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Technology, offshoring and the rise of non-routine jobs[☆]

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ABSTRACT

This paper documents the growing share of non-routine jobs in the labor force of thirty-seven advanced and emerging countries over the period 1999–2007. To examine the role of offshoring and technological change in driving this labor market development, we develop a task-based model of production in global value chains and propose a decomposition of changes in occupational labor demand. In the setup of the model, technological change affects the total number of workers with a certain occupation throughout the production chain, while task relocation consists of a shift in occupational labor demand from one location to another. For the empirical implementation we combine harmonized cross-country occupations data with world input-output tables. The results of our decomposition suggest that technological change increased the number of non-routine relative to routine occupations in all countries. The effect of task relocation is less strong, and works in the same direction for advanced countries such as Germany and the United States but in the opposite direction for emerging countries such as China and Poland.

1. Introduction

The global fragmentation of production in recent decades has given rise to increased trade in tasks, also known as offshoring or foreign outsourcing. Tasks that are relatively easy to offshore are those that require codifiable information rather than tacit knowledge (Leamer and Storper, 2001); can be summarized in a set of well-specified rules (Levy and Murnane, 2004); and do not require face-to-face contact (Blinder, 2009). At the same time, advances in information technology have changed the way in which certain tasks are being performed. Autor et al. (2003) argue that computers and robots tend to displace labor in the performance of routine and non-cognitive tasks. This is nowadays typically referred to as routine-replacing technological change.

Both offshoring and automation affect the demand for labor. However, their impact will differ across occupations and countries. Automa-

tion has been found to reduce the demand for workers with an occupation that is intensive in routine tasks (referred to as ‘routine jobs’ from now on).¹ The effect of trade in tasks, on the other hand, depends on whether the country under consideration engages in offshoring (thereby lowering the onshore demand for routine jobs) or is an offshore destination (such that the demand for routine jobs increases).² What is the overall effect on employment in routine relative to non-routine jobs? And how can we empirically disentangle the role of trade in tasks from that of technological change in driving employment changes?

This paper proposes a novel cross-country approach to study changes in occupational employment. We outline a task-based model of production in Global Value Chains (GVCs from now on) in which tasks are associated with occupations and these tasks are performed somewhere in the global economy. We use this model to motivate a decomposition of changes in occupational labor demand into the effects of technological change, task relocation and other factors. As pointed out

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¹ See e.g. Autor et al. (2003); Goos et al. (2014); Michaels et al. (2014).

² For the growing empirical literature on offshoring and tasks, see e.g. Becker et al. (2011); Baumgarten et al. (2013); Ebenstein et al. (2014).

by Reijnders et al. (2016), GVCs are a compelling unit of aggregation to study how technology and trade interact and shape the demand for labor. Within each value chain, decisions about offshoring and automation are reflected in the total employment by task in the value chain and the location of labor used to produce that task.

We empirically conceptualize a GVC as all activities that are directly or indirectly needed to produce an end-product that is used for final consumption (Timmer et al., 2014).³ An example of a global value chain is the production of a car that has its final assembly stage in Germany, while (some of the) other stages take place abroad (we will return to the example of cars finalized in Germany throughout the paper to illustrate and provide intuition).⁴ For the empirical implementation, we collect occupational data for a set of advanced and emerging countries, harmonize this data by mapping it to a common occupational classification, and link it to international input-output tables. Since we create a common occupational classification we can determine both the total demand for workers with a certain occupation in a value chain and its distribution across countries worldwide.

We make two contributions. First, we document an increase in the share of non-routine jobs in total employment for a group of advanced and major emerging countries during the period 1999–2007. The rise of non-routine jobs has been documented for the United States and West-European countries (see e.g. Autor et al. (2003); Goos et al. (2014); Cortes et al. (2017)). We contribute by documenting it for a set of middle-income and advanced economies. The countries covered are the 27 members of the European Union (per January 2007), Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey and the United States. In 37 out of these 40 countries (with the exception of Bulgaria, Latvia and Estonia) the share of non-routine occupations in the labor force went up.

Second, we provide new evidence on the role of technological change and task relocation in explaining the rise of non-routine jobs. For advanced countries, the impact from automation and the relocation of routine tasks on domestic demand for routine jobs is similar and therefore it is hard to empirically separate their effects. Our GVC approach offers one way to disentangle the two. Intuitively, automation affects the use of a certain task throughout the value chain, while task relocation consists of a shift in demand from one location to another. For example, if robots replace workers in some of the routine production tasks in the value chain of German cars then this will lower the number of routine jobs in the value chain. If instead the number of routine jobs is unchanged but fewer workers are employed in Germany and more in Poland, then we call this task relocation.⁵

The results from our decomposition analysis show that technological change increased the number of non-routine relative to routine occupations in all countries. In advanced countries this effect was much stronger than that of task relocation, suggesting that routine-replacing technological change is the main driving force behind the rise of non-routine jobs. Several offshore destination countries, such as China, Poland and Turkey, saw a decrease in the relative number of non-routine jobs due to task relocation. But also for these (and other emerging) countries, technological change was the dominant force behind employment changes.

A substantial body of related literature has examined the role of trade and technology in driving labor demand. A common approach has been to estimate short-run variable cost functions, with wage bill shares of low- and high-skilled workers as key dependent variables and

proxies for trade and technology as independent variables (e.g. Hanson, 2000; Morrison and Siegel, 2001; Hijzen et al., 2005; Michaels et al., 2014). Another (increasingly common) approach has been to exploit initial local area differences in exposure to automation and (Chinese) import competition to examine their effects on local labor markets (e.g. Autor et al., 2015; Pierce and Schott, 2016; Acemoglu and Restrepo, 2017). More closely related to our approach is Goos et al. (2014) who develop and test a task-based model to study labor demand in West-European countries. In contrast, we use a global value chain approach which allows for the joint analysis of labor market developments in advanced and emerging countries. In addition, instead of using proxies for the potential offshorability of occupations we are able to measure actual shifts in occupational labor demand due to task relocation.

Our measurement of labor demand in global value chains builds upon earlier research by Timmer et al. (2014), and Reijnders et al. (2016). These studies examine the demand for jobs in production networks, but classify jobs by the level of education of workers. We instead make use of occupations data, which allows us to determine whether workers are predominantly engaged in routine or non-routine tasks. Importantly, routine tasks are not exclusively performed by workers with a low or middling level of education, and vice versa it is also not true that only highly educated workers hold non-routine occupations as there are many non-routine low-skilled services occupations (Baumgarten et al., 2013; Autor, 2015; Marcolin et al., 2016). Our study therefore sheds new light on recent changes in demand for routine and non-routine jobs within global value chains and the role of task relocation and technological change therein.

This paper proceeds as follows. In Section 2 we describe the occupations database and show how the employment share of non-routine jobs has evolved over time. Section 3 lays down an analytical task-based model of production in global value chains and explains how we can measure occupational labor demand in GVCs by combining the occupations data with international input-output tables. In Section 4 we use the model to propose a decomposition of changes in occupational labor demand in GVCs. Section 5 shows how the decomposition results can help us understand the driving forces of employment changes. Section 6 provides concluding remarks.

2. The rise of non-routine jobs

In this section we describe our data sources and measures of employment, and document that the employment share of non-routine jobs in the workforce has increased in thirty-seven advanced and emerging countries over the time period 1999–2007.

2.1. Occupational employment data

The main data sources we use for occupational employment are annual labor Force Surveys and/or quinquennial or decadal Population Censuses. The forty countries covered are the 27 members of the European Union (per January 2007), Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey and the United States. For a country to be included in our analysis it needs to be part of an international input-output table. There are several of these available, with a different selection of countries. However, our analysis requires such tables in previous years' prices (further discussed in section 4). This leaves the World Input-Output Tables (WIOTs) as the only candidate, and we necessarily restrict the set of countries to those included in these tables. WIOTs are currently available in previous years' prices up to the year 2009. We limit the time period from 1999 to 2007, excluding 2008 and 2009 because the global financial crisis severely disrupted global value chains (Los et al., 2015).

For the United States we use the same data sources as Autor (2015), namely the 2000 Current Population Census and the annual American Community Surveys. Data for European countries comes from the harmonized individual level European Union labor Force Surveys, which

³ We can think of any good or service as being produced in a global value chain, although for some products (such as a car) the chain will be more 'global' than for others (such as the haircut provided by a local hairdresser).

⁴ Think of, for example, Porsche cars finalized in Leipzig or Volkswagens that roll out of the factory in Wolfsburg.

⁵ In the empirical implementation we will account for differences in productivity of workers across countries.

are also used by Goos et al. (2014). For the remaining countries we obtain the detailed occupations by industry data from national statistical offices. In Appendix Table A.1 we list the main sources of data for each country.⁶

To harmonize the data across countries, we make two mappings. First, national industry classifications are mapped to a common set of 35 ISIC revision 3.1 industries covering the overall economy. These include agriculture, mining, construction, utilities, 14 manufacturing industries, telecom, finance, business services, personal services, 8 trade and transport services industries and 3 public services industries (see Timmer et al., 2015). These industries are chosen so that they coincide with those distinguished in the WIOD.

