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GVCS, JOBS AND ROUTINE CONTENT OF OCCUPATIONS

Luca Marcolin, Sébastien Miroudot, and Mariagrazia Squicciarini

This work addresses the role of global value chains (GVCs), workforce skills, ICT, innovation and industry structure in explaining employment levels of routine and non-routine occupations. The analysis encompasses 28 OECD countries over the period 2000-2011. It relies on a new country-specific measure of routine intensity built using individual-level information from the OECD Programme for the International Assessment of Adult Competencies (PIAAC) survey, as well as on new industry-level Trade in Value Added (TiVA) indicators of offshoring and domestic outsourcing. The results suggest that employment in all types of occupations positively relate to innovation. With respect to offshoring patterns, a positive correlation is observed between the offshoring of inputs and domestic outsourcing with more routine-intensive jobs. Taken together, the results point to the existence of complex interactions between the routine content of occupations, skills, technology and trade, which do not allow for a neat identification of "winners" and "losers" in a GVC context.

Keywords: Global value chains, employment, occupation, technology, innovation, offshoring, outsourcing, routine tasks.

JEL Codes: F16, F23, J24, O33.

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Executive summary

This paper contributes to a better understanding of the impact of global value chains (GVCs) on employment by looking at the routine content of occupations. Routine tasks can be broadly defined as tasks that are accomplished following a set of specific and well-defined rules, whereas non-routine tasks typically entail performing more complicated activities, such as creative problem solving and decision making. The degree to which tasks can be "routinised" is regarded as an important determinant of firm strategies when it comes to the organisation of production and the sourcing of inputs.

The analysis focuses on the relationship between the routine intensity of occupations and trade in value-added (TiVA) patterns, looking more specifically at offshoring of inputs, domestic outsourcing, and offshoring of final assembly activities. It sheds light on the extent to which skills, ICT endowments, technological innovation and industry structure, including the services content of manufacturing, explain the distribution of jobs in GVCs and affect employment at the country and industry levels. To this end, it exploits new task-based measures of the routine content of occupations built on up-to-date, country-specific survey information contained in the OECD Programme for the International Assessment of Adult Competencies (PIAAC) database.

A new routine intensity index (RII) is constructed using responses to four PIAAC questions. These provide information related to individuals' own assessment of: (i) their degree of freedom in establishing the sequence of their tasks; (ii) their degree of freedom in deciding the type of tasks to be performed on the job; (iii) the frequency with which they plan their own activities; and (iv) the frequency with which they organise their own time. The approach improves on existing methodologies, especially those that base the definition of routine intensity on the association of occupational features (i.e. skills and job requirements) to routine and non-routine tasks.

The RII, which is calculated for countries, occupations and sectors in an independent fashion and at fairly disaggregated levels, is used to group occupations into four routine-intensity classes: 1) non-routine (NR), 2) low routine-intensive (LR), 3) medium routine-intensive (MR) and 4) high routine-intensive (HR) occupations. Combining the RII with information on employment derived from Labour Force Surveys, this analysis relies on a final dataset covering 28 countries (26 EU countries plus Turkey and the United States), 23 industries and 6 years over the period 2000-2011 (namely 2000, 2005, 2008, 2009, 2010, 2011, corresponding to the years for which TiVA data are available).

Important differences emerge across countries in the average proportion of employment accounted for by the occupations in the different routine intensity quartiles. The number of non-routine and low routine-intensive workers ranges between about 55% in Luxembourg and 20% in Italy during the years considered. Also, while the average share of workers employed in high routine-intensive occupations ranges from 20% (in Greece) to 35% (in the United Kingdom), the proportion of workers belonging to occupations in the central part of the distribution – i.e. LR and MR – varies between about 70% in many relatively smaller economies such as Luxembourg and the Czech Republic and about 35% in Poland and the United Kingdom. These notable differences mirror the extent to which economies differ along a number of structural features, including industry structure, the skill composition of the workforce, and the extent to which economies participate in GVCs.

Through an econometric analysis, this report provides some first evidence about the relative importance of these determinants in explaining the levels of employment observed in the four quartiles of routine intensity. The level of output, the role of capital (as a complement for labour) and labour compensation (i.e. wages) emerge as the main economic determinants of the demand for the various quartiles of workers. In addition, the levels of employment within each quartile are significantly correlated with skills, technological innovation, offshoring patterns and industry structure.

Comparatively higher skills are found to relate to more demand for non-routine and low routine-intensive occupations. A generally positive relationship can also be observed in the case of technology, in the form of both ICT-related capabilities (i.e. ICT intensity) and innovative output, as proxied by the number of patent families in the industry. ICT intensity exhibits a positive correlation with employment levels in non-routine occupations, and a negative one with high routine-intensive occupations. Technological innovation correlates positively with employment in all quartiles.

A positive correlation is generally observed between the home country employment in more routine-intensive occupations on the one hand and the offshoring of inputs and the domestic outsourcing of inputs from the same sector on the other hand. Conversely, in manufacturing the offshoring of final assembly reduces the demand for jobs in non-routine occupations. Also, a relatively higher service content of manufacturing is found to relate negatively with employment in high-routine occupations, as manufacturers may free resources by sourcing part of their in-house, high routine intensive-tasks to specialised firms.

Overall, the results point to the existence of complex interactions between the routine content of occupations, skills, technology, industry structure and trade, which do not allow for a clear identification of “winners” and “losers” in a GVC context. This strongly calls for caution to be applied when interpreting policies promoting the participation in GVCs as having a clear negative or positive general impact on specific categories of workers.

The analysis provides a number of implications for policies aiming at maximising the benefits of GVCs, through higher and better employment, as well as productivity growth, which, if confirmed in future analysis, would be of relevance to both industry and trade policy:

- No consistently negative impact of offshoring on the levels of employment of routine-intensive workers emerges, in contrast to what is found in some previous studies (e.g. Liu and Trefler, 2008). This report finds a positive and significant correlation between the offshoring of inputs and the level of employment of routine-intensive workers, particularly in manufacturing industries. Such a relationship is consistent with the specialisation of manufacturing firms in specific stages of the value chain: as they import more inputs that are further processed, they also rely relatively more on routine-intensive jobs. The inability of earlier studies to accurately disentangle input and output-related value added flows and the use of routine intensity measures based on both the skill and task components of occupations - two shortcomings that the TiVA and PIAAC databases allow to overcome when constructing the RII index - may contribute to explain the observed differences with previous analysis.

- The relationship between offshoring and employment seems to be related to the specialisation of countries: different results emerge for large and more mature "service-based" economies on the one hand and for European catching-up and transition economies, on the other hand. The latter are gaining employment in medium and high routine-intensive occupations, while the former experience more labour demand in non-routine occupations. While a more open trade regime might have facilitated such specialisation, this does not imply that trade policy may be able to reverse (some of) these trends, as they appear to be explained by more profound determinants, including the skill distribution of the workforce, technology endowment, innovation capabilities and industry structure.

- Manufacturing industries, which have been sourcing an ever greater share of their intermediate inputs from service industries during the period considered, see employment being negatively affected, especially in relatively highly routinisable jobs. Examples of high-routine activities which can be sourced from the service sectors are cleaning and accounting services. This, however, does not need to entail a net loss of employment for the economy as a whole, as lower manufacturing employment may be compensated by higher employment in the services industries from which such services are sourced. This ever-greater level of integration between firms in the same sector and across manufacturing and service industries needs being taken into account when designing effective industrial policies. The progressive "servitisation" of economies may in fact constitute an opportunity, e.g. for important productivity gains, but can also expose agents to challenges driven by, for example, the co-integration of the business cycle of services and manufacturing, and by services becoming indirectly more tradable through manufacturing production.

- Technological innovation matters and positively affects employment across all routine intensity quartiles. The stronger competitiveness that technological innovation may confer to companies, especially in manufacturing, seemingly translates into higher employment levels, and generally more so in the case of non-routine and low routine intensive occupations. This argues in favour of policies supporting investment in innovation-related activities, and calls for the need to design broad-based innovation policies able to foster productivity, growth and well-being (OECD, 2015).
- Additionally, the role played by ICTs and skills confirms the relevance of policies targeting skills and education when it comes to comparative advantages. A clear relationship emerges between the skill level of the workforce as well as ICT-related capabilities and innovation, and labour demand across quartiles of routine-intensity. ICT-related capabilities appear to be positively correlated with employment levels in all quartiles but the high-routine one, whereas high skills play a different role in manufacturing and services industries, depending on the proxy used to measure skill intensity. While it is unlikely that any policy may influence the routine-intensity of occupations, targeted skill policies, also and especially related to ICT capabilities, can help foster employment within and across countries, including in cases where offshoring leads to a workforce re-allocation that negatively impacts a given quartile.
- The results point to the possible existence of economies of scales and competition-related effects, whereby the number of firms and the proportion of big firms in an industry affect employment levels. The number of firms correlates negatively with employment levels in the overall sample, whereas the proportion of big firms is seemingly conducive to higher employment, especially in manufacturing. These relationships, which only affect selected quartiles of employment in service industries, point to the need of tailoring industrial policies depending on whether manufacturing or services industries are targeted, as the routine content of occupations differs importantly across industries (especially in high-routine occupations). Also, policies affecting firm creation and scaling up processes would need to be carefully designed, as they may shape employment in opposite directions, depending on the occupation(s) and industry(ies) targeted. For instance, in manufacturing the presence of big firms correlates positively with higher employment of routine workers, whereas it does not in the case of services. Hence, scaling up policies might have differential effects on aggregate employment levels depending on the structure of the economy and on whether manufacturing or services enterprises are targeted.
- The analysis emphasises the need for tailoring policies targeting industries, skill levels or regions, as results may differ depending on the routine content of occupations, thus posing new challenges to actions aimed at addressing the displacement of workers within and across industries. More generally, the increased level of competition and re-allocation of resources between firms within each industry and across industries and countries might have non-neutral consequences for employment. This underscores the need for well-functioning labour markets and appropriate labour market policies, able to strike the right balance between employment flexibility and aggregate welfare and to smooth the reallocation of the labour force according to the patterns of production and of trade in value added. Moreover, labour market policies need to be coupled with trade, industry and innovation and competition policies, creating the right business environment in a GVCs context.

Background

Over the past decades, the world has witnessed an ever growing movement of capital, intermediate inputs, final goods and people. Technological progress especially in transportation (i.e. containerisation) and information and communication technologies, alongside trade liberalisation in the form of reduction and elimination of tariffs and non-tariff barriers, have led to two seemingly antithetical phenomena: the fragmentation of production and greater economic integration.

Production has become functionally and geographically unbundled. Different goods and services, as well as their components, get simultaneously or sequentially[1] produced and assembled in different locations, often geographically clustered at the local and regional level (Baldwin, 2012), before reaching their target markets. Specialisation gains, co-ordination costs, as well as dispersion and agglomeration forces all contribute to shape production patterns. Such production patterns are generally termed "global supply chains" (GSC) in analysis focusing on the series of activities (i.e. stages) of which production is composed, or on the material provision of goods and services in the production network. The wording "global value chains" (GVC) conversely tends to be preferred when emphasis is on identifying the sources and quantifying the amount of value added generated over the production chain (see Baldwin and Lopez Gonzales, 2013, about the emergence and evolution of GSCs) and is consequently the term used in most of the OECD work (OECD, 2013).

At the same time as production gets articulated into a wide array of horizontal, vertical and mixed settings (see Santos-Paulino et al., 2008, for a discussion), the growing mobility of physical, financial and human capital, as well as of knowledge based assets, makes countries and regions progressively more economically integrated. While this interconnectedness may facilitate the propagation of shocks, it may on the other hand enable the redistribution of risks, allow economic agents to maximally profit from their comparative advantages and enhance the performance of countries' production systems. The channels through which trade may impact industry dynamics, economic growth and aggregate welfare range from the simple reduction of costs, to the selection of the most productive producers, and to improvements in the quality and technological content of the inputs used in the production process (Arkolakis et al., 2008; Arkolakis et al., 2010).

Indicators accounting for gross trade flows, their direction and size, have traditionally been used to assess the degree of interconnectedness of economies (Head and Mayer, 2004), and to mirror participation in global supply chains. Such indicators, however, remain silent about the extent to which value added and income are produced at home or abroad and about the use of and the returns to the different inputs of production, at either industry or country level. This makes it difficult to properly identify the contribution of trade to economic performance and societal well-being, and to provide policy makers with an accurate picture of economies' positioning along GVCs.

Indicators derived from the OECD-WTO Trade in Value Added (TiVA) database, and the Inter-Country Input-Output (ICIO) infrastructure that underpins it, have revealed the extent to which gross flow patterns differ from the sources and distribution of value added. They further highlight the increasing percentage of value added and gross trade that can be traced back to the value added of inputs produced domestically or abroad, and the heterogeneity and complexity of such flows. The increasing reliance of production for domestic or international consumption on intermediate inputs produced elsewhere stresses the importance for countries to position themselves in a way that allows them to exploit their comparative advantages and to benefit from GVCs.

1. Economic models generally assume production to happen in a sequential fashion. See, for example, Antràs and Chor's (2013) property rights-based model and Costinot et al.'s (2013) theoretical approach to GSCs.

While opening up new opportunities, participation in global markets nevertheless exposes economic agents to fierce competitive pressures and to structural changes. The way goods and services are produced across borders gets naturally reflected in the structure of labour markets. The relationship between international trade and the job market thus needs to be revisited in light of the pervasiveness of GVCs. Box 1 highlights some of the recent literature in this area.

Box 1. The relationship between trade in value added, skills and employment in the literature

A number of contributions have aimed to assess the impact of participation in trade on employment and wages (see e.g. Shepherd, 2013, and Wagner, 2012, for recent reviews and OECD 2012 for analytical work on trade and labour market outcomes). However, no true consensus has been reached on the direction of causality and the mechanisms at stake. The possibility to adjust labour markets to changes in trade and in the ownership, structure and boundaries of firms - including multinational enterprises – has been found to depend on a variety of factors. These range from the form of integration in the global economy, i.e. Foreign Direct Investment (FDI), offshore outsourcing, and international trade (see Rilla and Squicciarini, 2011, for a taxonomy); to other firms' characteristics (see Almeida, 2007, about ownership, and Egger and Kreickemeier, 2008, about wages); and the institutional setting of the country, in particular labour search frictions (Helpman and Itskhoki, 2010; Helpman et al., 2011). Also, it remains to be assessed whether the ambiguous evidence of the impact of higher engagement in international markets on wages and employment remains once looking at the context of global value chains in particular (Lopez-Gonzalez et al., 2015).

An important stream of research for labour market outcomes in the perspective of global value chains breaks trade down into its different production stages or 'tasks'. A task can be defined as "a discrete activity that needs to be accomplished within a defined period of time" (Lanz et al., 2013, p.196), and the distinction between tasks and intermediate inputs sometimes remains largely semantic (see Grossman and Rossi-Hansberg, 2008). Since each product may be the result of multiple tasks, a firm can be seen as an economic agent performing a number of actions and transactions, which can be carried out in-house or by external suppliers. A firm's competitive advantage or an industry's comparative advantage can therefore be defined in terms of the domestic (versus foreign) content of tasks. If the relative cost of carrying out certain tasks in house is higher than that of outsourcing (part of) them, the production process will likely be split across different producers and, possibly, countries, thus leading to (global) value chains. Many studies (e.g. Costinot et al., 2011; Blinder and Krueger, 2013) have investigated the characteristics of tasks which lend themselves to offshoring. An important determinant of offshorability has been found to be the degree of automation and codification of the tasks. Workers performing routinisable tasks are therefore likely to be more integrated in GVCs.

Evidence further suggests that high skilled workers tend to specialise in non-routine tasks, and that some low skill tasks can be complementary to high skill ones (e.g. cleaning services). As a consequence, understanding the link between offshoring and the industry skill distribution in a country is not straight-forward. Becker et al. 2013, for instance, show that an increase in the offshore employment share of an economy impacts wages differently depending on whether the measure of labour force characteristics is based on education, skill or the routine content of tasks. As analytical efforts move slowly away from gross trade flows to focus on trade in value added, changes in GVC positioning may correspond to changes in the skill content of the workforce.

