupations that are low in routine tasks but high in abstractness and service tasks appear to be positively related to the degree of industries' involvement in global production chains (the coefficient for the *GVC×AbsServ* variable is positive). That is, closer GVC ties drive down the wages of Western European workers

[35] Note the difference with respect to the values reported in Table 3 where FVA is expressed as export share or in monetary value.

[36] The results reported here refer to our preferred measure of wages: *gross1*. The results obtained with the other two measures of wages (*hw1* and *hw2*) are available on request.

Table 7 Estimation results by country subgroups (eq. 2)

	dep. var.: ln*wage*$_{ijct}$ (log of gross hourly wage – *gross1*)			
Workers from:	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.030***	0.040***	0.021***	0.037***
	[0.004]	[0.004]	[0.004]	[0.004]
age_i^2	−0.000***	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
sex_i	0.183***	0.132***	0.230***	0.230***
[=1 if male]	[0.009]	[0.009]	[0.013]	[0.018]
$marital\ status_i$	−0.008	0.000	−0.021	0.079***
[=1 if married]	[0.010]	[0.010]	[0.018]	[0.013]
$partner_i$	0.055***	0.068***	0.054***	0.034***
[=1 if living with a partner]	[0.010]	[0.010]	[0.018]	[0.009]
$children_i$	0.040***	0.025***	0.030**	0.052***
[=1 if living with children]	[0.007]	[0.008]	[0.012]	[0.006]
$part\text{-}time_i$	−0.027	−0.062***	−0.01	−0.213***
[=1 if working part-time]	[0.020]	[0.023]	[0.033]	[0.035]
$hieduc_i$	0.238***	0.234***	0.246***	0.506***
[=1 if having high education]	[0.016]	[0.015]	[0.025]	[0.023]
$mededuc_i$	0.095***	0.117***	0.064***	0.227***
[=1 if having medium education]	[0.014]	[0.013]	[0.021]	[0.018]
$AbsServ_i$	0.625***	0.504***	0.436***	0.370***
[=1 if if low in routine, high in abstractness & service task]	[0.027]	[0.044]	[0.043]	[0.060]
$Serv_i$	0.168***	0.121***	−0.038	0.032
[=1 if low in routine & abstractness, high in service task]	[0.020]	[0.037]	[0.041]	[0.050]
$GVC_{jct\text{-}1}$	−0.055**	−0.112**	0.000	0.006
	[0.023]	[0.051]	[0.016]	[0.769]
$GVC_{jct\text{-}1} \times AbsServ_i$	−0.007	−0.009	−0.001	2.845**
	[0.020]	[0.045]	[0.019]	[1.308]
$GVC_{jct\text{-}1} \times Serv_i$	0.018	0.03	0.038	1.945
	[0.029]	[0.055]	[0.027]	[1.294]
R^2	0.793	0.601	0.38	0.279
N	43,774	28,222	15,552	70,158

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance, $t = 2010$. OMS = EU Old member states (here: Germany, Spain, Finland, Greece, Ireland and Luxembourg); NMS = EU. New member states (here: Czech Republic, Estonia, Slovak Republic); E9 = OMS + NMS

Source: own elaboration with data from LIS and WIOD

Table 8 Estimation results by country subgroups (eq. 3)

