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GLOBAL VALUE CHAINS AND WAGES: INTERNATIONAL EVIDENCE FROM LINKED WORKER-INDUSTRY DATA[1]

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Abstract

Using a rich dataset on over 110,000 workers from nine European countries and the USA we study the wage response to industry dependence on foreign value added. We estimate a Mincerian wage model augmented with an input-output interindustry linkages measure accounting for task heterogeneity across workers. Low and medium-educated workers and those performing routine tasks experience (little) wage decline due to major dependency of their industries on foreign inputs. Workers from former EU15 are more in danger of unfavourable wage effects than workers from new EU member states. American workers employed in service industries are more exposed than manufacturing workers.

JEL: F14, F16, J31

Keywords: wage, global value chains, foreign value added, interindustry linkages

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1.Introduction

Labour market response to global production sharing[2] has recently become one of the main research themes in the labour economics and international economics literature (see Acemoglu & Autor 2011 or Van Reenen 2011 for a review). Increasing cross-country industrial interdependence due to offshoring has even been named 'the next industrial revolution' (Blinder 2006), while the structure of today's geographically dispersed production and trade can be described as a 'Factory World' (Los et al. 2015a). Unsurprisingly, related labour research has focused on potential cross-border job complementarity (among others: Harrison et al. 2007; Harrison & McMillan 2011) and the effects of production fragmentation on earnings and wages (Baumgarten et al. 2013; Ebenstein et al. 2014; Hummels et al. 2014; Geishecker et al. 2010).

In this paper, we focus on the latter aspect: the influence of cross-border production fragmentation on domestic workers' wages. In particular, we relate wage determination mechanisms to the intensification of linkages between industries in different countries. Our main interest is in assessing whether (and how) the wages of individual workers are affected by an increasing dependency of the industry in which they work on foreign value added (FVA).[3] Los et al. (2015) document that in almost all product chains the share of value added outside the country of completion has increased since 1995. However, despite the proliferation of literature on global value chains (from now on GVC[4]; among others, see Baldwin et al. 2012; Johnson 2014; Amador & di Mauro 2015; Amador & Cabral 2016; Los et al. 2015b) to the best of our knowledge there is a research gap concerning the explicit assessment of the FVA-wages nexus, especially in a micro-level setting allowing for a broader cross-country and cross-industry perspective.

We investigate the micro-level dimension of wage determination (Mincer 1974), but, importantly, we go beyond country-specific studies of the wage effects of production fragmentation (such as: Geishecker et al. 2008; Baumgarten et al. 2013; Ebenstein et al. 2014; Hummels et al. 2014). For this purpose we build a unique dataset matching micro-level and industry-level data for several economies (ten countries including

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[2] There are several terms used to describe the phenomenon of moving some parts of production abroad and relying on foreign inputs. Global production sharing, offshoring and international production fragmentation are among the most popular ones.

[3] Formally, the FVA share is defined as "the part of the value of final output of an industry that is contributed by industries in other countries" (Amador & di Mauro 2015, p. 37).

[4] Formally, 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 & di Mauro 2015, p.14; adopted from the GVC Initiative at Duke University).

nine European economies and the USA). Moreover, following the recent task-focused approach to the analysis of labour markets (Baumgarten et al. 2013; Autor 2015; Becker et al. 2013; Becker & Muendler 2015) we go beyond categorizing workers on the basis of their educational attainment[5] and we explore worker heterogeneity in terms of their occupations and the tasks they perform.

To the best of our knowledge, this is the first attempt to quantify the labour market consequences of the increasing dependence of industries on FVA in a multi-country microeconomic setting. Existing studies on the wage response to global production sharing with large country samples (e.g. Polgár & Wörz 2010 on the EU25; Parteka & Wolszczak-Derlacz 2015 on the EU27; Wolszczak-Derlacz & Parteka 2016 on 40 countries) have the disadvantage of dealing 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-level analysis (limited data access and/or high cost of data; problems of cross-country comparability and time consistency; computational difficulties stemming from the size of micro datasets), there are few studies that avoid the problematic nature of aggregated data. The existing micro-level evidence (which we describe in Section 2) is primarily country-specific and limited to developed countries: the US (Ebenstein et al. 2014 and Autor et al. 2014); Denmark (Hummels et al. 2014); the UK (Geishecker & Görg 2013); Germany (Geishecker et al. 2008 and Baumgarten et al. 2013).

The structure of our paper is as follows: in section 2 we set our contribution in the context of the existing literature. In section 3 we present our unique linked worker-industry dataset and the crucial descriptive statistics on value added structure and wages in the sample analysed. In section 4 we describe our augmented micro-level models and present the estimation results. Dealing with such a rich dataset allows us to explore several dimensions of heterogeneity in the response of wages to increasing interindustry linkages within GVCs. Finally, section 5 concludes. Our results can be summarised as follows: some workers are more at risk of experiencing wage cuts as a result of the involvement of their industries in GVCs; this result concerns low and medium educated workers and those performing occupations which are either highly routine or low in routine and abstractness but high in service task importance. The estimates indicate some cross-country and cross-industry heterogeneity, e.g. workers from former EU-15 countries, workers

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

employed in high-wage industries in more developed countries or American workers employed in service industries are more at danger of experiencing wage cuts.

2.Related literature

2.1 Literature on interindustry linkages and global value chains

In terms of the measurement of cross border production sharing, our study builds upon the recent vibrant literature on global value chains which describes the complex structure of production systems nowadays (Los et al. 2015b) and the so-called 'trade in value added' (see Mattoo et al. 2013; Amador & di Mauro 2015 for a review). The GVC literature follows the first wave of research on interindustry linkages measured using input-output data (Cella 1984; Dietzenbacher 1992) and that on the global fragmentation of production and international outsourcing (Feenstra & Hanson 1996; Feenstra & Hanson 1999; Hijzen et al. 2005).

Building on the notion of vertical specialization (Hummels et al. 2001)[6] and the foreign content of a country's exports, efforts have been made to precisely measure the dependence of countries and industries on inputs produced abroad. Hummels et al. (2001) proposed a method to decompose a country's exports into domestic and foreign-value-added[7] shares based on the country's input-output table. Johnson & Noguera (2012) combined input-output and bilateral trade data to compute the value-added content of bilateral trade. However, these methods were based on the assumption that the intensity of use of imported inputs is the same in production for export as in production for domestic sale. This assumption is violated in the case of processing exports. Koopman et al. (2012) introduced a generalized formula to compute the share of domestic value added in a country's gross exports when processing trade is prevalent.

The computation of input-output tables for several economies within the WIOD[8] project (Dietzenbacher et al. 2013; Timmer et al. 2015) facilitated further empirical work on GVCs. Using WIOD data, Koopman et al. (2014) proposed a more detailed decomposition of gross exports into various components, integrating the previous measures of vertical specialization and value-added trade into a unified framework. In particular, they identified double-counted terms in official trade statistics. Nevertheless, sector-level applications were still missing. Wang, Wei and Zhu (subsequently referred to as WWZ; Wang

[6] Hummels et al. (2001) defined vertical specialization as "*the use of imported inputs in producing goods that are exported.*"
[7] In line with Koopman et al. (2012) we use the terms 'domestic value added' and 'domestic content' interchangeably. Similarly, the terms 'foreign value added' and 'foreign content' mean the same thing.
[8] World Input Output Database.

et al. 2013) developed accounting framework at the country level, proposed by Koopman et al. (2014), to one that decomposes gross trade flows at the sector, bilateral, or bilateral sector level. Importantly, the WWZ method can be used to measure the position of an industry in an international production chain that varies by country, taking into account both offshoring and domestic production sharing. We rely on the WWZ method in our empirical work when we measure cross-country interindustry linkages.

2.2 Empirical evidence on labour market response to cross-country interindustry links

To the best of our knowledge, there are no studies that explicitly match information on industry involvement in GVCs and wages.[9] However, the information on the foreign value added employed in a given industry can be treated as a proxy for its involvement in international production sharing (Mattoo et al. 2013).[10] The evolution of the literature on the consequences for domestic workers of moving some parts of production abroad reflects common political worries about declining domestic employment or wages as results of offshoring (Blinder 2006). These worries are not always supported by real data[11] or by workers' perceptions of the offshorability of their jobs[12] (Brown et al. 2013) but the topic has become 'hot'. Unsurprisingly, much of the attention has been put on outcomes visible in the US labour market, considering primarily the effects of offshoring on developing countries, for instance on Mexico (as addressed in Sethupathy 2013). Recent US-focused research seems to have been particularly concerned with the results of labour market exposure to rising import competition from China (Autor et al. 2013 call it "the China syndrome" – this is 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 been performed to assess the response of labour markets to offshoring in single advanced Western European countries (e.g. Michel & 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 the polarization observed in labour markets (that is, rising

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[9] There are some recent studies on the relationship between GVC status and productivity (among others, see (Baldwin & Yan 2014); (Hagemejer 2015).

[10] This is in line with the concept of trading tasks, which concerns the disintegration of the production process and the adding of value at disparate locations (Grossman & Rossi-Hansberg 2006).

[11] For instance, Mankiw & 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 & McMillan (2011) conclude that "*offshoring by U.S.-based multinationals is associated with a quantitatively small decline in manufacturing employment.*"

[12] 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 even a quarter of American workers (Blinder & Krueger 2013).

employment in the highest and lowest paid occupations, observed in the US (Autor & Dorn 2013b) and in Europe (Goos et al. 2009; Goos et al. 2014), which can, at least partially, be attributed to offshoring practices.

The effects of global production sharing on wages are far from obvious. Typically, low-skilled workers have been perceived to be more exposed to wage drops or job losses due to offshoring, mainly resulting from declining demand for unskilled labour in developed countries (Feenstra & Hanson 1996; Feenstra & Hanson 1999; Geishecker et al. 2008; Hijzen 2007). However, the recent literature underlines the importance of a proper distinction between skills and tasks (Autor 2015). The insights from trade-in-tasks models of international trade (Grossman & Rossi-Hansberg 2008; Baldwin & Robert-Nicoud 2014) suggesting that the outcome of offshoring practices depends on the nature of the tasks performed are supported by empirical findings. For instance, Hummels et al. (2014) use matched Danish worker-firm data and find that offshoring tends to increase high-skilled wages and decrease low-skilled wages but the wage effects of offshoring vary across tasks (routine tasks suffer the most). Indeed, this is confirmed in a study on German workers by Baumgarten et al. (2013). They find that a higher degree of interactivity and, in particular, non-routine content effectively protects workers against the negative wage impact of relocation of production abroad.

There are few micro-level studies dealing with the consequences of cross-border production sharing on the labour markets of 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: they match micro-level data on wages with industry-specific measures of participation in global production fragmentation. Geishecker et al. (2010) find that low-skilled workers can suffer wage drops as a result of outsourcing but despite differences in labour market institutions among the countries analysed, the effects in the three countries are in fact quite similar and fairly small. A study by Goos et al. (2014) is the closest to ours in terms of country coverage (but not the specific topic). They link data from multiple sources (ELFS, ECHP, EU-SILK, LFS) for 16 European countries and the period 1993-2010 to describe the process of job polarization. They argue that technology can replace human labour in routine tasks (they call this "routine biased technological change"), find some support for the hypothesis that it is mainly routine jobs that are offshored, and show that institutional differences between countries and changes in the relative demand for labour due to changes in income or income inequality cannot explain much of the variation in employment.

However, their study does not refer explicitly to the relationship between wages and the value added structure of global production, which is our main research topic. To the best of our knowledge, there is no study that addresses this issue by matching micro-level and industry-level data for several European countries and the USA.

3. Data and descriptive statistics

3.1 The data

For the purpose of our study, we match industry-level data from the WIOD[13] with individual (personal) data from the Luxembourg Income Study (LIS) database. Given the restricted time span of the industrial statistics we need to calculate a measure of reliance on foreign value added (the WIOD includes data up to 2011), we use LIS wave 8, corresponding to the reference year 2010. A crucial issue related to building a linked worker-industry dataset is the matching between the information on the industry of employment of individuals present in the LIS database and the industries present in the WIOD data. We compute correspondence tables on a country-by-country basis,[14] and arrive at a set of 34 industries (both manufacturing and services; the list of industries is presented in Table 1A in the Appendix). In our sample we only consider workers aged between 24 and 65 and exclude military workers.[15] Table 2A in the Appendix provides summary statistics of the main characteristics of the workers included in our sample (overall and by country).

As a basic dependent variable in our wage regression we use the gross basic hourly wage for the main job (*gross1*).[16] This data is available for 10 countries (LIS wave 8): 9 European economies (CZE, DEU, ESP,

[13] WIOD's industry-level labour data, has so far been employed to analyse: 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 & Wolszczak-Derlacz 2015) and wage effects of offshoring to low-wage countries (Wolszczak-Derlacz & Parteka 2016). In particular, these studies document: a shrinking demand for medium-skill workers (Foster-McGregor et al. 2013), enhanced European specialisation towards jobs in services and more highly-skilled jobs (Timmer et al. 2013), a very slow conditional wage equalization process across the EU countries (Parteka & Wolszczak-Derlacz 2015), and a moderate negative impact of offshoring to low-wage countries on the wages of domestic low- and medium-skilled workers (Wolszczak-Derlacz & Parteka 2016).