Second, national occupation classifications are mapped to a single classification consisting of 11 different occupations, see Table 1.⁷ The main challenge in constructing a common occupational classification for a large set of countries is that national classifications need not be based on the same set of guiding principles. For example, the International Standard Classification of Occupations (ISCO) first categorizes workers by level of skill and thereafter by the area of specialization. Other classifications, such as the Chinese and Brazilian one, focus mostly on the area of expertise and less on the skill level. As a consequence, it is often not possible to separate professionals from associate professionals with a similar field of expertise, craft workers from machine operators, and workers in elementary occupations from more skilled workers in the same area. For example, in the Brazilian classification there is no distinction between informal salesmen and sales persons in stores. These restrictions have guided our choice of 11 occupations: they allow us to have as much detail as possible while at the same time minimizing the amount of classification errors. Our classification relates most naturally to the ISCO 88, and the corresponding 2-digit (and occasionally 3-digit) codes are listed in Table 1. For example, the occupation ‘Managers’ corresponds to ISCO 88 codes 12 and 13, and ‘Clerical workers’ to 41 and 42. Where possible, we have used crosswalks from national classifications to ISCO 88 as provided by statistical offices to guide our mapping.⁸

The structure of Table 1 is based on Autor et al. (2003), in that it classifies occupations as either routine or non-routine and manual or analytic/interactive.⁹ The distinction between routine and non-routine is based on the so-called Routine Task Intensity (RTI) index developed by Autor et al. (2015) and mapped into the ISCO 88 occupational classification by Goos et al. (2014). The RTI index is positive for production and clerical workers (e.g. it is 2.24 for office clerks, ISCO 88 code 41), suggesting that routine tasks are relatively prevalent in these jobs. In contrast, the RTI index is negative for drivers, support services workers, professionals and managers (e.g. it is –1.52 for managers of small firms, ISCO 88 code 13). We assume that the (relative) task content of occupations is both constant over time and across countries (and identical

to the one of the United States), so that the analysis focuses on changes in employment patterns across occupations.¹⁰ Production and clerical jobs are considered routine, whereas the other occupational groupings shown in Table 1 are non-routine.

For each country, industry and year in our dataset we calculate employment shares by occupation. For most countries we either have a time series or data for a year close to the starting year (1999) and ending year (2007) of the analysis, see Appendix Table A.1 for an overview. If we do not have information for a given year then we use interpolation or extrapolation while making sure that the employment shares always sum to one. These shares are subsequently multiplied with the number of persons employed by country-industry-year taken from the WIOD socio-economic accounts (Timmer et al., 2015).

2.2. Changes in employment shares between 1999 and 2007

In order to provide an aggregate picture of the type of jobs prevalent in a given country we sum over the different industries and calculate the employment share of routine and non-routine occupations. Fig. 1 shows the percentage point change in the employment share of non-routine jobs (relative to routine jobs) for selected countries between 1999 and 2007. These countries represent economies in our dataset at two different levels of economic development, advanced and emerging.¹¹

The top panel of Fig. 1 shows that there is an increase in the employment share of non-routine relative to routine jobs in all 9 advanced countries. This increase appears faster in France and the United Kingdom compared to South Korea and Japan, with the United States in between. Since many routine jobs tend to be in the middle of the wage distribution in advanced countries, whereas non-routine jobs are often either low-skilled low-wage or high-skilled high-wage services jobs, the decreasing employment share of routine jobs has been interpreted as evidence for job polarization (Autor et al., 2006; Ikenaga and Kamabayashi, 2016; Goos et al., 2014; Harrigan et al., 2016). Studies of job polarization typically focus on an individual country or a homogeneous set of countries. In contrast, we examine a heterogeneous sample of advanced and emerging countries. We argued above that the classification of routine task-intensive and non-routine task-intensive occupations is stable across countries. However, the ranking of occupations along the wage distribution, necessary to identify whether labor markets polarized, is likely to differ across countries because of differences in levels of economic development and wage-setting institutions. Therefore, we do not further pursue analysis of job polarization in the current paper, but will focus on explaining the demand for routine versus non-routine jobs.

Throughout this paper we use persons employed as the measure of employment and not hours worked because data on hours worked by occupation is often not available for the emerging countries included in our dataset. Using data on hours worked is likely to affect the documented changes in non-routine tasks. However, findings for European countries suggest that the main trend, a rise in non-routine jobs, is not qualitatively affected when using either data on employment or hours worked by occupation (see Goos et al. (2014)). If we assume that

⁶ The data sources and methodology are discussed in more detail in de Vries et al. (2016).

⁷ Agricultural occupations, armed forces, and the so-called ‘occupations not elsewhere classified’ are not included.

⁸ Concordance tables are available from the authors upon request. Not all categories are available for every country. For example, occupation data for some countries (e.g. for Australia and Canada) does not allow us to separate legislators from managers (both are non-routine analytical occupations). But this is an exception, because we have collected detailed occupations data on a country-by-country basis that often distinguishes more than 100 occupations (e.g. for the United States we distinguish 331 occupations, 149 for European countries, and 294 for Japan).

⁹ To analyze changes in employment shares of routine and non-routine jobs it is convenient to associate tasks with occupations, such that more routine task-intensive occupations are considered routine jobs. In practice, there is considerable variation in task intensity across occupations such that all jobs involve some degree of routine and non-routine tasks. It is difficult to address this type of heterogeneity in our analytical framework.

¹⁰ Dicarolo et al. (2016) use cross-country worker-level survey data and find that the ranking of occupations along the task dimension is stable across countries. Marcolin et al. (2016) use OECD PIAAC surveys to develop a routine intensity indicator. Managerial jobs always tend to involve more analytical and interpersonal tasks compared to plant operators, which tend to have a higher routine task content. Akçomak et al. (2016) examine changes in the task content within occupations and find that shifts in the intensive-margin can be explained by technological improvements but not by offshoring.

¹¹ Appendix Fig. F.1 shows all countries included in the analysis. In 37 out of these 40 countries (with the exception of Bulgaria, Latvia and Estonia) we find an increase in the employment share of non-routine jobs.

Table 1
Classification of occupations.

	Routine	Non-routine
Manual	Production workers [71–74, 81–82, 93]	Support services workers [51, 910, 912–916] Drivers [83]
Analytic/Interactive	Clerical workers [41–42]	Legislators [11] Managers [12–13] Engineering professionals [21, 31] Health professionals [22, 32] Teaching professionals [23, 33] Other professionals [24, 34] Sales workers [52, 911]

Notes: The numbers in brackets refer to ISCO 88 codes. The four different groups are based on Autor et al. (2003).

Fig. 1. Change in the employment share of non-routine jobs between 1999 and 2007.

Source: Harmonized cross-country occupations database, see main text. Notes: Selected advanced and emerging countries. Appendix Fig. F.1 shows the results for all countries included in the analysis.

skilled workers are better at non-routine tasks,¹² the increase in hours worked for high-educated men and the decrease in hours worked for low-educated men in the United States, see Bick et al. (2018), implies that using data on employment underestimates the rising share of non-routine jobs in the United States.

The bottom panel of Fig. 1 shows changes in the employment share of non-routine occupations in emerging countries. In emerging countries we also document an increase in the share of non-routine jobs, with the exception of Bulgaria, Latvia and Estonia (see Appendix Fig. F.1). In some emerging countries, such as Brazil, Indonesia and Mexico, the increase in the employment share of non-routine occupations is more than 4 percentage points. In other countries, the change in the employment share is moderate, in particular in China and Poland. Both China and Poland are known to be prominent offshore-destination countries and may thus have benefited from the relocation of routine jobs. During the period we analyze, Poland integrated in European production

networks in the run-up and after its accession to the European Union in 2004, whereas China's integration in global production networks accelerated after joining the WTO in 2001 (Marin, 2006). Yet, also in Poland and China there was an increase in the employment share of non-routine jobs.

In Appendix B we report changes in the non-routine employment share for an additional set of twelve low- and middle-income countries. These countries are not included in the WIOTs and we are therefore unable to examine their participation in global value chains and the role of technology and offshoring in driving the relative demand for non-routine jobs. However, using censuses with detailed information on occupations it is possible to calculate the employment share of routine and non-routine jobs. For nine out of the twelve low- and middle-income countries we also find an increase in non-routine jobs (see Appendix Fig. B.1).

3. Occupational employment in global value chains

What accounts for the increase in the share of non-routine jobs? To answer this question we proceed in two steps. First, in this section we outline a simple task-based model of occupational labor demand in global value chains. In addition we show how we can empirically

¹² Note however there is not a one-to-one mapping from schooling to tasks. For example, for the US, the share of college graduates involved in the “engineering task” (which is non-routine) is 58 percent in 1999 (62 percent in 2007) and about half consists of workers with less than a college degree (based on data from the 2000 Population Census and the 2007 American Community Survey).

identify the jobs involved in a given value chain by combining our occupational employment data with international input-output tables. In the next section we will use this model to propose a decomposition of changes in occupational labor demand into the contribution of technology, trade and other factors.

3.1. A task-based global value chain model

In line with recent literature (see e.g. Acemoglu and Autor, 2011; Goos et al., 2014), we model the production process of a global value chain as consisting of different tasks. The process then requires two steps. First, task output is produced in different countries worldwide using labor and other primary inputs. Second, the total output of each task across countries is used as an input into the production of a good that is sold to consumers. To be precise, we write the production function of GVC v as:

$$Y_v = F_v(T_{1v}, \dots, T_{jv}, \dots, T_{Jv}), \quad (1)$$

where Y_v is total output and T_{jv} is the input of task j . Following Baldwin and Robert-Nicoud (2014) we assume that within a GVC tasks are perfect complements. That is, in order to create a final product a fixed amount of each task is required and it is not possible to use a bit more of one in order to make up for a smaller amount of the other. For example, a car only works if it has 4 wheels, and not with 3 wheels and an additional hood. We denote by α_{jv} the amount of task j necessary to produce one unit of output for GVC v , so that $T_{jv} = \alpha_{jv} Y_v$.