The literature on employment in OECD economies has recently devoted much attention to the polarisation of jobs (Autor et al., 2006; Goos et al., 2009). The latter refers to the changes occurring in employment patterns whereby the share of occupations at both ends of the skill distribution (low-skilled and high-skilled jobs) increases, while employment in the middle of the distribution (mid-skilled jobs) declines. Technological change is generally held as one of the main factors behind this employment polarisation, as suggested by the literature on "skilled-biased technological change" (see, for example, Acemoglu, 2002; Autor et al., 2003). Information and Communication Technologies (ICT) have seemingly favoured non-routine tasks performed by high- and low-skilled workers, at the expense of routine tasks which are mainly performed by medium-skilled employees (Autor et al., 2003). Offshoring and the emergence of GVCs have also been found to play a role, as routine tasks have been increasingly offshored (Autor, 2010; Goos et al., 2014).

There is therefore a relationship between GVCs, trade, industry dynamics, and the routine and skill content of occupations that deserves to be more carefully studied, particularly in the context of the generation and distribution of value added, as captured in TiVA statistics. Policies aiming at fostering higher employment, better jobs and inclusive growth call for better evidence on the link between trade, skills and jobs and how this translates into the ability of economies to reap the benefits from their participation in GVCs.

A task based approach to measuring the routine content of occupations

This analysis addresses the relationship that exists between the routine intensity of occupations and trade in value-added (TiVA) patterns, and sheds light on the extent to which workforce skills, ICTs endowment and industry structure may shape such dynamics. To this end, it exploits newly proposed task-based measures of the routine content of occupations built on up-to-date, individual-level country-specific information contained in the OECD Programme for the International Assessment of Adult Competencies (PIAAC) database (see Marcolin et al., forthcoming, for details).

Routine tasks can be broadly defined as tasks that are accomplished following a set of specific and well-defined rules, whereas non-routine tasks typically entail performing more complicated activities, as creative problem solving and decision making (see Oldenski, 2012, for a discussion). As such, routine intensive tasks are not necessarily characterised by repetitive actions to be carried out in a short time span, but rather by actions that can be clearly identified and that follow pre-defined patterns. Routine intensive occupations are thus intended as occupations that are more intensive in the routine content of the tasks performed on the job.

Finding the right metric for the identification of the routine content of tasks is challenging. Previous studies have often relied on classifications linking occupations to sets of tasks and skills in a given country. These classifications are often based on the judgement of experts assigning scores to different indicators characterising the occupations. This is very different from asking individuals about the real content of their daily work. The methodology described in Marcolin et al. (forthcoming) moves away from ad-hoc choices in the selection of the features characterising the routine intensity of tasks with the aim to produces less arbitrary and more precise proxies for the latent unobserved phenomenon, i.e. the extent to which occupations are more or less routine intense.[2]

The new routine intensity index (RII) proposed is constructed using responses to four PIAAC questions providing information related to individuals' own assessment of:

- their degree of freedom in establishing the sequence of their tasks (*Sequentiability*)
- their degree of freedom in deciding the type of tasks to be performed on the job (*Flexibility*)
- the frequency with which they plan their own activities (*Plan_own*)
- the frequency with which they organise their own time (*Organise_own*).

These questions are chosen consistently with the stated definition of routine tasks as a set of codifiable, and hence sequentiable, actions. This is similar to what done by Oldenski (2012), who argue for the existence of a strict connection between autonomy on the jobs and routine intensity: a routine intensive job, in virtue of its codifiability, implies little autonomy for the employed individual at work.[3]

The approach followed in the construction of the RII differs from existing definitions of routine intensity, especially Autor et al.'s (2003) association of occupational features (i.e. skills and job requirements) to routine and non-routine tasks, and revises the importance of "finger dexterity" and "abstract reasoning" for the identification of routine intensive tasks.

2. The present approach may suffer from the bias derived by the subjective judgement of individuals about the nature of their jobs. As the questions used for the construction of the routine indicator cannot be found in other surveys or official databases, it is impossible to assess or net out such bias through external validation.

3. PIAAC does not explicitly ask for the degree of codifiability of the tasks performed by the surveyed individuals.

In Autor et al. (2003), “finger dexterity” identifies manual routine tasks, such as baking, special kinds of sewing, or packing of agricultural products. However, in the PIAAC survey occupations where individuals frequently require “finger dexterity” cannot be straight-forwardly identified as routinary, possibly also because of differences in what was meant by “finger dexterity” in the 1970s (as in Autor et al., 2003) and today, when finger dexterity seems to characterise manual jobs of a much higher value added such as arts and crafts.

Mathematical skills, which identify non-routine analytical tasks in Autor et al. (2003), are not taken into account in the new measures of routine content of occupations for two main reasons. The type of advanced mathematical skills tested in PIAAC do not seem to reflect the same flavour of sophisticated abstract reasoning captured by the “abstract non-routine” tasks in Autor et al. (2003). Moreover, anecdotal evidence suggests that even mathematically-intensive tasks can nowadays be codified and moved abroad, as it happens for instance with data mining. Hence, numerical proficiency, which may no longer be considered a good proxy for the routine content of tasks, is instead used to look at the skill content of occupations, i.e. a feature that is correlated with, but not perfectly mapping into, the routine content of occupations.

The RII can be calculated for occupations and sectors in an independent fashion and at fairly disaggregated levels (i.e. up to the three digit level of the 2008 International Standard Classification of Occupations, ISCO08, and of 4th revision of the International Standard Industrial Classification, ISIC4, respectively). It helps to group occupations into four routine-intensity classes, notably:

- non routine occupations (i.e. NR)
- low routine-intensive occupations (i.e. LR)
- medium routine-intensive occupations (i.e. MR)
- high routine-intensive occupations (i.e. HR).

This work departs from existing literature as it aims to assess the routine content of occupations purely on the basis of what workers do, i.e. the extent to which they may decide which tasks to carry out and the order to follow when doing so, irrespective of their educational level (i.e. whether owing a tertiary level education degree or not) and occupational title. In the absence of an *a priori* assumed positive relationship between skill endowment of the workforce and the routine content of occupations, this new methodology leads to identifying as non-routine (i.e. NR) workers belonging to ISCO08 class 613 “Mixed crop and animal producers”, who are generally classified as medium skilled workers, as well as a number of high-skilled workers including those in ISCO08 class 122, “Research and development managers”. In a similar fashion, a variety of skill levels is featured by high-routine occupations (i.e. HR): these range from high-skill occupations as ISCO08 class 321 “Medical imaging and therapeutic equipment technicians”, to medium-skill jobs as those in ISCO08 class 422 “Travel consultants and clerks”, to a number of low-skill occupations as e.g. ISCO08 class 931 “Mining and quarrying labourers”.

Also, it should be noticed that the proposed taxonomy of the routine content of occupations does not perfectly overlap with an automation concept and the consequent likelihood that workers might get displaced by machines. While this may at times be the case, for instance in relation to ISCO08 class 932 “Hand packers” where it is reasonable to imagine such a function to get fully automated in the future, it is surely not foreseeable in the case of ISCO08 class 541 “Security guards” or of ISCO08 class 532 “Home-based personal care workers”. The latter are both found to be routine intensive jobs, but the chance that they may get substituted by machines is slim, as they entail, among others, a high degree of interaction with the end user, the customer. A similar reasoning applies to occupations belonging to the central part of the routine distribution, i.e. those in LR and MR, and to the likelihood that they may get automated, irrespective of the skill level of the workforce. Examples of occupations which might be partially or totally displaced by further automation are ISCO08 class 331 “Securities and finance dealers and brokers", i.e. high-skill workers belonging to Q2, and ISCO08 class 732 "Printers", i.e. medium-skill jobs belonging to medium routine-intensive occupations.

The routine content of occupations: Data and some stylised facts

The PIAAC database contains information on the type of tasks that workers carry out on their job, as well as data about the workers themselves (e.g. gender, age), while guaranteeing maximal international comparability in terms of educational attainment, field of economic activity, and occupation. Educational attainment is measured according to the 1997 version of International Standard Classification of Education (ISCED1997), whereas industries are classified following the ISIC rev. 4 classification and occupations are defined according to the ISCO 2008 taxonomy.

In particular, PIAAC offers information on the individual's: employment status, employment sector; occupation; working hours; educational background; and a number of questions on skill use at work (OECD, 2013). The routine methodology is based on information related to individuals who are in employment, and for which their occupational title and industry of activity are known – including self-employed – in 22 OECD countries.[4] The sample is further reduced by excluding all individuals with missing information for at least one of the four variables of interest (*Sequentiability, Flexibility, Plan_own* and *Organise_own*), as these individuals would display a relatively low value of *Routine* due to the missing answer rather than because of the nature of their job and its routine intensity. The routine analysis therefore relies on the answers from a final sample of 105 526 PIAAC individuals, with the resulting sample containing information about 128 (ISCO2008) occupations in European countries present in PIAAC, and 127 occupations for the United States.

The mapping of 3-digit occupations into routine quartiles for the years 2011-2012 is then applied to national employment data sources available at the 2-digit sector and 3-digit occupation levels, to estimate the proportion of routine-intensive and non-routine jobs in 27 European countries and the United States.[5] When exploiting country-specific classifications, statistics for European countries for which PIAAC data are not available are based on the routine classification of the PIAAC-country that appears the most similar, in economic-structure terms. For instance, occupations in Luxembourg follow the same routine quartile classification of Belgium and the Netherlands, and Latvia and Lithuania the one obtained with Estonian data. When such an association of PIAAC and non-PIAAC countries is ambiguous (e.g. for Bulgaria), the classification based on pooled cross-country data is applied. As a consequence, the sample covered by this analysis is wider than the one covered by PIAAC, as far as European countries are concerned.

Information on national employment (employees and self-employed) at the 3 digit occupation and sector levels is taken from country-specific sources, in particular from the European Labour Force Surveys (EULFS) and the United States Occupational Employment Survey (OES). In an effort to exploit data sources which can be compared across country, the use of LFS-type data is preferred to Census-type information, when both are available. Microdata on employment have been accessed or aggregated at the three digit ISCO2008 and two digit ISIC4 levels. A conversion table is used to transform ISCO1988 occupational classes into ISCO2008 classes for the EULFS, NAICS sectors into

4. These are: Australia, Austria, Belgium, Canada, the Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, the United Kingdom, Ireland, Italy, Japan, Korea, the Netherlands, Norway, Poland, the Slovak Republic, Sweden and the United States. For Belgium, data refer to Flanders only; for the UK data refer to England and Northern Ireland only.

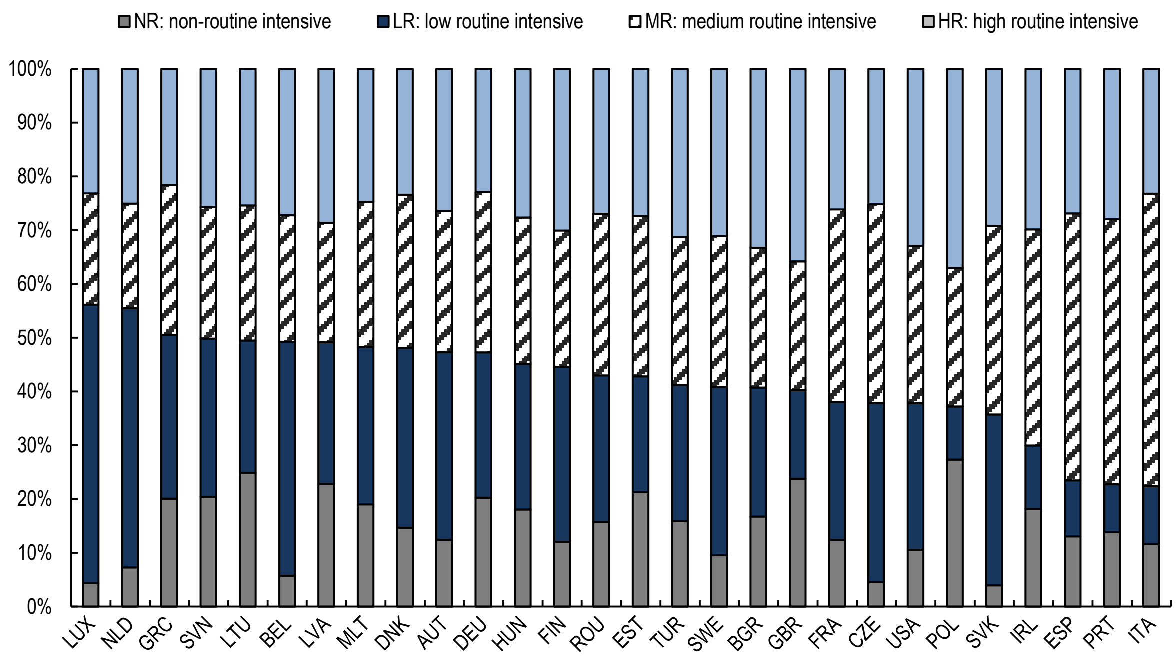
5. The European sample includes 26 Member States (Austria, Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, Malta, the Netherlands, Poland, Portugal, Romania the Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom) and Turkey. Croatia, Iceland, Norway and Switzerland were not included due to missing information in cost of employees by skill and in capital volumes for the considered time period and industry disaggregation level.

ISIC3 ones, and ISIC3 sectors into ISIC4 ones. The conversion of OES occupational classes into ISCO2008 classes relies a new mapping of SOC2010 into ISCO2008 occupations developed by Eckardt and Squicciarini (forthcoming). For a handful of other countries covered by the current wave of PIAAC (Australia, Canada, Japan, Korea), a classification of occupations in routine quartiles is available, but this could not be exploited to produce industry-level figures of employment by routine quartiles, due to the lack of employment data at the required industry and occupational disaggregation level at this stage.

Due to missing information for trade in value added (TiVA) variables, the sample covers the years 2000, 2005 and 2008 to 2011. Sourcing information for the number of firms by sector and size from the OECD Structural and Demographic Business Statistics (SDBS) Database further constraints the sample to exclude agriculture (ISIC3 sectors 01-05), public administration (sector 75), education (sector 80) and health and social work (sector 85).

As mentioned, the proposed classification of individuals in quartiles of routine intensity is based on 3-digit occupations, which should grant greater precision in the estimation of the exposure of employment to routinisation. By exploiting the matrix of employment by sector and occupation for each of the considered countries, it is possible to aggregate employment by routine quartile and sector. The distribution of employed individuals in the sample countries into quartiles of routine intensity is reported in Figure 1. A list of the used sector classification and the respective ISIC Rev.3 codes is reported in the Annex (Table A1).

Figure 1. Percentage of employment by quartile of routine intensity (average of 2000, 05, 08-11)



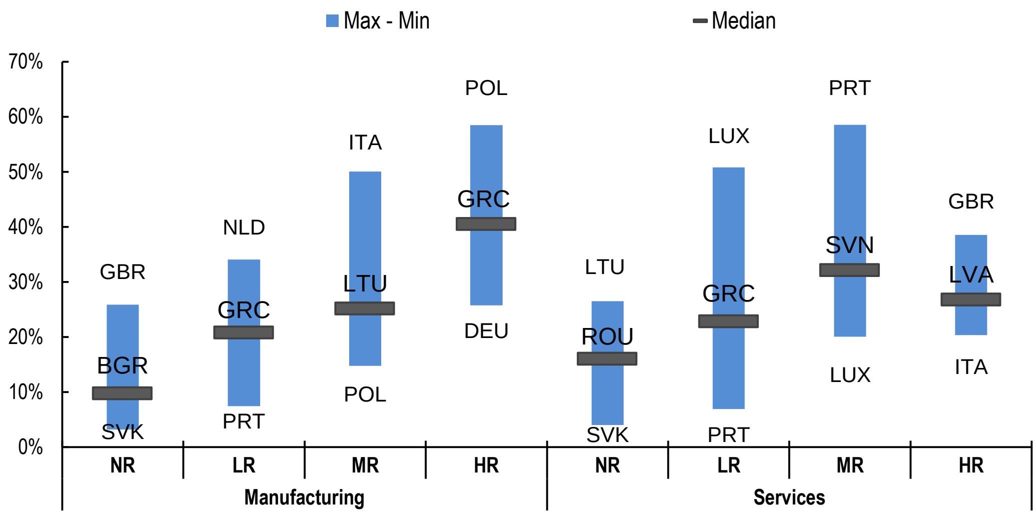
Source: Authors' own compilation based on PIAAC data, European Labour Force Survey and United States Occupational Employment Survey. Values by country, industry, year and quartile are first aggregated by country, quartile and year, then averaged across all years in the sample. The sample corresponds to the one used in the econometric analysis.

