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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 labour 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 labour market development, we develop a task-based model of production in global supply chains and propose a decomposition of changes in occupational labour 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 labour demand from one location to another. For the empirical implementation we combine harmonised 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. Task relocation increased demand for non-routine occupations in advanced countries, but its effect is much weaker compared to technological change.

Keywords: Global supply chains, trade, technology, tasks, occupations

JEL: D57, F16, F66, J21, O33

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1 Introduction

A striking feature of the labour market in advanced countries is the growing share of non-routine occupations in the labour force. This increase is often attributed to two key driving forces. The first is routine-biased technological change. Computers, robots, artificial intelligence, and other recent technological developments tend to displace labour in the performance of routine and non-cognitive tasks, but they are complementary to many non-routine abstract tasks (Autor et al. 2003; Goos et al. 2014). The second driving force is trade in tasks, or offshoring. Tasks that are relatively easy to offshore are those that require codifiable information rather than tacit knowledge (Leamer and Storper 2001); can be summarised in a set of well-specified rules (Levy and Murnane 2004); and do not require face-to-face contact (Blinder 2009).[1] As such, offshoring mostly affects workers in routine occupations. How can we empirically disentangle the role of trade in tasks from that of technological change in driving the rise of non-routine jobs?

This paper proposes a novel cross-country approach to study changes in occupational employment. We outline a task-based model of production in Global Supply Chains (GSCs 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 labour demand into the effects of technological change, task relocation and other factors. For the empirical implementation, we collect occupational data for a set of advanced and emerging countries, harmonise this data by mapping it to a common occupational classification, and link it to international input-output tables.

We empirically conceptualise a GSC as all activities that are directly or indirectly needed to produce an end-product that is used for final consumption (Timmer et al. 2014). An example of a global supply chain is the production of a car that has its final assembly stage in Germany (we will return to the example of cars finalised in Germany throughout the paper to illustrate

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

and provide intuition).[2] The main advantage of our GSC approach is that it encompasses all countries and products in the world.[3] Since we create a common occupational classification we can determine both the total demand for workers with a certain occupation in a supply 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 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 labour 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. Our GSC approach allows us to disentangle the two. Intuitively, automation affects the use of a certain task throughout the supply 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 supply chain of German cars then this will lower the number of routine jobs in the supply 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.[4]

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-biased 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

2. Think of, for example, Porsche cars finalised in Leipzig or Volkswagens that rolls out of the factory in Wolfsburg.

3. We can think of any good or service as being produced in a global supply 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. In the empirical implementation we will account for differences in productivity of workers across countries.

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.

There are several related empirical studies that examine the role of trade and technology in driving the demand for labour. Regressions based on cost functions are common in earlier literature that examined the demand for high versus low-skilled workers (e.g. Hansson 2000; Morrison and Siegel 2001; Hijzen et al. 2005), and in more recent studies on the demand for routine versus non-routine jobs (Michaels et al. 2014). Other studies exploit initial differences in exposure to (Chinese) import competition and automation across local labour markets (e.g. Autor et al. 2015; Pierce and Schott 2016; Acemoglu and Restrepo 2017). Our global supply chain perspective allows for the joint analysis of advanced and emerging countries, and determines the contribution of trade and technology in accounting for the growing share of non-routine jobs. One other important related study is by Goos et al. (2014), who estimate the parameters of a task-based model for West-European countries. Their findings suggest that routine-biased technological change has a significant effect on labour demand in Europe, whereas the effect from offshoring is insignificant. In contrast, we find that offshoring does affect labour demand although its effect is small compared to the effect from technological change. A potential reason for this difference is that Goos et al. (2014) use a proxy of the potential offshorability of occupations in their regression analysis, while we measure actual shifts in labour demand across countries.

Our measurement of labour demand in global production networks 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 the workers and do not provide a decomposition. 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). We aim to shed new light on the recent changes in labour demand within global supply chains and the nature of technological change.