As tasks can be performed in different countries, the total use of task j can be written as:

$$T_{jv} = \sum_c T_{jv}^c, \quad (2)$$

where T_{jv}^c is the amount of task j produced in country c on behalf of this GVC. We do not model the way in which the production of a certain task is allocated across countries but take this as observed by the data.¹³ In each country task output is created under constant returns to scale with labor and capital as inputs.¹⁴ The technology to produce a specific task is the same in all countries but there are Hicks-neutral differences in the ‘efficiency’ with which production factors are employed. We write:

$$T_{jv}^c = A^c G_{jv}(K_{jv}^c, N_{jv}^c), \quad (3)$$

where K_{jv}^c and N_{jv}^c are the input of capital and labor, respectively. The function G_{jv} is common across countries (but can differ by task and value chain) while A^c captures the country-specific level of Total Factor Productivity (TFP). Arguably, a multinational firm that decides to offshore a certain task to a different country but within the own organization might be able to produce at the TFP level of its home country. This is the assumption made by Baldwin and Robert-Nicoud (2014), but as they admit themselves it is hard to maintain with aggregate (industry-level) data only, as one cannot observe whether a task is outsourced to a related or an unrelated firm. We simplify by imposing that the relevant TFP level is that of the country in which a task is performed.

In the context of this model there are three types of ‘technology’ that affect production in a value chain. The first is the Total Factor Productivity (TFP) in each country, as captured by A^c . The second is the overall production function F_v and the third are the task production functions G_{jv} . These latter two together will be referred to as ‘GVC technology’ because they are specific to a value chain. We will return

to the distinction between country TFP and GVC technology in Section 4.2.

We follow the modeling approach in Goos et al. (2014) and assume that there is a one-to-one mapping between occupations and tasks, so that each task requires labor of a certain occupation and each occupation only performs that specific task. It follows that j is an index of both tasks and occupations and that N_{jv}^c is the demand for labor of occupation j in country c by value chain v . A given country c performs tasks for global value chains worldwide so that the total demand for workers with occupation j is given by:

$$L_j^c = \sum_v N_{jv}^c. \quad (4)$$

Below we will use the model to determine to what extent the relocation of tasks across countries and changes in GVC technology affect occupational labor demand.

3.2. Global value chain method and data

Timmer et al. (2014) propose a measure to study the production fragmentation of final products. Their measure is a decomposition that allocates the jobs and income embodied in final goods to the source countries along the global value chain that supply it.¹⁵ That is, jobs involved in the production of final goods are traced back to the countries in which those jobs were involved. A final product is consumed, which contrasts with intermediate inputs that are used further in the production process. Consumption is broadly defined to include household and government consumption as well as investment. For any given final product, a global value chain is defined as the value added of all activities that are directly or indirectly needed in the production process. Following Timmer et al. (2014) we identify a global value chain by the combination of a country and an industry in which the last stage of production takes place before delivery to the final user. An example of one such GVC which was referred to in the Introduction is final output from the transport equipment industry in Germany (or ‘German cars’ in short).

The world input-output table for a certain year shows how the output of a given industry in a given country is divided between final consumption and intermediate use by all other industries worldwide. It is described in detail in Timmer et al. (2015). In order to have a complete description of all flows in the global economy, the WIOTs also contains an input-output model for the ‘Rest of World’, which proxies for all other countries in the world, apart from the 40 already covered. This region’s share of world GDP is around 15 percent in 2008 measured at current exchange rates. We cover about 95 percent of global imports in our analysis. The remaining 5 percent is trade between countries in the rest-of-the-world region. This is based on data from UN COMTRADE for 2004. In 2004, 64.5 percent of global imports consisted of trade between the WIOT countries, 13.2 percent are WIOT countries’ imports from rest-of-the-world, 17.2 percent are rest-of-the-world imports from WIOT countries.¹⁶ In the WIOTs, the ‘Rest of World’ was modeled based on totals for industry output and final use categories from the UN

¹⁵ See Johnson (2018) for a description and comparison to other measures of trade in value added.

¹⁶ We examined time series information on employment at foreign affiliates by country of location for Sweden (from the OECD AMNE database) and for the United States (from surveys of U.S. direct investment abroad by the BEA). The employment share at foreign affiliates in countries not included in the sample roughly corresponds to the share of the ‘Rest of World’ in world GDP (about 15 percent) and suggests that the majority of employment at offshore affiliates are at countries included in our analysis, which did not alter substantially during the period considered.

¹³ This task allocation may for example depend on how easy it is to trade or communicate with certain countries.

¹⁴ This does not mean that there are no intermediate goods in the production process, but that task output is equal to value added.

National Accounts for non-covered countries (Timmer et al., 2015).¹⁷

We combine the occupations data described in Section 2.1 with data from the World Input-Output Database (Timmer et al., 2015) in order to find occupational employment in GVCs. In particular, we calculate the total number of workers with a given occupation j in country c that are employed on behalf of each value chain v , defined as N_{jv}^c above. We employ the method outlined in Timmer et al. (2014) to split up the value of output for final consumption of every GVC into the contribution made by each country-industry pair in the world. Intuitively, this means that we iteratively substitute out for the use of intermediate inputs. If a given GVC sources intermediate inputs from country-industry a , which in turn uses intermediate inputs from b , then both a and b show up as performing tasks for this value chain chain. Using occupational employment per dollar of output by country-industry, we then translate task output into a number of workers with a given occupation, for details see Appendix C. Finally, we sum over the industries within each country to obtain N_{jv}^c . Since we have substituted out for intermediate inputs in terms of the labor that was used to produce them, we can now think of the production process of a GVC in terms of labor only. Note that in principle we could do the same for the use of capital within a GVC, but this is not necessary for our purposes (see further below).

Table 2 shows the structure of the dataset that we obtain. For each GVC (columns) we have the number of workers with a given occupation employed in a given country (rows). Adding up across columns we obtain occupational employment in a given country L_j^c . Because we have harmonized the national occupational classifications to a common one, we can directly compare the demand for a certain occupation across countries within a given value chain.

3.3. Illustration: the value chain of German cars

We illustrate our approach using occupational labor demand for the global value chain of cars that have their final stage of assembly in Germany. This value chain has undergone major changes in its organizational and geographical structure during past decades (Sturgeon et al., 2008). Final vehicle assembly is largely kept close to end markets, mainly because of political sensitivities but increasingly also to customize products. At the same time, there has been a rapid increase in the international sourcing of parts and components. The availability of cheap workers has been one of the main attractions for German firms to offshore tasks to Asia and Eastern Europe (Marin, 2006).

Table 3 shows the number of jobs involved in the value chain of German cars in 1999 and 2007 for 4 out of the 11 occupations. Each of these occupations represents one cell of Table 1. In the interest of space we only list employment in the major contributing countries Germany, China and Poland and in bold the total number of jobs. Not surprisingly, most workers in the GVC of cars finalized in Germany are

Table 2
Data structure.

	GVC 1	GVC 2	...	GVC v	Total
Occupation 1					
Country 1	N_{11}^1	N_{12}^1		N_{1v}^1	L_1^1
Country 2	N_{21}^2	N_{22}^2		N_{2v}^2	L_2^2
⋮					
Country c	N_{c1}^c	N_{c2}^c		N_{cv}^c	L_c^c
Occupation 2					
Country 1	N_{21}^1	N_{22}^1		N_{2v}^1	L_2^1
Country 2	N_{21}^2	N_{22}^2		N_{2v}^2	L_2^2
⋮					
Country c	N_{c1}^c	N_{c2}^c		N_{cv}^c	L_c^c
⋮					
Occupation j					
Country 1	N_{j1}^1	N_{j2}^1		N_{jv}^1	L_j^1
Country 2	N_{j1}^2	N_{j2}^2		N_{jv}^2	L_j^2
⋮					
Country c	N_{j1}^c	N_{j2}^c		N_{jv}^c	L_j^c

production workers, amounting to roughly 1.4 million in 1999. This number increased by about 15 percent to 1.6 million in 2007. In Germany itself there was a decrease of 108 thousand production workers, while in China and Poland their numbers increased by 95 and 27 thousand, respectively. A similar pattern is observed for clerical workers: their number increased by 27 thousand (7 percent) between 1999 and 2007 in the GVC as a whole, with a decrease of 3 thousand in Germany but an increase of 6 thousand in China and 5 thousand in Poland. In contrast, the number of workers in two non-routine occupations shown in Table 3 (engineering professionals and support service workers) has increased in Germany.

One might interpret these findings as a relocation of production and back-office activities from Germany to emerging countries, decreasing the relative demand for routine occupations in Germany but increasing it in the offshore-destination countries. However, these employment changes are aggregate outcomes and are driven by trade, technological change, consumer preferences and other factors. Note also that in the GVC, the employment of workers performing routine tasks grew slower than for those performing non-routine tasks. This can be observed by comparing the increase in production and clerical jobs (15 and 7 percent respectively) to the increase in support services workers and engineering professionals (37 and 23 percent). Hence, there might be an important role for routine labor-saving technological change in explaining these changes in employment.

4. Decomposition of changes in occupational employment

This section outlines a decomposition of the changes in occupational employment that we documented in Section 2, based on the task-based model of value chain production introduced in Section 3. First we separate the employment changes that have occurred within global value chains from shifts between GVCs. This between effect captures changes in the share of a GVC in world demand (for example due to changes in consumer preferences). We also distinguish an income effect as world income increased during the period considered. Thereafter, we further decompose the effect within GVCs into the contributions of technological change and task relocation. Fig. 2 provides an overview of the proposed decomposition.