Across countries, important differences can be observed in the average proportion of employment accounted for by the occupations in the different routine intensity quartiles. The number of non-routine and low routine-intensive workers ranges between about 55% (in Luxembourg) and 20% (in Italy) during the years considered. Also, while the average share of workers employed in high routine-intensive occupations ranges between over 20% – 35% (in Greece and the United Kingdom, respectively) the proportion of workers belonging to occupations in the central part of the distribution – i.e. LR and MR – varies between about 70% (in many relatively smaller economies as Luxembourg and the Czech Republic) and about 35% (in Poland and the United Kingdom). These notable differences, which can be appreciated in Figure 1, mirror the extent to which economies vary along a number of structural features, including industry structure, innovative activities, the skill composition of the workforce and the extent to which economies participate in global value chains.

A high level of heterogeneity characterises employment by routine intensity when manufacturing and services industries are considered separately, the former including ISIC Rev.4 sectors 10 to 33, and 58, the latter ISIC Rev.4 sectors 41 to 82, and 95.[6] As can be seen from Figure 2 and detailed in Table 1, during the considered period, non-routine occupations accounted on average for 11% of employment in manufacturing and 15% in services, with economy-specific values that ranged between 4% (Luxembourg) and 26% (United Kingdom) in the case of manufacturing, and between 4% and 27%, in the Czech Republic and Lithuania respectively. Occupations in the middle of the routine intensity distribution, i.e. those belonging to LR and MR, accounted for 49% of manufacturing workers and 57% of services ones. The biggest difference can nevertheless be observed in terms of high-routine workers (HR), who accounted for an average 41% of employment in manufacturing and 28% in services industries.

Figure 2. Percentage of employment by quartile in manufacturing and services

Selected European countries and United States (average of 2000, 05, 08-11)



Source: Authors' own compilation based on PIAAC data, European Labour Force Survey and United States Occupational Employment Survey. Country-specific figures are reported in Table 1. Values by country, industry, and year are first aggregated by country, (macro-industry), quartile and year, then averaged across all years in the sample. The top of the bar displays the name of the economy mirroring the maximum value. The name above the median bar displays the name of the economy mirroring the median value. The name at the bottom of bar displays the name of the economy mirroring the minimum value.

6. This grouping, however, excludes community, social and personal services (ISIC Rev.4 sectors 59, 60, 90, 91, 92, 94 and 96) in light of their mixed public-private nature, and the willingness to be conservative in the presented results when distinguishing between services and manufacturing.

Table 1. Percentage of employment by quartile in total manufacturing and services employment

Selected European countries and United States (average of 2000, 05, 08-11)

	MANUFACTURING				SERVICES			
	Non Routine (NR)	Low Routine (LR)	Medium Routine (MR)	High Routine (HR)	Non Routine (NR)	Low Routine (LR)	Medium Routine (MR)	High Routine (HR)
AUT	11%	26%	28%	35%	11%	33%	28%	29%
BEL	5%	34%	21%	40%	8%	38%	25%	29%
BGR	10%	18%	21%	51%	17%	19%	33%	31%
CZE	4%	22%	35%	40%	4%	34%	40%	21%
DEU	18%	23%	34%	26%	20%	25%	30%	26%
DNK	15%	25%	29%	32%	16%	29%	34%	21%
ESP	6%	10%	42%	42%	13%	9%	52%	26%
EST	18%	18%	26%	39%	23%	17%	30%	30%
FIN	7%	31%	26%	35%	11%	30%	23%	36%
FRA	9%	19%	36%	36%	15%	25%	35%	26%
GBR	26%	17%	21%	36%	25%	15%	22%	39%
GRC	11%	21%	27%	41%	23%	23%	29%	25%
HUN	11%	22%	24%	42%	18%	22%	34%	26%
IRL	15%	9%	43%	33%	22%	10%	35%	33%
ITA	6%	10%	50%	34%	12%	10%	57%	20%
LTU	18%	16%	25%	41%	27%	17%	30%	26%
LUX	4%	34%	22%	41%	5%	51%	20%	24%
LVA	15%	17%	21%	46%	23%	22%	28%	27%
MLT	12%	27%	23%	38%	19%	22%	33%	25%
NLD	6%	34%	22%	39%	7%	42%	22%	29%
POL	16%	10%	15%	58%	20%	11%	35%	34%
PRT	6%	7%	41%	45%	13%	7%	59%	22%
ROU	10%	20%	24%	47%	16%	19%	36%	30%
SVK	3%	20%	30%	46%	4%	32%	40%	24%
SVN	14%	25%	17%	44%	21%	24%	32%	22%
SWE	5%	28%	27%	39%	9%	31%	26%	34%
TUR	8%	20%	22%	50%	16%	18%	32%	33%
USA	9%	23%	23%	45%	9%	24%	29%	38%
Average	11%	21%	28%	41%	15%	24%	33%	28%

Source: Authors' own compilation based on PIAAC data, European Labour Force Survey and United States Occupational Employment Survey. Values by country, industry, and year are first aggregated by country, (macro-industry), quartile and year, then averaged across all years in the sample. The sample corresponds to the one used in the econometric analysis.

Dividing the working population into two groups, i.e. between non-routine (NR and LR) and routine (MR and HR) occupations, also provides interesting information about the extent to which the distribution of employment varies across countries and industries. In manufacturing, non-routine occupations account for a share ranging between 14% (Portugal) and 43% (United Kingdom), whereas in services non-routine workers amount to 22% (in Italy and Spain) – 56% (in Luxembourg) of employment.

Routine intensity is likely to vary over time, for a number of reasons. These include technological and organisational change - and the consequent changes in the use of different occupational profiles that these might trigger, as well as changes in the type of tasks carried out on the job. In this work, changes over time of the routine indicator are only driven by changes in employment in the different occupations (and of occupations by sector), as data do not allow assessing the extent to which the routine content of occupations varies[7]. Similarly to what is done in existing studies, the routine content of occupations is held constant, and here reflects the values captured through PIAAC.

Figure 3 shows the employment patterns of routine occupations for the years 2000, 05, 08-11 for the United States, Europe and Turkey[8]. Routine employment is here defined as the sum of high- and medium-routine jobs. Trends are presented for the whole economy, the manufacturing and the service sectors, defined in the same way as in Figure 2 and Table 1. The top left panel of Figure 3 shows the trends for all countries; the top right one shows US only figures; the bottom left panel shows the employment patterns of routine occupations for the European countries for which data are available and for Turkey; and the bottom right panel shows the trends related to a subset of European economies, i.e. Eastern and Central-Eastern European countries, denoted as “transition countries”.

Manufacturing and services are again found to differ in their intensity in routine employment, with European countries displaying more routine intensive employment in manufacturing than in services, while the opposite holds true for the United States. In the United States it can also be observed a general decline of routine employment as a percentage of total employment, i.e. in the whole economy, as well as in manufacturing and services industries. This is also the case in European countries, but only until 2010, when the trends revert and the proportions of routine jobs increase again, especially in services. European “transition” countries[9] are found to be relatively more intensive in routine employment than the overall European sample, especially in manufacturing.

Existing studies suggest that high skilled workers tend to specialise in non-routine tasks. However, they also suggest that some low skill tasks can be complementary to high skill ones (e.g. cleaning services). Similarly, as mentioned, activities intensive in abstract reasoning may be exposed to the threat of offshoring nowadays too (e.g. data mining). As a consequence, understanding the link between routine intensity and the industry skill distribution in a country may be less than straight-forward. Becker et al. (2013), for instance, show that an increase in the offshore employment share of an economy impacts wages differently depending on whether the measure of labour force characteristics is based on education, skill or the routine content of tasks.

To shed light on these issues, a number of PIAAC skill-related variables have been correlated with the RII. These provide some descriptive elements on the relationship between the routine content of occupations and the skill level of the workforce. The measures of skill used capture the skill and the educational content of occupations in which the PIAAC individuals work, the skill use by individuals at work, and the skill endowment of the individuals themselves. Results shown in a companion paper (see Marcolin et al., forthcoming) suggest that the correlation between skill content and routine intensity is indeed negative, i.e. the more routine-intensive occupations tend to require lower level skills, but that this correlation is not necessarily very strong. As a consequence, highly skilled workers carrying out routine jobs could be affected by relocation and automation in a similar way as low skill routine workers routine could be.

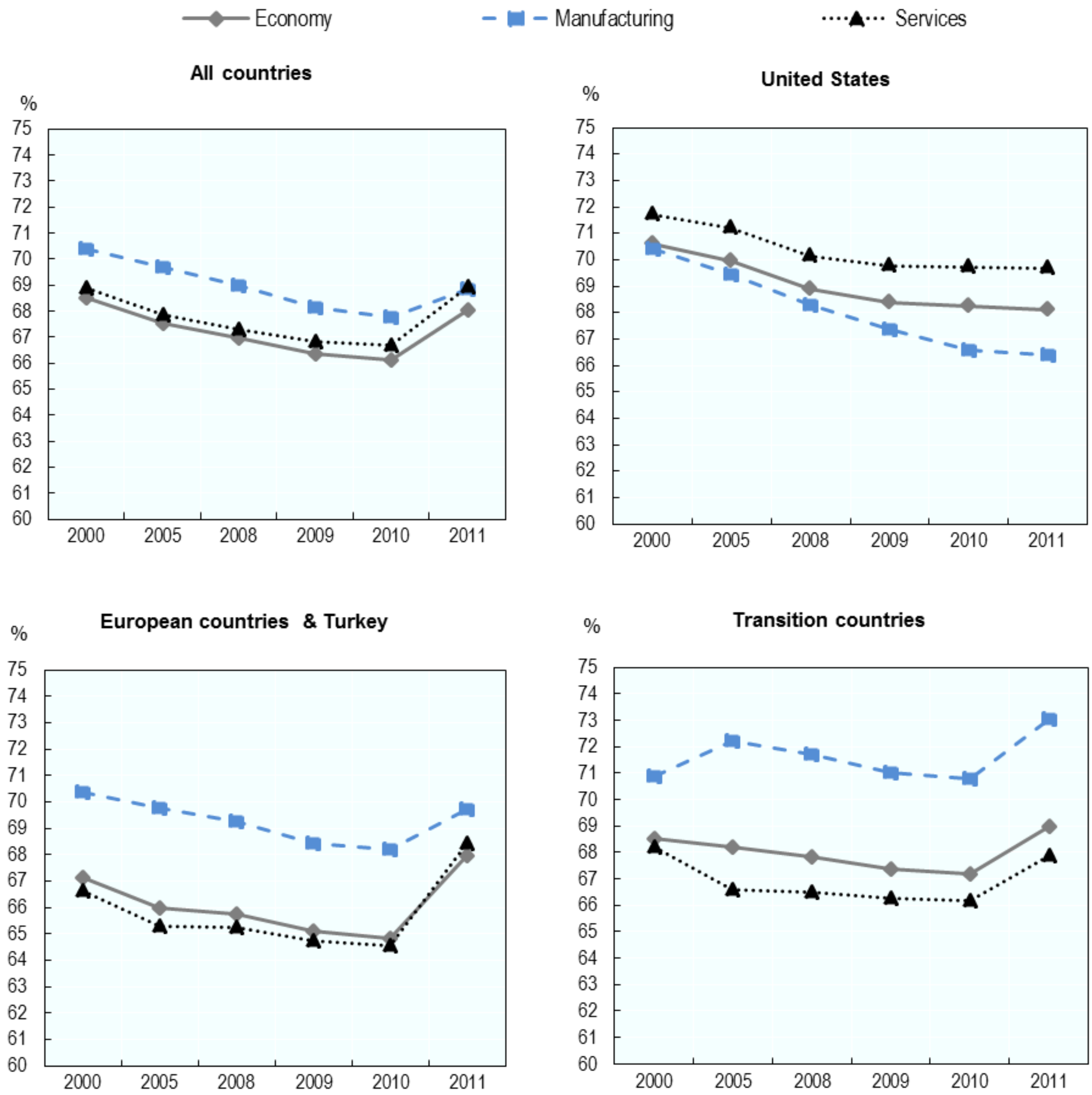
7. This shortcoming might be overcome once the next wave of the PIAAC data becomes available, as this should allow assessing the possible changes occurred in the routine content of occupations.

8. Aggregate yearly statistics are built as the sum of routine employment over the economies considered, divided by sum of total employment across the very same countries. This leads to having different results as compared to averaging country-specific proportions. As a consequence, figures are driven by employment dynamics in the more populated nations.

9. Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia.

Figure 3. Percentage of routine employment in manufacturing and services

Selected European countries and United States (2000, 05, 08-11)



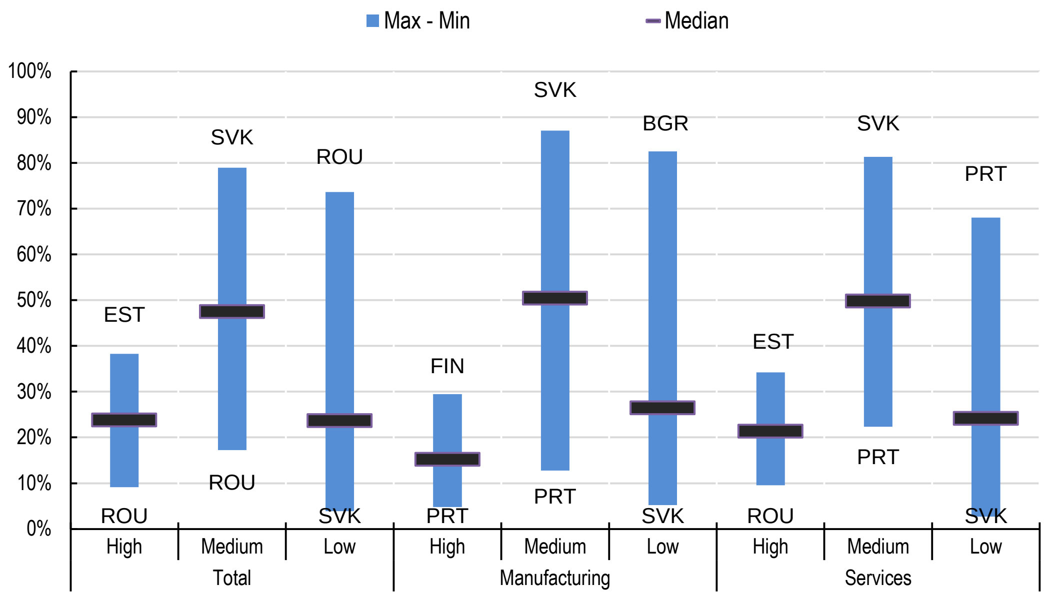
Note: Routine employment is defined as the sum of high- and medium-routine jobs, and is divided over total (aggregate) employment in the same geographical area. "European countries" include: Austria, Belgium, Bulgaria, the Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Iceland, Italy, Lithuania, Luxembourg, Latvia, Malta, the Netherlands, Poland, Portugal, Romania the Slovak Republic, Slovenia, Spain, Sweden and the United Kingdom. "Transition countries" refers to the Eastern and Central-Eastern European countries in the sample: Bulgaria, Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, Slovak Republic, and Slovenia.

Source: Authors' own compilation based on PIAAC data, European Labour Force Survey and United States Occupational Employment Survey.

In what follows, the analysis relies instead on a different approach and accounts for the skills of workers based on education categories, as reported in the World Input-Output Database (WIOD) Socio-Economic Accounts (Erumban et al., 2012).[10] Individuals are classified into high, medium and low-skill categories based on their 1-digit ISCED1997 educational attainment. Figure 4 displays minimum, median and maximum values in terms of percentage of hours worked by skill level in total economy, manufacturing and services. Table 2 details skill intensity at the country aggregate level (columns 2-4) and at the aggregate manufacturing (columns 5-7) and services (columns 8-10) level. Intensities are based on the number of hours worked by skill category in the industry.