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 supply chains and explains how we can measure occupational labour demand in GSCs 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 labour demand in GSCs. 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 Labour Force Surveys and/or quinquennial or decadal Population Censuses. The availability of detailed and reliable occupations data limits the time period we examine from 1999 to 2007. 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. These are the same countries as included in the World Input-Output Database (WIOD), which is essential for the analysis we wish to perform later on. Throughout this paper we use persons employed as the measure of employment and not hours worked because the latter is often not available for the emerging countries included in our dataset.[5] 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 harmonised individual level European Union Labour Force Surveys, which are also used by Goos et al. (2014). For the remaining countries we obtain the data from national statistical offices. In Appendix Table A.1 we list the main sources of data for each country.[6]

To harmonise 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 categorises workers by level of skill and thereafter by the area of specialisation. 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. These restrictions have guided our choice of 11 occupations: they allow us to have as much detail as possible while at the same time minimising the amount of classification errors. Our classification relates most natural to the

5. Whenever possible we aim to measure jobs in full-time equivalents. For Europe, results in Goos et al. (2014) appear similar when using persons employed or hours worked.

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

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

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

8. Concordance tables are available from the authors upon request.

9. To analyse 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. Dicarlo 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.

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).

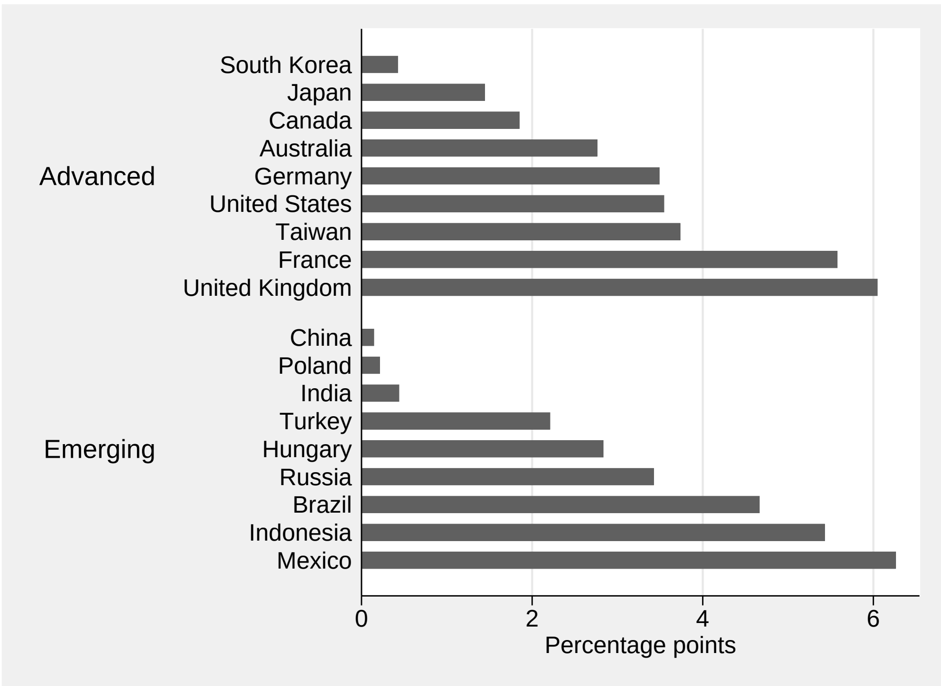
multiplied with the number of persons employed by country-industry-year taken from the WIOD socio-economic accounts (Timmer et al. 2015).

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. Figure 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]

11. Appendix Figure D.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.

Figure 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 Figure D.1 shows the results for all countries included in the analysis.

The top panel of Figure 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 polarisation (Autor et al. 2006; Ikenaga and Kambayashi 2016; Goos et al. 2014; Harrigan et al. 2016). Studies of job polarisation 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 labour markets polarised, is likely to differ across countries depending among others on their level of economic development and wage-setting institutions. Therefore, we do not further pursue analysis of job polarisation in the current paper, but will focus on explaining the demand for routine versus non-routine jobs.

The bottom panel of Figure 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 Figure D.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 analyse, 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. This is suggestive evidence that routine task relocation is not the main driving force of employment structure changes, but rather technological change.

3 Occupational employment in global supply 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 labour demand in global supply chains. In addition we show how we can empirically identify the jobs involved in a given supply 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 labour demand into the contribution of technology, trade and other factors.

3.1 A task-based Global Supply 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 supply chain as consisting of different tasks. The process then requires two steps. First, task output is produced in different countries worldwide using labour 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 GSC v as:

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

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 GSC 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 GSC 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:

$$T_{jv} = \sum_c T^c_{jv}, \tag{2}$$

where T^c_{jv} is the amount of task j produced in country c on behalf of this GSC. 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.[12] In each country task output is created under constant returns to scale with labour and capital as inputs.[13] 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:

$$T^c_{jv} = A^c G_{jv}(K^c_{jv}, N^c_{jv}), \tag{3}$$

where K^c_{jv} and N^c_{jv} are the input of capital and labour, respectively. The function G_{jv} is common across countries (but can differ by task and supply 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 organisation 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 supply 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 'GSC technology' because they

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

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

are specific to a supply chain. We will return to the distinction between country TFP en GSC technology in Section 4.2.