[14] This exercise had to be performed separately for every country, since the variable ind1_c (from LIS) was not standardized because the countries differ in their national classification categories. 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 USA, and the WIOD classification has 35 categories based on the CPA and NACE rev. 1 (ISIC rev 2) classifications. Correspondence tables are obtainable on request.

[15] We do not include in our analysis industry P: Private Households with Employed Persons (in which all values for FVA are either missing or zero). As a robustness check we further limit the industry and/or worker coverage, e.g. we exclude agricultural, forestry and fishery workers, employees from industry 23 (Coke, refined petroleum and nuclear fuel) and workers possessing more than one job.

[16] Overtime payments, bonuses and gratuities, family allowances and other social security payments made by employers, as well as ex gratia payments in kind supplementary to normal wage rates, are all excluded from the calculation of the basic gross hourly wage.

EST , FIN, GRC, IRL, LUX and SVK,) and the USA. As an alternative, to check the robustness of our results we construct crude proxies for hourly earnings based on information on paid employment income (*pile*)[17] and paid monetary employment income *(pmile)* divided by the number of hours worked.[18] In order to eliminate extreme observations and potential outliers from the sample, for all the alternative hourly wage measures we perform a correction at the top and at the bottom of the distribution. At the bottom, we trim the distribution so the observations with negative and zero hourly wages are set to missing; at the top, wages greater than ten times the national median are set to ten times the national median.[19] For those countries for which the nominal variables were originally expressed in national currencies, we use the bilateral exchange rates from the Penn World Table (PWT 8.1) and put all wages into dollars. As a robustness check, we use wages corrected for PPP (also from PWT 8.1).

In Table 1, we present the average values of the hourly wages in all ten countries in our sample. A comparison between the benchmark hourly wage data (*gross1*) and its proxies (*hw1, hw2*) proves that they can serve to perform a reasonable sensitivity analysis. However, wages clearly differ greatly across countries. In our worker sample, the average wage paid in US manufacturing (in 2010) amounts to 24.8 US$. In Europe, it ranges from only 5.4 US$ in the Slovak Republic to 32.9 US$ in Luxembourg. Similar huge cross-country wage differentials are typical for services too. However, within these two broad categories of activity there is also considerable cross-industry variability. This is illustrated in Figure 1. In a first step we calculate the average wages paid in the ten countries in every sector (using the information on the hourly wage of individuals employed in the sector) and then we plot boxplots showing the cross-country wage variation within each industry. Looking at the median (the lines inside each box) in manufacturing, the highest wages are paid in industry 24 (chemicals) and the lowest in industry 19 (leather and footwear). The lowest wages in manufacturing are typically paid in Central and East European countries: Estonia (industries 15t16, 17t18, 19, 24 and 36t37), the Czech Republic (industries 20 and 25) and in the Slovak Republic (industries 21t22, 23, 26, 27t28, 29, 30t33 and 34t35). The highest wages are found in Luxembourg for all sectors except 29, 30t33 and 36t37 (where Finland was the leader). In services, the median wage is the lowest in hotels and

[17] Monetary payments and the value of non-monetary goods and services received from regular and irregular dependent employment.
[18] We fill in missing values of hours worked (*hours* variable) using the Gaussian normal regression imputation method.
[19] All these steps were performed during an onsite visit to the LIS premises. We trim the distribution at the top because our interest is not so much in top income shares (Burkhauser et al. 2012; Atkinson et al. 2011) but rather in possible changes in wage determination due to production fragmentation which affect ‘normal’ workers. Alternatively, we considered excluding top percentile of wages – such a change does not alter the final conclusions.

restaurants and the highest in financial intermediation. However, here too wages differ considerably across countries: the lowest wages are again paid in the Slovak Republic and Estonia while the highest are registered for Luxembourg, Finland, Germany and Ireland. The USA appears to pay the highest wage among the 10 countries analysed in just one industry: 70 (real estate activities).

[Table 1 about here]

[Figure 1 about here]

In our dataset, workers are classified according to education level (three groups based on educational attainment: low, medium and high[20]) and according to the type of tasks mainly used in their occupation. We use original country-specific information on the occupation of each worker present in the LIS database (2-digit ISCO code) and then attribute it to one of three categories: *AbsServ* (low in routine, high in abstractness and service task importance), *Serv* (low in routine and abstractness, high in service task importance) and *Rout* (highly routine, low in abstractness and service task importance) – see Table 3A in the Appendix.[21] As demonstrated in Table 2, wages differ across educational groups (unsurprisingly, highly educated workers earn the most, while the differences between those with medium and low education are not so pronounced). In terms of tasks, those performing occupations low in routine but high in abstractness and service task importance earn the most (the *AbsServ* category, which covers such workers as managers, professionals, technicians and associate professionals). In manufacturing industries, these workers earn approximately twice more than workers performing mainly routine or simple service tasks.

[Table 2 about here]

3.2 Trends in GVC participation and foreign value added

In order to measure the dependence of domestic industries on foreign value added, we use the outcomes of Wang et al. (2013)'s decomposition performed on WIOD's data. We first decompose[22] gross exports into

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[20] According to the highest completed level of education. High corresponds to tertiary education completed (ISCED levels 5 or 6), medium to secondary education completed (ISCED levels 3 or 4), and low to less than secondary education completed (never attended, no completed education or education completed at ISCED levels 0, 1 or 2).
[21] We draw on Goos et al. (2014), who use the approach of Autor & Dorn (2013a) and Autor et al. (2015) to compute Routine Task Intensity index for occupations at the ISCO 2-digit 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 3A. We are constrained to use relatively aggregated data on occupations because most of the European countries reporting data to LIS rely on 2-digit ISCO codes. Very few countries provide more detailed information (e.g. in the LIS database workers in the US are classified into 526 occupations and workers in Germany into 288 occupations).
[22] We use the *decompr* package in R (Quast & Kummritz 2015).

four main components: domestic added value absorbed abroad (*DVA*),[23] added value first exported but eventually returned home (*RDV*), foreign value added (*FVA*) and pure double-counted terms (*PDC*).[24] *FVA,* reflecting vertical specialization (Hummels et al. 2001), can be treated as a proxy for involvement in global production sharing and offshoring.[25] Table 3 shows the effects of the basic WWZ decomposition and the dependence of industries on foreign value added (we use the information on *FVA* coming from all over the world, independently of the country of origin). The USA, where *FVA* in 2010 accounted for 11.9% of manufacturing exports and 3.8% of service exports, is less dependent on inputs produced offshore than the European countries (26.9% and 12% respectively). Additionally, manufacturing industries are in general more involved in global interindustry linkages than service activities. It should also be noted that economies which are typically perceived to be hosts of offshoring activity, such as countries in Central and Eastern Europe (the Czech Republic, the Slovak Republic and Estonia) also rely heavily on foreign inputs.

For the purpose of econometric analysis we multiply the export share of *FVA* (resulting from the WWZ decomposition) by the industry value of gross exports (from WIOD) to obtain the monetary value of *FVA* (expressed in US$) employed in each industry. In Table 3 we also report average annual growth rate of such monetary value of *FVA*. Generally, in all the countries in our sample we observe a rise in the value of foreign inputs directed to domestic industries– taking into account all industries in Europe it was rising at a pace of 7.2% per year, 5.5% in the USA. It indicates a deepening of global production sharing.

[Table 3 about here]

4.The impact of *FVA* dependence on wages – econometric analysis

4.1 Augmented micro-level wage model(s)

We aim to test empirically whether involvement in global production sharing and a major dependence of industries on foreign production exerts any impact on the wages of domestic workers employed in the industry. To do so, we estimate an augmented micro-level wage model using our unique dataset matching individual and industry-specific data for ten countries. Our empirical strategy is based on

[23] Note that domestic value added in a country's exports and value-added exports are different concepts. "*This concept [domestic value-added in a country's exports] only looks 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)

[24] For a detailed derivation of the decomposition see the Appendix of Wang et al. (2013).

[25] Before Koopman et al. (2014) and Wang et al. (2013)'s decomposition became popular, simplified offshoring measures based on input-output tables from the WIOD were used. For instance, Parteka & Wolszczak-Derlacz (2015) and Foster-McGregor et al. (2013) use the ratio of imported intermediates to the domestic sector's value added.

linking microdata on wages with industry-level measures of cross-country interindustry linkages. The strategy is thus similar to Baumgarten et al. (2013) and Geishecker et al. (2010) in the sense that as these authors we merge micro level data on labour market outcomes with industry level data on production sharing.

We consider three alternative specifications of the model. The first one,

$$ln\text{wage}_{ijct} = \alpha + \beta X_{it} + \sum_{e-1} \gamma_e Educ_{eit} + \delta Ind_{jct} + \theta lnFVA_{jct-1} + D_j + D_c + D_{jc} + \varepsilon_{ijct} \text{ , (1)}$$

relates the log of the gross hourly wage (ln*wage,* where *wage*={*gross1, hw1, hw2*}) of worker *i* employed in industry *j* in country *c* at time *t* to: a basic set of individual characteristics typically present in the Mincer equation – here denoted as *X* (*sex*,[26] *age*, *age*^{2}, marital and family status,[27] part-time employment[28]); information on the educational level of the worker (high, medium or low) – denoted as *Educ*={*high*, *medium*, *low*}, where low education is the omitted category in the model; the characteristics of the industry of employment (*Ind*) – we consider the log of its value added (ln*VA)* proxying for industry size; and finally information on the foreign value added in the industry (ln*FVA*).[29] *FVA* is expressed in monetary terms (in US$) but by including in our specification the size of the industry we eliminate the problem of greater foreign value added due to greater production, especially in big countries. In eq. (1) parameter *θ* represents the elasticity of hourly wages with respect to cross-country interindustry linkages. Following Ebenstein et al. (2014), *FVA* enters the model as a lag in order to allow for the time needed for wage adjustment to materialize. Additionally, D_j represents industry dummy variables, allowing for all the remaining industry-specific characteristics or wage regulations, and D_c is the country dummy (capturing all country-specific labour market conditions and wage-setting mechanisms).[30] Finally, in order to control for any other unobserved heterogeneity, we include a two-dimensional industry-country panel identification: D_{jc}.

The second specification,

$$lnwage_{ijct} = \alpha + \beta X_{it} + \sum_{e-1} \gamma_e Educ_{eit} + \delta Ind_{jct} + \sum_n \theta_n \, Task_{nit} lnFVA_{jct-1} + D_j + D_c + D_{jc} + \varepsilon_{ijct} \text{ , (2)}$$

[26] *sex*=1 if male.

[27] 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.

[28] As a robustness check, we add more information about work characteristics (possessing one or more jobs, size and company ownership, work experience, supervising other workers). However, these additional variables are not available for all ten countries.

[29] We use *FVA* expressed as percentage of gross exports and data on industry-level exports from the WIOD to calculate the industry-specific value of *FVA* used in our specifications. It is not expressed as a share of industry output because *VA* enters the models as a separate explanatory variable.

[30] In the robustness section we will add more information about the characteristics of labour market institutions which vary across countries.

allows us to take into account the heterogeneity of wage responses to *FVA* according to the type of tasks performed by single workers: variable *Task* $=\{AbsServ, Serv, Rout\}$. The coefficient associated with the interaction term θ_n represents the elasticity of hourly wage of workers belonging to a given (*n*) task category with respect to the reliance on *FVA* typical for their industry of employment.

The third specification,

$$lnwage_{ijct} = \alpha + \beta X_{it} + \sum_{n-1} \gamma Task_{ni} + \delta Ind_{jct} + \sum_e \theta_e \, Educ_{eit} lnFVA_{jct-1} + D_j + D_c + D_{jc} + \varepsilon_{ijct} \,, \quad (3)$$

focuses on the heterogeneity of wage responses to *FVA* according to the workers' educational group (*Educ*). Here, the omitted category for the task dummies is the routine one. Hence, comparison of the estimation results of models (2) and (3) will allow us to check which workers are affected the most by global interindustry linkages: the common assumption would be to expect the low and/or medium educated and those performing routine tasks to be more at risk than the highly educated and/or those performing non-routine tasks.

Our estimation strategy is to use weighted regressions[31] with cluster-robust standard errors, where the clusters refer to country-industry pairs.

4.2 Basic estimation results

In Table 4 we report the estimation results for basic specification (1), where the Mincerian model is only augmented with the log of industry size and the dependence of the industry on *FVA*. In separate columns we report the estimates obtained using alternative wage measures as dependent variable – first the preferred one (*gross1*) and then those based on imputed earnings data (*hw1*, *hw2*). All the variables referring to personal characteristics have the expected sign: older, male, better educated workers living with a partner and/or children and not working part time earn more. In this basic specification our main variable of interest, ln*FVA*, does not turn out to affect wages in a statistically significant way.