Figure 4. Percentage of hours worked by skill level in total economy, manufacturing and services

Selected European countries and United States (2000, 05, 08-11)



Source: Authors' own compilation based on PIAAC data, European Labour Force Survey and United States Occupational Employment Survey. Country-specific figures are reported in Table 2. The top of the bar displays the name of the economy mirroring the maximum value. The name above the median bar displays the name of the economy mirroring the median value. The name at the bottom of bar displays the name of the economy mirroring the minimum value.

An unweighted average of country-specific values shows that the considered sample is mostly composed by medium-skill hours worked (49%) and slightly more intensive in low-skill (28%) rather than high-skill (23%) hours worked. This is especially the case for manufacturing (33% vs 16% of total hours worked in the sector). However, country specificities remain, with a marked importance of high skill intensity in manufacturing for Finland (30% of manufacturing hours on average across the considered years) and in services for Estonia (34%), and notably high proportions of low-skill hours in Portugal for both manufacturing and services (82% and 68%, respectively). Countries differ especially in their intensity of low-skill employment (as measured by the coefficient of variation across country

10. The choice is constrained by current data availability of cost of employees by skill level, which is needed in the econometric analysis and is sourced from the WIOD Socio-Economic Accounts at this stage. Furthermore, this guarantees a higher degree of comparison of the presented results with existing studies.

values), both in manufacturing and services, while dispersion is higher for manufacturing than for services when high- and medium-skill intensities are considered.

Table 2. Percentage of hours worked by skill level, in total manufacturing and services employment

Selected European countries and United States (2000, 05, 08-11)

	TOTAL			MANUFACTURING			SERVICES		
	HIGH	MEDIUM	LOW	HIGH	MEDIUM	LOW	HIGH	MEDIUM	LOW
AUT	16%	67%	18%	14%	67%	19%	14%	69%	17%
BEL	18%	59%	23%	15%	58%	27%	18%	59%	24%
BGR	11%	20%	70%	5%	13%	82%	11%	24%	65%
CZE	16%	79%	6%	7%	84%	9%	16%	80%	5%
DEU	24%	61%	15%	22%	61%	17%	21%	63%	16%
DNK	29%	47%	24%	24%	49%	27%	23%	50%	27%
ESP	31%	24%	45%	26%	20%	54%	29%	26%	45%
EST	38%	53%	8%	25%	64%	11%	34%	57%	9%
FIN	33%	47%	20%	30%	51%	19%	30%	49%	21%
FRA	30%	45%	25%	23%	49%	28%	29%	46%	25%
GBR	26%	48%	26%	26%	48%	26%	24%	49%	27%
GRC	23%	44%	32%	14%	43%	43%	22%	49%	29%
HUN	19%	67%	13%	11%	70%	19%	18%	72%	10%
IRL	25%	44%	31%	25%	44%	31%	26%	45%	30%
ITA	15%	46%	39%	7%	45%	48%	13%	48%	38%
LTU	33%	60%	7%	21%	72%	7%	33%	62%	5%
LUX	29%	43%	28%	17%	50%	33%	27%	43%	30%
LVA	27%	63%	9%	17%	68%	15%	25%	66%	9%
MLT	14%	24%	62%	6%	15%	79%	12%	25%	62%
NLD	30%	43%	28%	20%	44%	35%	28%	43%	30%
POL	16%	74%	10%	12%	80%	8%	18%	77%	5%
PRT	11%	19%	70%	5%	13%	82%	10%	22%	68%
ROU	9%	17%	74%	6%	14%	81%	10%	24%	66%
SVK	17%	79%	4%	8%	87%	5%	16%	81%	3%
SVN	21%	66%	13%	13%	65%	22%	20%	72%	7%
SWE	26%	57%	17%	16%	64%	21%	22%	60%	18%
TUR	13%	26%	62%	8%	27%	65%	12%	30%	58%
USA	28%	63%	9%	24%	63%	12%	27%	64%	9%
Average	23%	49%	28%	16%	51%	33%	21%	52%	27%

Source: Authors' own compilation based on WIOD data, European Labour Force Survey and United States Occupational Employment Survey. Values by country, industry, and year are first aggregated by country, (macro-industry) and year, then averaged across all years in the sample. The sample corresponds to the one used in the econometric analysis.

Offshoring and the value added content of trade

Analysis of the extent to which employment in occupations that differ in their routine intensity is shaped by offshoring and participation in GVCs requires new metrics, able to account for value added patterns and not only for gross trade flows. While offshoring is often perceived as a threat to domestic employment, it is through global sourcing that companies increase their productivity and the income of their workers. Offshoring, which is central in the rise and expansion of GVCs, can be defined as the unbundling of some activities in the firm's value chain and their relocation abroad in order to exploit cost opportunities or other types of location-specific advantages. An activity which is offshored can either remain in the boundaries of the firm (e.g. through the creation of an affiliate abroad) or be outsourced to an independent company (offshore outsourcing).

Offshoring is ideally measured at the level of the firm, where it is possible to identify the unbundling of the activity and its relocation in a different country. The phenomenon is more difficult to assess at the aggregate level where one can observe the activities performed abroad but not necessarily the fact that they were previously carried out in the domestic economy. Nevertheless, various measures of offshoring have been developed at the aggregate or industry-level, relying in particular on trade statistics. The most commonly used was first proposed by Feenstra and Hanson (1996) and is based on the share of imported intermediate inputs in total purchases of industries. Imports of intermediate goods (generally excluding energy inputs) can be derived from trade statistics and the information found in input-output tables. The latter also provide information on the purchases of industries.

Such an offshoring index has three types of limitations. First, in the absence of information on imported intermediate services, the measure can only cover material offshoring. Second, a proportionality assumption is generally applied to identify imported inputs whereby the share of inputs imported by each industry, relative to its total demand, is the same as the economy-wide imports relative to total demand (Feenstra and Jensen, 2012). Lastly, the measure looks at imported inputs and cannot capture the relocation of final assembly activities which are prevalent in some GVCs (Milberg and Winkler, 2010). Also, the technological and skill content of offshored inputs and final goods can significantly differ depending on the country of origin of the goods, and this may in turn imply a different degree of substitutability with employment. The above-mentioned GVC indicators have therefore been calculated distinguishing between offshoring to high and to low-medium income countries.

In order to address these issues, this report relies on new offshoring indicators derived from the OECD Inter-Country Input-Output (ICIO) tables that are used to create the OECD-WTO Trade in Value Added (TiVA) database[11]. In this global input-output framework, information on both goods and services traded is available, either as inputs or as final products. The proportionality assumption is not fully relaxed, but trade in intermediate goods is estimated through the UN Broad Economic Categories (BEC) classification and therefore it is not assumed that industries are importing inputs in the same proportion as all products. Some additional TiVA indicators can also be used as proxies for the offshoring of final assembly in manufacturing industries.

New indicators based on the OECD ICIO and TiVA database

The June 2015 update of the OECD ICIO covers 61 countries, 34 industries and 7 years (1995, 2000, 2005 and all years between 2008 and 2011). Data are available for all the countries covered in the PIAAC survey. Constructing a global input-output table presents many challenges, and entails making a number of assumptions, as well as reconciling and balancing data. Due to lack of information on services trade, the data are generally weaker for services industries. However, the

11. Technical documentation for the construction of the OECD ICIO is available at http://oe.cd/tiva .

underlying input-output structure comes from national accounts and trade data are aligned with this framework thus providing more consistent measures of offshoring.[12]

Following Feenstra and Hanson (1999), one can distinguish between 'narrow' and 'broad' offshoring measures. Narrow offshoring considers only inputs from the same industry while broad offshoring includes inputs from all other industries (excluding energy inputs). As the objective is to identify activities that have been relocated abroad (and not just the imports of intermediates that were never produced in the domestic economy), narrow offshoring is expected to be closer to the targeted information. But firms are also outsourcing and offshoring activities that belong to a different industry. This is especially true for services offshoring, where services previously provided "in-house" (and accounted for, for example, in a manufacturing activity) become inputs from a different industry.

Using the OECD ICIO, two different offshoring indices are calculated. The first one is the original Feenstra and Hanson (1999) ratio of imported intermediate inputs to intermediate consumption for industry *k* in country *i*:

$$Input\_Offshoring_{ik} = \frac{\sum_{j;j\neq i} Z_{ijkk}}{\sum_j \sum_l Z_{ijkl}} \qquad (1)$$

where Z_{ijkl} is the matrix of intermediate consumption in the global input-output matrix reporting the intermediate consumption of industry *k* in country *i* for inputs produced by country *j* in industry *l*. The numerator excludes inputs from country *i* in order to consist only of imported intermediate inputs and takes only the inputs from the same industry (l = k), so that it identifies narrow offshoring. In the denominator, country *i*'s inputs are included as well as all sourcing industries in order to have the sum of all intermediate consumptions from industry *k*, which is equal to gross output minus value added in the input-output framework.

The extent to which industries rely on foreign inputs is shaped by a wide array factors, including the quality and the technological content embodied in the purchased inputs, the cost of the factors of production, the skills of the workforce and the routine content of the jobs needed. If the value added content of the offshored inputs translates into productivity gains for the industry, offshoring may free resources to employ more workers – most likely workers performing tasks offering the highest expected marginal return – thus affecting employment. Alternatively, foreign input may entail less employment in the home country, if a substitution effect dominates. As a consequence, the sign of the correlation between input offshoring and employment levels across occupations differing in their routine content is an empirical question. As offshored inputs sourced from developing and developed countries may imply different degrees of complementarity or substitutability with routine employment, in an extra specification *Input_Offshoring* is split between offshoring from high- vs offshoring from low- or medium-income countries, with income levels determined following the World Bank Atlas method.[13]

To complement this offshoring index, a second measure is introduced based on final consumption in country *i* of value added produced in country *j* embodied in final products exported from *j* to *i*:

12. To test for the robustness of the econometric results on a complete time series from 2000 to 2011, regressions were also run using indicators built on WIOD world input-output tables. WIOD provides yearly data for the period 1995-2011 for 40 countries and 35 industries. For more details on the WIOD database see Timmer et al. (2014). The econometric results are unaltered when using WIOD data.

13. Low income economies displayed a gross national income (GNI) per capita, calculated according to the World Bank Atlas Method, of USD 1 045 or less in 2014; middle-income economies a GNI per capita of more than USD 1 045 but less than USD 12,736; high-income economies a GNI per capita of USD 12 736 or more.

$$Offshoring\_final\_assembly_{ik} = \frac{\sum_{j;j\neq i} vBF_{ijkk}}{Final\_demand_{ik}} \quad (2)$$

where vBF_{ijkl} are imports of value-added from industry *l* in country *j* embodied in products of industry *k* consumed in country *i*. *vBF* is a matrix derived from the literature on trade in value-added (Johnson and Noguera, 2012) which is obtained by multiplying the value added vector of the global input-output matrix by the (global) Leontief inverse and by a vector of final demand in country *i*. It provides a full matrix of bilateral flows of value added between countries and industries in order to satisfy final demand in country *i*. By excluding flows of domestic value added in this matrix, one can calculate the foreign value added embodied in domestic final demand. Only value added from the same foreign industry is considered to obtain a narrow offshoring measure (summing across vBF_{ijkk}). As assembly is typically characterised by low value added, the offshoring of final assembly is likely to relate in a negative way with routine jobs in particular. The opposite might happen in case the typical final product of an industry is a high value added good or service (e.g. marketing). Also, it is possible that offshoring the last phases of production entails a reduction in the personnel devoted to control and coordination, which are non-routine jobs. Thus, the sign of link between employment across different quartiles of routine intensity and the offshoring of assembly is a priori ambiguous.

This second offshoring measure does not include the foreign inputs used by domestic firms but only the foreign value added coming through final products and originating in the same industry in the foreign country. It is still an imperfect proxy because it includes any foreign value added from this industry (coming through foreign final products) independently of any offshoring activity of the firms located in country *i*.

A domestic outsourcing index is added to the list of variables to be tested in the econometric analysis, in order to better understand whether outsourcing in the home country rather than offshoring has an impact on the demand for routine-intensive tasks. The outsourcing measure is the domestic share of intermediate consumption in gross output:

$$Domestic\_Outsourcing_{ik} = \frac{\sum_j \sum_l Z_{ijkl}}{Y_{ik}} \quad (3)$$

where the numerator is the sum of domestic intermediate consumptions in industry k and $Y_{ik}$is gross output. The more companies outsource activities and buy inputs from firms in the domestic economy, the higher the level of domestic intermediate consumption relative to gross output. The relationship between domestic outsourcing and employment in occupations of different routine intensity is likely to reflect, among others, the degree of substitutability of workers across occupations, and the employment-creating efficiency gains obtained by outsourcing parts of the production process to economic agents which are specialised in a given task. As this indicator is restricted to sourcing of inputs from the same industry, overall employment may thus be positively affected simply because the jobs lost in some firms due to outsourcing are created again in other firms which are specialised in the outsourced tasks, i.e. because of the fragmentation of production itself. Finally, a variable accounting for the service content of manufacturing is added in the specification used to analyse employment patterns in manufacturing.

$$ServCont_{ik} = \frac{\sum_j \sum_s Z_{ijks}}{Y_{ik}} \quad (4)$$

where the numerator is the sum of domestic and foreign intermediate consumption made by industry *k* of all services industries *s* in any country *j* and $Y_{ik}$is gross output. The more manufacturing companies use services inputs, purchased both at home and abroad, the higher the services content of gross manufacturing output.

This variable tries to capture whether and to what extent the observed increasing content of services in manufacturing relates to employment patterns across quartiles of routine intensity. Recent studies suggest that manufacturing has been increasingly incorporating higher services inputs, and that the service content of manufacturing affects productivity and performance in GVCs (see e.g. Lodefalk, 2014, and Francois and Hoekman, 2011). While it is possible to distinguish domestic and foreign sourcing of services, the specification used here considers them together, as statistics suggests that foreign services still account for a minor share of outsourced services, and results would therefore mirror the domestic component anyway. If firms in manufacturing industries substitute in-house low-value added service tasks with purchased ones, for instance to reduce the firm's wage bill related to such services or to increase their quality, a higher service content of manufacturing may translate into a reduction of routine jobs especially. Conversely if firms purchase business services so as to reduce the degree of complexity of in-house production, such service outsourcing would impact non-routine employment too, and in particular managerial occupations (see, e.g., Berlingieri, 2015).

The model

Empirical specification and variables used

The role of offshoring, technology and skills in the demand for labour at different levels of routine-intensity is analysed estimating the model specified in (5). This specification is adapted from the framework presented in Berman et al. (1994) and Feenstra and Hanson (1996). In a short-run variable translog cost function (which assumes second-order differentiability), the operating cost of an industry is a function of the relative wage of the optimal skill mix in the industry, and of fixed and variable inputs. In the short-run both output and capital are semi-fixed, while employment by skill is a variable input in the production function. By minimising the cost function according to factor prices, one can express the cost share for each factor in total costs as a function of the relative price of inputs and the quantities of inputs and output. Further determinants of factor cost shares can be searched for in any variable affecting costs and production (Feenstra and Hanson, 2001).