We follow the modelling 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 labour 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 labour of occupation j in country c by supply chain v. A given country c perform tasks for global supply chains worldwide so that the total demand for workers with occupation j is given by:

$$L_j^c = \sum_v N_{jv}^c. \tag{4}$$

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

3.2 Global Supply Chain data

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 GSCs. In particular, we calculate the total number of workers with a given occupation j in country c that are employed on behalf of each supply chain v, defined as N_{jv}^c above.

The WIOD covers the same 35 industries in 40 countries as our occupations data, plus 'the rest of the world'.[14] 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. Following Timmer et al. (2014) we identify a global supply chain by the combination of a country and an industry in which the last stage of production takes place, which means that there are 1435 GSCs (41 times 35) in total. An example of

14. 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 China, India, Indonesia, Brazil, Russia, and Mexico. Results for the Rest of the World are not reported. Different assumptions to estimate the occupation-industry-year shares for the Rest of the World, such as using a weighted average, do not qualitatively affect our results on the role of task relocation and technological change in driving demand for non-routine jobs.

one such GSC which was referred to in the Introduction is final output from the transport equipment industry in Germany (or 'German cars' in short).

We employ the method outlined in Timmer et al. (2014) to split up the value of output for final consumption of every GSC 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 GSC 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 supply 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 B. Finally, we sum over the industries within each country to obtain N^c_{jv}. Since we have substituted our for intermediate inputs in terms of the labour that was used to produce them, we can now think of the production process of a GSC in terms of labour only. Note that in principle we could do the same for the use of capital within a GSC, but this is not necessary for our purposes (see further below).

Table 2 shows the structure of the dataset that we obtain. For each GSC (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^c_j. Because we have harmonised the national occupational classifications to a common one, we can directly compare the demand for a certain occupation across countries within a given supply chain.

3.3 Illustration: The supply chain of German cars

We illustrate our approach using occupational labour demand for the global supply chain of cars that have their final stage of assembly in Germany. This supply chain has undergone major changes in its organisational 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 customise products. At the same time, there has been a rapid increase in the international sourcing of parts and components. The availability

Table 2: Data structure

	GSC 1	GSC 2	···	GSC v	Total
Occupation 1					
Country 1	N_{11}^1	N_{12}^1		N_{1v}^1	L_1^1
Country 2	N_{11}^2	N_{12}^2		N_{1v}^2	L_1^2
⋮					
Country c	N_{11}^c	N_{12}^c		N_{1v}^c	L_1^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_{21}^c	N_{22}^c		N_{2v}^c	L_2^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

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 supply 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 GSC of cars finalised in Germany are 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 GSC 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 GSC, 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 labour-saving technological change in explaining these changes in employment.

Table 3: Employment in the global supply chain of cars finalized in Germany, by occupation

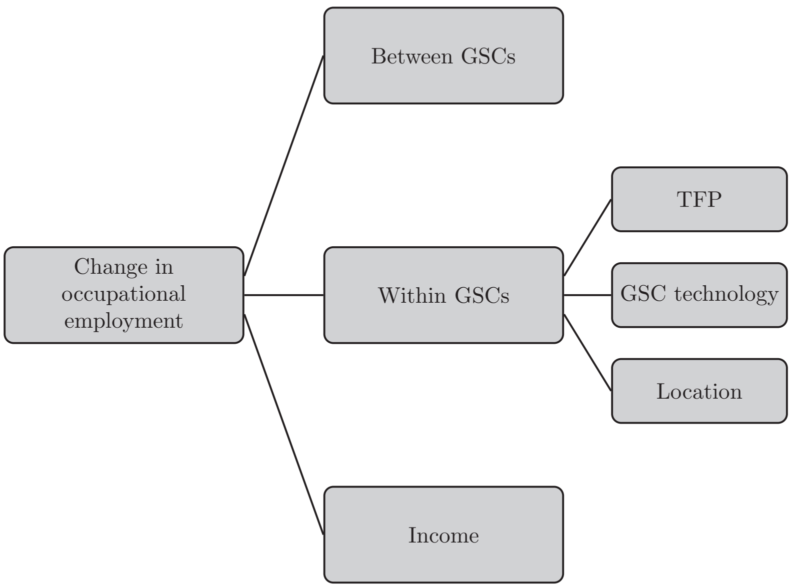
	1999	2007	Change	% Change
Production workers	**1,401**	**1,605**	**204**	**15%**
Germany	685	577	−108	−16%
China	95	189	95	100%
Poland	35	63	27	77%
Clerical workers	**376**	**404**	**27**	**7%**
Germany	221	218	−3	−1%
China	17	23	6	34%
Poland	6	11	5	85%
Support services workers	**230**	**315**	**85**	**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	**3,353**	**4,030**	**677**	**20%**
Germany	1,664	1,671	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 GSC of cars finalized in Germany. The contribution from 3 countries, namely Germany, China and Poland, by occupation is distinguished.