	dep. var.: ln*wage*$_{ijct}$ (log of gross hourly wage – *gross1*)			
Workers from	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.030***	0.040***	0.021***	0.037***
	[0.004]	[0.004]	[0.004]	[0.004]
age_i^2	−0.000***	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
sex_i	0.183***	0.132***	0.230***	0.234***
[=1 if male]	[0.009]	[0.009]	[0.013]	[0.018]
$marital\ status_i$	−0.008	0	−0.021	0.080***
[=1 if married]	[0.010]	[0.010]	[0.018]	[0.013]
$partner_i$	0.055***	0.068***	0.054***	0.035***
[=1 if living with a partner]	[0.010]	[0.010]	[0.018]	[0.009]
$children_i$	0.040***	0.025***	0.030**	0.052***
[=1 if living with children]	[0.007]	[0.008]	[0.012]	[0.006]
$part\text{-}time_i$	−0.027	−0.062***	−0.01	−0.213***
[=1 if working part-time]	[0.020]	[0.023]	[0.033]	[0.035]
$hieduc_i$	0.240***	0.234***	0.241***	0.488***
[=1 if having high education]	[0.018]	[0.017]	[0.028]	[0.027]
$mededuc_i$	0.093***	0.114***	0.058**	0.213***
[=1 if having medium education]	[0.016]	[0.015]	[0.025]	[0.020]
$AbsServ_i$	0.624***	0.503***	0.436***	0.393***
[=1 if low in routine, high in abstractness & service task]	[0.026]	[0.044]	[0.043]	[0.058]
$Serv_i$	0.169***	0.125***	−0.035	0.051
[=1 if low in routine & abstractness, high in service task]	[0.020]	[0.037]	[0.041]	[0.047]
$GVC_{jct\text{-}1}$	−0.065	−0.121**	−0.018	−0.582
	[0.048]	[0.060]	[0.043]	[1.044]
$GVC_{jct\text{-}1} \times hieduc_i$	−0.014	−0.003	0.015	2.588*
	[0.042]	[0.049]	[0.048]	[1.309]
$GVC_{jct\text{-}1} \times mededuc_i$	0.016	0.026	0.022	1.749**
	[0.037]	[0.047]	[0.040]	[0.770]
R^2	0.793	0.601	0.38	0.278
N	43,774	28,222	15,552	70,158

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance, t = 2010. OMS = EU Old member states (here: Germany, Spain, Finland, Greece, Ireland and Luxembourg); NMS = EU. New member states (here: Czech Republic, Estonia, Slovak Republic); E9 = OMS + NMS

Source: own elaboration with data from LIS and WIOD

(regardless of task type) but exert an upward push on the earnings of American workers in the more demanding occupations.

The results of the cross-country comparison in Table 8, where the interaction terms refer to the education level of workers, are similar. Of course, the estimates for *hieduc* confirm that the better educated earn more everywhere, but most especially in the U.S., where the coefficient is twice as high as in Europe. And only in the U.S. does employment in industries with stronger GVC ties produce a statistically significant upward variation in the wages of high- and medium-skilled employees.

This evidence needs to be interpreted in the light of the ambiguous theoretical predictions concerning the impact on factor prices (Section 2.1). The outcomes typical of the US labour market suggest that efficiency gains from upstream GVC involvement allow for wage gains for more educated workers performing demanding tasks in an advanced economy. The potential positive role of a GVC-driven productivity effect akin to that posited in offshoring models (Grossman and Rossi-Hansberg, 2008) and in line with the predictions of Acemoglu et al. (2015) is thus empirically confirmed.

4.4 The Estimation Results – Cross-Industry Heterogeneity

Thus far the results are for all 34 industries in our sample. To inquire into inter-industry heterogeneity we first split the sample between manufacturing and services (see Table 11). The results for eq.2 and eq. 3 are reported in Table 9. In a specification taking into account task interaction terms (eq.2), the negative correlation between GVC involvement and wages applies to workers in both manufacturing and services, but is stronger for service industries. There is no statistically significant variation according to task. Additionally, the traditional division of workers by education (eq.3) does not reveal any significant difference between services and manufacturing.

An interesting question is whether the response of individual wages to GVC involvement depends on the industry's overall wage level. In other words, are workers in low-wage industries likely to suffer even more from the intensive exploitation of foreign inputs? To look into this we use the precise classification of low-wage countries at the industry level developed by Wolszczak-Derlacz and Parteka (2018),[37] taking classification 4, defining an industry as "low-wage" in a country if it pays wages lower than 50% of the global average for the industry. Table 10 reports the results for eq.2 and eq.3 splitting the sample into low-wage and high-wage industries. The estimates suggest that the downward wage pressure exerted by GVC ties mainly concerns workers in high-wage industries, which we can interpreted as a sort of convergence mechanism. This effect is not specific to any group of workers as defined by task or education.

4.5 Robustness Checks

We perform a series of sensitivity checks, starting with changes in the type of measurement of some variables. First, as we have seen, most of the benchmark results – i.e. those with direct measurement of the gross hourly wage (*gross1*) – remain

[37] In particular, we use the file with LWC classifications accompanying the electronic version of the paper and available at: http://link.springer.com/article/10.1007%2Fs10663-016-9352-4#SupplementaryMaterial