Existing studies have proposed several determinants of the changes in the labour demand (more precisely, demand shifters), related to both global value chains and technology (e.g. Hijzen et al., 2005; Michaels et al., 2014). The present paper adapts the specification of Berman et al. (1994) and Feenstra and Hanson (1996) by looking at factor use, rather than cost shares, and quartiles of routine rather than skill intensity. This reflects the assumption that employment by routine quartile is a variable input in the production function, too. The model is estimated with Zellner's (1962, 1963) 'Seemingly Unrelated Regressions' (SUR) as we expect the equation errors to be correlated[14] and is specified as:

$$Ln\left(N_{q,i,k,t}\right) = \beta_0 + \beta_1 Ln\left(VA_{i,k,t}\right) + \beta_2 Ln\left(CAP_{i,k,t}\right) + \beta_3 Ln\left(WAGE_{i,k,t}\right) + \beta_4 WAGEDIFF_{i,k,t} + \beta_5 Ln\left(H_{i,k,t}\right) + \beta_6 H\_hs_{i,k,t} + \beta_7 \ln(NF_{i,k,t}) + \beta_8 NF\_LARGE_{i,k,t} + \beta_9 TECH_{i,k,t} + \varphi_i + \gamma_k + \theta_t + \varepsilon_{q,i,k,t} \quad (5)$$

where $Ln\left(N_{q,i,k,t}\right)$ is the log of employment in country *i* and industry *k* at year *t* in the four quartiles of routine-intensity previously described (i.e. NR, LR, MR, HR). The main variables explaining the level of employment in the different routine-intensive quartiles are:[15]

- Value-added ($VA_{i,k,t}$): the higher the level of output and of value-added in the industry, the higher the employment. This variable implies that the rest of the model is estimated for a given level of output.
- Capital ($CAP_{i,k,t}$): the demand for labour is affected by capital in the industry, either through a substitution effect (e.g. more capital is used instead of workers) or in a complementary relationship (e.g. more capital is needed in association with additional workers). Two variables are alternatively used to measure capital: real fixed assets (the stock of capital) or gross fixed

14. The results of estimating equation (5) on the sample of all countries and industries are reported in Table 3.

15. Table A2 in the Annex provides a more comprehensive description of each variable and how they were constructed. Summary statistics are also presented in Table A3.

capital formation (capital flows), to investigate whether the flow and the stock of capital play a different role.

- Wage ($WAGE_{i,k,t}$): the higher the wage in the industry, the lower employment should be, if a cost effect dominates. Wages corresponds to average wages in the corresponding industries and are calculated dividing labour compensation by the number of workers.
- Wage difference ($WAGEDIFF_{i,k,t}$): a variable relating the wage of high-skilled workers to the average wage. It indicates how dispersed are wages in a given industry and is used to investigate the possible existence of skill premia.
- Total hours worked ($H_{i,k,t}$): the number of hours worked controls for the overall level of employment and allows interpreting the results as the impact of each variable on the relative employment in each quartile. A positive sign is expected for this variable since more hours worked should imply more employment.
- Ratio of hours worked by high-skilled workers ($H\_HS_{i,k,t}$): as done in the case of wages, this variable aims to verify whether the proportion of high-skill work in the total number of hours worked relates to employment in each routine-intensity quartile. The baseline estimator, included in all regressions, measures the intensity in high skills in the industry as the number of hours worked by employees with upper-secondary and tertiary education over total hours worked in the sector. In an extra specification (ref. Table 6), this is substituted by the ratio between the number of workers employed in the quartile of routine intensity in high-skilled occupations according to the ILO (2012) definition, and the total number of workers employed in high-skilled occupations, always in a given sector.
- Number of firms ($\ln(NF_{i,k,t})$): This variable is included to control for the structure of the industry and the degree of competition, as the higher the number of firms in an industry, the likely more contestable the market.
- Relative number of large firms ($NF\_LARGE_{i,k,t}$): control variable also aiming to capture some industry specificities and to account for industry-specific firm heterogeneity. Data availability constraints at the two-digit sector level currently hinder using widely adopted measures as concentration ratios or the Herfindahl index - to be possibly considered in future work.
- Technology ($TECH_{i,k,t}$): variable aiming to capture the role of technology and innovation, and especially of ICT-related technologies, in explaining the distribution of employment across quartiles of routine-intensity. The specification used here is one of ICT-intensity, measured as the proportion of ICT-related employment in the industry. More precisely, it is constructed as the proportion of workers employed in the business functions “ICT services” and “Engineering and related technical services” in a given industry, over total industry employment. This is obtained summing EULFS and US CPS employment operating in the occupations classified in these business functions, for each sector.
  - The mapping of ISCO88/ISCO08 occupations into business functions is sourced from Miroudot (2015). An employment-based measure is preferred over ICT capital intensity for two main reasons. First, it can be argued that the number of workers devoted to ICT and engineering-intensive tasks is a better proxy for the company-specific use of ICT and, more broadly, technology-related activities than the value of ICT equipment that companies may be endowed with, as the latter may only partially be exploited. Second, estimates of ICT capital at the two digit sectoral level from National Accounts are available only for a limited number of countries covered in the present analysis. Nevertheless, in a robustness specification, the impact of ICT gross fixed capital formation is tested (see Table A2 for more information on the country and industry coverage).

- For manufacturing industries, a measure based on the number of patent families is added as a second control for technological capabilities. Being an output measure of firms' inventive activities, the number of patents owned by firms in a given industry may better capture the technological content of the production and the innovativeness of the sector. While other proxies of the technological content of the production can be used, as e.g. R&D, the choice made in this study is driven by a number of considerations. Among them, the fact that R&D is an investment measure, whereas patents mirror output (see e.g. Griliches, 1990); and the fact that R&D expenditure encompasses labour costs as well - which are already captured through other measures.
    - A first indicator (*Number of Patents*) is constructed as the number of patent families filed at the five largest Intellectual Property Offices (IPOs) worldwide, the so-called "IP5", which handle 80% of the world's patent applications (see Dernis et al., 2015, for details about the definition and the construction of IP5 families). Patents are allocated to industries using a conversion from patent classes (IPC) to sectoral classes (NACE) derived from Van Looy et al. (2014). While relying on such a correspondence does not represent a first best approach, as it is mainly valid for manufacturing and thus hinders the use of patent data in the services-related analysis, it nevertheless allows allocating patent filings for all countries considered in the analysis. A more robust approach, which is also pursued in the present work and leads to a second indicator called *Number of Patents (Matched*), entails matching patents to firms on the basis of companies' names and patent assignees' data, and then grouping patents on the basis of the main sector of activity where firms operate (see Squicciarini and Dernis, 2013, for details). While this procedure leads to more accurate results, as it provides information about all industries, it can only be implemented on countries for which firm-specific information is sufficiently good. This entails restricting the study to: Austria, Belgium, Canada, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, and the United States. For more details on the variable construction, see Table A2.
- In addition to the above variables, fixed effects for countries, industries and years are added in all specifications, to account for any unobserved time-invariant determinant. If institutions are time-invariant in the considered sample, their effect, too, is controlled for by country and industry fixed effects. In an extra specification (results not reported, but available upon request), the introduction of country-year dummies – to control for macroeconomic dynamics not captured by prices – does not alter the economic intuition of the results detailed below.

Table A2 in the Annex describes the variables used in the current version of this analysis, whereas their average value in the considered sample, and in the sample of manufacturing and services industries, is presented in Table A3. Differences between averages for services and manufacturing have been tested and found significant at the 1% level for all considered variables (F-test with unequal variances). Services kept in the sample invest more and produce more value added, but they are less capital intensive and less productive (in the sense of value added per hour), as well as less ICT intensive. This is the case despite their higher intensity in high skill (in terms of hours worked). The average hourly remuneration and the remuneration of an hour of work of high skill workers are lower in services than in manufacturing, too.[16] The average number of firms in the industry is higher and services offshore their inputs less frequently than manufacturing, but they do relatively more domestic outsourcing. A table of pairwise correlations among these variables is also reported in the Annex (Table A4). Most notably, both ICT intensity and the number of patents in the industry are positively correlated with the described offshoring and domestic outsourcing indexes.

16. Such differences may be driven by the exclusion of high value-added services as e.g. financial services.

First empirical results

The goodness of fit of the model, which is extremely high, likely depends on the key determinants of labour demand being included in the equation together with fixed effects controlling for most unobserved variables. All explanatory variables used in the empirical model have the expected signs and significance, with differences that are observed across quartiles of routine-intensity.

Value-added appears to be positively and significantly correlated with employment in all quartiles of routine intensity, with the magnitude of the coefficients suggesting that more output leads to more employment, and more markedly so the higher the routine-intensity of the workforce.

Table 3. Regression results for all countries and industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Quartile:	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**
Log(VA)	0.112***	0.103***	0.095***	0.145***	0.130***	0.171***	0.153***	0.196***
	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.015)
Log(GFCF)	0.046***	0.161***	0.133***	0.139***				
	(0.014)	(0.013)	(0.014)	(0.014)				
Log(Capital)					0.020**	0.064***	0.052***	0.071***
					(0.010)	(0.010)	(0.010)	(0.010)
ICT Intensity	0.500***	0.252**	0.261**	-1.028***	0.486***	0.169	0.179	-1.128***
	(0.122)	(0.111)	(0.114)	(0.114)	(0.122)	(0.113)	(0.115)	(0.115)
Log(Wage)	-0.166***	-0.172***	-0.193***	-0.253***	-0.176***	-0.217***	-0.232***	-0.287***
	(0.029)	(0.027)	(0.027)	(0.028)	(0.029)	(0.027)	(0.027)	(0.027)
Wage Diff	0.007***	0.004***	0.005***	0.008***	0.007***	0.004**	0.005***	0.008***
	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
Log(H)	0.503***	0.483***	0.525***	0.606***	0.504***	0.489***	0.532***	0.609***
	(0.016)	(0.015)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)	(0.015)
H_hs	0.017***	0.008***	0.007***	0.002**	0.017***	0.010***	0.009***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Log(NF)	-0.015**	-0.010*	-0.014**	-0.019***	-0.016**	-0.011*	-0.015**	-0.020***
	(0.007)	(0.006)	(0.006)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
NF_large	0.002*	0.003***	0.001	0.002**	0.002*	0.003***	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Observations	3,052	3,052	3,052	3,052	3,056	3,056	3,056	3,056
R-squared	0.949	0.956	0.962	0.959	0.949	0.955	0.961	0.958
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: The dependent variable is the logarithm of employment in the quartile of routine intensity, with NR= non-routine, LR=low routine intensity, MR=medium routine intensity, and HR = high routine intensity. "Wage diff" stands for the difference between average wage in the industry ("Wage") and the average wage of skilled workers in the industry; "Log(H)" stands for the (logarithm of the) number of hours worked in the industry, "H_hs" for the ratio between hours worked by skilled workers and total hours worked in the industry. "Log(NF)" stays for the (logarithm of the) number of firms operating in the industry, "NF_large" for the ratio between the number of large firms and the total number of firms operating in the industry. Robust standard errors are reported in parenthesis. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

The two capital variables show similar results when pooling all countries and industries as in Table 3, suggesting a robust complementary relationship between capital and labour across all quartiles of routine intensity, everything else held constant. Also, capital results in a stronger complementary relationship with the more routine-intensive occupations as suggested by the progressively bigger size of its coefficient for the more routine-intensive quartiles. This result holds whether capital is measured as a stock (real fixed assets) or as a flow (real GFCF).

Persistent and robust results also emerge with respect to the role of technology as a driver of employment for all routine quartiles but the bottom one. While the effect is generally decreasing in magnitude from NR to HR, it sometimes turns insignificantly different from zero for LR and MR (as in the case of services industries), and turns significant and negative in the case of high-routine occupations. ICT intensity therefore seems to have a polarising impact on employment depending on the routine intensity of jobs, with changes in the ICT intensity of industries being correlated with lower employment in routine-intensive jobs and higher employment in less routine ones.

With respect to wages and hours worked, results are persistent across all quartiles and support the hypotheses about higher average costs of labour (in the form of wages) leading to less employment, and increasing wages of skilled workers having a positive, albeit small, impact on the demand for labour across all quartiles. This suggests the possible existence of unobserved productivity gains, whereby high-skills workers increase returns in excess to their cost: i.e. although skilled workers are more costly, companies are willing to pay more to benefit from their skills, in all routine quartiles. A similar result holds true for skill intensity in the industry, when measured as the proportion of skilled hours in total hours worked. Increasing the overall hours worked leads to higher employment for all classes of workers, too. More variation in the estimated coefficients emerges whether looking at manufacturing and services industries separately.

The industry structure-related variables exhibit a generally negative coefficient in the case of the number of firms and a small positive coefficient for the relative number of large firms. This suggests that the presence of a higher number of firms for a given level of output may lead to diseconomies of scale and that the presence of a relatively higher number of big firms entails relatively higher levels of employment, especially so in more routine-intensive occupations in the case of manufacturing.

Results for manufacturing and services industries

The model specified in (5) is also estimated separately for manufacturing and services industries, adding the offshoring and outsourcing variables described in Section 3. The model thus becomes:

$$Ln(N_{q,i,k,t}) = \beta_0 + \beta_1 Ln(VA_{i,k,t}) + \beta_2 Ln(CAP_{i,k,t}) + \beta_3 Ln(WAGE_{i,k,t}) + \beta_4 WAGEDIFF_{i,k,t} + \beta_5 Ln(H_{i,k,t}) + \beta_6 H\_HS_{i,k,t} + \beta_7 Ln(NF_{i,k,t}) + \beta_8 NF\_LARGE_{i,k,t} + \beta_9 TECH_{i,k,t} + \beta_{10} GVC_{i,k,t} + \varphi_i + \gamma_k + \theta_t + \varepsilon_{q,i,k,t} \quad (6)$$

- In the estimation for manufacturing industries, $TECH_{i,k,t}$ corresponds to the ICT intensity and to the number of IP5 patent families. In addition to the offshoring of inputs and domestic outsourcing, a variable assessing the level of offshoring of final assembly activities is also added.
- For services, as the number of patents is not available for all industries[17]; technology is therefore only accounted for through the ICT intensity variable. Likewise, the offshoring of final assembly makes less sense and is not included.[18]

17. An extra specification in paragraph 7, however, estimates the relevance of patents in services, too. Such a specification exploits a different indicator for the number of patent families by industry, which is available for services but only for a restricted number of countries (*Number of Patents (Matched))*. In the interest of exploiting the largest available sample in the analysis, the baseline estimations do not use the matched indicator.

Results are presented in Table 4. Value added appears to always correlate positively with levels of employment in all routine quartiles. Capital investment, in the form of both flows (i.e. real GFCF) and stock (i.e. real fixed assets), is also positively correlated with manufacturing employment in all occupations, whereas the correlation is weaker for less routine occupations in services industries. Capital seems therefore complementary with all types of labour in manufacturing sectors, and with routine-intensive employment in both services and manufacturing, everything else held constant.

Technology

In manufacturing, the proportion of ICT-related workers exhibits a positive correlation with the level of non-routine employment and a negative one with high routine-intensive jobs, thus confirming the evidence obtained from the complete sample. It suggests that a relatively higher ICT intensity can substitute for part of the more routine jobs. The same is true also for services, where in addition no significant relationship emerges between ICT intensity and non-routine jobs. This points to the possible existence of a “reverse polarization” effect, whereby the tails of the distributions are negatively affected by an increase in ICT intensity, whereas jobs whose routine content is low and medium may benefit from ICT intensity in all industries considered. It should be highlighted, however, that such (reverse) polarisation is different from the polarisation described in previous studies, as it refers to the distribution of employment by routine intensity rather than by skill intensity.

Innovative output, as proxied by the number of IP5 patents filed by the companies in the industry, always exhibits a positive correlation with employment levels in manufacturing, across all quartiles.[19] This result goes in the same direction of recent analysis by Aghion et al. (2015) who find innovativeness, as measured by patents, to relate positively with the top income share and upward social mobility. The innovative output of firms in the industry seemingly benefit both the top and the bottom of the distribution of employment (by routine intensity), although the magnitude of the effect remains stronger for relatively less routine-intensive occupations. Multiple channels may justify such overall positive effects on employment across quartiles, including, but not exclusively: (i) the complementarity between innovation and other firm-specific capabilities, as in the case of R&D and production workers; (ii) knowledge spillovers within the industry; (iii) productivity improvements related to innovative output, which free up resources to hire workers in different sections of the production chain.

Input offshoring

For manufacturing industries, the offshoring of inputs has a positive and significant effect on high routine occupations (HR), but not on other quartiles. This result departs from the early literature on offshoring and the routine content of occupations, and supports recent work by Blinder and Krueger (2013) who argue that the correlation between routine content of occupations and the likelihood to be offshored is weak. This may be strengthened by the evidence reported in Table 5, which distinguishes between input offshoring to high vs low- and medium-income countries (columns 9 to 12 for manufacturing industries), whereby sourcing inputs from low- and medium-income countries positively impacts routine-intensive employment. This may be partially explained by the fact that, compared to previous studies, the present analysis does distinguish between skill intensity and routine intensity of occupations.

18. The omission of this variable that can be calculated for services industries as well does not alter the results. The variable is found significant but its interpretation is more complicated as there is no real offshoring of final assembly in the case of services. What is captured then is more the level of foreign competition for final services.