4 Decomposition of changes in occupational employment

This section outlines a decomposition of the rise in non-routine jobs that we documented in Section 2, based on the task-based model of supply chain production introduced in Section 3. First we separate the employment changes that have occurred within global supply chains from shifts between GSCs. This between effect captures changes in the share of a GSC 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 GSCs into the contributions of technological change and task relocation. Figure 2 provides an overview of the proposed decomposition.

Figure 2: Decomposition



4.1 Within, between and income effects

Starting from equation 4, we write the demand by GSC v for labour of occupation j in country c as:

$$N^c_{jv} = \frac{N^c_{jv}}{p_v Y_v} \frac{p_v Y_v}{W} W, \tag{5}$$

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

(1) *within*: changes in occupational labour per dollar of output $N^c_{jv}/[p_v Y_v]$.

(2) *between*: changes in the GSC share of world demand $p_v Y_v / W$.[15]

(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 GSC might lead to cost savings and lower prices, which results in a shift in demand between GSCs (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 input-output tables in previous' year prices and do the decomposition year-by-year before we add up to arrive at the final result.[16]

4.2 Disentangling technological change and task relocation

In order to be able to further decompose the effects on occupational labour demand from changes within GSCs 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 labour 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, $A^c N^c_{jv}$ is the number of efficiency units of occupation-j labour from country c used in GSC v. Note that the actual

15. Changes in the GSC 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.

16. 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.

number of workers coincides with the number of efficiency units only if TFP is equal to 1. We can then write:

$$N_{jv}^{c} = \frac{e_{jv} T_{jv}^{c}}{A^{c}}, \tag{6}$$

where e_{jv} is the number of efficiency units of labour required to create one unit of output of task j in GSC v, which is the same for all countries. 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.[17] TFP in the United States in the initial year is normalised to unity, so that 'efficiency units' essentially correspond to 'United States workers in 1999'.

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

$$\frac{N_{jv}^{c}}{p_v Y_v} = \frac{1}{A^{c}} \frac{e_{jv} T_{jv}}{p_v Y_v} \frac{T_{jv}^{c}}{T_{jv}}. \tag{7}$$

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

(1a) *TFP*: changes in Total Factor Productivity A^{c}

(1b) *GSC technology*: changes in occupational efficiency units per dollar of output $e_{jv} T_{jv} / [p_v Y_v]$

(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 labour demand. As workers become more efficient, fewer of them are required to produce a given amount of task output.

17. 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.

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

$$\frac{e_{jv}T_{jv}}{p_vY_v} = \frac{e_{jv}\alpha_{jv}}{p_v}. \tag{8}$$

As explained in Section 3.1 above, there are two components to GSC technology. The first is the task production function G_{jv}, which is captured by the number of efficiency units of labour e_{jv} that are needed to produce one unit of task output. For example, if labour is replaced by machines then e_{jv} decreases (while the required amount of capital goes up). The second component of GSC 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 GSC technology can go in either direction. Importantly, we do not make any a priori assumptions about the nature of technological change in a GSC (for example whether it is biased against the use of a certain occupation), but instead let the data speak for itself.