4.1. Within, between and income effects

Starting from equation (4), we write the demand by GVC v for labor of occupation j in country c as:

¹⁷ We estimate the occupational employment shares for the Rest of the World as an unweighted average for each of the occupation-industry-year shares of Brazil, Russia, India, China, Indonesia, and Mexico (BRICIM). We used basic trade data available via the World Integrated Trade Solution (WITS) from the World Bank to compare the industrial composition of exports from BRICIM to the non-sampled countries. We regressed the export shares in the non-sampled countries on the export shares of the BRICIM countries (excluding the constant). This gives coefficients that can be used to weight the BRICIM countries in order to minimize the sum of squared differences in export shares between the actual export shares of non-sampled countries and those of the weighted average of BRICIM. We used this weighting scheme as an alternative to the unweighted average in order to calculate occupational employment shares for the Rest of the World and redid the empirical analysis. Alternative estimates of occupation shares for the Rest of the World affect the results for countries on the contribution of task relocation and GVC technological change to changes in the employment share of non-routine jobs, but our main conclusions remained unchanged.

Table 3

Employment in the global value chain of cars finalized in Germany, by occupation.

	1999	2007	Change	% Change
Production workers	1401	1605	204	15%
Germany	685	577	−108	−16%
China	95	189	95	100%
Poland	35	63	27	77%
Clerical workers	376	404	27	7%
Germany	221	218	−3	−1%
China	17	23	6	34%
Poland	6	11	5	85%
Support services workers	230	315	85	37%
Germany	72	88	16	22%
China	43	63	19	44%
Poland	5	6	1	25%
Engineering professionals	355	436	80	23%
Germany	237	261	24	10%
China	5	12	7	126%
Poland	6	11	5	82%
Total	3353	4030	677	20%
Germany	1664	1671	7	0%
China	252	403	151	60%
Poland	74	133	59	79%

Notes: Employment in thousands of jobs. Numbers may not sum due to rounding. This illustration shows results for 4 out of the 11 occupational groupings and total employment. The numbers in bold show overall employment of each occupation in the GVC of cars finalized in Germany. The contribution from 3 countries, namely Germany, China and Poland, by occupation is distinguished.

Fig. 2. Decomposition.

$$N_{jv}^c = \frac{N_{jv}^c}{p_v Y_v} \frac{p_v Y_v}{W} W, \quad (5)$$

where p_v is the price of GVC v , $p_v Y_v$ the output value of GVC v , and $W = \sum_v p_v Y_v$ world income. This allows us to decompose changes in occupational labor demand into three distinct components:

- (1) *within*: changes in occupational labor per dollar of output $N_{jv}^c/[p_v Y_v]$.
- (2) *between*: changes in the GVC share of world demand $p_v Y_v/W$.¹⁸

¹⁸ Changes in the GVC share are partly related to the relocation of final assembly stages. We extended the framework to take this into account. This increased the contribution from task relocation in driving employment structure changes, but only marginally so. It did not qualitatively change the results.

- (3) *income*: changes in world income W .

Two remarks are in order. First, as this is an accounting exercise we do not mean to imply that these components are independent of each other. For example, changes within a GVC might lead to cost savings and lower prices, which results in a shift in demand between GVCs (Grossman and Rossi-Hansberg, 2008). Second, a potential concern is that the relative magnitude of each component could be driven by changes in output prices instead of changes in employment and output volumes. To avoid this we use world input-output tables in previous years' prices and do the decomposition year-by-year before we add up to arrive at the final result.¹⁹

4.2. Disentangling technological change and task relocation

In order to be able to further decompose the effects on occupational labor demand from changes within GVCs we need to specify the task production function G_{jv} in (3). In particular, we assume that for each task the production factors capital and labor are perfect complements. In other words, they have to be used in fixed proportions. This implies that the required amounts do not vary across countries when we correct for differences in factor productivity, irrespective of differences in relative factor prices. We make this correction by expressing factor demands in terms of 'efficiency units'. For example, $A^c N_{jv}^c$ is the number of efficiency units of occupation- j labor from country c used in GVC v . Note that the actual number of workers coincides with the number of efficiency units only if TFP is equal to 1. We can then write:

$$N_{jv}^c = \frac{e_{jv} T_{jv}^c}{A^c}, \quad (6)$$

where e_{jv} is the number of efficiency units of labor required to create one unit of output of task j in GVC v , which is the same for all

¹⁹ To compute the volume growth of output between 1999 and 2000, we subtract the 1999 output in current prices from the 2000 output in previous years' prices. Similarly, we use output expressed in 2000 current prices and in 2001 previous years' prices, which provides the volume growth between 2000 and 2001, and so on.

countries. We use a TFP correction at the country level, which affects routine and non-routine jobs equally, and we can therefore ignore it when we examine the relative occupational labor demand effects from GVC technology.²⁰ We implement the efficiency correction empirically by constructing a measure of TFP for each country and each year in our dataset using the Penn World Tables (PWT), release 9.0 (Feenstra et al., 2015). From the PWT we take a cross-sectional TFP measure in 1995 and extrapolate it over time using the country-specific TFP series at constant national prices.²¹ TFP in the United States in the initial year is normalized to unity, so that ‘efficiency units’ essentially correspond to ‘United States workers in 1999’. Using the country-specific TFP measure (A^c) and the estimate of N_{jv}^c and T_{jv}^c (see section 3.2) we can calculate e_{jv} .

Using (6), the within effect of the decomposition presented in equation (5) can be written as:

$$\frac{N_{jv}^c}{p_v Y_v} = \frac{1}{A^c} \frac{e_{jv} T_{jv}^c}{p_v Y_v} \frac{T_{jv}^c}{T_{jv}} \quad (7)$$

This allows us to distinguish three separate components of the within effect:

- (1a) *TFP*: changes in Total Factor Productivity A^c
- (1b) *GVC technology*: changes in occupational efficiency units per dollar of output $e_{jv} T_{jv}^c / [p_v Y_v]$
- (1c) *Location*: changes in the task share T_{jv}^c / T_{jv}

We will discuss each of these in turn. First, if the level of Total Factor Productivity in a country increases then this ceteris paribus leads to a loss of labor demand. As workers become more efficient, fewer of them are required to produce a given amount of task output.

Second, we have summarized the production technology of a value chain by the total use of efficiency units of occupational labor (per dollar of output). We can write this as:

$$\frac{e_{jv} T_{jv}^c}{p_v Y_v} = \frac{e_{jv} \alpha_{jv}}{p_v} \quad (8)$$

As explained in Section 3.1 above, there are two components to GVC technology. The first is the task production function G_{jv} , which is captured by the number of efficiency units of labor e_{jv} that are needed to produce one unit of task output. For example, if labor is replaced by machines then e_{jv} decreases (while the required amount of capital goes up). The second component of GVC technology is the overall production function F_v as reflected in the task weights α_{jv} . For example, if over time the production process relies more strongly on service tasks then the corresponding α_{jv} goes up. We are not able to separate the two types of technology with the data that we have, and for each occupation the overall effect of changes in GVC technology can go in either direction. Importantly, we do not make any a priori assumptions about the nature of technological change in a GVC (for example whether it is biased against the use of a certain occupation), but instead let the data speak for itself.

The final term in (7) is the share of country c in the total output of task j within value chain v . We refer to this as ‘location’ because the distribution of these task shares across countries shows where the

activity of a value chain is located. Empirically we can identify the task share by dividing the number of efficiency units of labor of occupation j employed in country c by the total number throughout the chain:

$$\frac{T_{jv}^c}{T_{jv}} = \frac{A^c N_{jv}^c}{\sum_c A^c N_{jv}^c} \quad (9)$$

As the shares sum to one, it follows that relocation of tasks is a zero-sum game: If one country gains then another one loses out.

Our approach is not without caveats. Technology is specific to the task and GVC and assumed to affect countries equally. But countries that participate in a GVC may invest differently in automation and other technologies (Acemoglu and Zilibotti, 2001). This may bias the estimated GVC technology effect. For example, suppose countries A and B participate in GVC v , and country A invests in automation affecting labor demand in a routine task j , but country B does not. The decrease in demand for routine jobs in country A will then partly be attributed to task relocation towards country B (because the task shares change), implying that we underestimate the effect of GVC technology in accounting for the rise of non-routine jobs.

4.3. Trends in technological change and task relocation across GVCs

To illustrate, Fig. 3 shows how changes in GVC technology have affected the demand for labor of different types of occupations. It plots the number of efficiency units employed per 100 dollar of output in 1999 versus 2007 for each GVC (at constant prices).²² Although there is clearly a lot of heterogeneity among GVCs, a general pattern can be observed. The simple regression line in each plot gives an indication to what extent the use of labor has decreased (slope parameter β lower than 1) or increased ($\beta > 1$). Note that for most occupations the slope parameter is below unity which means that GVC technological change tends to be labor-saving. The only exception is non-routine manual occupations, suggesting that on average GVC production made more use of the type of tasks associated with these occupations in 2007 than it did in 1999. The pattern of technological change across occupations indicates that it is ‘routine-replacing’ in the sense that the demand for occupations that are intensive in routine tasks ($\beta = 0.85$ and $\beta = 0.86$), has decreased more than that for non-routine occupations ($\beta = 1.01$ and $\beta = 0.96$).

Fig. 4 illustrates one of the important trends in task relocation: a shift in task production from advanced to emerging countries.²³ For each GVC ending in an advanced country it plots the total task share of emerging countries in 2007 against the initial share in 1999. For all occupations the simple regression line has a slope greater than 1, so that there is indeed a tendency for the share of emerging countries to increase. Task relocation to emerging countries appears strongest for routine manual jobs ($\beta = 1.30$). This suggests routine jobs are more likely to be offshored compared to non-routine jobs.