19. Although this relationship turns weaker or insignificantly different from zero for medium routine-intensive employment, depending on the control for capital endowment in the sector.

In the case of services, the impact of input offshoring is of a different nature. The most routine-intensive workers are not significantly impacted by offshoring, whereas MR and NR (although to a lesser extent) workers are. The positive coefficient for LR occupations may be explained by the fact that when inputs are offshored, services companies may decide to rely on slightly more routine-intensive jobs, although still above the median (i.e. LR). For instance, when bookkeeping functions are offshored, companies do not need accountants anymore, and may substitute (part of) them with administrative staff carrying out relatively more routine-intensive tasks, such as e.g. making sure that the necessary documents are sent and received on time, or reach the right persons and/or functions. These results are to some extent driven by the composition of the sample in terms of the countries sourcing the inputs from abroad, and the country from which inputs are sourced.

These patterns are further explored in Table 5, where it emerges that medium routine-intensive employment (MR) is strongly negatively affected in the G7 countries included in the study, the so called "G5 countries".[20] This might be explained by the fact that, possibly, in G5 countries offshorable jobs are likely to be less routine-intensive than in the overall sample, and thus an effect on MR rather than HR employment - albeit comparability is limited by differences in the sample size. Moreover, medium routine-intensive employment in services is negatively correlated with sourcing of inputs from low and medium-income countries, which are likely to display a lower technological content and therefore be a substitute, rather than a complement, to high routine employment.

Taken together, the patterns observed in the case of input offshoring seem to suggest that input offshoring pursues, among others, economies of scale, whereby a relatively higher number of routine-intensive workers are employed.

Domestic outsourcing

Turning to the domestic outsourcing variable, a positive and significant coefficient across all categories of routine-intensity in manufacturing industries emerges, although this effect is significantly different from zero for the most routine intensive jobs only (i.e. MR and HR). This positive effect is to be expected, as in the case of domestic outsourcing, activities stay in the domestic economy. Also, as could be expected, outsourcing nevertheless slightly modifies the composition of labour demand in terms of routine intensity, with outsourcing leading to relatively more jobs in routine-intensive occupations, which is what one would expect when production is fragmented and tasks are broken down across firms. The last point holds true for services as well. However, in the case of services, domestic outsourcing relates negatively to the less routine intensive jobs, and significantly so for LR (i.e. the same group that is positively affected by input offshoring). It suggests the following relationships between offshoring and domestic outsourcing: the more services companies rely on foreign inputs, the more they tend to substitute non-routine (NR) with low routine workers (LR). At the same time, domestic outsourcing partially sheds low routine-intensive jobs in favour of those which are more routine intensive, i.e. MR and HR.

Offshoring of final assembly

Offshoring of final assembly in manufacturing industries negatively impacts non-routine quartiles of employment in a significant manner. This suggests that when final assembly is offshored, not only occupations related to the production and core assembly (likely to be found in HR) are lost, but so are some supervision and support activities that involve the least routine-intensive workers. It is also consistent with a mode of production whereby R&D and production are complementary, so that when one (i.e. assembly of final stages of production) is offshored, employment in the other also decreases (as R&D occupations are non-routine). Table 5 complements this result by showing that non-routine jobs are negatively affected by offshoring of assembly in catching-up countries, but not in G5 countries.

20. They are: France, Germany, United Kingdom, Italy and the United States.

Service content of manufacturing

The service content of manufacturing, as proxied by the value of intermediate goods sourced from the service sectors as a percentage of output in a given manufacturing sector, in general negatively correlates with employment. The coefficient is significant and especially large for employment in high-routine occupations, across specifications. This negative relationship between service input outsourcing (either domestically or abroad) and high routine employment in manufacturing suggests the existence of some substitutability between high-routine employment and intermediate inputs provided by service industries to the manufacturing production process. Firms may be reducing their wage bill by externalising some of their high-routine in-house services to the sector which performs such services as core activity. This could be the case, for instance, for accounting or cleaning services. It should also be noticed that the highlighted negative correlation may not imply a net loss of employment in the economy, but rather a shift in the composition of employment between manufacturing and services in the same economy. Indeed a higher proportion of such service inputs in manufacturing are sourced domestically rather than abroad.

Further results about the service content of manufacturing (ref. Table A5 in the Annex) show that the negative correlation with high routine employment persists when the sample is restricted to transition countries, while this is not the case for G5 countries.[21] On the contrary, a higher service content of manufacturing polarises employment by routine intensity in G5 countries, as both high routine and non-routine jobs are positively affected by this sourcing strategy, while medium routine jobs are strongly negatively affected by it. [22]

Skills

The controls used to account for the effect that wage levels have on labour demand and on overall employment levels persistently and significantly exhibit the expected coefficients: for a given level of output, the more costly human resources are, the lower the demand; and the higher the number of hours worked, the more the workers employed.[23] For manufacturing, also the share of high skilled hours in total hours, and the difference between the average wage and the average wage of the high skilled keep the same sign as in the overall sample. In services, instead, differences in wages seemingly lead to a polarisation effect, whereby NR and HR workers get more demanded, and the demand for LR and MR jobs is unaffected. However, again, the coefficients observed are very small. The skill intensity in terms of hours worked plays a marginal role in affecting employment across quartiles in services.

21. This is not the case when the sample is split between G5 and transition economies in Table 5 (columns 1 to 8). However, these results are not comparable with the baseline, because, among others, they are based on the pooled sample of manufacturing and service industries. As both the proportion of inputs sourced from the service industries and the relationship between service input sourcing and employment differ between manufacturing and services, the reported estimates in columns 1 to 8 are not fully informative with respect to the link between service content of manufacturing and employment by routine intensity.

22. A separate set of regressions was estimated introducing one GVC indicator at a time. This approach has the advantage of identifying the relationship between each GVC indicator and employment, independently on industries' intensity in other GVC components. However, the correlations between GVC indicators shown in Table A4 suggest that the coefficient of single GVC indicators may suffer from omitted variable bias. The main estimations therefore prefer controlling for all GVC intensities of interest at the same time.

23. The variable “hours worked” reflects the total number of hours of work the industry has used in the production process and does not capture the average number of hours worked by an individual in a given industry. More hours worked and more employed workers therefore need not be negatively correlated.

Table 4. Regression results for manufacturing and services industries

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
				MANUFACTURING								SERVICES				
Quartile:	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**
Log(VA)	0.108***	0.116***	0.147***	0.117***	0.117***	0.147***	0.184***	0.145***	0.147***	0.171***	0.096**	0.328***	0.061	0.244***	0.113***	0.349***
	(0.019)	(0.018)	(0.020)	(0.018)	(0.018)	(0.017)	(0.018)	(0.017)	(0.048)	(0.049)	(0.045)	(0.045)	(0.046)	(0.048)	(0.043)	(0.043)
Log(GFCF)	0.071***	0.139***	0.153***	0.142***					-0.107***	0.149***	0.128***	0.124***				
	(0.018)	(0.017)	(0.018)	(0.017)					(0.027)	(0.028)	(0.026)	(0.026)				
Log(Capital)					0.060***	0.080***	0.078***	0.091***					0.038	0.041	0.130***	0.115***
					(0.012)	(0.011)	(0.012)	(0.011)					(0.024)	(0.025)	(0.023)	(0.022)
ICT Intensity	0.924***	0.465***	0.121	-0.918***	0.940***	0.479***	0.124	-0.925***	-0.142	0.773**	0.988***	-0.874**	-0.273	0.953**	1.140***	-0.726**
	(0.124)	(0.115)	(0.125)	(0.114)	(0.123)	(0.115)	(0.125)	(0.114)	(0.374)	(0.382)	(0.354)	(0.349)	(0.375)	(0.386)	(0.351)	(0.347)
Log(Number Patents)	0.065***	0.073***	0.020	0.037***	0.063***	0.075***	0.023*	0.036***								
	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)	(0.012)	(0.011)								
Input Offshoring	-0.132	-0.001	0.078	0.413***	-0.067	0.094	0.162	0.486***	-0.549*	0.674**	-1.203***	0.219	-0.592*	0.728**	-1.162***	0.259
	(0.145)	(0.135)	(0.146)	(0.134)	(0.144)	(0.134)	(0.146)	(0.133)	(0.329)	(0.337)	(0.312)	(0.307)	(0.331)	(0.342)	(0.310)	(0.307)
Domestic Outsourcing	0.224	0.120	0.516**	0.349*	0.222	0.136	0.544***	0.366**	-0.223	-1.001***	0.170	0.951***	-0.248	-1.056***	0.032	0.828***
	(0.201)	(0.187)	(0.202)	(0.185)	(0.201)	(0.187)	(0.204)	(0.185)	(0.232)	(0.237)	(0.220)	(0.216)	(0.234)	(0.242)	(0.219)	(0.217)
Offshoring Final Assembly	-0.680***	-0.260	0.208	-0.289	-0.576***	-0.175	0.265	-0.180								
	(0.220)	(0.204)	(0.221)	(0.202)	(0.221)	(0.207)	(0.225)	(0.204)								
ServCont	-0.181	-0.116	-0.087	-0.324***	-0.129	-0.020	0.018	-0.212*								
	(0.131)	(0.122)	(0.132)	(0.121)	(0.131)	(0.122)	(0.133)	(0.121)								
Log(Wage)	-0.194***	-0.189***	-0.250***	-0.218***	-0.190***	-0.198***	-0.264***	-0.225***	-0.471***	-0.270**	-0.307***	-0.621***	-0.448***	-0.289***	-0.310***	-0.626***
	(0.029)	(0.027)	(0.029)	(0.027)	(0.029)	(0.027)	(0.029)	(0.027)	(0.103)	(0.105)	(0.097)	(0.096)	(0.103)	(0.107)	(0.097)	(0.096)
Wage Diff	0.006***	0.004***	0.006***	0.006***	0.006***	0.003***	0.005***	0.006***	0.063***	0.011	0.020	0.057***	0.058***	0.011	0.014	0.052**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.022)	(0.022)	(0.021)	(0.020)	(0.022)	(0.023)	(0.021)	(0.020)
Log(H)	0.391***	0.455***	0.471***	0.569***	0.388***	0.461***	0.481***	0.577***	0.688***	0.421***	0.488***	0.412***	0.669***	0.437***	0.489***	0.415***
	(0.020)	(0.019)	(0.020)	(0.018)	(0.020)	(0.018)	(0.020)	(0.018)	(0.046)	(0.047)	(0.043)	(0.043)	(0.046)	(0.048)	(0.043)	(0.043)
H_hs	0.019***	0.013***	0.010***	0.008***	0.020***	0.016***	0.013***	0.011***	0.005*	0.000	-0.000	0.000	0.005	0.001	-0.001	0.000
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Log(NF)	-0.002	-0.008	0.001	-0.009	-0.002	-0.008	0.001	-0.009	0.025	-0.027	0.009	-0.034*	0.029	-0.031	0.008	-0.036*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.020)	(0.021)	(0.019)	(0.019)	(0.020)	(0.021)	(0.019)	(0.019)
NF_large	-0.001	0.007***	0.003**	0.005***	-0.001	0.007***	0.003**	0.005***	0.018*	-0.004	0.005	0.002	0.021**	-0.006	0.008	0.004
	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.011)	(0.011)	(0.010)	(0.010)	(0.011)	(0.011)	(0.010)	(0.010)
Observations	1,814	1,814	1,814	1,814	1,818	1,818	1,818	1,818	839	839	839	839	839	839	839	839
R-squared	0.949	0.959	0.960	0.968	0.949	0.959	0.959	0.968	0.955	0.945	0.965	0.963	0.955	0.943	0.965	0.963
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Note: "ServCont" stands for the input service content of manufacturing production.

Table 5. Regression results by country and by origin of inputs

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
	G5(FRA, DEU, GBR, ITA, USA)				Catching-up economies				By origin: Manufacturing				By origin: Services			
Quartile:	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**
ICT Intensity	0.891***	1.091***	1.321***	-0.146	0.592***	0.189	0.172	-0.998***	0.938***	0.481***	0.120	-0.929***	-0.270	0.956**	1.147***	-0.727**
	(0.326)	(0.384)	(0.310)	(0.323)	(0.198)	(0.179)	(0.179)	(0.171)	(0.123)	(0.115)	(0.125)	(0.114)	(0.375)	(0.386)	(0.350)	(0.347)
Input Offshoring	1.038*	-0.409	-2.587***	-0.067	0.498***	0.414***	0.290*	0.729***								
	(0.605)	(0.714)	(0.576)	(0.601)	(0.176)	(0.159)	(0.159)	(0.152)								
Domestic Outsourcing	0.757**	0.517	1.447***	0.060	-0.573***	-0.121	0.122	-0.222	0.229	0.128	0.555***	0.379**	-0.274	-1.075***	-0.021	0.835***
	(0.306)	(0.361)	(0.292)	(0.304)	(0.164)	(0.148)	(0.148)	(0.142)	(0.201)	(0.187)	(0.204)	(0.185)	(0.238)	(0.245)	(0.222)	(0.220)
Offshoring Final Assembly	-0.271	-0.054	-0.294	0.450	-0.464**	-0.151	-0.009	-0.230	-0.571***	-0.181	0.273	-0.170				
	(0.330)	(0.389)	(0.314)	(0.327)	(0.185)	(0.168)	(0.168)	(0.160)	(0.221)	(0.207)	(0.225)	(0.204)				
ServCont	0.534*	-0.694*	-0.599*	0.969***	-0.405***	-0.232*	0.156	-0.066	-0.129	-0.021	0.018	-0.211*				
	(0.322)	(0.380)	(0.307)	(0.320)	(0.140)	(0.127)	(0.127)	(0.121)	(0.131)	(0.122)	(0.133)	(0.121)				
Log(Number Patents)									0.063***	0.075***	0.023*	0.036***				
									(0.012)	(0.011)	(0.012)	(0.011)				
Input Offshoring from HighInc									-0.213	0.246	-0.065	0.221	-0.130	1.069	-0.226	0.142
									(0.226)	(0.210)	(0.229)	(0.208)	(0.764)	(0.788)	(0.714)	(0.707)
Input Offshoring from MedLow Inc									0.190	-0.172	0.564	0.952***	-2.118	-0.393	-4.248**	0.644
									(0.339)	(0.316)	(0.344)	(0.313)	(2.294)	(2.365)	(2.145)	(2.123)
Observations	591	591	591	591	1,441	1,441	1,441	1,441	1,818	1,818	1,818	1,818	839	839	839	839

Note: Columns 1 to 8 split the sample in different geographical areas. The G5 group includes France, Germany, Italy, the United Kingdom and the Unites States. Catching-up economies include Bulgaria, Czech Republic, Estonia, Greece, Hungary, Ireland, Latvia, Lithuania, Poland, Portugal, Slovak Republic, Slovenia, Spain and Turkey. Columns 9 to 16 split the overall sample (across all countries) in manufacturing and services, like in Table 4, but further distinguish between input offshoring from high income countries ("HighInc") and medium-low income countries ("MedLowInc"). Further, omitted controls are the same as in previous tables. The complete tables are available upon request.

Industry structure

Finally, the variables used to account for industry structure and possible competition effects (i.e. the overall number of firms and the proportion of large firms in the industry) suggest that, everything else held constant, having more firms does not matter for employment (except for, perhaps, high routine-intensive employment in services). The presence of a higher number of large firms conversely does benefit employment, in particular in the case of non-routine occupations in services, and of all but non-routine occupations in manufacturing, suggesting the existence of economies of scale. While it is reasonable to expect that at least some of these firms are multinational enterprises, the data do not allow distinguishing between domestic only companies and multinational corporations.

Further results and robustness tests

Table 6 explores the robustness of the proposed results to different proxies for technology. In the first panel, a new estimator of the the count of IP5 patent families in the sector is proposed. Instead of exploiting the conversion table between technology and industrial classes of Van Looy et al. (2014), as in Table 4, patents are allocated to sectors using patenting firms' information, as in Squicciarini and Dernis (2013). As matched patent-firm information is available for both manufacturing and services, the control for innovative output of the sector is now included in the overall sample as well, although this is restricted to Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Spain, Sweden, and the United States (see Table A2 for more explanations).