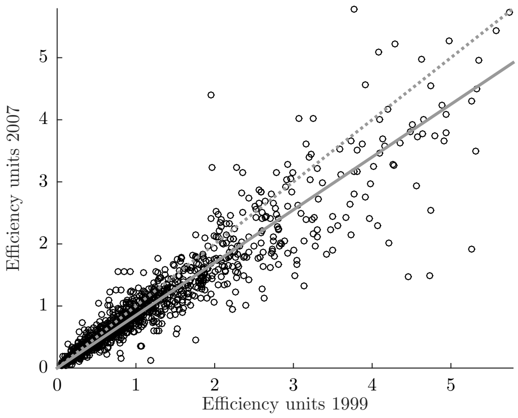
To illustrate, Figure 3 shows how changes in GSC technology have affected the demand for labour of different types of occupations. It plots the number of efficiency units employed per 100 dollar of output in 1999 versus 2007 for each GSC (at constant prices).[18] Although there is clearly a lot of heterogeneity among GSCs, a general pattern can be observed. The simple regression line in each plot gives an indication to what extent the use of labour 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 GSC technological change tends to be labour-saving. The only exception is non-routine manual occupations, suggesting that on average GSC 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-biased' in the sense that the demand for occupations that are intensive

18. To be precise, we first compute the number of efficiency units per 100 dollar of GSC 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.

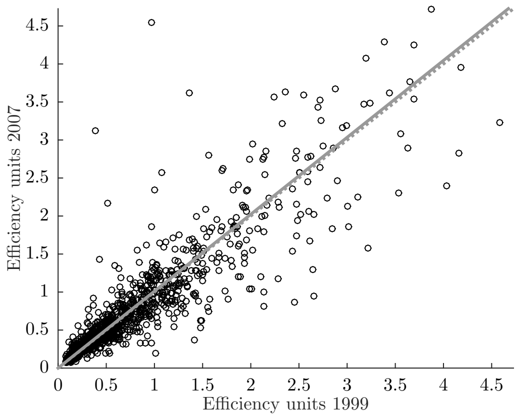
in routine tasks ($\beta = 0.85$ and $\beta = 0.86$), has decreased more than that for non-routine occupations ($\beta = 1.01$ and $\beta = 0.96$).

Figure 3: Technological change within Global Supply Chains, 1999-2007

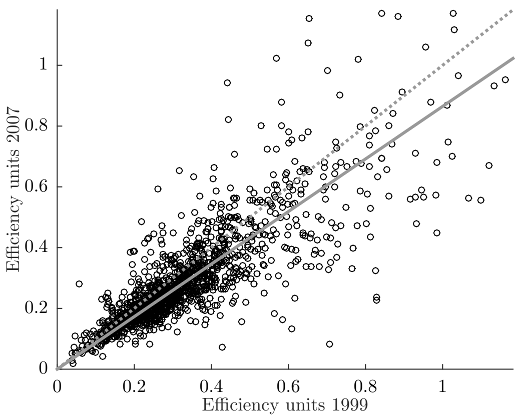
(a) Routine, Manual ($\beta = 0.85$)



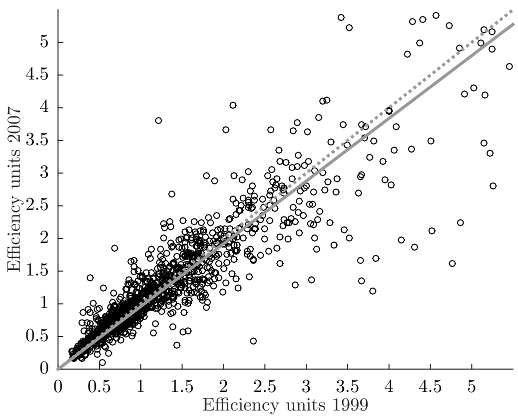
(b) Non-routine, Manual ($\beta = 1.01$)



(c) Routine, Analytic/Interactive ($\beta = 0.86$)



(d) Non-routine, Analytic/Interactive ($\beta = 0.96$)

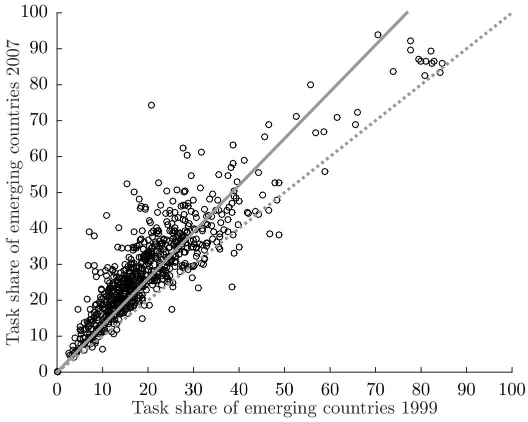


Notes: The number of efficiency units in each year are given per 100 dollar of output. The solid line shows the regression line, with its slope given in brackets. To calculate the regression coefficient, all observations below the 1st and above the 99th quantile were removed. The dotted line is a 45° line.