Table 9 Estimation results by industry type – manufacturing versus services (eq. 2 and eq.3)

	dep. var.: ln$wage_{ijct}$ (log of gross hourly wage – *gross1*)			
	Manuf – eq.2	Services –eq.2	Manuf – eq.3	Services – eq.3
age_i	0.031***	0.034***	0.031***	0.034***
	[0.005]	[0.004]	[0.005]	[0.003]
age_i^2	−0.000***	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
sex_i	0.227***	0.172***	0.227***	0.171***
[=1 if male]	[0.013]	[0.010]	[0.013]	[0.010]
marital status$_i$	−0.025	0.006	−0.025	0.007
[=1 if married]	[0.022]	[0.011]	[0.022]	[0.011]
$partner_i$	0.073***	0.050***	0.073***	0.050***
[=1 if living with a partner]	[0.024]	[0.010]	[0.024]	[0.010]
$children_i$	0.044***	0.038***	0.044***	0.037***
[=1 if living with children]	[0.010]	[0.008]	[0.010]	[0.007]
part-time$_i$	−0.095***	−0.050**	−0.095***	−0.050**
[=1 if working part-time]	[0.034]	[0.021]	[0.034]	[0.021]
$hieduc_i$	0.223***	0.268***	0.221***	0.274***
[=1 if having high education]	[0.027]	[0.019]	[0.034]	[0.020]
$mededuc_i$	0.070***	0.099***	0.074***	0.095***
[=1 if having medium education]	[0.019]	[0.014]	[0.025]	[0.014]
$AbsServ_i$	0.765***	0.471***	0.760***	0.470***
[=1 if low in routine, high in abstractness & service task]	[0.081]	[0.031]	[0.081]	[0.031]
$Serv_i$	0.217***	0.104***	0.242***	0.108***
[=1 if low in routine & abstractness, high in service task]	[0.080]	[0.027]	[0.083]	[0.026]
GVC_{jct-1}	−0.045***	−0.284**	−0.037	−0.217
	[0.017]	[0.114]	[0.040]	[0.138]
$GVC_{jct-1} \times AbsServ_i$	−0.01	0.052		
	[0.019]	[0.084]		
$GVC_{jct-1} \times Serv_i$	0.048	0.137		
	[0.031]	[0.135]		
$GVC_{jct-1} \times hieduc_i$			0.000	−0.103
			[0.046]	[0.108]
$GVC_{jct-1} \times mededuc_i$			−0.009	0.121
			[0.038]	[0.113]
R^2	0.811	0.747	0.811	0.747
N	17,113	87,107	17,113	87,107

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance, $t = 2010$

Source: own elaboration with data from LIS and WIOD

Table 10 Estimation results by industry type – high wage (HW) versus low wage (LW) industries (eq. 2 and eq.3)

	dep. var.: ln*wage*$_{ijct}$ (log of gross hourly wage – *gross1*)			
Workers employed in:	LW - eq.2	HW -eq.2	LW - eq.3	HW -eq.3
age_i	0.018***	0.039***	0.018***	0.039***
	[0.005]	[0.003]	[0.005]	[0.003]
age_i^2	−0.000***	−0.000***	−0.000***	−0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
sex_i	0.238***	0.153***	0.239***	0.153***
[=1 if male]	[0.013]	[0.008]	[0.013]	[0.008]
marital status$_i$	−0.018	0.008	−0.018	0.008
[=1 if married]	[0.017]	[0.011]	[0.017]	[0.011]
$partner_i$	0.051***	0.068***	0.051***	0.068***
[=1 if living with a partner]	[0.019]	[0.009]	[0.019]	[0.009]
$children_i$	0.028**	0.032***	0.028**	0.031***
[=1 if living with children]	[0.012]	[0.007]	[0.012]	[0.007]
part-time$_i$	0.001	−0.068***	0.001	−0.068***
[=1 if working part-time]	[0.036]	[0.020]	[0.036]	[0.020]
$hieduc_i$	0.251***	0.262***	0.244***	0.269***
[=1 if having high education]	[0.026]	[0.018]	[0.030]	[0.020]
$mededuc_i$	0.066***	0.109***	0.058**	0.107***
[=1 if having medium education]	[0.023]	[0.014]	[0.028]	[0.015]
$AbsServ_i$	0.626***	0.518***	0.628***	0.515***
[=1 if low in routine, high in abstractness & service task]	[0.035]	[0.034]	[0.034]	[0.033]
$Serv_i$	0.307***	0.073**	0.316***	0.075**
[=1 if low in routine & abstractness, high in service task]	[0.037]	[0.030]	[0.034]	[0.030]
GVC_{jct-1}	−0.003	−0.112**	−0.022	−0.107*
	[0.016]	[0.049]	[0.043]	[0.061]
$GVC_{jct-1} \times AbsServ_i$	0.006	−0.032		
	[0.020]	[0.042]		
$GVC_{jct-1} \times Serv_i$	0.04	0.047		
	[0.029]	[0.057]		
$GVC_{jct-1} \times hieduc_i$			0.025	−0.067
			[0.050]	[0.051]
$GVC_{jct-1} \times mededuc_i$			0.025	0.029
			[0.041]	[0.046]
R^2	0.381	0.615	0.381	0.615
N	13,471	100,461	13,471	100,461