[Table 4 about here]

Does this mean that dependence of industries on foreign inputs does not affect wages in any way? In order to answer this question, we have to take into account the type of tasks workers perform. Table 5

[31] 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 about the rules, practices and definitions applied during the harmonization process to ensure consistency over the LIS datasets together with sample-selection and weighting procedures, see: LIS guidelines at: http://www.lisdatacenter.org/wp-content/uploads/our-lis-documentation-harmonisation-guidelines.pdf). Furthermore, the individual weights are normalized to 10,000 by country. As a result, in our multi-country analysis workers from each country are intended to have the same weight and the results are not driven by countries with large numbers of observations.

reports the results referring to eq. 2. The coefficients associated with the interaction terms (*Task** ln*FVA*) indicate that the wages of workers employed in occupations which are either high in service task importance (but low in routine and abstractness) or highly routine (but low in abstractness and service task importance) are negatively affected by a major dependence of their industries on inputs coming from abroad. Occupations low in routine but high in abstractness service task importance do not experience a wage loss due to major use of *FVA*. Note that this result holds after having accounted for the education level of workers and their other personal characteristics.

[Table 5 about here]

When we directly link reliance on foreign inputs with the educational level of workers (estimation results for model 3 – reported in Table 6), it is evident that the negative effect of *FVA* on wages only concerns workers with low or medium education. Highly educated workers (with university education) are not affected, while those performing demanding non-routine tasks (*AbsServ* category) can even benefit.

[Table 6 about here]

However, we note that the magnitude of the coefficients associated with the *FVA* variable is small (the point estimates never exceed 0.05 in absolute terms). A rise in an industry's use of *FVA* of 1% is associated with a drop in the hourly wage of less than 0.05%. For instance, assuming gross hourly wage of approx. 18 US$ (mean value in our country sample, in manufacturing, see Table 1) and yearly time of work of 1820 hours (35 hours per week) this would translate into 16.3 US$ gross earnings drop per year due 1% increase in global production sharing (18x1820x0.05/100). Between 1995 and 2010 the value of FVA employed in manufacturing was rising at a pace of 4.9% per year (see Table 3). Hence, annual wage drop due to FVA is equal to approx. 80 US$ (16.3x4,9). In services, it would be higher and equal to approx. 153 US$ (FVA rose by 9.4% per year). Still, the impact of an industry's intensive use of foreign inputs on individual wages might appear to be negative for some groups of workers (less educated, performing routine tasks) but is rather small. Individual wages are determined primarily by the personal characteristics of the worker and the type of performed tasks.

4.3 Estimation results – accounting for cross-country heterogeneity

Our sample is composed of 10 different countries so we check whether the results hold for country subgroups. We consider eq. 2 (Table 7) and eq.3 (Table 8)[32] crucial, and split the sample into: only European

[32] The results reported here refer to our preferred measure of wages: *gross1*. The results obtained with the other two

countries (E9), EU new member states (the Czech Republic, Estonia, the Slovak Republic), EU old member states (Germany, Spain, Finland, Greece, Ireland and Luxembourg) and, for comparison, we also report the results only for the US. As Table 7 reports, a major reliance of industries on foreign inputs negatively affects the wages of workers in Europe performing service-oriented and routine tasks (the estimated coefficients associated with *Serv*×ln*FVA* and *Rout*×ln*FVA* are negative and statistically significant, but very small in magnitude). This effect is typical for old EU member states (*OMS*), while in new member states (*NMS*) some workers – those performing occupations low in routine but high in abstractness and service task importance – appear to benefit from a major involvement of their industries in global value chains.

As shown in Table 8, workers with low and medium education from Europe (old member states) and from the USA experience small downward pressure on wages if their industry relies more on foreign inputs.

[Table 7 about here]

[Table 8 about here]

4.4 Estimation results – accounting for cross-industry heterogeneity

So far, we have considered 34 industries. In Table 9 and Table 10 we report the results of estimations (eq. 2 and eq. 3 respectively) where the sample is split into workers employed in manufacturing and in services. Services are additionally divided into market and non-market services based on the classification used in Inklaar & Timmer (2008) (see Table 1A).

As shown in Table 9, the negative impact of *FVA* on individual wages concerns workers performing simple occupations high in service task importance (*Serv* category) or highly routine (*Rout* category) and in service sectors. This effect is stronger in non-market services. For market services, in addition to the negative pressure on the wages of workers in the *Serv* and *Rout* task categories, workers performing demanding tasks (*AbsServ* category) benefit from a major dependence of their industries on foreign inputs. This latter effect is also present in manufacturing (as shown by a positive and statistically significant interaction between *AbsServ and FVA).* In the case of manufacturing, the effect on other categories of occupation is not significant.

When it comes to the traditional division of workers according to their education (Table 10), *FVA* is negatively correlated with the wages of low educated workers (independently of the type of industry) and medium-educated workers employed in non-market services, while the impact on highly educated workers

measures of wages (*hw1* and *hw2*) are obtainable upon request.

employed in market services is positive. Note, however, that as previously stated, the elasticities are small in magnitude. For example, a rise in *FVA* of 1% is associated with a drop in the wages of workers with less than secondary education of 0.02 to 0.05% (depending on the industry they are employed in).

[Table 9 about here]

[Table 10 about here]

Another interesting question is whether the response of individual wages to the involvement of industries in global value chains depends on the type of industry in terms of its overall wage level. In other words, are workers employed in industries already paying low wages likely to suffer even more as a result of intensive use of foreign inputs? In order to check this, we use the precise classification of low-wage countries at the industry level developed by Wolszczak-Derlacz & Parteka (2016).[33] We rely on their classification 4, in which industry i in country c is classified as low wage (LW) if the wage level in this industry is below a threshold set at 50% of the average wage paid globally in the industry.

Table 11 and Table 12 report the results of eq.2 and eq.3 where the sample is split into workers employed in low-wage (LW) and high-wage (HW) industries. The estimates of the coefficients associated with the interaction terms shown in Table 11 suggest that the negative pressure on wages concerns workers performing non-abstract tasks (*Serv* and *Rout*) and employed in industries typically paying more. Upward pressure is typical for the wages of workers performing demanding tasks and employed in low-wage industries. This is in line with a hypothesis of wage convergence. However, as Parteka & Wolszczak-Derlacz (2015) find, the impact of cross-border production sharing on wage convergence is low – this is also visible in the magnitude of the estimated coefficients in our model. Similarly, Table 12 shows that in HW industries poorly and medium-educated employees are at risk of a wage drop from international production sharing (for LW industries the interaction term between *loweduc*/*mededuc* and *FVA* is not statistically significant). The opposite is true for the highly educated: in the case of LW industries they seem to benefit from an increase in wages, while the effect is not significant in HW industries.

[Table 11 about here]

[Table 12 about here]

[33] 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

4.5 Robustness checks

[The results relating to this section are reported in at the end of the paper – additional material]

We perform several sensitivity checks to prove the robustness of our results. First of all, as already shown, the results remain stable – with respect to the benchmark ones obtained with the directly measured gross hourly wage (*gross1* variable) – when the dependent variable is measured in terms of income per hour (variables *hw1* and *hw2*).

Second, we investigate a potential endogeneity problem in our model. This is connected with the reverse causality between the use of foreign inputs and domestic wages (*FVA* may affect wages but at the same time the decision to rely on foreign value added can be determined by the level of wages paid at home). To address this issue in our baseline specification we include the lagged values of *FVA*, but alternatively – in case it does not fully solve the endogeneity concern – we employ instrumental variable techniques in which *FVA* is predicted on the basis of a gravity equation.[34] We test the endogeneity of *FVA* and, as reported in Table 4A, using the gravity instruments we are not able to reject the null hypothesis (of exogeneity). It seems that in the case of a model based on individual wages, the endogeneity bias is not a problem (individual wages do not affect industry aggregates such as *FVA*). Still, in Table 4A for the purpose of illustration we report the IV estimates of eq. 2 and eq. 3 (corresponding to Table 5 and Table 6). The instrument validity is confirmed by under-identification and weak identification tests (Staiger & Stock 1997) and the IV specification results are very similar to the benchmark ones (reported in the main text).

Although we believe that the set of country, industry and country-industry fixed effects should control for any unobserved heterogeneity, we augment our models with additional variables which describe labour market conditions. We use information on wage setting mechanism coordination (from 1 – none – to 5 – centralised), union density,[35] and the type of national minimum wage regulations (0 – non statutory, 1 – some sectors, 2 – national level).[36] None of these variables are statistically significant and adding them

[34] Foreign value added exports are predicted from a gravity model for bilateral trade flows between a given reporter country and its 39 partners (bilateral *FVA* come from Wang et al. (2013)'s decomposition performed with WIOD data. The model is run separately for all the industries. The regressors are taken from the CEPII database and include: the reporter's and partner's value added for a given industry, distance between countries, dummies for a common border, common language, common currency, former colonial relationship and membership of a common regional trade agreement. The predicted *FVA* are estimated using the Poisson pseudo maximum likelihood method – PPML (Silva & Tenreyro 2006), and are summed across all the partner countries. A similar strategy is employed by Parteka & Wolszczak-Derlacz (2015).

[35] No data for Greece and the USA.

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

does not change our baseline results: a weak and negative association between industry *FVA* dependence and the wages of poorly and medium-educated workers and those performing non-abstract tasks.

Next, we add more information about job characteristics to our baseline specification, such as possessing more than one job, the size and ownership of the company, and supervising other workers. We did not include them in our baseline specifications since they are not available for all ten of the countries. Although these job characteristics are all statistically significant and have the expected sign (e.g. those working in a small-size company have lower wages and employees who supervise other workers earn more), they alter neither the magnitude nor the statistical significance of the crucial *FVA* interaction terms. The results remain stable.

Finally, we investigate industry heterogeneity more deeply. We run the regressions eliminating industries one by one, checking whether the results are driven by any specific industry. In this exercise we also investigate the inclusion in our sample of some questionable industries, e.g. Coke, refined petroleum and nuclear fuel. The domestic value added of this industry depends heavily on the internal availability of natural resources and consequently foreign value added reflects a purchase of inputs in the form of natural resources rather than production displacement. The estimations are conducted for the group of all industries (with one industry eliminated each time) as well as their subgroups (manufacturing, services, market services and non-market services) and are analogous to the specification reported in Tables 9 and 10. The coefficients of the interaction terms between the task classification and *FVA* and between the education level and *FVA* are not significantly altered by this exercise: the mean values of the interaction coefficients overlap with the coefficient from the baseline pooled regression. This indicates that the estimates obtained are not sensitive to the exclusion of any specific industry.

5.Conclusions

The main aim of this paper has been to contribute to the empirical literature on the effects of global production sharing and global value chains on wages. In particular, we were interested in assessing whether (and how) the wages of individual workers from various countries are affected by an increasing dependency of their industry of employment on foreign value added. We have thus contributed to the literature showing the effects of production sharing on workers performed from single-country perspective.

For this purpose, we have built a unique dataset matching micro-level and industry-level data for workers from several economies (ten countries including nine European economies, at different stages of economic development, and the USA) which allows us to address cross-country and cross-industry differences in the response of individual wages to production sharing. We have employed recently elaborated precise ways of measuring country and industry positions in global value chains and reliance on foreign inputs. Moreover, apart from the standard division of workers into skill categories based on education, we have accounted for their heterogeneity in terms of the tasks they perform.

We have used a Mincerian wage model augmented by measures of cross-country interindustry linkages (conditional on a large set of individual controls and industry and country fixed effects). The results suggest that low and medium-educated workers and those employed in highly routine occupations and/or occupations low in routine and abstractness but high in service task importance can be at risk of experiencing wage cuts. However, wage drops experienced by workers as a result of a major dependence of their industry on foreign inputs are not very high in magnitude (e.g. in manufacturing approx. 80 US$ annually).

Country and industry heterogeneity may also play a role. For example, in Europe workers from the old member states (former EU15) are more in danger of unfavourable wage effects than workers from new EU member states. In the US, highly educated workers might even expect positive changes to their wages due to international production sharing, but workers employed in service industries are more at risk than those employed in manufacturing ones, as well as those in high-wage industries (in relation to low-wage industries). However, taking into account cross-country and cross-industry heterogeneity does not change our general conclusion. Wage effects of production sharing concern mainly workers who are less educated and/or perform less demanding tasks but individual wages are determined primarily by the personal characteristics of the worker and the role played by cross-country industry links within a global value chain is not very large.