The impact of technology on employment gives results that are positive across all quartiles, signalling strong complementarity between innovation and employment, even more than in the main baseline estimation for manufacturing reported in previous paragraphs.[24] The direction of the correlation between employment on the one side, and ICT intensity, input offshoring and domestic outsourcing remains the same, although proxies for GVCs overall lose significance with respect to the baseline sample, but keep the expected sign. Offshoring of assembly activities does not impact non-routine employment under this specification, while domestic outsourcing correlates positively (albeit weakly) only with high routine intensive employment.

Almost all results persist when an extra control for ICT investment (GFCF) in real terms is included in the econometric specification, together with the real capital stock[25]. It is interesting to note that ICT intensity remains a significant factor in explaining employment by quartiles even when ICT investment is controlled for, with the exception of service industries where only medium routine-intensive related employment is still affected. This is coherent with the intuition that the availability of ICT technologies and their use contribute to different extents to the performance of industries, where the latter is proxied by the number of workers employed in ICT business functions. The number of IP5 patent families only affects (positively) non-routine jobs. Moreover, domestic outsourcing in service industries now plays a stronger role in decreasing non-routine employment from NR to MR, contrary to the specification in Table 4, where this was true for LR only (albeit in a different sample).

24. Comparisons between the two proxies for innovative output of the sector are based on estimations where the sample was restricted to have non-missing values for both proxies (tables not reported).

25. ICT GFCF, however, is also contained in the capital stock for a given year, so that the model in the second panel of Table 6 may be mis-specified. However, when the capital stock is replaced by real non-ICT GFCF thus avoiding double-counting, the results do not change much. A specification with the capital stock is preferred to be coherent with the other panels in Table 6.

Table 6. Regression results with new proxies for technology and skills

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	All				Manufacturing				Services			
Quartile:	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**
Patents (Matched)												
ICT Intensity	0.577***	0.685***	0.830***	-0.401**	1.064***	0.926***	0.714***	-0.468***	-1.355*	-0.025	2.039***	0.033
	(0.188)	(0.192)	(0.179)	(0.172)	(0.189)	(0.173)	(0.179)	(0.168)	(0.733)	(0.854)	(0.654)	(0.618)
Log(Number Patents Matched)	0.049***	0.039***	0.029***	0.031***	0.057***	0.047***	0.025**	0.035***	0.042*	0.056**	-0.029	-0.019
	(0.011)	(0.011)	(0.010)	(0.010)	(0.013)	(0.012)	(0.013)	(0.012)	(0.023)	(0.027)	(0.021)	(0.020)
Input Offshoring					-0.580*	0.214	-0.143	0.601*	-0.097	-0.444	-3.061***	0.106
					(0.348)	(0.318)	(0.330)	(0.310)	(0.808)	(0.942)	(0.722)	(0.682)
Domestic Outsourcing					0.093	0.234	0.198	0.308*	-0.065	-1.888***	-0.120	1.398***
					(0.201)	(0.184)	(0.190)	(0.179)	(0.348)	(0.405)	(0.311)	(0.293)
Offshoring Final Assembly					0.517	0.270	0.151	-0.068				
					(0.369)	(0.337)	(0.349)	(0.328)				
ServCont					-0.440*	-0.177	-0.468**	-0.400*				
					(0.243)	(0.222)	(0.230)	(0.216)				
Observations	1,379	1,379	1,379	1,379	900	900	900	900	372	372	372	372
ICT GFCF												
Log(ICT GFCF)	0.121***	0.109***	0.104***	0.104***	0.078***	0.079***	0.051**	0.075***	-0.084***	0.066**	0.086***	-0.012
	(0.018)	(0.016)	(0.016)	(0.017)	(0.027)	(0.023)	(0.026)	(0.024)	(0.028)	(0.030)	(0.026)	(0.028)
ICT Intensity	0.299*	0.261*	0.409***	-0.858***	0.910***	0.763***	0.579***	-0.572***	0.141	0.208	1.472***	-0.279
	(0.169)	(0.150)	(0.155)	(0.163)	(0.164)	(0.140)	(0.158)	(0.144)	(0.577)	(0.604)	(0.541)	(0.569)
Log(Number Patents)					0.086***	0.092***	-0.017	0.012				
					(0.019)	(0.016)	(0.018)	(0.016)				
Input Offshoring					-0.316	-0.031	0.093	0.644***	-0.126	1.048**	-1.112***	0.244
					(0.242)	(0.207)	(0.234)	(0.214)	(0.395)	(0.414)	(0.371)	(0.390)
Domestic Outsourcing					0.895***	0.243	0.611**	0.439*	-0.607**	-1.177***	-0.797***	1.483***
					(0.291)	(0.249)	(0.282)	(0.257)	(0.289)	(0.302)	(0.271)	(0.285)
Offshoring Final Assembly					0.257	-0.434	0.368	-0.528				
					(0.371)	(0.317)	(0.358)	(0.327)				
ServCont					-0.133	-0.502**	-0.287	-0.959***				
					(0.230)	(0.197)	(0.223)	(0.203)				
Observations	1,766	1,766	1,766	1,766	995	995	995	995	524	524	524	524
Skill by quartile												
ICT Intensity	1.217***	0.305***	0.031	-1.179***	1.257***	0.473***	-0.112	-1.022***	1.270***	0.793**	0.203	-0.817**
	(0.119)	(0.111)	(0.118)	(0.117)	(0.126)	(0.119)	(0.131)	(0.120)	(0.325)	(0.353)	(0.354)	(0.342)
Log(Number Patents)					0.087***	0.112***	0.058***	0.060***				
					(0.012)	(0.011)	(0.012)	(0.011)				
Input Offshoring					-0.068	0.322**	0.177	0.582***	-0.672**	0.492	-0.901***	0.236
					(0.146)	(0.139)	(0.150)	(0.137)	(0.280)	(0.314)	(0.301)	(0.303)
Domestic Outsourcing					0.231	0.153	0.747***	0.441**	-0.381*	-0.856***	-0.034	0.917***
					(0.200)	(0.191)	(0.207)	(0.189)	(0.199)	(0.223)	(0.213)	(0.216)
Offshoring Final Assembly					-0.015	-0.142	0.399*	-0.071				
					(0.222)	(0.211)	(0.229)	(0.210)				
ServCont					-0.214	-0.138	-0.036	-0.258**				
					(0.135)	(0.128)	(0.139)	(0.127)				
Skill Intensity (quartile)	0.017***	0.012***	0.010***	0.013***	0.014***	0.008***	0.010***	0.009***	0.020***	0.023***	0.015***	0.030***
	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.007)
Observations	3044	3,044	3,044	3,044	1,809	1,809	1,809	1,809	839	839	839	839

Note: Columns 1 to 4 cover the entire sample, columns 5 to 8 the manufacturing sectors only, columns 9 to 12 the services sectors. The first and second panel assess the robustness of results to different proxies for technology (Number of patents, ICT GFCF). The third panel controls for a proxy of skill intensity computed by routine quartile. Further omitted controls are the as in previous tables. The complete tables are available upon request.

The last panel of Table 6 computes skill intensity at the routine quartile level. Skill intensity by routine quartile and sector is measured as the number of employees in the sector and routine quartile who work in skilled occupations according to the ILO classification of occupations, as a percentage of all skilled workers in the sector. The results suggest that increasing the number of high skilled workers in an industry positively affects employment across all quartiles, in both manufacturing and services. The relationship between ICT intensity and employment by quartile is now the same for the complete and split samples. The correlations between GVC variables and employment by quartile do not change in sign, although their significance may differ with respect to the baseline specifications shown in Tables 4 and 5. In all the specifications of Table 6, the service content of manufacturing consistently correlates negatively with manufacturing employment in all quartiles, although their significance changes across quartiles depending on the specification. Coherently with the baseline estimations, though, employment in high routine manufacturing jobs is always negatively affected by greater sourcing of inputs from the services sector. When a control for ICT GFCF is included, this negative relation extends to low routine jobs, but this may be driven by the characteristics of the restricted sample (testing the same specification without controlling for ICT gives the same intuition for the service content of manufacturing).

Three last sets of estimations test the robustness of the results presented so far. The first one restricts the sample to PIAAC countries only. As for non-PIAAC countries the classification of occupations in routine quartiles is derived from similar countries by economic structure, or from the overall sample, the relationships of interest between technology, GVC and employment by routine intensity may be estimated with error. Secondly, we test for the possibility that the results obtained may be affected by the gaps in the time series characterising the baseline sample. Exploiting the complete time series from WIOD, the years 2001-2004 and 2006-2007 are added to the sample, and the appropriate GVC indicators computed from those data. Last, it is possible that the complementary relationship between capital and employment levels may take time to manifest itself. That is why an extra specification estimates equation (6) with lagged real capital and GFCF. Tables reporting these estimations are omitted, as they confirm the results obtained with the baseline, but they are available upon request.

Preliminary conclusions and policy implications

The above analysis is preliminary and the data will be analysed in more detail in future work. Therefore, one has to be cautious drawing overly prescriptive policy implications of the work. Nevertheless, there are interesting and important implications for policies aiming at maximising employment and growth through GVCs.

The reason why it is important to look at the routine-intensity of occupations is that educational levels or skill endowments are not fully explaining the fragmentation of production and the type of activities in which countries specialise. The degree to which each job can be transformed into a set of routine tasks that are codified and based on rules is found to be an important determinant in the analysis of the relationship between offshoring, ICTs, skills and jobs. As a consequence, this issue deserves more attention from policymakers.

The above analysis has several implications for policies aiming at maximising the benefits of GVCs, through higher and better employment, as well as productivity growth, which, if confirmed in future analysis, would be of relevance to both industry and trade policy:

- No consistently negative impact of offshoring on the levels of employment of routine-intensive workers emerges across specifications, as conversely found by some existing studies. This report finds a positive and significant correlation between the offshoring of inputs and the level of employment of routine-intensive workers, particularly in manufacturing industries. Such a relationship is consistent with the specialisation of manufacturing firms in specific stages of the value chain: as they import more inputs that are further processed, they also rely relatively more on routine-intensive jobs. The inability of earlier studies to accurately disentangle input and output-related value added flows and the use of routine intensity measures based on both the skill and task components of occupations - two shortcomings that the TiVA and PIAAC databases allow to overcome when constructing the RII index - may partly explain the observed differences with previous analysis.

- The relationship between offshoring and employment seems to be related to the specialisation of countries: different results emerge for large and mature more "service-based" economies on the one hand and for European countries characterised as catching-up and transition economies, on the other hand. The latter are gaining employment in medium and high routine-intensive occupations, while the former seemingly experience more labour demand in non-routine occupations. While a more open trade regime might have facilitated such specialisation, this does not imply that trade policy may be able to reverse (some of) these trends, as they appear to be explained by more profound determinants, including the skill distribution of the workforce, technology endowments, innovation capabilities and industry structure.

- Manufacturing industries, which have been sourcing an ever greater share of their intermediate inputs from service industries during the period considered, see employment being negatively affected, especially in relatively highly routine intensive jobs. Examples of high-routine activities which can be sourced from the service sectors are cleaning and accounting services. This, however, does not need to entail a net loss of employment for the economy as a whole, as lower manufacturing employment may be compensated by higher employment in the services industries from which such services are sourced. This ever-greater level of integration between firms in the same sector and across manufacturing and service industries needs to be taken into account when designing industrial policies. The progressive "servitisation" of economies, i.e. the propensity of manufacturing firms to add service components to their traditional products, may in fact constitute an opportunity, e.g. for important productivity gains. A strong and innovative service sector may thus provide better inputs to, and increase the competitiveness of the manufacturing sector. However, it can also expose agents to challenges driven by e.g. the co-integration of the business cycle of services and manufacturing, and by services becoming indirectly more tradable through manufacturing production.

- Technological innovation does matter and positively so for employment across all routine intensity quartiles. The stronger competitiveness that technological innovation may confer to companies, especially in manufacturing, seemingly translates into generally higher employment levels, and generally more so in the case of non-routine and low routine intensive occupations. This argues in favour of policies supporting investment in innovation-related activities, and calls for the need to design broad-based innovation policies able to foster productivity, growth and well-being (OECD, 2015). While policies supporting innovation may trigger or amplify processes of creative destruction and thus be disruptive for employment in non-innovative companies, the empirical evidence presented so far suggests that the overall effect on industry employment is positive, irrespective of its routine content.

- Additionally, the role played by ICTs and skills confirms the relevance of policies targeting skills and education when it comes to developing comparative advantages. A clear relationship emerges between the skill level of the workforce as well as ICT-related capabilities and innovation, and labour demand across quartiles of routine-intensity. ICT-related capabilities appear to be positively correlated with employment levels in all quartiles but for the high-routine one, whereas high skills play a different role in manufacturing and services industries, depending on the proxy used to measure skill intensity. While it is unlikely that any policy may influence the routine-intensity of occupations, targeted skill policies, also and especially related to ICT capabilities, can indeed play a role for employment within and across countries, including in cases where offshoring leads to a workforce re-allocation that negatively impacts a given quartile.

- The results also point to the possible existence of economies of scales and competition-related effects, whereby the number of firms and the proportion of big firms in an industry affect employment levels. The number of firms correlates negatively with employment levels in the overall sample, whereas the proportion of big firms is seemingly conducive to higher employment, especially in manufacturing. These relationships, which only affect selected quartiles of employment in service industries, point to the need of tailoring industrial policies depending on whether manufacturing or services industries are targeted, as the routine content of occupations differs importantly across industries (especially in high-routine occupations). Also, policies affecting firm creation and scaling up processes would need to be carefully designed, as they may shape employment in opposite directions, depending on the occupation(s) and industry(ies) targeted.

- The analysis emphasises the need for tailoring policies towards specific industries, skill levels or regions, as results may differ depending on the routine content of occupations, thus posing new challenges to actions aimed at addressing the displacement of workers within and across industries.

More generally, the increased level of competition and re-allocation of resources between firms within each industry and across industries and countries that participation in GVCs is likely to trigger might have non-neutral consequences for employment. This in addition calls for well-functioning labour markets and appropriate labour market policies, able to strike the right balance between employment flexibility and aggregate welfare and that can help smooth the reallocation of the labour force according to the patterns of production and trade in value added. Moreover, labour market policies need to be coupled with trade, industry and innovation and competition policies, creating the right business environment in a GVCs context.