Normalized weighted regression with cluster-robust standard errors; all specifications include industry and country fixed effects as well as country-industry panel identification. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers, performing *Rout* tasks = highly routine, low in abstractness and service importance, $t = 2010$. Classification of industries into low wage (LW) and high wage (HW) based on Wolszczak-Derlacz and Parteka (2018)

Source: own elaboration with data from LIS and WIOD

unchanged when wages are measured as income per hour (*hw1* and *hw2*). Second, we consider a different measure of GVC involvement, namely FVA as export share rather than in proportion to the industry's output. Again, the results hold.

Next we investigate a potential problem of endogeneity. As in the theoretical setting of Kohler (2004), there is potential reverse causality: the decision to use inputs from abroad may itself be determined by the level of wages paid at home. To address this issue in our baseline specification we include the lagged values of our GVC involvement metric (FVA/output); and alternatively – in case this procedure does not entirely dispel endogeneity concerns – we adopt instrumental variable techniques, relying on the values predicted by a gravity equation, see results in Table 14.[38]

We also supplement our models with additional variables for labour market conditions (for instance, union wage-setting might interfere with north-south trade and production sharing effects, as in Arnold and Trepl 2015). We use the degree of wage-setting coordination, on a scale from 1 (no coordination) to 5 (centralised wage-setting), trade union density,[39] and the type of national minimum wage regulations (0 for– non-statutory, 1 for regulation in some sectors only, 2 for national regulation).[40] In most specifications these factors are not statistically significant (with the exception of a negative correlation between national minimum wage regulation and wages as measured by *gross1*) and adding them to the regression does not change the baseline results.

Next, we add more information on job characteristics, such as having more than one job, company size and ownership, and supervisory status. These are left out of the baseline specifications because they are not available for all ten countries. While these characteristics are statistically significant and have the expected signs (i.e. workers in small companies earn less, employees who supervise others earn more), in most cases their inclusion does not alter either the magnitude or the statistical significance of the crucial GVC variable.

Finally, we look more closely into industry heterogeneity. We run the regressions eliminating industries one by one and checking to see whether the results are driven by any specific industry. In this exercise we also investigate the inclusion of some questionable industries, such as coke, refined petroleum and nuclear fuel, where the use of FVA reflects the purchase of natural resource inputs and not the displacement of production. The estimates turn out not to be sensitive to the exclusion of any specific industry.

[38] To construct the instrument for the GVC variable we take the foreign value added embodied in exports predicted by a gravity model for bilateral trade flows between a reporting country and its 39 partners (bilateral FVA data are from the decomposition on WIOD data in Wang et al. (2013). We run the model separately for all the industries (j). The regressors, taken from the CEPII database, consist of: the reporting country (i) and partner country (p) value added for a given industry (VA_{ijt} and VA_{pjt}), distance between the countries (D_{ip}), dummies for common border ($border_{ip}$), common language ($language_{ip}$), common currency ($currency_{ip}$), former colonial relationship ($Colony_{ip}$) and membership of a regional trade agreement (RTA_{ipt}). Specifically, we estimate $FVA_{ijpt} = \alpha + \beta_1 lnVA_{ij\ t} + \beta_2 lnVA_{pjt} + \beta_3 lnD_{ip} + \beta_4 border_{ip} + \beta_5 languageip + \beta_6\ currency_{ip} + \beta_7 \mathrm{Colony}_{ip} + \beta_8 RTA_{ipt} + \varepsilon_{ijpt}$, where j is sector, i reporter country, p partner country. The predicted FVAs are estimated using the Poisson pseudo maximum likelihood method (Silva and Tenreyro 2006), and are summed across all the partner countries. A similar strategy is used by Parteka and Wolszczak-Derlacz (2015).