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Data:

Luxembourg Income Study (LIS) Database, http://www.lisdatacenter.org (multiple countries; wave 8). Luxembourg: LIS
World Input Output Database www.wiod.org

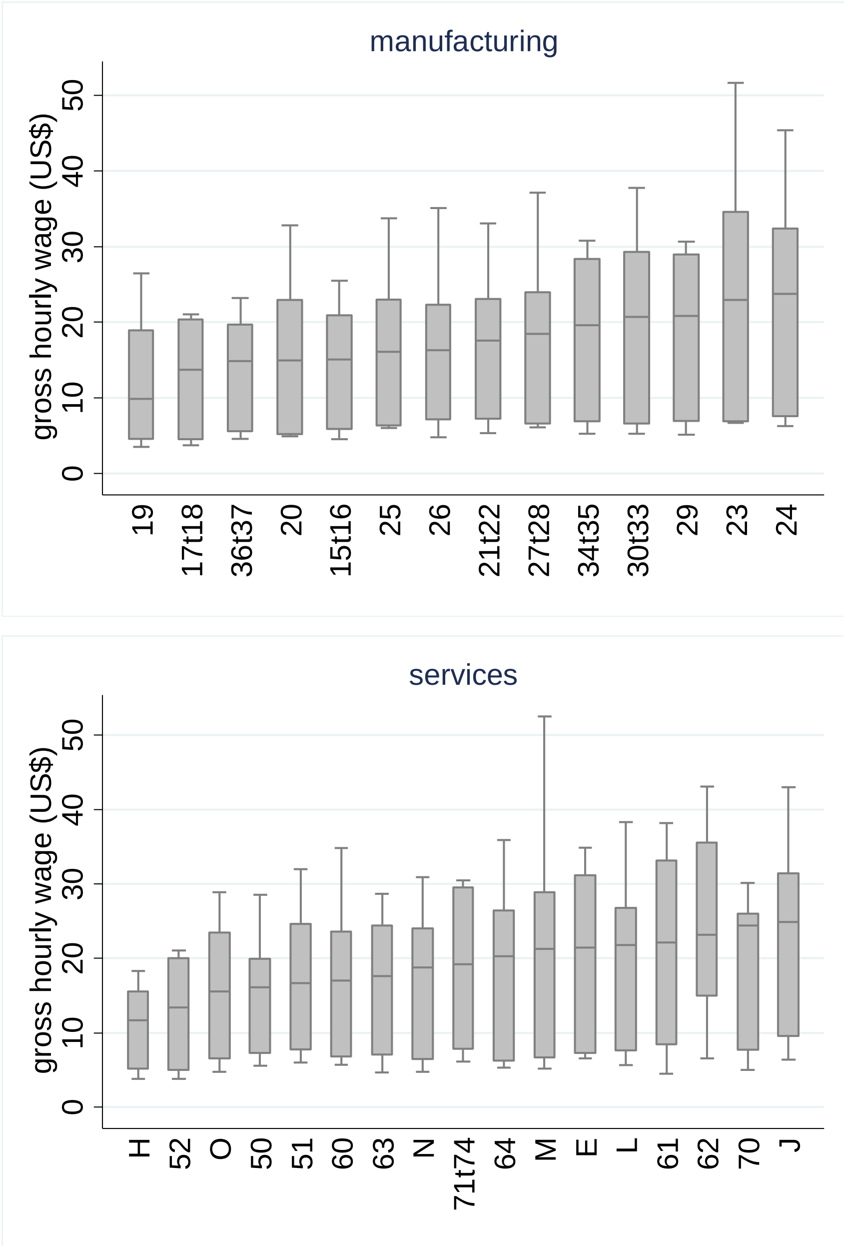
Tables and Figures

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)	16.9	18.0	17.8	17.2	17.9	17.7
All countries (10)	17.7	18.7	18.6	17.9	18.6	18.4

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

Figure 1. Comparison of hourly wages* across industries: variation among countries



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

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: 10 countries (listed in Table 1), t=2010.
Source: own compilation based on LIS data (wave 8)

Table 2. Comparison of hourly wages* (in US$) across occupations (tasks) and educational groups

	manufacturing			services		
task	all countries	E9	USA	all countries	E9	USA
AbsServ	30.0	24.2	35.1	27.1	22.9	29.1
Rout	14.6	11.7	18.0	17.1	13.3	19.3
Serv	14.2	12.4	16.6	14.6	13.3	15.6
	manufacturing			services		
education	all countries	E9	USA	all countries	E9	USA
high	31.8	27.9	34.0	27.9	24.3	29.4
medium	15.3	12.3	19.4	16.2	14.1	17.6
low	13.4	13.3	13.5	13.9	14.8	12.8

Note: *gross1 – gross hourly wage (variable directly obtainable from LIS). Average values across workers within industries. Sample: 10 countries (listed in Table 1), t=2010
Source: own compilation based on LIS data (wave 8)

Table 3. Dependence of industries on foreign value added - FVA (by country)

	FVA in 2010 [%]*			annual growth rate 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)	15.5	26.9	12.0	7.2	5.0	9.4
All countries (10)	14.5	25.4	11.2	7.1	4.9	9.1

Notes: * 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 8.0
Source: own elaboration based on WWZ methodology and WIOD data

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

	Dep: var: ln$wage_{ijct}$ (log of gross hourly wage)		
	gross1	*hw1*	*hw2*
age_i	0.033*** [0.003]	0.036*** [0.003]	0.036*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.189*** [0.008]	0.199*** [0.008]	0.195*** [0.008]
marital status$_i$ [=1 if married]	0.001 [0.010]	0.000 [0.011]	-0.002 [0.011]
$partner_i$ [=1 if living with a partner]	0.067*** [0.010]	0.074*** [0.010]	0.075*** [0.010]
$children_i$ [=1 if living with children]	0.043*** [0.007]	0.045*** [0.007]	0.045*** [0.007]
part-time$_i$ [=1 if working part-time]	-0.089*** [0.021]	-0.061*** [0.021]	-0.062*** [0.021]
lnVA_{jct} [value added – industry size]	0.041*** [0.012]	0.046*** [0.012]	0.045*** [0.012]
$mededuc_i$ [=1 if having medium education]	0.181*** [0.016]	0.169*** [0.016]	0.167*** [0.016]
$hieduc_i$ [=1 if having high education]	0.528*** [0.022]	0.506*** [0.022]	0.501*** [0.022]
lnFVA_{jct-1}	-0.012 [0.008]	-0.011 [0.007]	-0.012 [0.007]
R^2	0.728	0.668	0.676
N	113972	120786	120764

Notes: 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. Sample: workers from 10 countries, t=2010.

Source: own elaboration with data from LIS and WIOD

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

	dep. var: $\ln wage_{ijct}$ (log of gross hourly wage)		
	gross1	*hw1*	*hw2*
age_i	0.032*** [0.003]	0.035*** [0.003]	0.034*** [0.003]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.184*** [0.008]	0.194*** [0.008]	0.189*** [0.008]
marital status$_i$ [=1 if married]	0.002 [0.010]	0.001 [0.011]	0.000 [0.011]
$partner_i$ [=1 if living with a partner]	0.062*** [0.010]	0.070*** [0.010]	0.070*** [0.010]
$children_i$ [=1 if living with children]	0.043*** [0.007]	0.045*** [0.007]	0.045*** [0.007]
$part\text{-}time_i$ [=1 if working part-time]	-0.069*** [0.020]	-0.042** [0.020]	-0.043** [0.020]
$\ln VA_{jct}$ [value added – industry size]	0.037*** [0.013]	0.041*** [0.012]	0.039*** [0.012]
$mededuc_i$ [=1 if having medium education]	0.161*** [0.018]	0.150*** [0.018]	0.148*** [0.018]
$hieduc_i$ [=1 if having high education]	0.443*** [0.028]	0.424*** [0.028]	0.422*** [0.028]
$AbsServ \times \ln FVA_{jct-1}$	0.010 [0.010]	0.012 [0.009]	0.011 [0.009]
$Serv \times \ln FVA_{jct-1}$	-0.030*** [0.008]	-0.027*** [0.007]	-0.027*** [0.007]
$Rout \times \ln FVA_{jct-1}$	-0.026*** [0.008]	-0.025*** [0.008]	-0.024*** [0.008]
R^2	0.738	0.676	0.684
N	113972	120786	120764

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*AbsServ* = low in routine, high in abstractness and service task importance; *Serv* = low in routine & abstractness, high in service task importance; *Rout* = highly routine, low in abstractness and service task importance). Sample: workers in 10 countries, t=2010.
Source: own elaboration with data from LIS and WIOD

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

	dep. var: ln$wage_{ijct}$ (log of gross hourly wage)		
	gross1	*hw1*	*hw2*
age_i	0.030*** [0.003]	0.033*** [0.003]	0.032*** [0.003]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.184*** [0.008]	0.194*** [0.009]	0.189*** [0.008]
marital status$_i$ [=1 if married]	0.006 [0.009]	0.005 [0.011]	0.004 [0.011]
$partner_i$ [=1 if living with a partner]	0.055*** [0.010]	0.063*** [0.010]	0.064*** [0.010]
$children_i$ [=1 if living with children]	0.040*** [0.007]	0.042*** [0.007]	0.042*** [0.007]
part-time$_i$ [=1 if working part-time]	-0.068*** [0.020]	-0.041** [0.020]	-0.043** [0.020]
$\ln VA_{jct}$ [value added – industry size]	0.045*** [0.012]	0.049*** [0.011]	0.047*** [0.012]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness & service task importance]	0.349*** [0.017]	0.343*** [0.016]	0.334*** [0.016]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	-0.021 [0.015]	0.000 [0.015]	-0.006 [0.015]
$hieduc \times \ln FVA_{jct-1}$	0.004 [0.010]	0.005 [0.009]	0.004 [0.009]
$mededuc \times \ln FVA_{jct-1}$	-0.021*** [0.008]	-0.020*** [0.008]	-0.021*** [0.007]
$loweduc \times \ln FVA_{jct-1}$	-0.041*** [0.008]	-0.039*** [0.007]	-0.039*** [0.007]
R^2	0.741	0.678	0.686
N	113972	120786	120764

Notes: 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: *Rout* = highly routine, low in abstractness and service task importance. Classification of occupations according to tasks performed in Table 3A; Sample: workers from 10 countries, t=2010.
Source: own elaboration with data from LIS and WIOD

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

	dep. var: ln$wage_{ijct}$ (log of gross hourly wage – *gross1*)			
Sample: workers in	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.031*** [0.004]	0.042*** [0.004]	0.023*** [0.004]	0.036*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.185*** [0.009]	0.138*** [0.010]	0.223*** [0.013]	0.207*** [0.014]
marital status$_i$ [=1 if married]	-0.006 [0.010]	0.002 [0.011]	-0.015 [0.019]	0.072*** [0.012]
$partner_i$ [=1 if living with a partner]	0.062*** [0.011]	0.076*** [0.011]	0.055*** [0.020]	0.033*** [0.011]
$children_i$ [=1 if living with children]	0.043*** [0.008]	0.024*** [0.008]	0.038*** [0.013]	0.045*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.049** [0.022]	-0.078*** [0.025]	-0.047 [0.037]	-0.155*** [0.026]
$\ln VA_{jct}$ [value added – industry size]	0.032*** [0.012]	0.042*** [0.015]	0.002 [0.017]	0.017*** [0.005]
$mededuc_i$ [=1 if having medium education]	0.155*** [0.019]	0.174*** [0.019]	0.135*** [0.024]	0.195*** [0.015]
$hieduc_i$ [=1 if having high education]	0.429*** [0.030]	0.415*** [0.031]	0.440*** [0.047]	0.464*** [0.028]
$AbsServ \times \ln FVA_{jct-1}$	0.008 [0.011]	0.003 [0.010]	0.050*** [0.009]	0.009 [0.006]
$Serv \times \ln FVA_{jct-1}$	-0.030*** [0.008]	-0.032*** [0.008]	-0.002 [0.008]	0.003 [0.013]
$Rout \times \ln FVA_{jct-1}$	-0.027*** [0.009]	-0.030*** [0.008]	0.008 [0.008]	-0.014 [0.010]
R^2	0.773	0.561	0.332	0.317
N	43814	28255	15559	66322

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). 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. The regression for the USA has additional individual variables: *Second job*$_i$, *Small size*$_i$, *Private industry*$_i$, and occupational dummies.
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*)			
Sample: workers from	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.030*** [0.004]	0.041*** [0.004]	0.020*** [0.005]	0.035*** [0.005]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.183*** [0.009]	0.131*** [0.010]	0.228*** [0.013]	0.208*** [0.014]
marital status$_i$ [=1 if married]	-0.002 [0.010]	0.006 [0.011]	-0.014 [0.017]	0.077*** [0.012]
$partner_i$ [=1 if living with a partner]	0.054*** [0.011]	0.067*** [0.012]	0.050** [0.020]	0.034*** [0.010]
$children_i$ [=1 if living with children]	0.039*** [0.008]	0.024*** [0.008]	0.030*** [0.012]	0.043*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.050** [0.021]	-0.081*** [0.024]	-0.037 [0.035]	-0.155*** [0.025]
$\ln VA_{jct}$ [value added – industry size]	0.042*** [0.012]	0.048*** [0.014]	0.011 [0.016]	0.024*** [0.001]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.351*** [0.018]	0.356*** [0.022]	0.307*** [0.027]	0.547*** [0.034]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	-0.016 [0.016]	0.005 [0.019]	-0.071*** [0.022]	0.153*** [0.030]
$hieduc \times \ln FVA_{jct-1}$	0.000 [0.011]	-0.003 [0.010]	0.051*** [0.012]	0.021*** [0.004]
$mededuc \times \ln FVA_{jct-1}$	-0.020** [0.009]	-0.021*** [0.008]	0.015 [0.010]	-0.019*** [0.002]
$loweduc \times \ln FVA_{jct-1}$	-0.039*** [0.008]	-0.042*** [0.007]	-0.002 [0.011]	-0.050*** [0.003]
R^2	0.776	0.568	0.341	0.306
N	43814	28255	15559	66322

Notes: 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: *Rout* = highly routine, low in abstract & service task importance. Classification of occupations according to tasks performed in Table 3A; 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. The regression for the USA has additional individual variables: *Second job*$_i$, *Small size*$_i$, *Private industry*$_i$, and occupation dummies.