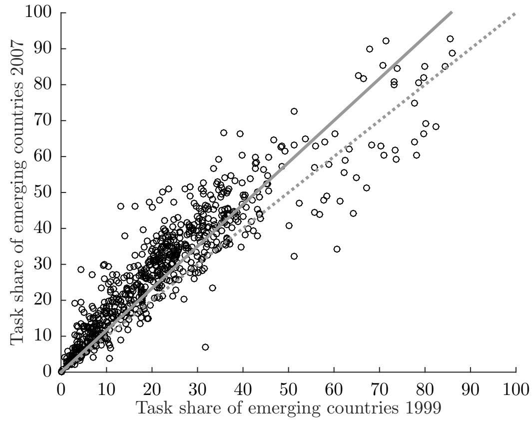
The final term in (7) is the share of country c in the total output of task j within supply chain v. We refer to this as 'location' because the distribution of these task shares across countries shows where the activity of a supply chain is located. Empirically we can identify the task share by dividing the number of efficiency units of labour of occupation j employed

Figure 4: Task relocation within Global Supply Chains, 1999-2007

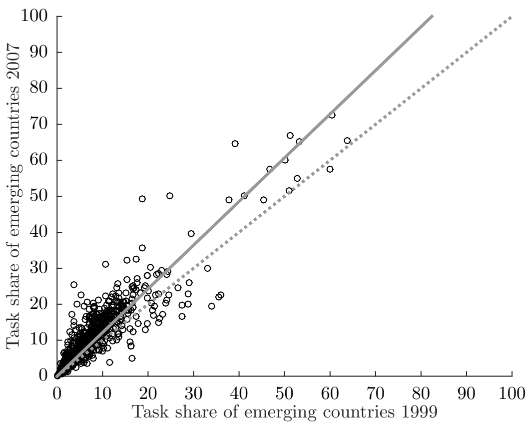
(a) Routine, Manual ($\beta = 1.30$)



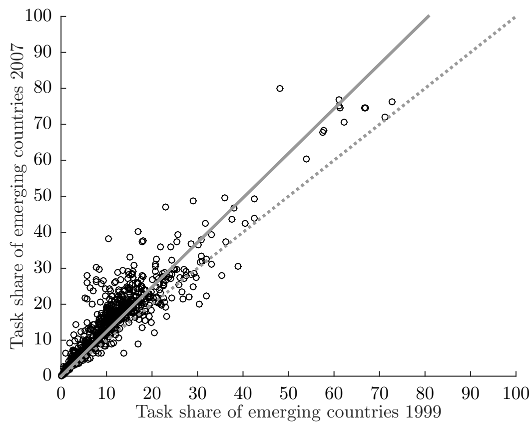
(b) Non-routine, Manual ($\beta = 1.17$)



(c) Routine, Analytic/Interactive ($\beta = 1.21$)



(d) Non-routine, Analytic/Interactive ($\beta = 1.24$)



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

in country c by the total number throughout the chain:

$$\frac{T_{jv}^{c}}{T_{jv}} = \frac{A^{c} N_{jv}^{c}}{\sum_{c'} A^{c'} N_{jv}^{c'}}. \tag{9}$$

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. Figure 4 illustrates one of the important trends in task relocation: a shift in task production from advanced to emerging countries.[19] For each GSC ending in an advanced country it plots the total task share of emerging countries in 2007 against the initial share in 1999. For almost 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.

4.3 Illustration: The supply chain of German cars

The task-based model of production in Global Supply Chains motivates a decomposition of changes in occupational labour demand into the effects of technological change, task relocation and other factors. Here, we illustrate the decomposition by returning to the example of the supply 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.

The first column shows the change in employment attributed to TFP (this is the first term in equation (7)). For the German car GSC as a whole this effect is negative. This suggests that on average countries participating in this supply 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.

19. The 'rest of the world' is also included in the share of emerging countries.

Table 4: Decomposition results for the global supply chain of cars finalized in Germany

	Within			Between	Income	Total
	TFP	GSC 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 GSC of cars finalized in Germany due to the different factors. The contribution from 3 countries, namely Germany, China and Poland, by occupation is distinguished.

The GSC 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.[20] This coincides with our findings in the previous section regarding the pattern of technological change. Technological change within the GSC is such that less labour 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 GSC 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 labour demand for this GSC.