[39] No data for Greece or the U.S.

[40] ICTWSS database on the Institutional Characteristics of Trade Unions, Wage Setting, State Intervention and Social Pacts, 1960–2011, () constructed by Jelle Visser (version 4.0, April 2013).

To sum up, none of the robustness procedures alters the conclusion: on the whole there is a negative but weak correlation between the closeness of an industry's tie-in with GVCs and individual workers' wages.

5 Conclusions

The paper contributes to the empirical literature on the effects that cross-border production sharing – global value chains – and the resulting production links have on national labour markets. Specifically, we assess how the wages of individual workers in various countries are affected by the extent to which industries are tied into GVCs. We have constructed a unique dataset matching micro-level and industry-level data for workers in ten economies at different stages of economic development, nine European plus the United States. This enables us to address international and cross-industry differences in the response of wages to production sharing. This approach represents a considerable advance over previous country-specific studies designed to estimate the wage impact of fragmentation or value added trade on wages. And to gauge the extent to which industries are tied into global production structures, we have employed precise, recently developed methods of measuring country and industry involvement in GVCs, based on export decomposition. Finally, in addition to the standard division of workers into skill, or educational, categories, we have also factored in heterogeneity according to tasks.

We apply a Mincerian wage model augmented by measures of GVC ties conditional on a large set of controls, an approach that enables us to determine whether cross-border production links affect wage setting mechanisms driven primarily by worker characteristics. First of all, the results for the entire sample indicate an inverse (albeit weak) correlation between degree of an industry' involvement in GVCs and wage levels. Other things constant, occupation in an industry with a 1% higher FVA share of output means an hourly wage just 0.06% lower than a similar worker in another industry would earn. Second, while working in industries with closer GVC ties does exert some downward pressure on wages, for the entire sample of ten countries this effect is not unambiguously related to workers' educational or task profile. Workers performing highly routine tasks earn less, but it is hard to ascribe this to the involvement of their countries or industries in global production networks.

Further, our perspective permits examination of national and industry heterogeneity. Strong GVC ties push the wages of Western European employees down (regardless of type of task) but have a positive effect on the earnings of American workers in the most demanding occupations. Our estimates also indicate that the impact of GVC ties on wages is not specific to manufacturing but extends to services as well; however, it mainly affects workers in high-wage industries. Nevertheless, the magnitude of these effects confirms that individual wages are determined primarily by the personal characteristics of the worker and the tasks typical of the occupation.

Direct comparison of our findings with the results of previous studies is not straightforward. There is not much research inquiring explicitly into the wage impact of foreign trade in value added. To be sure, our results are in line with the finding of Shen and Silva (2018: 496–500), namely the generally insignificant effect of value added trade on wages, but their result is conditional on how far upstream or downstream the industry is within the GVC. Another point of reference is analyses based, like ours, on the WIOD input-output data; however, to date these have adopted a strictly industry-level perspective and first-generation offshoring measures, as in Foster-McGregor et al. (2013), Parteka and Wolszczak-Derlacz (2015) or Wolszczak-Derlacz and Parteka (2018). In particular, the latter two studies conclude that the potential inverse correlation between production fragmentation and wages does emerge in the regression results and may involve certain categories of worker (the less skilled); but the magnitude of the effect, or its economic impact, is small. This accords well with the present paper's findings on micro-level wage data.

Some country-specific micro-level studies find a negative relationship between industry-level measures of international outsourcing and individual wages (Geishecker and Görg 2008 and Baumgarten et al. 2013 for Germany); others indicate only weak wage effects of international exposure (Ebenstein et al. 2014 on workers in the U.S.). Our analysis explicitly addresses national specificities. We have shown that although there is some variation between the effects in Europe and in the U.S., national labour market institutions do not play a significant role in shaping the response of wages to GVC ties. This concords with Geishecker et al. (2010), a micro-level study concluding that labour market institutions play only a minor role in helping to determine the wage effect of international outsourcing in three Western European countries. All these studies, however, have a different perspective, focused specifically on offshoring. This is why the present analysis of the way in which wages in different countries are affected by GVC ties represents new and valuable complementary evidence.