Source: own elaboration with data from LIS and WIOD

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

	dep. var: $\ln wage_{ijct}$ (log of gross hourly wage – *gross1*)			
	Manuf	Service	Market services	Non market services
age_i	0.034*** [0.005]	0.035*** [0.003]	0.040*** [0.004]	0.031*** [0.005]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.233*** [0.012]	0.175*** [0.009]	0.192*** [0.013]	0.146*** [0.013]
marital status$_i$ [=1 if married]	-0.026 [0.022]	0.011 [0.012]	0.019 [0.015]	0.007 [0.018]
$partner_i$ [=1 if living with a partner]	0.075*** [0.024]	0.056*** [0.011]	0.046*** [0.014]	0.061*** [0.018]
$children_i$ [=1 if living with children]	0.049*** [0.010]	0.041*** [0.008]	0.052*** [0.012]	0.029*** [0.010]
part-time$_i$ [=1 if working part-time]	-0.095*** [0.035]	-0.077*** [0.022]	-0.110*** [0.025]	-0.053* [0.031]
$\ln VA_{jct}$ [value added – industry size]	0.032* [0.016]	0.031* [0.017]	0.01 [0.015]	0.056** [0.026]
$mededuc_i$ [=1 if having medium education]	0.091*** [0.020]	0.172*** [0.021]	0.111*** [0.016]	0.220*** [0.041]
$hieduc_i$ [=1 if having high education]	0.300*** [0.028]	0.464*** [0.033]	0.334*** [0.019]	0.568*** [0.056]
$AbsServ \times \ln FVA_{jct-1}$	0.027** [0.012]	0.001 [0.010]	0.037*** [0.007]	-0.001 [0.013]
$Serv \times \ln FVA_{jct-1}$	-0.012 [0.012]	-0.040*** [0.008]	-0.010* [0.006]	-0.037*** [0.010]
$Rout \times \ln FVA_{jct-1}$	-0.013 0.803	-0.041*** 0.724	-0.016** 0.722	-0.034*** 0.736
R^2	0.803	0.724	0.722	0.736
N	17122	87134	43247	42285

Notes: 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 category: low-educated workers. Classification of occupations according to performed tasks in Table 3A (*AbsServ* = low in routine, high in abstractness and service task importance; *Serv* = low in routine & abstract, high in service task importance; *Rout* = highly routine, low in abstractness and service task importance). Sample: workers from 10 countries, t=2010. Market services: 50, 51, 52, 60, 61, 62, 63, 64 70, 71t74, J, H. Non-market services: M, N, L, O.
Source: own elaboration with data from LIS and WIOD

Table 10. Estimation results by industry type – manufacturing versus services (eq. 3)

	dep. var: ln$wage_{ijct}$ (log of gross hourly wage – *gross1*)			
	Manuf	Service	Market services	Non market services
age_i	0.033*** [0.005]	0.033*** [0.004]	0.039*** [0.004]	0.028*** [0.005]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.230*** [0.012]	0.174*** [0.010]	0.193*** [0.013]	0.155*** [0.016]
marital status$_i$ [=1 if married]	-0.023 [0.022]	0.014 [0.011]	0.022 [0.015]	0.005 [0.016]
$partner_i$ [=1 if living with a partner]	0.073*** [0.024]	0.048*** [0.011]	0.042*** [0.013]	0.055*** [0.018]
$children_i$ [=1 if living with children]	0.047*** [0.010]	0.037*** [0.008]	0.045*** [0.012]	0.027*** [0.010]
part-time$_i$ [=1 if working part-time]	-0.095*** [0.036]	-0.074*** [0.021]	-0.101*** [0.023]	-0.058* [0.031]
$\ln VA_{jct}$ [value added – industry size]	0.046** [0.021]	0.042*** [0.016]	0.021 [0.014]	0.069*** [0.024]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.309*** [0.016]	0.367*** [0.023]	0.332*** [0.021]	0.435*** [0.049]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	-0.001 [0.016]	-0.01 [0.018]	0.018 [0.020]	0.005 [0.037]
$hieduc \times \ln FVA_{jct-1}$	0.008 [0.018]	-0.003 [0.010]	0.028*** [0.006]	-0.006 [0.015]
$mededuc \times \ln FVA_{jct-1}$	-0.018 [0.017]	-0.028*** [0.007]	-0.001 [0.005]	-0.029*** [0.008]
$loweduc \times \ln FVA_{jct-1}$	-0.030* [0.018]	-0.051*** [0.008]	-0.021*** [0.006]	-0.048*** [0.011]
R^2	0.804	0.728	0.724	0.739
N	17122	87134	43247	42285

Notes: 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 category: *Rout.* Classification of occupations according to tasks performed in Table 3A; *high*, *medium* and *low* correspond to high, medium and primary education respectively. Sample: workers in 10 countries, t=2010. Market services industry codes:50, 51, 52, 60, 61, 62, 63, 64 70, 71t74, J, H. Non market services: M, N, L, O.

Source: own elaboration with data from LIS and WIOD

Table 11. Estimation results by industry type – high wage (HW) versus low wage (LW) industries (eq. 2)

	dep. var: ln*wage*$_{ijct}$ (log of gross hourly wage)					
	gross1		*hw1*		*hw2*	
Workers employed in	LW	HW	LW	HW	LW	HW
age$_i$	0.020*** [0.004]	0.040*** [0.003]	0.018*** [0.004]	0.044*** [0.004]	0.017*** [0.005]	0.044*** [0.004]
age$_i^2$	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex$_i$ [=1 if male]	0.236*** [0.013]	0.150*** [0.008]	0.239*** [0.015]	0.164*** [0.009]	0.230*** [0.015]	0.161*** [0.009]
marital status$_i$ [=1 if married]	-0.011 [0.016]	0.01 [0.011]	0.000 [0.019]	0.005 [0.012]	-0.008 [0.019]	0.006 [0.012]
partner$_i$ [=1 if living with a partner]	0.053*** [0.020]	0.075*** [0.011]	0.055** [0.022]	0.081*** [0.010]	0.061*** [0.023]	0.080*** [0.010]
children$_i$ [=1 if living with children]	0.030** [0.013]	0.034*** [0.007]	0.031** [0.014]	0.036*** [0.008]	0.033** [0.014]	0.035*** [0.008]
part-time$_i$ [=1 if working part-time]	0.137*** [0.026]	0.167*** [0.018]	0.133*** [0.023]	0.155*** [0.018]	0.126*** [0.027]	0.155*** [0.018]
lnVA_{jct} [value added – industry size]	0.439*** [0.055]	0.431*** [0.028]	0.435*** [0.053]	0.410*** [0.028]	0.428*** [0.055]	0.408*** [0.028]
mededuc$_i$ [=1 if having medium education]	-0.021 [0.037]	-0.091*** [0.021]	0.021 [0.036]	-0.062*** [0.022]	0.026 [0.036]	-0.063*** [0.022]
hieduc$_i$ [=1 if having high education]	0.004 [0.018]	0.057*** [0.019]	0.006 [0.024]	0.057*** [0.017]	0.018 [0.022]	0.055*** [0.017]
AbsServ×lnFVA_{jct-1}	0.050*** [0.011]	0.005 [0.010]	0.052*** [0.011]	0.007 [0.009]	0.044*** [0.010]	0.006 [0.009]
Serv×lnFVA_{jct-1}	0.002 [0.011]	-0.035*** [0.008]	0.008 [0.010]	-0.032*** [0.007]	0.000 [0.009]	-0.031*** [0.007]
Rout×lnFVA_{jct-1}	0.011 [0.010]	-0.032*** [0.008]	0.012 [0.010]	-0.029*** [0.008]	0.007 [0.009]	-0.029*** [0.008]
R^2	0.336	0.586	0.289	0.523	0.29	0.526
N	13477	100495	14301	106485	14293	106471

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*AbsServ* = low in routine, high in abstractness and service task importance; *Serv* = low in routine & abstractness, high in service task importance; *Rout* = highly routine, low in abstractness and service task importance). Sample: workers in 10 countries, t=2010. Classification of industries into low wage (LW) and high wage (HW) based on Wolszczak-Derlacz & Parteka (2016).

Source: own elaboration with data from LIS and WIOD

Table 12. Estimation results by industry type – high wage (HW) versus low wage (LW) industries (eq. 3)

	dep. var: $\ln wage_{ijct}$					
	gross1		*hw1*		*hw2*	
Sample: workers employed in	LW	HW	LW	HW	LW	HW
age_i	0.017*** [0.005]	0.039*** [0.003]	0.014*** [0.005]	0.043*** [0.004]	0.013** [0.005]	0.042*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.240*** [0.013]	0.148*** [0.008]	0.243*** [0.015]	0.162*** [0.009]	0.233*** [0.014]	0.160*** [0.009]
marital status$_i$ [=1 if married]	-0.012 [0.016]	0.015 [0.011]	0.000 [0.019]	0.009 [0.012]	-0.008 [0.020]	0.01 [0.012]
$partner_i$ [=1 if living with a partner]	0.047** [0.021]	0.067*** [0.010]	0.050** [0.023]	0.075*** [0.010]	0.056** [0.024]	0.074*** [0.010]
$children_i$ [=1 if living with children]	0.028** [0.012]	0.031*** [0.007]	0.028** [0.014]	0.033*** [0.008]	0.030** [0.013]	0.032*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.018 [0.036]	-0.089*** [0.021]	0.024 [0.036]	-0.061*** [0.021]	0.03 [0.036]	-0.062*** [0.022]
$\ln VA_{jct}$ [value added – industry size]	0.012 [0.017]	0.062*** [0.017]	0.012 [0.021]	0.063*** [0.015]	0.026 [0.019]	0.061*** [0.015]
$AbServ_i$ [=1 if occupation low in routine, high in abstract & service task importance]	0.300*** [0.031]	0.359*** [0.018]	0.294*** [0.032]	0.349*** [0.017]	0.277*** [0.033]	0.344*** [0.017]
$Serv_i$ [=1 if occupation low in routine & abstract, high in service task importance]	-0.064*** [0.023]	-0.006 [0.017]	-0.043* [0.023]	0.011 [0.016]	-0.057** [0.024]	0.009 [0.016]
$hieduc \times \ln FVA_{jct-1}$	0.050*** [0.014]	-0.003 [0.009]	0.055*** [0.014]	-0.002 [0.008]	0.047*** [0.013]	-0.002 [0.009]
$mededuc \times \ln FVA_{jct-1}$	0.017 [0.011]	-0.027*** [0.008]	0.021 [0.021]	-0.026*** [0.007]	0.012 [0.010]	-0.026*** [0.007]
$loweduc \times \ln FVA_{jct-1}$	0.000 [0.012]	-0.047*** [0.008]	0.002 [0.012]	-0.045*** [0.007]	-0.005 [0.011]	-0.045*** [0.007]
R^2	0.342	0.592	0.288	0.526	0.288	0.529
N	13477	100495	14301	106485	14293	106471

Notes: 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 category: *Rout.* Classification of occupations according to tasks performed in Table 3A; Sample: workers in 10 countries, t=2010. Classification of industries into low wage (LW) and high wage (HW) based on Wolszczak-Derlacz & Parteka (2016)

Source: own elaboration with data from LIS and WIOD

Appendix

Table 1A. List of industries and their classification

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

Table 2A. 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)	Luxem-bourg (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	,	0,14	0,08	0,21	0,57	0,01	0,07
Job characteristic											
Private sector	0,77	0,84	,	0,74	0,71	0,73	0,79	0,71	0,88	,	,
Supervisor	0,24	,	0,29	0,19	,	,	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.*	114890	70321	6359	3768	5596	7238	1323	2419	4769	5443	7654

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

Table 3A. 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	*Serv*
93	Laborers in mining, construction, manufacturing and transport	[9]elementary occupations	*Serv*

Note:
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 based on Goos et al. (2014).

Table 4A. Endogeneity tests for FVA when the dependent variable ln*wage*$_{ijct}$ is measured by *gross1*, *hw1* or ln*hw2*

	ln*gross1*$_{ijct}$	ln*hw1*$_{ijct}$	ln*hw2*$_{ijct}$
Test stat [χ^2 (1)]	0.331	0.169	0.124
p-value	0.565	0.681	0.725

Notes: GMM distance test based on the gravity instrument lnFVA_{ijct}. H0: the regressor can be treated as exogenous; computed with xtivreg2 in STATA.