4.4. Illustration: the value chain of German cars

The task-based model of production in Global Value Chains motivates a decomposition of changes in occupational labor demand into the effects of technological change, task relocation and other factors. Here, we illustrate the decomposition by returning to the example of the value chain of cars that have their final stage of assembly in Germany. In Table 4 we report the decomposition results for 4 of the 11 occupations and total employment, and the contribution from 3 of the 40 countries.

²² To be precise, we first compute the number of efficiency units per 100 dollar of GVC output in 1999. Then we calculate the yearly changes for 2000 up to 2007 based on input-output tables in previous year prices and add these up to arrive at the number for 2007.

²³ The ‘rest of the world’ is also included in the share of emerging countries.

²⁰ In the absence of efficiency measures by task, we prefer to use a country TFP measure since this affects all occupations equally. GVC-specific productivity measures would render our decomposition un-interpretable.

²¹ We have performed two robustness checks with different measures of TFP but our main conclusions remained unchanged. First we used the cross-sectional TFP measure of the PWT in each year and multiplied it by the TFP level at constant national prices of the United States in the same year. Second we took the measure developed by Inklaar and Diewert (2016). The advantage of the latter is that it is consistently estimated across time and across space. A disadvantage is that Luxembourg and Indonesia are not included, which is why it is not our preferred measure.

Notes: The number of efficiency units in each year are given per 100 dollar of output. The solid line shows the regression line, with its slope given in brackets. To calculate the regression coefficient, all observations below the 2.5th and above the 97.5th quantile were removed. The dotted line is a 45° line.

Fig. 3. Technological change within Global Value Chains, 1999–2007.

The first column shows the change in employment attributed to TFP (this is the first term in equation (7)). For the German car GVC as a whole this effect is negative. This suggests that on average countries participating in this value chain have become more productive, which *ceteris paribus* would result in a loss of employment. Since TFP is defined at the country level, the sign of this effect is necessarily the same for all occupations within a given country.

The GVC technology effect (the second term in (7)) is reported in the second column and is negative for 3 of the 4 occupations shown, with support services workers as the exception.²⁴ This coincides with our findings in the previous section regarding the pattern of technological change. Technological change within the GVC is such that less labor is needed per unit of final output, except for non-routine manual occupations (which include support services workers).

The effect of location in column 3 (the final term in (7)) reveals that tasks in the German car GVC have been relocated from Germany towards China and Poland. For example, the number of production workers in Germany decreased by 141 thousand while it increased by 116 and 28 thousand in China and Poland, respectively. Note that although changes in the task allocation across countries sum to zero in

terms of efficiency units (as explained in the previous section), in terms of the actual number of jobs this need not be the case. In this example, tasks have on average moved to countries with a lower TFP level such that the overall location effect is an increase in labor demand for this GVC.

The positive between effect (the second term in (5)) suggests that cars that have been finalized in Germany capture a larger share of world demand in 2007 than they did in 1999. Finally, the pen-ultimate column shows that the largest increase in employment comes from an overall rise in world income (the last term in (5)). Adding up all terms results in the total change in employment by occupation between 1999 and 2007, as shown in the final column of Table 4. This number coincides with that reported in Table 3.

5. The rise of non-routine jobs: trade or technology?

In this section we shift our focus from employment changes within global value chains to those occurring at the country level. This requires summation over countries of the decomposition results for the 1435 GVCs in our data. For example, if we look at Germany then we do not only take into account the employment of German workers in the German car GVC (as in Table 4 above), but also in the French car GVC, the Japanese electronics GVC, etcetera. We narrow our focus in two directions. First, although the decomposition is still performed at

²⁴ Since for each occupation GVC technology is defined at the value chain level, the sign of this effect is necessarily the same for all countries within a given occupation.

Notes: Each observation represents a GVC ending in an advanced country.

Fig. 4. Task relocation within Global Value Chains, 1999–2007.

the most detailed level our occupations classification allows (the 11 different occupations given in Table 1), we aggregate the results so that they apply to routine and non-routine jobs. Second, we only discuss the effect of changes in GVC technology and task relocation on the demand for labor and relegate full decomposition results to Appendix D.

Panel (a) of Fig. 5 shows the percentage change in the number of routine jobs (horizontal axis) and non-routine jobs (vertical axis) that is attributed to GVC technological change. Each observation is a country (40 in total) with emerging countries indicated by white dots and advanced countries by black dots. The first thing to notice is that there is substantial heterogeneity among countries in the effects of technological change on employment. The reason for this is that GVCs differ in the nature and extent of technological change (recall Fig. 3) and that countries differ in the extent of their involvement in each value chain. For example, the number of German workers involved in the GVC of German cars is greater than that involved in the GVC of French cars, and therefore employment in Germany will be more strongly affected by technological change in the former than in the latter. From Fig. 5(a) it is clear that technological change within GVC is related to reduced demand for routine workers in nearly all countries. For non-routine jobs the pattern is less clear, with most countries showing an increase and some a decrease. For every country, the percentage change in routine jobs is always lower than that in non-routine jobs, consistent with the routinization hypothesis put forth in Autor et al. (2003).²⁵ We will

come back to the effect of technological change on the relative demand for the two types of jobs in Section 5.1 below.

The role of task relocation is illustrated in panel (b) of Fig. 5. There is a positive relationship between the percentage change in routine and non-routine jobs. For advanced countries both are usually negative (an exception is Germany, which saw a small increase in non-routine employment). Among the emerging countries there is a subset which has attracted both routine and non-routine jobs. Nevertheless, for typical offshore destinations such as China and Poland the percentage increase in routine jobs is greater than that in non-routine jobs. Perhaps surprisingly, Mexico does not seem to benefit from task relocation (it is located in the south-west quadrant, together with advanced countries such as the United States and the United Kingdom). A possible reason for this is that Mexico already became integrated in global value chains in the early 1990s following the signing of the North American Trade Agreement (NAFTA) in 1994.

5.1. The relative demand for non-routine and routine jobs

In Section 2 we highlighted an important trend in the labor market of both advanced and emerging countries: the increasing employment share of non-routine jobs. In this section we show how our decomposition results can shed light on whether and to what extent technological change and offshoring have contributed to this trend.

We do so by calculating hypothetical changes in employment shares under the assumption that the total change in the number of jobs equals that attributed to GVC technological change or to task relocation by the

²⁵ All points fall to the left of a 45° line.

Table 4
Decomposition results for the global value chain of cars finalized in Germany.

	Within			Between	Income	Total
	TFP	GVC technology	Location			
Production workers	−193	−216	189	52	371	204
Germany	−47	−91	−141	17	155	−108
China	−43	−18	116	7	32	95
Poland	−9	−8	28	2	13	27
Clerical workers	−40	−62	19	12	98	27
Germany	−17	−35	−13	6	55	−3
China	−6	−3	10	1	5	6
Poland	−1	−1	5	0	2	5
Support services workers	−42	28	17	11	72	85
Germany	−6	9	−10	3	21	16
China	−18	5	17	2	14	19
Poland	−1	1	0	0	1	1
Engineering professionals	−42	−13	19	15	102	80
Germany	−20	−7	−23	9	65	24
China	−3	−1	8	0	2	7
Poland	−1	0	4	0	2	5
Total	−460	−224	303	132	926	677
Germany	−128	−100	−239	51	422	7
China	−101	−16	177	15	76	151
Poland	−18	−8	53	5	27	59

Notes: In thousands of jobs. Numbers may not sum due to rounding. The numbers shown in the final column match with those reported in Table 3. The decomposition shows results for 4 out of the 11 occupational groupings and total employment. The numbers in bold show overall employment changes of each occupation in the GVC of cars finalized in Germany due to the different factors. The contribution from 3 countries, namely Germany, China and Poland, by occupation is distinguished.

(a) Due to GVC technological change

(b) Due to task relocation

Notes: Each observation is a country.

Fig. 5. Percentage change in routine and non-routine jobs.

decomposition. For example, the decomposition results show that in the United States, task relocation resulted in a loss of 2.2 million routine jobs and 2.7 million non-routine jobs. Given an initial employment level of 54.6 million routine and 88.3 non-routine jobs, this corresponds to an increase in the employment share of non-routine jobs from 61.80% to 62.05% or 0.25 percentage points.

Fig. 6 shows the results for the same countries as in Fig. 1. Three main conclusions emerge. First, technological change within GVCs increases the demand for non-routine jobs relative to routine jobs. This is true for nearly all countries included in our analysis, see

Appendix Fig. F.2 for the complete list.²⁶ Thus, both in advanced and emerging countries we find that technological change is routine-replacing.

A potential alternative interpretation of our finding on the increased demand for non-routine jobs due to technological change points at the rising share of high-educated workers. A rise in the relative supply of educated workers would alter relative wages and may induce firms to substitute non-routine for routine tasks. This will not arise in our analysis as it is based on a Leontief production function, where the elasticity of substitution between tasks is assumed to be zero. This is crucial for

²⁶ The only exception is Greece, but the decrease in the employment share of non-routine workers is very small.

Fig. 6. The contribution of task relocation and GVC technological change to changes in the employment share of non-routine jobs.

Source: Decomposition result using the harmonized cross-country occupations database and the World Input-Output Tables. Notes: Appendix Fig. F.2 shows the results for all countries included in the analysis.

our identification of technological change. We measure eleven tasks, such as fabrication, managerial, engineering, and transportation tasks. In our setup, managerial tasks cannot substitute for say transportation tasks. Moreover, to investigate substitution elasticities across tasks, we would need “task prices”. Task prices can only implicitly be derived as they are potentially produced by combinations of workers with various levels of educational attainment (as in the canonical task-model by Acemoglu and Autor (2011)). There is not a one-to-one mapping from schooling to tasks. For example, for the US, the share of college graduates involved in the “engineering task” (which is non-routine) is 58 percent in 1999 (62 percent in 2007) and the remainder consists of workers with less than a college degree.²⁷ Within tasks, changes in the relative wage of college and non-college educated workers will indeed give rise to conventional substitution effects. But that is not the focus of this paper.