The positive between effect (the second term in (5)) suggests that cars that have been finalised 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 supply chains to those occurring at the country level. This requires summation over countries of the decomposition results for the 1435 GSCs 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 GSC (as

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

in Table 4 above), but also in the French car GSC, the Japanese electronics GSC, etcetera. We narrow our focus in two directions. First, although the decomposition is still performed at 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 GSC technology and task relocation on the demand for labour and relegate full decomposition results to Appendix C.

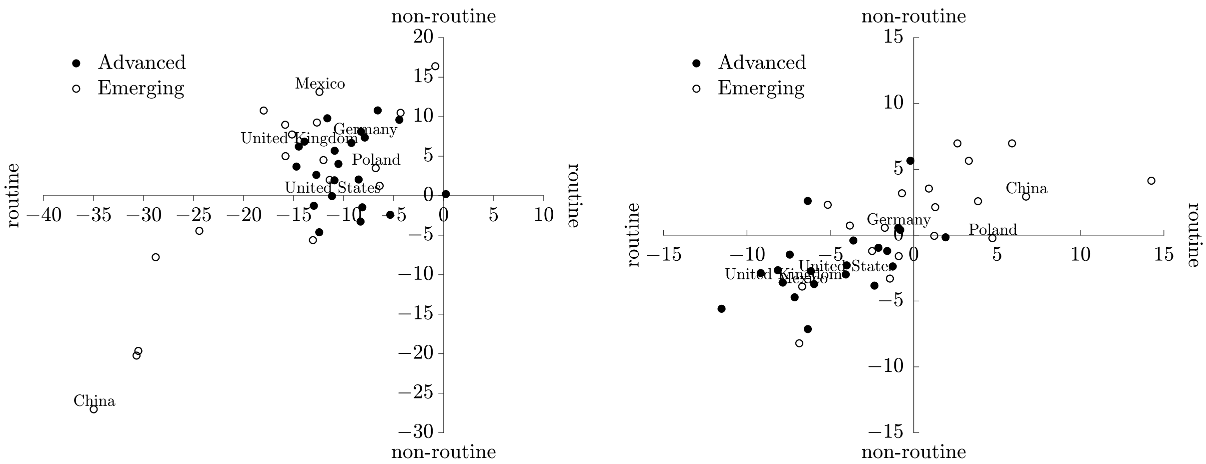
Panel (a) of Figure 5 shows the percentage change in the number of routine jobs (horizontal axis) and non-routine jobs (vertical axis) that is attributed to GSC technological change. Each observation is a country (40 in total) with emerging countries indicated by white dots and advanced countries by 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 GSCs differ in the nature and extent of technological change (recall Figure 3) and that countries differ in the extent of their involvement in each supply chain. For example, the number of German workers involved in the GSC of German cars is greater than that involved in the GSC of French cars, and therefore employment in Germany will be more strongly affected by technological change in the former than in the latter. From Figure 5(a) it is clear that technological change within GSC 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 routinisation hypothesis put forth in Autor et al. (2003). 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 Figure 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 supply chains in the early 1990s following the signing of the North American Trade Agreement (NAFTA) in 1994.

Figure 5: Percentage change in routine and non-routine jobs

(a) Due to GSC technological change

(b) Due to task relocation



Notes: Each observation is a country.

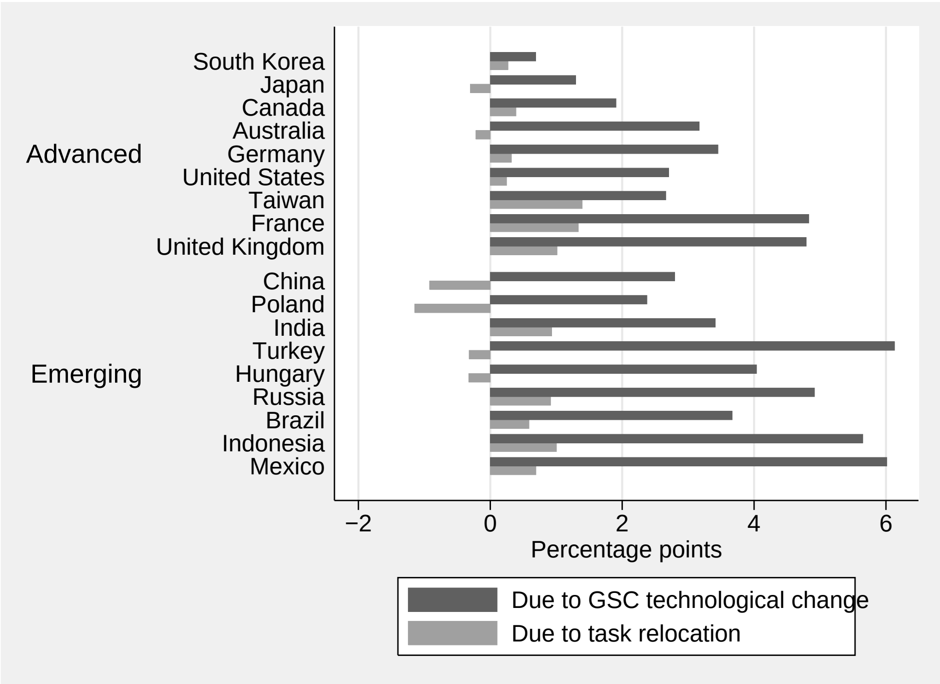
5.1 The relative demand for non-routine and routine jobs