ADDITIONAL MATERIAL - ROBUSTNESS

Table 5A. IV estimation results of eq. 2 and eq. 4 for *gross1* – corresponding to Column 1 in Tables 5 and 6

	(1)	*(2)*
age_i	0.031*** [0.003]	0.030*** [0.003]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.179*** [0.008]	0.182*** [0.008]
marital status$_i$ [=1 if married]	0.003 [0.010]	0.004 [0.009]
$partner_i$ [=1 if living with a partner]	0.059*** [0.010]	0.056*** [0.010]
$children_i$ [=1 if living with children]	0.043*** [0.007]	0.040*** [0.007]
$part\text{-}time_i$ [=1 if working part-time]	-0.058*** [0.021]	-0.063*** [0.020]
$\ln VA_{jct}$	0.029* [0.016]	0.045*** [0.012]
$mededuc_i$ [=1 if having medium education]	0.153*** [0.018]	
$hieduc_i$ [=1 if having high education]	0.412*** [0.025]	
$AbsServ \times \ln FVA_{jct}$	0.033*** [0.008]	
$Serv \times \ln FVA_{jct}$	-0.024*** [0.008]	
$Rout \times \ln FVA_{jct}$	-0.014* [0.008]	
$AbServ_i$		0.319*** [0.014]
$Serv_i$		-0.029* [0.016]
$hieduc \times \ln FVA_{jct}$		0.008 [0.011]
$mededuc \times \ln FVA_{jct}$		-0.028** [0.011]
$loweduc \times \ln FVA_{jct}$		-0.055*** [0.012]
Under-identification	0.000	0.000
Weak identification	43.672	14.690
N	113944	113944

Notes: 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*. $\ln FVA_{jct}$ 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.

Table 6A. Estimation results by country subgroups (eq. 2) – corresponding to Table 7. Dep. var : ln*hw1*

	dep. var: ln$wage_{ijct}$ (*hw1*)			
Sample:	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.035*** [0.004]	0.046*** [0.004]	0.024*** [0.004]	0.035*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.193*** [0.009]	0.150*** [0.010]	0.226*** [0.014]	0.219*** [0.013]
marital status$_i$ [=1 if married]	-0.005 [0.012]	0.003 [0.012]	-0.011 [0.021]	0.056*** [0.011]
$partner_i$ [=1 if living with a partner]	0.070*** [0.011]	0.078*** [0.010]	0.066*** [0.021]	0.044*** [0.010]
$children_i$ [=1 if living with children]	0.046*** [0.008]	0.029*** [0.009]	0.037*** [0.013]	0.040*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.042* [0.023]	-0.070*** [0.026]	-0.017 [0.037]	0.001 [0.027]
lnVA_{jct}	0.036*** [0.012]	0.043*** [0.015]	0.007 [0.023]	0.011 [0.011]
$mededuc_i$ [=1 if having medium education]	0.143*** [0.018]	0.158*** [0.019]	0.132*** [0.025]	0.207*** [0.015]
$hieduc_i$ [=1 if having high education]	0.409*** [0.029]	0.394*** [0.031]	0.431*** [0.046]	0.475*** [0.028]
$AbsServ \times \ln FVA_{jct-1}$	0.010 [0.010]	0.005 [0.010]	0.048*** [0.009]	0.005 [0.017]
$Serv \times \ln FVA_{jct-1}$	-0.026*** [0.008]	-0.028*** [0.008]	0.000 [0.008]	0.001 [0.015]
$Rout \times \ln FVA_{jct-1}$	-0.025*** [0.008]	-0.028*** [0.008]	0.006 [0.008]	-0.017 [0.017]
R^2	0.705	0.487	0.265	0.288
N	50168	33539	16629	66681

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). t=2010. OMS=EU. Old member states (Germany, Spain, Finland, Greece, Ireland and Luxembourg); NMS = EU New member states (Czech Republic, Estonia, Slovak Republic); E9=OMS+NMS. The regression for the USA has additional individual variables: *Second job*$_i$*, Small size*$_i$*, Private sector*$_i$*,* and occupation dummies.

Source: own elaboration with data from LIS and WIOD

Table 7A. Estimation results by country subgroups (eq. 2) – corresponding to Table 7. Dep. var: ln*hw2*)

	dep. var: ln$wage_{ijct}$ (*hw2*)			
Sample:	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.034*** [0.004]	0.046*** [0.004]	0.022*** [0.005]	0.035*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.188*** [0.009]	0.149*** [0.010]	0.217*** [0.013]	0.219*** [0.013]
marital status$_i$ [=1 if married]	-0.006 [0.011]	0.002 [0.012]	-0.015 [0.020]	0.056*** [0.011]
$partner_i$ [=1 if living with a partner]	0.070*** [0.011]	0.078*** [0.010]	0.069*** [0.021]	0.044*** [0.010]
$children_i$ [=1 if living with children]	0.046*** [0.008]	0.029*** [0.009]	0.036*** [0.013]	0.040*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.043* [0.023]	-0.072*** [0.026]	-0.008 [0.037]	0.001 [0.027]
$\ln VA_{jct}$	0.034*** [0.012]	0.041*** [0.015]	0.017 [0.021]	0.011 [0.011]
$mededuc_i$ [=1 if having medium education]	0.141*** [0.019]	0.157*** [0.019]	0.127*** [0.027]	0.207*** [0.015]
$hieduc_i$ [=1 if having high education]	0.406*** [0.029]	0.392*** [0.031]	0.424*** [0.048]	0.475*** [0.028]
$AbsServ \times \ln FVA_{jct-1}$	0.009 [0.010]	0.005 [0.010]	0.043*** [0.008]	0.005 [0.017]
$Serv \times \ln FVA_{jct-1}$	-0.026*** [0.008]	-0.028*** [0.008]	-0.005 [0.008]	0.001 [0.015]
$Rout \times \ln FVA_{jct-1}$	-0.024*** [0.008]	-0.028*** [0.008]	0.004 [0.007]	-0.017 [0.017]
R^2	0.713	0.485	0.264	0.248
N	50146	33525	16621	70618

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). t=2010. OMS=EU Old member states (Germany, Spain, Finland, Greece, Ireland and Luxembourg); NMS = EU. New member states (Czech Republic, Estonia, Slovak Republic); E9=OMS+NMS. The regression for the USA has additional individual variables: *Second job*$_i$*, Small size*$_i$*, Private sector*$_i$, and occupation dummies.

Source: own elaboration with data from LIS and WIOD

Table 8A. Estimation results (eq.3) by country subgroups (corresponding to Table 8) Dep. var: ln*hw1*)

	dep. var: ln$wage_{ijct}$ *(hw1)*			
Sample:	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.033*** [0.004]	0.045*** [0.004]	0.020*** [0.005]	0.034*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.192*** [0.010]	0.147*** [0.010]	0.230*** [0.014]	0.221*** [0.013]
marital status$_i$ [=1 if married]	-0.001 [0.011]	0.006 [0.012]	-0.009 [0.019]	0.061*** [0.011]
$partner_i$ [=1 if living with a partner]	0.063*** [0.011]	0.071*** [0.011]	0.061*** [0.021]	0.044*** [0.010]
$children_i$ [=1 if living with children]	0.043*** [0.008]	0.028*** [0.009]	0.031** [0.012]	0.037*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.043* [0.023]	-0.072*** [0.025]	-0.008 [0.035]	0.002 [0.027]
$\ln VA_{jct}$	0.047*** [0.012]	0.052*** [0.015]	0.014 [0.020]	0.012*** [0.001]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.345*** [0.018]	0.347*** [0.021]	0.299*** [0.028]	0.445*** [0.029]
$Serv_i$ [=1 if occupation low in routine & abstract, high in service task importance]	0.007 [0.015]	0.027 [0.018]	-0.053** [0.022]	-0.163*** [0.024]
$hieduc \times \ln FVA_{jct-1}$	0.002 [0.010]	-0.003 [0.009]	0.051*** [0.012]	0.026*** [0.005]
$mededuc \times \ln FVA_{jct-1}$	-0.020** [0.008]	-0.022*** [0.008]	0.015 [0.010]	-0.013*** [0.002]
$loweduc \times \ln FVA_{jct-1}$	-0.037*** [0.008]	-0.041*** [0.007]	-0.002 [0.011]	-0.046*** [0.004]
R^2	0.707	0.49	0.268	0.277
N	50168	33539	16629	66681

Notes: 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 category: *Rout*. Classification of occupations according to tasks performed in Table 3A t=2010. OMS=EU Old member states (Germany, Spain, Finland, Greece, Ireland and Luxembourg); NMS = EU. New member states (Czech Republic, Estonia, Slovak Republic); E9=OMS+NMS. The regression for the USA has additional individual variables: *Second job*$_i$*, Small size*$_i$*, Private sector*$_i$, and occupation dummies.
Source: own elaboration with data from LIS and WIOD.

Table 9A. Estimation results (eq.3) by country subgroups (corresponding to Table 8) Dep. var: ln*hw2*

	dep. var: ln$wage_{ijct}$ *(hw2)*			
Sample:	*Europe (E9)*	*EU OMS*	*EU NMS*	*USA*
age_i	0.032*** [0.004]	0.044*** [0.004]	0.019*** [0.005]	0.034*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.187*** [0.009]	0.145*** [0.010]	0.220*** [0.013]	0.221*** [0.013]
marital status$_i$ [=1 if married]	-0.003 [0.011]	0.006 [0.013]	-0.014 [0.019]	0.061*** [0.011]
$partner_i$ [=1 if living with a partner]	0.063*** [0.011]	0.071*** [0.011]	0.064*** [0.021]	0.044*** [0.010]
$children_i$ [=1 if living with children]	0.043*** [0.008]	0.029*** [0.009]	0.030** [0.012]	0.037*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.045** [0.023]	-0.074*** [0.026]	0.001 [0.035]	0.002 [0.027]
$\ln VA_{jct}$	0.044*** [0.012]	0.050*** [0.015]	0.027 [0.019]	0.012*** [0.001]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.335*** [0.018]	0.343*** [0.021]	0.282*** [0.028]	0.445*** [0.029]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	0.001 [0.016]	0.025 [0.018]	-0.065*** [0.022]	-0.163*** [0.024]
$hieduc \times \ln FVA_{jct-1}$	0.001 [0.010]	-0.003 [0.009]	0.045*** [0.011]	0.026*** [0.005]
$mededuc \times \ln FVA_{jct-1}$	-0.020** [0.008]	-0.022*** [0.008]	0.009 [0.009]	-0.013*** [0.002]
$loweduc \times \ln FVA_{jct-1}$	-0.037*** [0.008]	-0.040*** [0.007]	-0.008 [0.010]	-0.046*** [0.004]
R^2	0.714	0.488	0.265	0.277
N	50146	33525	16621	66681

Notes 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 category: *Rout*. Classification of occupations according to tasks performed in Table 3A; t=2010. OMS=EU Old member states (Germany, Spain, Finland, Greece, Ireland and Luxembourg); NMS = EU. New member states (Czech Republic, Estonia, Slovak Republic); E9=OMS+NMS. The regression for the USA has additional individual variables: *Second job*$_i$, *Small size*$_i$, *Private sector*$_i$, and occupation dummies.
Source: own elaboration with data from LIS and WIOD

Table 10A. Estimation results by industry type – manufacturing versus services, *hw1* (eq. 2)

	dep. var: $\ln wage_{ijct}$ *(hw1)*			
	Manuf	Service	Market services	Non market services
age_i	0.034*** [0.006]	0.039*** [0.004]	0.044*** [0.006]	0.036*** [0.005]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.255*** [0.015]	0.181*** [0.010]	0.198*** [0.014]	0.151*** [0.012]
marital status$_i$ [=1 if married]	-0.007 [0.022]	0.007 [0.012]	0.009 [0.017]	0.003 [0.018]
$partner_i$ [=1 if living with a partner]	0.068*** [0.024]	0.064*** [0.011]	0.056*** [0.013]	0.071*** [0.018]
$children_i$ [=1 if living with children]	0.055*** [0.011]	0.040*** [0.008]	0.056*** [0.014]	0.021** [0.008]
$part\text{-}time_i$ [=1 if working part-time]	-0.100** [0.040]	-0.049** [0.022]	-0.070*** [0.024]	-0.034 [0.032]
$\ln VA_{jct}$	0.036** [0.015]	0.032* [0.017]	0.030** [0.014]	0.039 [0.028]
$mededuc_i$ [=1 if having medium education]	0.101*** [0.018]	0.154*** [0.022]	0.094*** [0.016]	0.199*** [0.045]
$hieduc_i$ [=1 if having high education]	0.335*** [0.024]	0.435*** [0.034]	0.320*** [0.021]	0.528*** [0.060]
$AbsServ \times \ln FVA_{jct-1}$	0.028** [0.011]	0.000 [0.010]	0.034*** [0.008]	-0.004 [0.012]
$Serv \times \ln FVA_{jct-1}$	-0.008 [0.011]	-0.038*** [0.008]	-0.011* [0.007]	-0.033*** [0.010]
$Rout \times \ln FVA_{jct-1}$	-0.011 0.76	-0.042*** 0.665	-0.017** 0.648	-0.034*** 0.689
R^2	18052	92186	45749	44732
N	0.034***	0.039***	0.044***	0.036***

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers in 10 countries, t=2010. Market services: 50, 51, 52, 60, 61, 62, 63, 64 70, 71t74, J, H. Non market services: M, N, L, O.
Source: own elaboration with data from LIS and WIOD