Second, offshoring has lowered the relative demand for routine jobs in most major advanced countries, including France, Germany, the United Kingdom, and the United States. The opposite effect is observed in several emerging countries that benefited from the relocation of routine tasks, such as China, Hungary, Poland and Turkey.

Third, GVC technological change has a much greater impact on the employment share of non-routine workers than task relocation.²⁸ For example, in the United States technological change can account for a 2.7 percentage points increase in the share of non-routine jobs, but task relocation only for a 0.25 percentage point increase. The dominance of technology over trade in explaining labor market trends is in line with previous findings by Autor et al. (2003) and Goos et al. (2014) for advanced countries. Its role in accounting for the rise of non-routine jobs helps explain why most countries in our dataset experience an increase in the share of non-routine jobs, even though some countries

in our analysis are important offshore destinations for routine tasks.²⁹

6. Concluding remarks

In many countries, there has been an increase in the share of non-routine jobs in the labor force. For several advanced countries these changes in occupational employment have been documented and analyzed (e.g. Autor et al., 2003; Goos et al., 2014; Cortes et al., 2017). This paper uses a cross-country harmonized occupations database and documents an increase in the employment share of non-routine jobs in the majority of advanced and emerging countries during the period 1999–2007. To interpret this trend in the United States, several studies (e.g. Caines et al., 2017; Cortes et al., 2017) have proposed theoretical frameworks that build on Acemoglu and Autor (2011) and Autor and Dorn (2013). These models examine the role of advances in automation technology but abstract from offshoring.

We examine the rise of non-routine jobs through the lens of a global value chain model. In particular, for each value chain we look at changes in the use of occupational labor per dollar of output (defined as ‘GVC technology’) and shifts in the share captured by each country (‘task relocation’). Our findings suggest that technological change within global value chains tends to drive down the demand for routine relative to non-routine jobs. The relocation of routine tasks further contributed to increased relative demand for non-routine jobs in advanced countries, although this effect was smaller compared to the effect from technological change. In several emerging countries, including China and Poland, task relocation increased the demand for routine jobs, but also in these countries the effect from technological change

²⁷ Based on data from the 2000 Population Census and the 2007 American Community Survey.

²⁸ Results for all countries suggest that only in Latvia the increase in demand for routine jobs due to task relocation is larger than technological change biased in favor of demand for non-routine jobs (see Appendix Fig. F.2).

²⁹ In the analysis we have treated the production of any good or service as a global value chain, regardless of how ‘global’ the production process actually is. This might bias our results against the role of trade in explaining changes in the demand for labor. To investigate this, we restrict attention in Appendix E to a subset of GVCs in which offshoring is most common, namely the global value chains of manufactured goods. Our conclusion that technology is more important than trade in explaining the increased employment share of non-routine jobs is unchanged when we restrict attention to manufacturing GVCs.

biased against routine jobs was stronger.

Our findings are based on a decomposition that is essentially an ex-post accounting exercise. The results are useful empirical findings, but we do not claim to have determined a causal effect. The decomposition analysis abstracts from the inter-relatedness of technological change and task relocation. For example, an improvement in information technology may reduce demand for routine jobs throughout the value chain, but it may also affect the ease at which a routine task can be relocated. Preliminary regression analysis suggests that the change in demand for non-routine jobs due to the GVC technology component is positively related (and therefore complementary) to changes in task shares outside the country of completion, whereas the opposite relation

is observed for routine jobs, but clearly more research is needed here.

The decomposition analysis and the occupations database presented in this paper open up other interesting avenues for future research. The estimated effects of technological change and task relocation within global value chains can be correlated with direct measures of technology, such as robot adoption, and trade costs by industry. An interesting research question is whether global value chains that observe more task relocation and technological change also observe an increase in their market shares. Finally, using the data presented here and by extending recent models of trade in value added it becomes feasible to explore the type of tasks countries specialize within global value chains and how these specialization patterns evolve over time.

A. Data sources

Table A.1
Sources of occupational data by country.

Country	Source(s)	Years
Australia	Labor Force: Employed Persons Quarterly Large Source Dataset	1999–2007
Brazil	National Household Sample Survey (PNAD)	1999–2007
Canada	Canadian Labor Force Survey	1999–2007
China	Population census	2000, 2010
EU members ^a	Labor force survey	1999–2007 ^b
India	National Sample Survey	2000, 2004–2006, 2008
Indonesia	National Labor Force Survey (Sakernas)	2000–2007 ^c
Japan	Population census	1995, 2000, 2005, 2010
Mexico	Population census	2000, 2010
Russia	Labor force survey	2000, 2008
South-Korea	Korea Labor and Income Panel Study (KLIPS)	1999–2007
Taiwan	Manpower survey	1999–2007
Turkey	Labor force survey	2007
United States	Population census	2000
	American community surveys	2000–2007

Notes:

^a We examine the 27 countries that are a member of the EU (per January 2007).

^b Bulgaria and Malta from 2000 onward; Poland from 2004 onward.

^c We drop 2000–2002 because of anomalies in the data.

B. The rise of non-routine jobs in other low-income and emerging countries

Appendix Fig. B.1 shows changes in the employment share of non-routine jobs for several developing countries. These countries are not included in the World Input-Output Database and we are therefore unable to examine their participation in global value chains and the role of technology and offshoring in driving demand for non-routine jobs. However, using available censuses with detail on occupations, it is possible to calculate the employment share of routine and non-routine jobs. For nine out of twelve developing countries in Appendix Fig. B.1 we find an increase in non-routine jobs. In three countries, Cambodia, Malawi, and Tanzania, there is a decline in the share of non-routine jobs during the period examined.³⁰ The increase in non-routine jobs is small in Vietnam. It is more than five percentage points in Botswana, Ghana, Mozambique, and South Africa. Overall, it provides further evidence that also many developing countries experience a rise in non-routine jobs.

³⁰ The period varies by country depending on the timing of censuses, see notes to Appendix Fig. B.1.

Notes: Census data for Cambodia (1998, 2008); Malawi (1998, 2008), Tanzania (2002, 2012), Belarus (1999, 2009), Vietnam (1999, 2009), Uruguay (1996, 2006), Ecuador (2001, 2010), Dominican Republic (2002, 2010), South Africa (1996, 2007), Ghana (2000, 2010), Mozambique (1997, 2007), Botswana (2001, 2011). Occupations distinguished in the national classifications are mapped into routine- and non-routine task-intensive occupations.

Source: IPUMS International, version 6.5 (Minnesota Population Center, 2017). The authors also wish to acknowledge the statistical offices for making the underlying data available.

Fig. B.1. Change in the employment share of non-routine jobs, low- and middle-income countries.

C. Methodology

C.1. World input-output tables

The World Input-Output Database (WIOD, November 2013 release) provides data on $m_i = 35$ industries and $m_c = 41$ countries, including one that captures ‘the rest of the world’. The basic structure of the world input-output table for a given year is given in Fig. C.1. The units of observations are the $m_i m_c = 1435$ unique country-industry pairs. The $m_i m_c \times m_i m_c$ matrix $\mathbf{Z}$ records the flows of output for intermediate use between industries worldwide. The entry in row a and column b equals the use (in United States dollars) by industry-country b of intermediate inputs provided by a . The $m_i m_c \times m_c m_f$ matrix $\mathbf{F}$ contains for each country-industry the output for final use in every country and in $m_f = 5$ different categories: final consumption expenditures by households, non-profit organizations and the government, and investment in fixed capital and inventories by firms. Gross output for each country-industry pair is given by the $m_i m_c \times 1$ supply vector $\mathbf{s}$. Because total supply is by necessity equal to total intermediate and final use, the following equation has to hold:

$$\mathbf{s} = \mathbf{Z}\mathbf{1}_{m_i m_c} + \mathbf{F}\mathbf{1}_{m_c m_f}, \quad (\text{C.1})$$

where $\mathbf{1}$ is a vector of ones and the subscript denotes its dimension. In other words, if we sum up over the elements of $\mathbf{Z}$ and $\mathbf{F}$ in a given row, then we arrive at the corresponding value of $\mathbf{s}$. Similarly, if we sum up over a column of $\mathbf{Z}$ to obtain the total worth of intermediate inputs used in a given country-industry and include its value added (an element of the $1 \times m_i m_c$ vector $\mathbf{v}'$) then we also arrive at total output of this country-industry.

Notes: The data consists of m_i industries, m_c countries and m_f final demand categories. Z is the matrix of intermediate use, F is the matrix of final demand, s is the vector of gross output and v is the vector of value added.

Fig. C.1. Structure of a World Input-Output Table.

We use this data to construct two new matrices. The first is the $m_i m_c \times m_i m_c$ matrix $A = Z \text{diag}(s)^{-1}$ of intermediate use coefficients, where $\text{diag}(s)$ is the $m_i m_c \times m_i m_c$ matrix with the successive elements of the output vector s on the diagonal. A typical element of A is the dollar value of the intermediate input use of one industry (row) per dollar of output of another (column). Second, we add up across final demand categories and countries to derive the $m_i m_c \times 1$ vector $f = F \mathbf{1}_{m_c m_f}$ of final demand. The identity given in (C.1) can then be rewritten as:

$$s = As + f. \quad (\text{C.2})$$

Under the assumption that the coefficients in A are the same for every dollar of output produced, we can solve for s to obtain:

$$s = Bf, \quad (\text{C.3})$$

where $B = [I - A]^{-1}$ is the so-called Leontief inverse with I the $m_i m_c \times m_i m_c$ identity matrix. A given column of B contains the dollar value of output of all industries in all countries required to produce one dollar of final output for the corresponding industry-country pair.