Clearly, important areas are left open for future research. Above all, further theoretical work is needed on the mechanisms behind the labour market effects of GVCs and the impact of foreign value added on factor prices. Further, as Feenstra (2017: 18) argues, the potential wage loss due to production fragmentation should be viewed in light of GVC-driven productivity gains affecting price levels. That is, even if some workers suffer downward wage pressure (but the effect, we find, is small), at the same time they gain thanks to lower final goods prices. Similarly, the net employment effects of value added trade also depend on productivity increases within GVCs (Los et al. 2015c). Estimating the efficiency gains from value added trade is beyond the scope of our paper and accordingly constitutes another interesting direction for future research.

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Appendix

Table 11 List of industries and their classification

Code	description	Manufacturing	Services
15 t16	Food, Beverages and Tobacco	x	0
17 t18	Textiles and Textile Products	x	0
19	Leather, Leather and Footwear	x	0
20	Wood and Products of Wood and Cork	x	0
21 t22	Pulp, Paper, Paper, Printing and Publishing,	x	0
23	Coke, Refined Petroleum and Nuclear Fuel	x	0
24	Chemicals and Chemical Products	x	0
25	Rubber and Plastics	x	0
26	Other Non-Metallic Mineral	x	0
27 t28	Basic Metals and Fabricated Metal	x	0
29	Machinery, Nec	x	0
30 t33	Electrical and Optical Equipment	x	0
34 t35	Transport Equipment	x	0
36 t37	Manufacturing, Nec; Recycling	x	0
50	Sale, maintenance and repair of motor vehicles and motorcycles; retail sale of fuel	0	x
51	Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles	0	x
52	Retail Trade, Except of Motor Vehicles and Motorcycles; Repair of Household Goods	0	x
60	Inland Transport	0	x
61	Water Transport	0	x
62	Air Transport	0	x
63	Other Supporting and Auxiliary Transport Activities; Activities of Travel Agencies	0	x
64	Post and Telecommunications	0	x
70	Real Estate Activities	0	x
71 t74	Renting of M&Eq and Other Business Activities	0	x
AtB	Agriculture, Hunting, Forestry and Fishing	0	0
C	Mining and Quarrying	0	0
E	Electricity, Gas and Water Supply	0	x
F	Construction	0	0
H	Hotels and Restaurants	0	x
J	Financial Intermediation	0	x
L	Public Admin and Defence; Compulsory Social Security	0	x
M	Education	0	x
N	Health and Social Work	0	x
O	Other Community, Social and Personal Services	0	x

Table 12 Summary statistics of the sample (overall and by country)

	All countries (10)	USA	Europe (E9)								
			Czech Republic (CZE)	Estonia (EST)	Finland (FIN)	Germany (DEU)	Greece (GRC)	Ireland (IRL)	Luxembourg (LUX)	Slovak Republic (SVK)	Spain (ESP)
Personal characteristics											
Age	42,82	43,44	42,12	42,95	44,00	44,92	42,38	42,48	41,38	42,68	42,01
Sex (Male = 1)	0,54	0,53	0,56	0,48	0,52	0,50	0,59	0,52	0,57	0,53	0,57
Married (Married = 1)	0,62	0,63	0,64	0,50	0,55	0,63	0,72	0,66	0,59	0,66	0,66
Live with partner	0,73	0,69	0,74	0,70	0,76	0,75	0,72	0,75	0,71	0,69	0,73
Possessing child/children	0,65	0,64	0,61	0,61	0,67	0,58	0,70	0,77	0,71	0,58	0,66
Immigrant	0,16	0,18	0,04	0,16	n.a.	0,14	0,08	0,21	0,57	0,01	0,07
Job characteristic											
Private sector	0,77	0,84	n.a.	0,74	0,71	0,73	0,79	0,71	0,88	n.a.	n.a.
Supervisor	0,24	n.a.	0,29	0,19	n.a.	n.a.	0,16	0,34	0,28	0,14	0,24
Services	0,71	0,80	0,60	0,64	0,72	0,70	0,73	0,78	0,78	0,66	0,73
Part time	0,13	0,14	0,04	0,07	0,09	0,28	0,06	0,26	0,19	0,03	0,12
Number of obs.*	114,890	70,321	6359	3768	5596	7238	1323	2419	4769	5443	7654

* n with non-missing information on hourly wage; the number of observations in the regressions can be lower than reported here due to missing values in some of the explanatory variables. n.a. – not available

Source: own compilation based on LIS data (wave 8)