Table 11A. Estimation results by industry type – manufacturing versus services, *hw2* (eq. 2)

	dep. var: ln$wage_{ijct}$ *(hw2)*			
	Manuf	Service	Market services	Non market services
age_i	0.035*** [0.006]	0.038*** [0.004]	0.043*** [0.006]	0.036*** [0.005]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.250*** [0.015]	0.178*** [0.009]	0.194*** [0.014]	0.149*** [0.012]
marital status$_i$ [=1 if married]	-0.011 [0.022]	0.005 [0.012]	0.007 [0.017]	0.001 [0.017]
$partner_i$ [=1 if living with a partner]	0.069*** [0.024]	0.065*** [0.011]	0.058*** [0.013]	0.070*** [0.017]
$children_i$ [=1 if living with children]	0.054*** [0.011]	0.040*** [0.008]	0.056*** [0.013]	0.022** [0.008]
part-time$_i$ [=1 if working part-time]	-0.100** [0.040]	-0.050** [0.022]	-0.072*** [0.025]	-0.033 [0.032]
lnVA_{jct}	0.039*** [0.014]	0.029* [0.017]	0.025* [0.014]	0.039 [0.028]
$mededuc_i$ [=1 if having medium education]	0.098*** [0.018]	0.153*** [0.022]	0.092*** [0.016]	0.200*** [0.045]
$hieduc_i$ [=1 if having high education]	0.327*** [0.025]	0.434*** [0.034]	0.316*** [0.021]	0.529*** [0.060]
$AbsServ$×lnFVA_{jct-1}	0.027** [0.011]	0.000 [0.010]	0.034*** [0.008]	-0.004 [0.012]
$Serv$×lnFVA_{jct-1}	-0.009 [0.011]	-0.038*** [0.008]	-0.011 [0.007]	-0.033*** [0.010]
$Rout$×lnFVA_{jct-1}	-0.011 0.767	-0.041*** 0.672	-0.016* 0.654	-0.034*** 0.696
R^2	18049	92170	45735	44730
N	0.035***	0.038***	0.043***	0.036***

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers in 10 countries, t=2010. Market services: 50, 51, 52, 60, 61, 62, 63, 64 70, 71t74, J, H. Non market services: M, N, L, O. Source: own elaboration with data from LIS and WIOD

Table 12A. Estimation results by industry type – manufacturing versus services, *hw1* (eq. 3)

	dep. var: ln$wage_{ijct}$ *(hw1)*			
	Manuf	Service	Market services	Non market services
age_i	0.034*** [0.006]	0.036*** [0.004]	0.042*** [0.006]	0.033*** [0.005]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.253*** [0.015]	0.180*** [0.010]	0.197*** [0.014]	0.159*** [0.015]
$marital\ status_i$ [=1 if married]	-0.005 [0.022]	0.009 [0.012]	0.012 [0.017]	0 [0.016]
$partner_i$ [=1 if living with a partner]	0.066*** [0.024]	0.057*** [0.011]	0.052*** [0.012]	0.067*** [0.018]
$children_i$ [=1 if living with children]	0.053*** [0.011]	0.036*** [0.009]	0.050*** [0.014]	0.020** [0.009]
$part\text{-}time_i$ [=1 if working part-time]	-0.098** [0.040]	-0.046** [0.021]	-0.061** [0.024]	-0.04 [0.031]
lnVA_{jct}	0.051** [0.020]	0.043*** [0.016]	0.043*** [0.014]	0.052** [0.024]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.309*** [0.018]	0.360*** [0.023]	0.321*** [0.025]	0.422*** [0.045]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	0.018 [0.016]	0.007 [0.019]	0.022 [0.024]	0.024 [0.034]
$hieduc$×lnFVA_{jct-1}	0.011 [0.017]	-0.004 [0.009]	0.026*** [0.007]	-0.009 [0.013]
$mededuc$×lnFVA_{jct-1}	-0.018 [0.017]	-0.028*** [0.007]	-0.005 [0.006]	-0.028*** [0.008]
$loweduc$×lnFVA_{jct-1}	-0.032* [0.017]	-0.048*** [0.008]	-0.020*** [0.007]	-0.041*** [0.013]
R^2	0.76	0.667	0.649	0.69
N	18052	92186	45749	44732

Notes: 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: *Rout*. Classification of occupations according to tasks performed in Table 3A; *high*, *medium* and *low* correspond to high, medium and primary education respectively. Sample: workers in 10 countries, t=2010. Market services: 50, 51, 52, 60, 61, 62, 63, 64 70, 71t74, J, H. Non market services: M, N, L, O.
Source: own elaboration with data from LIS and WIOD

Table 13A. Estimation results by industry type – manufacturing versus services, *hw2*, (eq. 3)

	dep. var: ln$wage_{ijct}$ (hw2)			
	Manuf	Service	Market services	Non market services
age_i	0.034***	0.036***	0.041***	0.033***
	[0.006]	[0.004]	[0.006]	[0.005]
age_i^2	-0.000***	-0.000***	-0.000***	-0.000***
	[0.000]	[0.000]	[0.000]	[0.000]
sex_i	0.248***	0.176***	0.193***	0.157***
[=1 if male]	[0.015]	[0.010]	[0.014]	[0.015]
marital status$_i$	-0.009	0.008	0.01	-0.001
[=1 if married]	[0.022]	[0.012]	[0.017]	[0.016]
$partner_i$	0.067***	0.058***	0.053***	0.066***
[=1 if living with a partner]	[0.024]	[0.011]	[0.012]	[0.018]
$children_i$	0.052***	0.037***	0.051***	0.021**
[=1 if living with children]	[0.011]	[0.008]	[0.013]	[0.009]
part-time$_i$	-0.098**	-0.047**	-0.064**	-0.04
[=1 if working part-time]	[0.040]	[0.022]	[0.025]	[0.031]
lnVA_{jct}	0.053***	0.040**	0.038***	0.053**
	[0.019]	[0.016]	[0.014]	[0.023]
$AbServ_i$	0.296***	0.354***	0.311***	0.424***
[=1 if occupation low in routine, high in abstractness and service task importance]	[0.019]	[0.023]	[0.025]	[0.044]
$Serv_i$	0.013	0.003	0.018	0.025
[=1 if occupation low in routine and abstractness, high in service task importance]	[0.016]	[0.019]	[0.024]	[0.034]
$hieduc$×lnFVA_{jct-1}	0.011	-0.004	0.026***	-0.009
	[0.017]	[0.009]	[0.007]	[0.013]
$mededuc$×lnFVA_{jct-1}	-0.018	-0.028***	-0.004	-0.028***
	[0.017]	[0.007]	[0.006]	[0.007]
$loweduc$×lnFVA_{jct-1}	-0.032*	-0.047***	-0.019***	-0.040***
	[0.017]	[0.008]	[0.007]	[0.012]
R^2	0.767	0.673	0.655	0.697
N	18049	92170	45735	44730

Notes: 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 category: *Rout.* Classification of occupations according to tasks performed in Table 3A; *high*, *medium* and *low* correspond to high, medium and primary education respectively. Sample: workers in 10 countries, t=2010. Market services: 50, 51, 52, 60, 61, 62, 63, 64 70, 71t74, J, H. Non market services: M, N, L, O.
Source: own elaboration with data from LIS and WIOD

Table 14A. Robustness estimation of eq.2 – accounting for heterogeneous wage response to FVA due to performed tasks, controlling for wage setting coordination (*Coord*)

	dep. var: $\ln wage_{ijct}$		
	gross1	*hw1*	*hw2*
age_i	0.032*** [0.003]	0.035*** [0.003]	0.034*** [0.003]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.184*** [0.008]	0.194*** [0.008]	0.189*** [0.008]
marital status$_i$ [=1 if married]	0.002 [0.010]	0.001 [0.011]	0 [0.011]
$partner_i$ [=1 if living with a partner]	0.062*** [0.010]	0.070*** [0.010]	0.070*** [0.010]
$children_i$ [=1 if living with children]	0.043*** [0.007]	0.045*** [0.007]	0.045*** [0.007]
$part\text{-}time_i$ [=1 if working part-time]	-0.069*** [0.020]	-0.042** [0.020]	-0.043** [0.020]
$\ln VA_{jct}$	0.037*** [0.013]	0.041*** [0.012]	0.039*** [0.012]
$mededuc_i$ [=1 if having medium education]	0.161*** [0.018]	0.150*** [0.018]	0.148*** [0.018]
$hieduc_i$ [=1 if having high education]	0.443*** [0.028]	0.424*** [0.028]	0.422*** [0.028]
$Coord_{ct}$ [wage setting coordination]	1.946 [1.891]	-0.121 [1.749]	-0.045 [1.734]
$AbsServ \times \ln FVA_{jct-1}$	0.01 [0.010]	0.012 [0.009]	0.011 [0.009]
$Serv \times \ln FVA_{jct-1}$	-0.030*** [0.008]	-0.027*** [0.007]	-0.027*** [0.007]
$Rout \times \ln FVA_{jct-1}$	-0.026*** [0.008]	-0.025*** [0.008]	-0.024*** [0.008]
R^2	0.738	0.676	0.684
N	113972	120786	120764

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers from 10 countries, t=2010. Additional variable: $Coord_{ct}$ – degree of wage-setting coordination (ICTWSS).

Source: own elaboration with data from LIS and WIOD.

Table 15A. Robustness estimation of eq.3 – accounting for heterogeneous wage response to FVA due to different education level, controlling for wage setting coordination (*Coord*)

	dep. var: ln$wage_{ijct}$		
	gross1	*hw1*	*hw2*
age_i	0.030*** [0.003]	0.033*** [0.003]	0.032*** [0.003]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.184*** [0.008]	0.194*** [0.009]	0.189*** [0.008]
marital status$_i$ [=1 if married]	0.006 [0.009]	0.005 [0.011]	0.004 [0.011]
$partner_i$ [=1 if living with a partner]	0.055*** [0.010]	0.063*** [0.010]	0.064*** [0.010]
$children_i$ [=1 if living with children]	0.040*** [0.007]	0.042*** [0.007]	0.042*** [0.007]
part-time$_i$ [=1 if working part-time]	-0.068*** [0.020]	-0.041** [0.020]	-0.043** [0.020]
lnVA_{jct}	0.045*** [0.012]	0.049*** [0.011]	0.047*** [0.012]
$AbServ_i$ [=1 if occupation low in routine, high in abstract & service task importance]	0.349*** [0.017]	0.343*** [0.016]	0.334*** [0.016]
$Serv_i$ [=1 if occupation low in routine & abstract, high in service task importance]	-0.021 [0.015]	0.000 [0.015]	-0.006 [0.015]
$Coord_{ct}$ [wage setting coordination]	2.127 [1.636]	0.223 [1.568]	0.31 [1.553]
hieduc×lnFVA_{jct-1}	0.004 [0.010]	0.005 [0.009]	0.004 [0.009]
mededuc×lnFVA_{jct-1}	-0.021*** [0.008]	-0.020*** [0.008]	-0.021*** [0.007]
loweduc×lnFVA_{jct-1}	-0.041*** [0.008]	-0.039*** [0.007]	-0.039*** [0.007]
R^2	0.741	0.678	0.686
N	113972	120786	120764

Notes: 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: *Rout* = highly routine, low in abstractness and service task importance. Classification of occupations according to tasks performed in Table 3A; sample: workers in 10 countries, t=2010. Additional variable: $Coord_{ct}$ – degree of wage-setting coordination (ICTWSS).
Source: own elaboration with data from LIS and WIOD.

Table 16A. Robustness estimation of eq.2 – accounting for heterogeneous wage response to FVA due to performed tasks, controlling for national minimum wage setting (NMW)

	dep. var: ln*wage*$_{ijct}$		
	gross1	*hw1*	*hw2*
age$_i$	0.032*** [0.003]	0.035*** [0.003]	0.034*** [0.003]
age$_i^2$	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex$_i$ [=1 if male]	0.184*** [0.008]	0.194*** [0.008]	0.189*** [0.008]
marital status$_i$ [=1 if married]	0.002 [0.010]	0.001 [0.011]	0 [0.011]
partner$_i$ [=1 if living with a partner]	0.062*** [0.010]	0.070*** [0.010]	0.070*** [0.010]
children$_i$ [=1 if living with children]	0.043*** [0.007]	0.045*** [0.007]	0.045*** [0.007]
part-time$_i$ [=1 if working part-time]	-0.069*** [0.020]	-0.042** [0.020]	-0.043** [0.020]
lnVA_{jct}	0.037*** [0.013]	0.041*** [0.012]	0.039*** [0.012]
mededuc$_i$ [=1 if having medium education]	0.161*** [0.018]	0.150*** [0.018]	0.148*** [0.018]
hieduc$_i$ [=1 if having high education]	0.443*** [0.028]	0.424*** [0.028]	0.422*** [0.028]
NMW_{ct} [national minimum wage setting]	-2.762 [2.285]	-0.212 [2.112]	-0.304 [2.094]
AbsServ×lnFVA_{jct-1}	0.01 [0.010]	0.012 [0.009]	0.011 [0.009]
Serv×lnFVA_{jct-1}	-0.030*** [0.008]	-0.027*** [0.007]	-0.027*** [0.007]
Rout×lnFVA_{jct-1}	-0.026*** [0.008]	-0.025*** [0.008]	-0.024*** [0.008]
R^2	0.738	0.676	0.684
N	113972	120786	120764

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers from 10 countries, t=2010. Additional variable: NMW_{ct} – type of national minimum wage setting (ICTWSS).