As in Timmer et al. (2014) we define a global value chain as a country-industry pair that delivers a product for final use. This means that each GVC corresponds to a column of the matrix B and that we can think of each cell within a column as the task output that the corresponding industry delivers to this GVC. The dollar value of final demand for each GVC ($p_v Y_v$ in the main text) is given by the elements of the vector f .

C.2. Occupational employment

To go from task output to employment levels we use occupations data to find the $m_i m_c \times 1$ vector q_j of labor with occupation j employed per dollar of gross output in each industry-country pair. It follows that $Q_j = \text{diag}(q_j)B$ is the matrix that gives for each GVC (columns) the amount of labor that has been used to perform the tasks allocated to the different industries worldwide (rows) per dollar of final output. By summing over all industries in a given country we find the $m_c \times m_i m_c$ matrix N_j , of which the element in row c and column v corresponds to $N_{jv}^c / [p_v Y_v]$: the demand for occupational labor in country c by GVC v per dollar of final output.

In this notation, occupational employment in a given country can be written as:

$$L_j^c = \sum_v \frac{N_{jv}^c}{p_v Y_v} p_v Y_v = i_c' N_j f, \quad (\text{C.4})$$

where i_c is a $m_c \times 1$ selection vector which equals 1 for country c and 0 otherwise.

C.3. Decomposition

We can express final demand for each global value chain as a share of world GDP W (a scalar) by defining $d = f/W$ so that we obtain:

$$L_j^c = \sum_v \frac{N_{jv}^c}{p_v Y_v} \frac{p_v Y_v}{W} W = i_c' N_j d W. \quad (\text{C.5})$$

which corresponds to equation (5) aggregated over all GVCs for a given country. In the decomposition exercise we separate changes in the labor

requirements matrix $\mathbf{N}_j$ from those in the final demand shares $\mathbf{d}$ and world income W . For two consecutive years, say year t and $t + 1$, we use an input-output table in current year prices for t and in previous year prices for $t + 1$ so that both use the prices of year t . The three-way decomposition is then given by:

$$L_{j,t+1}^c - L_{j,t}^c = \mathbf{i}'_c \mathbf{N}_{j,t+1} \mathbf{d}_{t+1} W_{t+1} - \mathbf{i}'_c \mathbf{N}_{j,t} \mathbf{d}_t W_t$$

$$= \underbrace{\mathbf{i}'_c [\mathbf{N}_{j,t+1} - \mathbf{N}_{j,t}] \mathbf{d}_{t+1} W_{t+1}}_{\text{within}} + \underbrace{\mathbf{i}'_c \mathbf{N}_{j,t} [\mathbf{d}_{t+1} - \mathbf{d}_t] W_{t+1}}_{\text{between}} + \underbrace{\mathbf{i}'_c \mathbf{N}_{j,t} \mathbf{d}_t [W_{t+1} - W_t]}_{\text{income}}. \quad (\text{C.6})$$

This decomposition is not unique as it alters with the weights applied to the expressions. For that reason, we also compute its polar form (obtained by switching the initial and final year weights) and then take the average of the two. Dietzenbacher and Los (1998) demonstrate that the average of all the potential decompositions is close to the average of the two polar decompositions.

We perform the decomposition for all consecutive years between 1999 and 2007 and add up the corresponding elements to arrive at the total presented in Appendix D and discussed in the main text.

D. Decomposition results for all countries

Tables D.1 and D.2 show the decomposition results for non-routine and routine occupations, respectively. All numbers reported are in thousands of jobs (note that agricultural occupations, armed forces, and the so-called ‘occupations not elsewhere classified’ are not included). The first column gives the employment level in 1999, and the second column the change in employment between 1999 and 2007. This change is subsequently decomposed into a ‘within’, a ‘between’ and an ‘income’ component, of which the ‘within’ component is further decomposed by ‘TFP’, ‘GVC technology’ and ‘location’, see Section 4.

Table D.1
Decomposition for non-routine occupations.

	Initial	Change	Within			Between	Income
			TFP	GVC technology	Location		
Australia	5108	1320	−400	487	−367	136	1464
Austria	2224	368	−131	42	57	−210	612
Belgium	2535	436	−36	91	−74	−228	683
Bulgaria	1762	228	−38	−347	−59	215	457
Brazil	34743	16659	−1459	5667	1215	76	11160
Canada	9049	1819	−58	−425	−211	0	2514
China	190511	54368	−73363	−51645	5498	119145	54733
Cyprus	182	56	−19	2	10	9	53
Czech Republic	2913	367	−852	267	61	127	764
Germany	23710	2217	−1899	1727	121	−4024	6293
Denmark	1751	260	−53	69	−99	−129	472
Spain	8715	3919	367	489	−242	615	2690
Estonia	376	54	−122	7	−6	77	99
Finland	1467	254	−179	118	−55	−31	402
France	14294	2741	−702	967	−386	−1111	3973
United Kingdom	18446	3360	−2138	1133	−672	−100	5137
Greece	2241	587	−280	3	−107	341	630
Hungary	2310	166	−429	102	−2	−114	610
Indonesia	28270	8334	−3586	−1279	1958	3819	7422
India	89130	23801	−14207	−18106	2798	26516	26800
Ireland	996	355	−63	−15	−10	147	296
Italy	12970	2903	723	332	−197	−1622	3667
Japan	30822	221	−989	−1033	−744	−4669	7655
South Korea	10923	2321	−1565	−273	39	1037	3082
Lithuania	819	127	−329	85	57	104	210
Luxembourg	152	57	−8	16	−6	9	46
Latvia	576	123	−347	95	24	197	154
Mexico	18304	7227	345	2391	−722	−337	5550
Malta	86	14	1	−5	−7	2	23
Netherlands	5497	653	−314	−74	−11	−415	1468
Poland	7254	911	−1259	248	−20	86	1856
Portugal	2408	430	1	159	−30	−365	665
Romania	3237	528	−1343	248	−40	806	857
Russia	40041	6671	−16532	3565	275	8408	10955
Slovakia	1244	133	−355	61	28	71	326
Slovenia	452	109	−96	48	2	26	128
Sweden	2828	423	−461	275	−13	−151	773
Turkey	7589	1843	−1407	−596	192	1492	2163
Taiwan	4671	934	−575	92	262	−128	1283
United States	88315	10499	−7969	−112	−2672	−2213	23465

Notes: In thousands of jobs.

Table D.2
Decomposition for routine occupations.

	Initial	Change	Within			Between	Income
			TFP	GVC technology	Location		
Australia	3234	383	–234	–141	–204	114	849
Austria	1355	–60	–68	–147	–86	–81	322
Belgium	1400	–77	–17	–205	–128	–77	351
Bulgaria	932	236	–20	–284	–13	302	251
Brazil	21366	4430	–760	–165	201	–714	5867
Canada	5065	543	–37	–627	–202	54	1353
China	162521	45163	–59261	–56734	11002	105883	44274
Cyprus	109	20	–11	–7	4	5	29
Czech Republic	1919	–71	–518	–242	25	197	466
Germany	13774	–856	–1003	–1077	–122	–1941	3286
Denmark	835	–63	–22	–87	–96	–52	194
Spain	5906	1252	231	–640	–362	358	1665
Estonia	175	33	–59	–20	–2	66	47
Finland	647	4	–73	–53	–38	6	162
France	8366	–589	–393	–1158	–679	–411	2052
United Kingdom	10345	–1051	–1039	–1491	–809	–134	2421
Greece	1265	148	–154	4	–90	51	338
Hungary	1573	–76	–276	–188	20	–14	383
Indonesia	22605	801	–2823	–5505	601	2868	5662
India	74525	18241	–11103	–22828	–500	31055	21616
Ireland	591	153	–37	–48	–12	84	166
Italy	8545	–85	419	–1082	–632	–938	2147
Japan	29216	–1445	–921	–2408	–357	–4911	7152
South Korea	7124	1361	–1033	–376	–55	790	2035
Lithuania	396	56	–157	–17	24	106	101
Luxembourg	93	25	–4	–6	–2	11	27
Latvia	262	76	–168	27	37	105	74
Mexico	12943	902	196	–1599	–861	–170	3336
Malta	55	1	0	–7	–4	–2	14
Netherlands	2222	5	–119	–287	43	–185	553
Poland	4385	506	–736	–295	208	243	1086
Portugal	1911	–116	5	–175	–30	–385	468
Romania	2966	–220	–1133	–448	–73	722	711
Russia	15827	–335	–6009	–2497	–601	4809	3963
Slovakia	772	–6	–200	–122	–40	170	186
Slovenia	337	–19	–58	–60	–6	26	80
Sweden	1248	–66	–180	–144	–45	6	298
Turkey	5655	762	–953	–1624	220	1637	1482
Taiwan	4025	126	–441	–339	–7	–97	1010
United States	54580	–2185	–4610	–6056	–2204	–2632	13316

Notes: In thousands of jobs.

E. Global value chains of manufactured goods

In the analysis in the main text we have treated the production of any good or service as a global value chain, regardless of how ‘global’ the production process actually is. This might bias our results against the role of trade in explaining changes in the demand for labor. To investigate this, we restrict attention to a subset of GVCs in which offshoring is most common, namely the global value chains of manufactured goods. Recall that we identify a global value chain by the industry and country in which the final stage of production takes place, but that it includes all contributing industries as well. Hence, employment in manufacturing GVCs does not only consist of workers in manufacturing industries, but also in service industries that deliver output for intermediate use to these industries (which means that they perform one of the required tasks). For example, when we consider employment in the GVC of German cars then this includes employees in the UK financial services sector when they provide financial business services to this value chain.