Table 13 Classification of occupations according to tasks performed

code	occupation	occupation (10-category ISCO recode)	Type*
12	Corporate managers	[1]managers	*AbsServ*
13	Managers of small enterprises	[1]managers	*AbsServ*
21	Physical, mathematical and engineering professionals	[2]professionals	*AbsServ*
22	Life science and health professionals	[2]professionals	*AbsServ*
24	Other professionals	[2]professionals	*AbsServ*
31	Physical, mathematical and engineering associate professionals	[3]technicians and associate professionals	*AbsServ*
32	Life science and health associate professionals	[3]technicians and associate professionals	*AbsServ*
34	Other associate professionals	[3]technicians and associate professionals	*AbsServ*
41	Office clerks	[4]clerical support workers	*Serv*
42	Customer service clerks	[4]clerical support workers	*Serv*
51	Personal and protective service workers	[5]service and sales workers	*Serv*
52	Models, salespersons and demonstrators	[5]service and sales workers	*Serv*
71	Extraction and building trades workers	[7]craft and related trades workers	*Rout*
72	Metal, machinery and related trade work	[7]craft and related trades workers	*Rout*
73	Precision, handicraft, craft printing and related trade workers	[7]craft and related trades workers	*Rout*
74	Other craft and related trade workers	[7]craft and related trades workers	*Rout*
81	Stationary plant and related operators	[8]plant and machine operators, and assemblers	*Rout*
82	Machine operators and assemblers	[8]plant and machine operators, and assemblers	*Rout*
83	Drivers and mobile plant operators	[8]plant and machine operators, and assemblers	*Rout*
91	Sales and service elementary occupations	[9]elementary occupations	*Rout*
93	Laborers in mining, construction, manufacturing and transport	[9]elementary occupations	*Rout*

AbsServ low in routine, high in abstractness and service task importance, *Serv* low in routine and abstractness, high in service task importance, *Rout* highly routine, low in abstractness and service task importance

Source: own elaboration partly based on Goos et al. (2014)

Table 14 IV estimation results of eq. 2 and eq. 3 for *gross1* – corresponding to Column 1 in Tables 5 and 6

Workers from	*(1)*	*(2)*
age_i	0.031***	0.031***
	[0.003]	[0.003]
age_i^2	−0.000***	−0.000***
	[0.000]	[0.000]
sex_i	0.185***	0.185***
[=1 if male]	[0.008]	[0.008]

Table 14 (continued)

Workers from	*(1)*	*(2)*
$marital\ status_i$	0.000	0.000
[=1 if married]	[0.009]	[0.009]
$partner_i$	0.055***	0.056***
[=1 if living with a partner]	[0.009]	[0.009]
$children_i$	0.040***	0.040***
[=1 if living with children]	[0.006]	[0.006]
$part\text{-}time_i$	−0.045**	−0.045**
[=1 if working part-time]	[0.019]	[0.019]
$hieduc_i$	0.104***	0.096***
[=1 if having high education]	[0.014]	[0.016]
$mededuc_i$	0.269***	0.265***
[=1 if having medium education]	[0.017]	[0.019]
$AbsServ_i$	0.605***	0.606***
[=1 if if low in routine, high in abstractness & service task]	[0.025]	[0.024]
$Serv_i$	0.160***	0.164***
[=1 if low in routine & abstractness, high in service task]	[0.020]	[0.019]
$GVC_{jct\text{-}1}$	−0.139***	−0.177***
	[0.049]	[0.066]
$GVC_{jct\text{-}1} \times AbsServ_i$	0.006	
	[0.026]	
$GVC_{jct\text{-}1} \times Serv_i$	0.053	
	[0.037]	
$GVC_{jct\text{-}1} \times hieduc_i$		0.029
		[0.040]
$GVC_{jct\text{-}1} \times loweduc_i$		0.061
		[0.039]
Under-identification	0.000	0.000
Weak identification	7.366	7.618
N	113,932	113,932

Normalized weighted regression with cluster-robust standard errors; all specifications include sector and country fixed effects as well as country-industry panel. *, **, *** denote statistical significance at 1, 5, 10% respectively; default categories: low-educated workers and *Rout*. GVC_{jct} treated as an endogenous variable and instrumented on the basis of the gravity equation, as explained in the main text. 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)

Source: own calculations with data from WIOD

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Further Reading

World Input Output Database (WIOD) www.wiod.org
Luxembourg Income Study (LIS) Database, http://www.lisdatacenter.org (multiple countries; wave 8). Luxembourg: LIS, remote access is possible through LISSY.