Source: own elaboration with data from LIS and WIOD.

Table 17A. Robustness estimation of eq.3 – accounting for heterogeneous wage response to FVA due to different education level, controlling for national minimum wage setting (NMW)

	dep. var: ln$wage_{ijct}$		
	gross1	*hw1*	*hw2*
age_i	0.030*** [0.003]	0.033*** [0.003]	0.032*** [0.003]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.184*** [0.008]	0.194*** [0.009]	0.189*** [0.008]
marital status$_i$ [=1 if married]	0.006 [0.009]	0.005 [0.011]	0.004 [0.011]
$partner_i$ [=1 if living with a partner]	0.055*** [0.010]	0.063*** [0.010]	0.064*** [0.010]
$children_i$ [=1 if living with children]	0.040*** [0.007]	0.042*** [0.007]	0.042*** [0.007]
part-time$_i$ [=1 if working part-time]	-0.068*** [0.020]	-0.041** [0.020]	-0.043** [0.020]
lnVA_{jct}	0.045*** [0.012]	0.049*** [0.011]	0.047*** [0.012]
$AbServ_i$ [=1 if occupation low in routine, high in abstract & service task importance]	0.349*** [0.017]	0.343*** [0.016]	0.334*** [0.016]
$Serv_i$ [=1 if occupation low in routine & abstract, high in service task importance]	-0.021 [0.015]	0.000 [0.015]	-0.006 [0.015]
NMW_{ct}	-2.98 [1.977]	-0.627 [1.894]	-0.733 [1.876]
$hieduc$×lnFVA_{jct-1}	0.004 [0.010]	0.005 [0.009]	0.004 [0.009]
$mededuc$×lnFVA_{jct-1}	-0.021*** [0.008]	-0.020*** [0.008]	-0.021*** [0.007]
$loweduc$×lnFVA_{jct-1}	-0.041*** [0.008]	-0.039*** [0.007]	-0.039*** [0.007]
R^2	0.741	0.678	0.686
N	113972	120786	120764

Notes: 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: *Rout* = highly routine, low in abstractness and service task importance. Classification of occupations according to performed tasks in Table 3A; Sample: workers in 10 countries, t=2010. Additional variable: NMW_{ct} – type of national minimum wage setting (ICTWSS).
Source: own elaboration with data from LIS and WIOD.

Table 18A. Robustness estimation of eq.2 – accounting for heterogeneous wage response to FVA due to tasks performed, controlling for union density (UD)

	dep. var: ln$wage_{ijct}$		
	gross1	*hw1*	*hw2*
age_i	0.030*** [0.004]	0.033*** [0.004]	0.032*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.186*** [0.009]	0.195*** [0.010]	0.190*** [0.009]
marital status$_i$ [=1 if married]	-0.005 [0.010]	0 [0.012]	-0.002 [0.012]
$partner_i$ [=1 if living with a partner]	0.055*** [0.011]	0.062*** [0.011]	0.063*** [0.011]
$children_i$ [=1 if living with children]	0.040*** [0.008]	0.045*** [0.008]	0.045*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.053** [0.022]	-0.046* [0.024]	-0.047** [0.024]
lnVA_{jct}	0.029** [0.013]	0.035*** [0.013]	0.032** [0.013]
$mededuc_i$ [=1 if having medium education]	0.159*** [0.020]	0.145*** [0.021]	0.144*** [0.021]
$hieduc_i$ [=1 if having high education]	0.435*** [0.031]	0.416*** [0.031]	0.412*** [0.032]
UD_{ct} [union density]	0.151 [0.108]	0.144 [0.089]	0.153 [0.190]
$AbsServ$×lnFVA_{jct-1}	0.007 [0.011]	0.009 [0.011]	0.009 [0.011]
$Serv$×lnFVA_{jct-1}	-0.031*** [0.009]	-0.026*** [0.009]	-0.026*** [0.009]
$Rout$×lnFVA_{jct-1}	-0.027*** [0.009]	-0.026*** [0.009]	-0.025*** [0.009]
R^2	0.778	0.715	0.723
N	42491	47620	47598

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers in 10 countries, t=2010. Additional variable: UD_{ct} – union density (ICTWSS).
Source: own elaboration with data from LIS and WIOD

Table 19A. Robustness estimation of eq.3 – accounting for heterogeneous wage response to FVA due to different education level, controlling for the union density (UD)

	dep. var: ln$wage_{ijct}$		
	gross1	*hw1*	*hw2*
age_i	0.029*** [0.004]	0.031*** [0.004]	0.031*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.186*** [0.010]	0.195*** [0.010]	0.189*** [0.010]
marital status$_i$ [=1 if married]	-0.001 [0.010]	0.003 [0.011]	0.002 [0.011]
$partner_i$ [=1 if living with a partner]	0.047*** [0.011]	0.055*** [0.011]	0.056*** [0.011]
$children_i$ [=1 if living with children]	0.036*** [0.008]	0.041*** [0.008]	0.041*** [0.008]
part-time$_i$ [=1 if working part-time]	-0.053** [0.022]	-0.045* [0.024]	-0.047* [0.024]
lnVA_{jct}	0.040*** [0.013]	0.045*** [0.013]	0.043*** [0.014]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.357*** [0.019]	0.349*** [0.018]	0.338*** [0.019]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	-0.017 [0.017]	0.005 [0.017]	-0.002 [0.017]
UD_{ct}	0.115 [0.098]	0.117 [0.081]	0.126 [0.081]
hieduc×lnFVA_{jct-1}	-0.001 [0.011]	0.001 [0.011]	0.001 [0.011]
mededuc×lnFVA_{jct-1}	-0.021** [0.009]	-0.020** [0.009]	-0.020** [0.009]
loweduc×lnFVA_{jct-1}	-0.039*** [0.009]	-0.037*** [0.009]	-0.037*** [0.009]
R^2	0.782	0.717	0.725
N	42491	47620	47598

Notes: 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 category: *Rout* = highly routine, low in abstractness and service task importance. Classification of occupations according to performed tasks in Table 3A; sample: workers in 10 countries, t=2010. Additional variable: UD_{ct} – union density (ICTWSS).
Source: own elaboration with data from LIS and WIOD.

Table 20A. Robustness estimation of eq.2 for gross1 – accounting for heterogeneous wage response to FVA due to performed tasks, with additional job characteristics

	(1)	(2)	(3)	(4)
age_i	0.028*** [0.003]	0.033*** [0.003]	0.038*** [0.004]	0.027*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.197*** [0.008]	0.185*** [0.009]	0.178*** [0.011]	0.175*** [0.010]
marital status$_i$ [=1 if married]	-0.005 [0.010]	0.001 [0.011]	0.005 [0.013]	-0.01 [0.013]
$partner_i$ [=1 if living with a partner]	0.067*** [0.010]	0.065*** [0.011]	0.075*** [0.012]	0.058*** [0.013]
$children_i$ [=1 if living with children]	0.043*** [0.007]	0.046*** [0.007]	0.045*** [0.009]	0.046*** [0.009]
part-time$_i$ [=1 if working part-time]	-0.047** [0.022]	-0.070*** [0.021]	-0.073*** [0.024]	0.005 [0.023]
$\ln VA_{jct}$	0.035*** [0.013]	0.041*** [0.015]	0.045** [0.019]	0.041*** [0.014]
$mededuc_i$ [=1 if having medium education]	0.177*** [0.019]	0.167*** [0.019]	0.157*** [0.023]	0.151*** [0.021]
$hieduc_i$ [=1 if having high education]	0.467*** [0.030]	0.455*** [0.030]	0.443*** [0.035]	0.421*** [0.035]
$AbsServ \times \ln FVA_{jct-1}$	0.011 [0.011]	0.008 [0.011]	0.005 [0.013]	0.000 [0.013]
$Serv \times \ln FVA_{jct-1}$	-0.029*** [0.008]	-0.031*** [0.008]	-0.034*** [0.010]	-0.031*** [0.010]
$Rout \times \ln FVA_{jct-1}$	-0.025*** [0.009]	-0.029*** [0.009]	-0.032*** [0.011]	-0.024** [0.010]
Second job$_i$	0.002 [0.025]			
Small size$_i$		-0.120*** [0.012]		
Private sector$_i$			-0.083*** [0.029]	
$Supervise_i$				0.173*** [0.010]
R^2	0.74	0.736	0.668	0.788
N	107775	108031	94275	31413
Number of countries	9 [No IRL]	9 [No FIN]	7 [No CZE, ESP, SVK]	7 [No DEU, FIN, US]

Notes: 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 category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers in 10 countries, t=2010.
Source: own elaboration with data from LIS and WIOD.

Table 21A. Robustness estimation of eq.3 for gross1 – accounting for heterogeneous wage response to FVA due to different education level, with additional job characteristics

	(1)	*(2)*	*(3)*	*(4)*
age_i	0.027*** [0.003]	0.031*** [0.003]	0.036*** [0.004]	0.025*** [0.004]
age_i^2	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]	-0.000*** [0.000]
sex_i [=1 if male]	0.197*** [0.008]	0.188*** [0.009]	0.175*** [0.011]	0.175*** [0.010]
marital status$_i$ [=1 if married]	-0.001 [0.009]	0.005 [0.011]	0.012 [0.012]	-0.005 [0.013]
$partner_i$ [=1 if living with a partner]	0.059*** [0.010]	0.059*** [0.011]	0.065*** [0.012]	0.053*** [0.013]
$children_i$ [=1 if living with children]	0.038*** [0.007]	0.041*** [0.007]	0.041*** [0.009]	0.040*** [0.009]
part-time$_i$ [=1 if working part-time]	-0.045** [0.021]	-0.067*** [0.020]	-0.069*** [0.023]	0.004 [0.023]
$\ln VA_{jct}$	0.041*** [0.012]	0.046*** [0.014]	0.051*** [0.017]	0.050*** [0.015]
$AbServ_i$ [=1 if occupation low in routine, high in abstractness and service task importance]	0.353*** [0.018]	0.355*** [0.018]	0.380*** [0.021]	0.307*** [0.023]
$Serv_i$ [=1 if occupation low in routine and abstractness, high in service task importance]	-0.022 [0.016]	-0.016 [0.016]	-0.011 [0.020]	-0.045** [0.018]
$hieduc \times \ln FVA_{jct-1}$	0.006 [0.011]	0.002 [0.011]	-0.002 [0.012]	-0.006 [0.013]
$mededuc \times \ln FVA_{jct-1}$	-0.020** [0.009]	-0.022** [0.009]	-0.024** [0.010]	-0.022** [0.011]
$loweduc \times \ln FVA_{jct-1}$	-0.041*** [0.008]	-0.042*** [0.009]	-0.042*** [0.011]	-0.039*** [0.010]
Second job$_i$	0.001 [0.025]			
Small size$_i$		-0.122*** [0.012]		
Private sector$_i$			-0.092*** [0.027]	
$Supervise_i$				0.158*** [0.011]
R^2	0.743	0.738	0.675	0.79
N	107775	108031	94275	31413
Number of countries	9 [No IRL]	9 [No FIN]	7 [No CZE, ESP, SVK]	7 [No DEU, FIN, US]

Notes: 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: *Rout* = highly routine, low in abstractness and service task importance. Classification of occupations according to tasks performed in Table 3A; sample: workers in 10 countries, t=2010.
Source: own elaboration with data from LIS and WIOD.

Table 22A. Robustness estimation of eq.2 for gross1 by industry type – exploiting industry heterogeneity (eliminating industries one at a time, mean values of coefficients), corresponding to Table 9 in the main text

	All industries	Manuf	Service	Market services	Non market services
$AbsServ \times \ln FVA_{jct-1}$	0.010	0.027***	0.001	0.037***	-0.002
$Serv \times \ln FVA_{jct-1}$	-0.030***	-0.012	-0.040***	-0.010*	-0.040***
$Rout \times \ln FVA_{jct-1}$	-0.026***	-0.013	-0.040***	-0.016**	-0.038***

Notes: 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 of the majority of specifications (statistical specification of unique regressions may differ); default category: low-educated workers. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers in 10 countries, t=2010.
Source: own elaboration with data from LIS and WIOD.

Table 23A. Robustness estimation of eq.3 for *gross1* by industry type – exploiting industry heterogeneity (eliminating industries one at a time, mean values of coefficients), corresponding to Table 10 in the main text

	All industries	Manuf	Service	Market services	Non market services
$hieduc \times \ln FVA_{jct-1}$	0.004	0.008	-0.003	0.028***	-0.007
$mededuc \times \ln FVA_{jct-1}$	-0.021***	-0.018	-0.028***	-0.001	-0.032***
$loweduc \times \ln FVA_{jct-1}$	-0.041***	-0.030**	-0.051***	-0.021***	-0.049***

Notes: 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 of the majority of specifications (statistical specification of unique regressions may differ; default categories: *Rout* = highly routine, low in abstractness and service task importance. Classification of occupations according to tasks performed in Table 3A (*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). Sample: workers from 10 countries, t=2010.
Source: own elaboration with data from LIS and WIOD.