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Annex

Table A1. List of industries

Number	ISIC equivalent	Name	Description
1	C01T05	Agriculture	Agriculture, hunting, forestry and fishing
2	C10T14	Mining	Mining and quarrying
3	C15T16	Food products	Food products, beverages and tobacco
4	C17T19	Textiles & apparel	Textiles, textile products, leather and footwear
5	C20	Wood	Wood and products of wood and cork
6	C21T22	Paper, print, publish	Pulp, paper, paper products, printing and publishing
7	C23	Coke, petroleum	Coke, refined petroleum products and nuclear fuel
8	C24	Chemicals	Chemicals and chemical products
9	C25	Rubber & plastics	Rubber and plastics products
10	C26	Non-metallic minerals	Other non-metallic mineral products
11	C27T28	Metals	Basic metals and fabricated metal products
12	C29	Machinery	Machinery and equipment, nec
13	C30T33	Electronics	Computer, electronic and optical equipment, elecrtical machinery and apparatus nec
14	C34T35	Transport equipment	Motor vehicles, trailers, semi-trailers and other transport equipment
15	C36T37	Other manufacturing	Manufacturing nec; recycling
16	C40T41	Utilities	Electricity, gas and water supply
17	C45	Construction	Construction
18	C50T52	Wholesale & retail	Wholesale and retail trade; repairs
19	C55	Hotels & restaurants	Hotels and restaurants
20	C60T63	Transport & storage	Transport and storage
21	C64	Post & telecoms	Post and telecommunications
22	C65T67	Finance & insurance	Financial intermediation
23	C70T74	Business services	Real estate activities, renting of machinery and equipment, computer and related activities, R&D and other business activities
24	C75	Public admin	Public admin. and defence; compulsory social security
25	C80	Education	Education
26	C85	Health	Health and social work
27	C90T93	Other services	Other community, social and personal services
28	C95	Private households	Private households with employed persons

Table A2. Variables description

Variables	Description
Employment by Routine Intensity (NR, LR, MR, HR)	Number of employees in the industry, by quartile of routine intensity. "NR" identifies the non-routine intensive employment, HR the high routine intensive one. The mapping of 3-digit ISCO occupations into quartiles of routine intensity is defined using Programme for International Assessment of Adult Competencies (PIAAC) and according to the methodology in Marcolin et al. (2015). Source: European Labour Force Survey and United States Occupational Employment Statistics.
Value Added	Deflated by value-added specific deflators at the industry/country level. Source: OECD Annual National Accounts Database.
Gross Fixed Capital Formation	Deflated by GFCF specific deflators at the industry/country level sourced from WIOD. For selected European countries, the time series is extended using the growth rate in GFCF sourced from Eurostat. Source: Eurostat, OECD Annual National Accounts Database, and WIOD.
Capital	Stock of total fixed assets in volume terms. Source: OECD Annual National Accounts Database.
Average Wage	Average labour compensation per hour worked in the industry. Labour compensations in current prices are deflated by value added deflators at the industry/country level. Source: WIOD
Wage Difference	Difference between the average labour compensation per hour worked for high skilled workers in the industry, and "Average Wage". Classification of hours into three skill categories (High, Medium, Low) is based on workers' educational attainment as recorded in ISCED1997 classes. High-skill workers have attained a tertiary education degree; medium-skill workers have attained an upper secondary or post-secondary non-tertiary education degree; low skilled workers have attained primary or lower secondary education. Source: WIOD and Erumban et al. (2012)
Total Hours Worked	Number of hours worked in the industry. Source: WIOD
High Skill/Total Hours	Ratio between the number of hours worked by high skill workers and total number of hours worked, by industry. Classification of hours into three skill categories (High, Medium, Low) is based on workers' educational attainment as recorded in ISCED1997 classes. High-skill workers have attained a tertiary education degree; medium-skill workers have attained an upper secondary or post-secondary non-tertiary education degree; low skilled workers have attained primary or lower secondary education. Source: WIOD and Erumban et al. (2012)
Skill intensity in the quartile	The numerator of this ratio is the number of employees in the industry who are working in high-skill occupations falling under a given routine intensity quartile. The definition of high-skill occupations is given by grouping category 3 and 4 in ILO (2012), and therefore includes ISCO 1-digit occupations 1 to 3. The denominator of this ratio is the total number of so-defined high-skilled people in the industry. Source: European Labour Force Survey and United States Occupational Employment Statistics, and PIAAC Database.
Number Firms	Number of firms per industry. Source: OECD Structural and Demographic Business Statistics (SDBS) Database.

Table A2. Variables description (*cont*.)

Variables	Description
Number Large / Total Firms	Ratio between the number of large firms and total number of firms operating in an industry. Large firms have 500 employees or more. This information is not available for selected sectors, such as agriculture (ISIC3 sectors 01-05), public administration (sector 75), education (sector 80) and health and social work (sector 85). Source: OECD Structural and Demographic Business Statistics (SDBS) Database.
Number of Patent families	Number of patent families filed at the 5 largest Intellectual Property Offices (IPOs) worldwide, which handle 80 percent of the world's patent applications (see Dernis et al., 2015, for details about the definition and the construction of IP5 families). A conversion from patent classes (IPC) to sectoral classes (NACE) is derived from Van Looy et al. (2014). Source: OECD Microdata Lab.
Number of Patent families (Matched)	Number of patent families filed at the 5 largest Intellectual Property Offices (IPOs) worldwide, based on the methodology presented in Squicciarini and Dernis (2013). Patent data from the OECD Patent database are linked to firm data from a commercial dataset (ORBIS®), for firms employing 20 or more employees, for the years 1999-2011. As no numeric firm identifier is available in patent documents, firms are linked to patent assignees' names by means of string matching algorithms designed to optimise the precision of the match. Only countries for which the matching rate is above 80% of patents in the late 2000s are considered, thus restricting the sample to Austria, Belgium, Canada, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, Norway, Spain, Sweden, Switzerland, the United States. All sectors in these countries are covered. Source: OECD Microdata Lab.
ICT Intensity	Proportion of workers employed in the business functions "ICT services" and "Engineering and related technical services" in a given industry, over total industry employment. This was obtained summing EULFS and US CPS employment (by industry) operating in the occupations classified in these business functions. The mapping of ISCO88/ISCO08 occupations into business functions is sourced from TAD/TC/WP/RD(2015)4.
ICT Gross Fixed Capital Formation	Investment (GFCF) in ICT equipment by industry. Information in current prices for the SNA2008 definition of ICT equipment is sourced from the national accounts from the OECD Annual National Accounts Database and Eurostat. For Germany, Ireland, Poland, Slovenia, and Spain, GFCF according to the SNA1993 definition is exploited instead, as sourced from the OECD National Accounts and EUKLEMS. Information is missing for Bulgaria, Greece, Hungary, Lithuania, Latvia, Malta, Romania, and Turkey for the entire economy, and for Estonia and Poland for the manufacturing and Post and Telecommunication sectors. Investment in current prices is deflated using GFCF specific deflators at the industry/country level from WIOD. Sources: Eurostat, EUKLEMS, OECD Annual National Accounts Database, and WIOD.
Input Offshoring (Narrow),	Index of offshoring of intermediate inputs from the same industry. The methodology for the construction of these variables is explained in the body of the text. The indicator can be computed distinguishing between offshoring from high- vs. low/medium-income countries, based on the GNI per capita of the offshoring country, as computed by the World Bank (see footnote 10). Source: OECD Trade in Value Added (TiVA) Database.
Domestic Outsourcing (Narrow)	Index of outsourcing of intermediate inputs to other companies in the sector in the same country. The methodology for the construction of this variable is explained in the body of the text. Source: OECD Trade in Value Added (TiVA) Database.
Offshoring of Assembly (Narrow)	Index of offshoring of assembly of final goods in the same industry. The methodology for the construction of this variable is explained in the body of the text. Source: OECD Trade in Value Added (TiVA) Database.
Service Content of Manufacturing (ServCont)	Index of the service content of manufacturing, i.e. the consumption of service intermediate goods by manufacturing sectors. The methodology for the construction of this variable is explained in the body of the text. Source: OECD Trade in Value Added (TiVA) Database.

Table A3. Summary statistics for the main variables of interest

Selected European countries and United States, 2000-2011(with gaps)

TOTAL SAMPLE	Obs	Mean	Std. Dev.	Min	Max
Log(VA)	3,052	3.73	2.28	0	10.35
Log(GFCF)	3,052	2.56	2.03	0	9.26
Log(ICT GFCF)	1,766	0.92	1.09	0	5.75
Log(Capital)	3,052	8.93	2.70	0	16.71
ICT Intensity	3,052	0.11	0.09	0	1
Input Offshoring (Narrow)	3,052	0.08	0.08	0	0.68
Domestic Outsourcing (Narrow)	3,052	0.10	0.08	0	0.53
Log(Average Wage)	3,052	0.48	0.68	0	6.40
Wage Difference	3,052	0.58	4.97	0	192.28
Log(Total Hours Worked)	3,052	5.10	1.92	0.03	11.77
High Skill/Total Hours	3,052	0.20	0.13	0.01	1
Log(Number Firms)	3,052	7.97	2.67	0	14.13
Number Large/Total Firms	3,052	0.03	0.08	0	1
MANUFACTURING					
Log(VA)	1,814	3.41	2.16	0	9.48
Log(GFCF)	1,814	2.13	1.79	0	7.86
Log(ICT GFCF)	995	0.68	0.86	0	4.35
Log(Capital)	1,814	8.31	2.52	0	13.92
ICT Intensity	1,814	0.12	0.09	0	1
Log(Number Patents)	1,814	2.71	2.32	0	9.80
Log(Number Patents Matched)	900	3.50	2.15	0	8.48
Input Offshoring (Narrow)	1,814	0.10	0.09	0	0.68
Domestic Outsourcing (Narrow)	1,814	0.09	0.06	0	0.38
Offshoring of Assembly (Narrow)	1,814	0.15	0.08	0.01	0.46
Service content	1,814	0.09	0.06	0.01	0.59
Log(Average Wage)	1,814	0.53	0.74	0	6.40
Wage Difference	1,814	0.75	6.37	0	32.28
Log(Total Hours Worked)	1,814	4.54	1.58	0.03	8.66
High Skill/Total Hours	1,814	0.20	0.12	0.03	0.97
Log(Number Firms)	1,814	7.34	2.26	0	11.97
Number Large/Total Firms	1,814	0.03	0.06	0	1
SERVICES					
Log(VA)	839	4.64	2.35	0.16	10.35
Log(GFCF)	839	3.44	2.23	0	9.26
Log(ICT GFCF)	524	1.43	1.31	0	5.75
Log(Capital)	839	10.11	2.66	0	16.71
ICT Intensity	839	0.09	0.08	0	0.39
Log(Number Patents Matched)	372	3.26	2.32	0	8.77
Input Offshoring (Narrow)	839	0.03	0.05	0	0.38
Domestic Outsourcing (Narrow)	839	0.11	0.09	0	0.42
Log(Average Wage)	839	0.42	0.59	0	3.24
Wage Difference	839	0.35	1.25	0	14.11
Log(Total Hours Worked)	839	6.66	1.82	2.07	11.77
HighSkill/Total Hours	839	0.19	0.13	0.01	0.61
Log(Number Firms)	839	10.15	2.28	0	14.13
Number Large/Total Firms	839	0.01	0.02	0	0.27

Source: Authors' own compilation based on OECD Annual National Accounts Database, OECD Microdata Lab, OECD Structural and Demographic Business Statistics Database, OECD Trade in Value Added Database, and PIAAC data; European Labour Force Survey and United States Occupational Employment Survey; EUKLEMS and World Input-Output Database. Values by country, industry, and year are averaged across all years, industries and countries. The sample corresponds to the one used in the econometric analysis. Offshoring of assembly, number of patents and offshoring of service inputs are only reported for the manufacturing sample. The number of patents (matched) and data for ICT GFCF are available for both services and manufacturing, but only for fewer countries (see Table A2).

Table A4 Pairwise correlations between variables of interest

Selected European countries and United States, 2000-2011 (with gaps)

	Log(VA)	Log(GFCF)	Log(ICT GFCF)	Log(Capital)	ICT Intensity	Log(Num. Patents)	Input Offshoring	Domestic Outsourcing	Offshoring Assembly	Service Content Manuf	Log(Wage)	Wage Difference	Log(Total Hours)	High Skill /Total Hours	Log(Num. Firms)	Num. Large/ Total Firms
Log(VA)	1															
Log(GFCF)	0.939***	1														
Log(ICT GFCF)	0.724***	0.745***	1													
Log(Capital)	0.931***	0.943***	0.693***	1												
ICT Intensity	0.117***	0.128***	0.0272	0.167***	1											
Log(Num. Patents)	0.544***	0.423***	0.414***	0.449***	0.276***	1										
Input Offshoring	-0.118***	-0.111***	-0.164***	-0.149***	0.0924***	-0.0310	1									
Domestic Outsourcing	0.166***	0.177***	0.112***	0.206***	0.0920***	0.0271	0.0577**	1								
Offshoring Assembly	-0.284***	-0.252***	-0.256***	-0.282***	-0.0630***	-0.0308	0.467***	-0.400***	1							
Service Content Manuf	0.176***	0.184***	0.186***	0.180***	-0.146***	0.101***	-0.167***	0.191***	-0.0434*	1						
Log(Wage)	0.547***	0.545***	0.236***	0.482***	0.215***	0.0793***	0.0825***	-0.0627***	0.0280	0.0313	1					
Wage Difference	0.159***	0.125***	-0.0221	0.107***	0.104***	-0.0482*	0.0169	-0.0457*	-0.0106	-0.0245	0.450***	1				
Log(Total Hours)	0.635***	0.602***	0.583***	0.602***	-0.191***	0.407***	-0.225***	0.222***	-0.352***	0.257***	-0.0708***	-0.0531**	1			
High Skill /Total Hours	-0.00185	0.0237	0.0588*	0.0389*	0.294***	0.0599**	0.0531**	-0.0294	0.0119	0.00433	0.0378*	-0.0211	-0.226***	1		
Log(Num. Firms)	0.542***	0.486***	0.441***	0.497***	-0.218***	0.295***	-0.228***	0.163***	-0.346***	0.234***	-0.0467*	-0.0616***	0.815***	-0.184***	1	
Num. Large /Total Firms	-0.0435*	-0.0290	-0.0569*	-0.0149	0.237***	0.0160	-0.0191	0.0302	-0.0276	-0.114***	0.0184	0.0343	-0.138***	0.102***	-0.331***	1

Table A5. Regression results for manufacturing, by G5 and catching-up economies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manufacturing only							
	G5				**Catching-up countries**			
	NR	**LR**	**MR**	**HR**	**NR**	**LR**	**MR**	**HR**
Log(VA)	0.089*	0.162***	0.331***	0.213***	-0.010	0.064***	0.183***	0.082***
	(0.053)	(0.054)	(0.050)	(0.051)	(0.027)	(0.024)	(0.024)	(0.022)
Log(Capital)	0.394***	0.362***	0.211***	0.423***	0.065***	0.107***	0.110***	0.162***
	(0.062)	(0.064)	(0.059)	(0.060)	(0.022)	(0.020)	(0.020)	(0.018)
ICT Intensity	1.873***	1.972***	0.525*	-1.242***	0.546***	0.266	0.300	-1.097***
	(0.330)	(0.336)	(0.312)	(0.319)	(0.211)	(0.191)	(0.192)	(0.170)
Input Offshoring	0.272	-0.352	-2.339***	-0.675	0.152	0.029	0.580***	0.599***
	(0.589)	(0.601)	(0.557)	(0.570)	(0.200)	(0.181)	(0.181)	(0.161)
Domestic Outsourcing	1.429***	1.171***	1.079***	0.885**	-0.358	-0.258	0.427**	-0.257
	(0.393)	(0.401)	(0.372)	(0.381)	(0.218)	(0.198)	(0.198)	(0.176)
Offshoring Final Assembly	0.029	-0.545	-1.081	1.998***	-0.291	0.305	0.300	-0.050
	(0.747)	(0.762)	(0.706)	(0.724)	(0.296)	(0.268)	(0.269)	(0.238)
ServCont	1.123**	1.047**	-1.272***	1.416***	0.026	-0.424***	0.123	-0.286*
	(0.442)	(0.451)	(0.418)	(0.428)	(0.181)	(0.164)	(0.165)	(0.146)
Log(Wage)	-0.171	-0.566***	-1.244***	-0.976***	-0.159***	-0.058	-0.387***	-0.226***
	(0.151)	(0.154)	(0.143)	(0.146)	(0.060)	(0.054)	(0.054)	(0.048)
Wage Diff	0.059	0.122***	0.252***	0.243***	0.007***	0.001	0.008***	0.006***
	(0.039)	(0.040)	(0.037)	(0.038)	(0.002)	(0.002)	(0.002)	(0.002)
Log(H)	0.328***	0.236***	0.133**	0.244***	0.579***	0.543***	0.544***	0.678***
	(0.059)	(0.060)	(0.056)	(0.057)	(0.033)	(0.030)	(0.030)	(0.027)
H_hs	0.011***	0.002	-0.010***	0.005	0.016***	0.014***	0.014***	0.010***
	(0.004)	(0.004)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Log(NF)	0.002	0.010	-0.015	-0.028***	0.009	-0.021**	0.020*	0.011
	(0.010)	(0.011)	(0.010)	(0.010)	(0.012)	(0.010)	(0.010)	(0.009)
NF_large	-0.002	-0.002	-0.005***	0.003**	0.001	0.007***	0.002	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)
Observations	370	370	370	370	868	868	868	868
R-squared	0.956	0.956	0.950	0.959	0.897	0.928	0.944	0.964
Industry FE	YES	YES	YES	YES	YES	YES	YES	YES
Country FE	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Note: Columns 1 to 8 split the sample in different geographical areas. The G5 group includes France, Germany, Italy, the United Kingdom and the Unites States. Catching-up economies include Bulgaria, Czech Republic, Estonia, Greece, Hungary, Ireland, Latvia, Lithuania, Poland, Portugal, Slovak Republic, Slovenia, Spain and Turkey.