Notes: Each observation is a country. Only employment in manufacturing global value chains is included.

Fig. E.1. Percentage change in routine and non-routine jobs in manufacturing GVCs.

Fig. E.1 is the counterpart of Fig. 5 but restricts attention to employment in manufacturing GVCs. By comparing panel (b) in the two figures we see that task relocation plays indeed a more important role in manufacturing GVCs: the percentage change in the number of routine and non-routine jobs is larger (in absolute terms) for most countries. However, this is also true for the effect of technological change in panel (a). What does this mean for the relative importance of trade and technology? Fig. E.2 shows that our conclusion that technology is more important than trade in explaining the increased employment share of non-routine jobs is unchanged when we restrict attention to manufacturing GVCs.

Fig. E.2. The contribution of task relocation and GVC technological change to changes in the employment share of non-routine jobs in manufacturing GVCs.

Source: Decomposition result using the harmonized cross-country occupations database and the World Input-Output Tables. Notes: Selected advanced and emerging countries appear in ascending order of the percentage point change in the employment share of non-routine jobs due to task relocation between 1999 and 2007.

F. Changes in employment shares for all countries

Fig. F.1 shows the change in the employment share of non-routine jobs for all countries in our sample (similar to Fig. 1). Fig. F.2 reports the hypothetical change in the employment share of non-routine jobs attributed to technological change within GVCs and task relocation for all countries in our sample (similar to Fig. 6).

Fig. F.1. Change in the employment share of non-routine jobs between 1999 and 2007, all countries.

Source: Harmonized cross-country occupations database, see main text. Notes: Countries are grouped in advanced and emerging countries and appear in ascending order of the change in the employment share of non-routine jobs between 1999 and 2007.

Fig. F.2. Changes in the employment share of non-routine jobs due to technological change and task relocation, all countries.

Source: Decomposition result using the harmonized cross-country occupations database and the World Input-Output Tables. Notes: Countries appear in ascending order of the percentage point change in the employment share of non-routine jobs due to task relocation between 1999 and 2007.

References

- Acemoglu, D., Autor, D.H., 2011. Skills, tasks and technologies: implications for employment and earnings. In: Ashenfelter, O., Card, D.E. (Eds.), *Handbook of Labor Economics*, vol. 4. Elsevier, Amsterdam, pp. 1043–1171.
- Acemoglu, D., Restrepo, P., 2017. Robots and Jobs: Evidence from US Labor Markets. mimeo MIT.
- Acemoglu, D., Zilibotti, F., 2001. Productivity differences. *Q. J. Econ.* 115 (3), 563–606.
- Akçomak, Semih, Kok, Suzanne, Rojas-Romagosa, Hugo, 2016. Technology, offshoring and the task content of occupations in the United Kingdom. *Int. Lab. Rev.* 155 (2), 201–230.
- Autor, D., 2015. Why are there still so many jobs? The history and future of workplace automation. *J. Econ. Perspect.* 29, 3–30.
- Autor, D., Murnane, R.J., Levy, F., 2003. The skill content of recent technological change: an empirical exploration. *Q. J. Econ.* 118 (4), 1279–1334.
- Autor, D., Katz, L.F., Kearney, M.S., 2006. The polarization of the US labor market. *Am. Econ. Rev.* 96 (2), 189–194.
- Autor, D., Dorn, D., Hanson, G., 2015. Untangling trade and technology: evidence from local labour markets. *Econ. J.* 125, 621–646.
- Autor, David, Dorn, David, 2013. The growth of low-skill service jobs and the polarization of the us labor market. *Am. Econ. Rev.* 103 (5), 1553–1597.
- Baldwin, R., Robert-Nicoud, F., 2014. Trade in goods and trade in tasks: an integrating framework. *J. Int. Econ.* 92, 51–62.
- Baumgarten, Daniel, Geishecker, Ingo, Görg, Holger, 2013. Offshoring, tasks, and the skill-wage pattern. *Eur. Econ. Rev.* 61, 132–152.
- Becker, S.O., Ekholm, K., Muendler, M.A., 2011. Offshoring and the onshore composition of tasks and skills. *J. Int. Econ.* 90, 91–106.
- Bick, A., Brüggemann, B., Fuchs-Schündeln, N., 2018. Hours Worked in Europe and the US: New Data, New Answers. Mimeo University of Arizona.
- Blinder, Alan S., 2009. How many US jobs might be offshorable? *World Econ.* 10, 41–78.
- Caines, Colin, Hoffmann, Florian, Kambourov, Gueorgui, 2017. Complex-task biased technological change and the labor market. *Rev. Econ. Dynam.* 25, 298–319.
- Cortes, Guido Matias, Jaimovich, Nir, Siu, Henry E., 2017. Disappearing routine jobs: who, how, and why? *J. Monetary Econ.* 91, 69–87.
- de Vries, G.J., Miroudot, S., Timmer, M., 2016. Functional Specialization in International Trade: an Exploration Using Occupations Data. mimeo Groningen Growth and Development Centre, University of Groningen.
- Dicarlo, Emanuele, Lo-Bello, Salvatore, Monroy-Taborda, Sebastian, Ana-Maria Oviedo, Sanchez-Puerta, Maria L., Santos, Indhira, 2016. The Skill Content of Occupations across Low and Middle Income Countries: Evidence from Harmonized Data. mimeo World Bank.

- Dietzenbacher, E., Los, B., 1998. Structural decomposition techniques: sense and sensitivity. *Econ. Syst. Res.* 10 (4), 307–324.
- Ebenstein, Avraham, Harrison, Ann, McMillan, Margaret, Phillips, Shannon, 2014. Estimating the impact of trade and offshoring on american workers using the current population surveys. *Rev. Econ. Stat.* 96 (4), 581–595.
- Feenstra, R.C., Inklaar, R., Timmer, M.P., 2015. The next generation of the penn world table. *Am. Econ. Rev.* 105 (10), 3150–3182.
- Goos, M., Manning, A., Salomons, A., 2014. Explaining job polarization: routine-biased technological change and offshoring. *Am. Econ. Rev.* 104 (8), 2509–2526.
- Grossman, G.M., Rossi-Hansberg, E., 2008. Trading tasks: a simple theory of offshoring. *Am. Econ. Rev.* 98 (5), 1978–1997.
- Hansson, Pär, 2000. Relative demand for skills in Swedish manufacturing: technology or trade? *Rev. Int. Econ.* 8 (3), 533–555.
- Harrigan, J., Reshef, A., Toubal, F., 2016. The March of the Techies: Technology, Trade, and Job Polarization in France, 1994–2007. NBER Working Paper 22110.
- Hijzen, A., Görg, H., Hine, R.C., 2005. International outsourcing and the skill structure of labour demand in the United Kingdom. *Econ. J.* 115 (506), 860–878.
- Ikenaga, Toshie, Kambayashi, Ryo, 2016. Task polarization in the Japanese labor market: evidence of a long-term trend. *Ind. Relat.* 55 (2), 267–293.
- Inklaar, Robert, Diewert, W. Erwin, 2016. Measuring industry productivity and cross-country convergence. *J. Econom.* 191 (2), 426–433.
- Johnson, R.C., 2018. Measuring global value chains. *Ann. Rev. Econ.* 10 (1), 207–236.
- Leamer, Edward E., Storper, Michael, 2001. The economic geography of the internet age. *J. Int. Bus. Stud.* 32 (4), 641–665.
- Levy, Frank, Murnane, Richard J., 2004. *The New Division of Labor*. Princeton University Press, Princeton.
- Los, B., Timmer, M.P., de Vries, G.J., 2015. How global are global value chains? a new approach to measure international fragmentation. *J. Reg. Sci.* 55 (1), 66–92.
- Marcolin, L., Miroudot, S., Squicciarini, M., 2016. The Routine Content of Occupations: New Cross-country Measures Based on Piac. OECD Trade Policy Papers, No. 188.
- Marin, D., 2006. A new international division of labor in Europe: outsourcing and offshoring to eastern Europe. *J. Eur. Econ. Assoc.* 4, 612–622.
- Michaels, G., Natraj, A., van Reenen, J., 2014. Has ICT polarized skill demand? Evidence from eleven countries over 25 years. *Rev. Econ. Stat.* 96 (1), 60–77.
- Morrison, C.J., Siegel, D.S., 2001. The impacts of technology, trade and outsourcing on employment and labor composition. *Scand. J. Econ.* 103 (2), 241–264.
- Pierce, J.R., Schott, P.K., 2016. The surprisingly swift decline of US manufacturing employment. *Am. Econ. Rev.* 106 (7), 1632–1662.
- Reijnders, L.S.M., Timmer, M.P., Ye, X., 2016. Offshoring, Biased Technical Change and Labor Demand: New Evidence from Global Value Chains, vol. 164. Groningen Growth and Development Centre Research Memorandum.
- Sturgeon, T., van Biesebroeck, J., Gereffi, G., 2008. Value chains, networks, and clusters: reframing the global automotive industry. *J. Econ. Geogr.* 8 (3), 297–321.
- Timmer, M.P., Erumban, A.A., Los, B., Stehrer, R., de Vries, G.J., 2014. Slicing up global value chains. *J. Econ. Perspect.* 28 (2), 99–118.
- Timmer, M.P., Dietzenbacher, E., Los, B., Stehrer, R., de Vries, G.J., 2015. An illustrated user guide to the world input output database: the case of global automotive production. *Rev. Int. Econ.* 23, 575–605.