In Section 2 we highlighted an important trend in the labour 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 GSC technological change or to task relocation by the 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.

Figure 6: The contribution of task relocation and GSC 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: 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. Appendix Figure D.2 shows the results for all countries included in the analysis.

Figure 6 shows the results for the same countries as in Figure 1. Three main conclusions emerge. First, technological change within GSCs increases the demand for non-routine jobs relative to routine jobs. This is true for nearly all countries included in our analysis, see Appendix Figure D.2 for the complete list.[21] Thus, both in advanced and emerging countries we find that technological change is routine-biased.

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

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

opposite effect is observed in several emerging countries that benefited from the relocation of routine tasks, such as China, Hungary, Poland and Turkey.

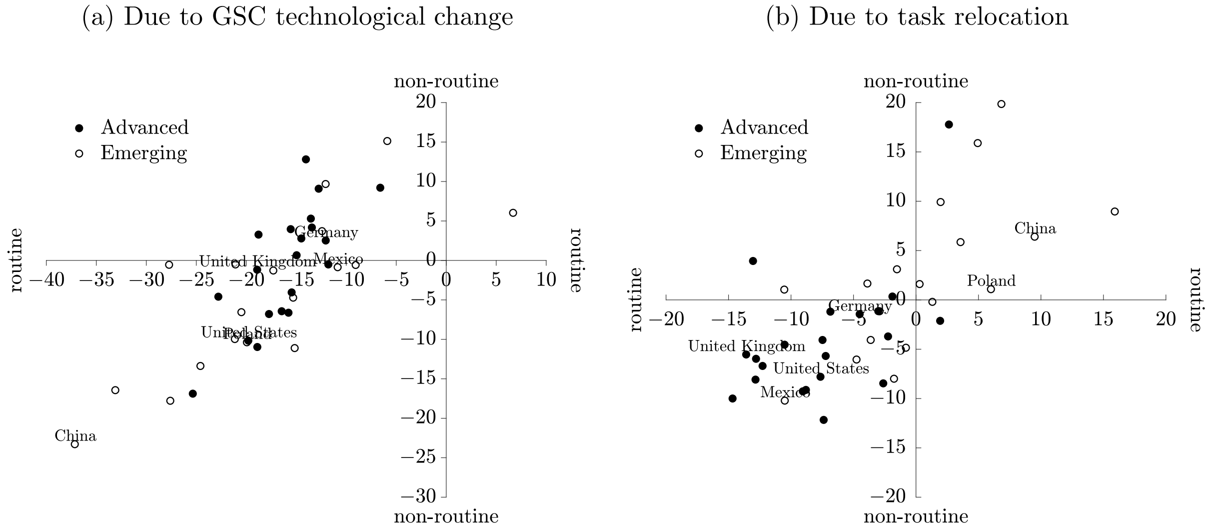
Third, GSC technological change has a much greater impact on the employment share of non-routine workers than task relocation.[22] For example, in the United States technological change can account for a 2.7 percentage points increase in the share of non-routine jobs, but task relocation only for a 0.25 percentage point increase. The dominance of technology over trade in explaining labour 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.

5.2 Global supply chains of manufactured goods

In the analysis above we have treated the production of any good or service as a global supply 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 labour. To investigate this, we restrict attention to a subset of GSCs in which offshoring is most common, namely the global supply chains of manufactured goods. Recall that we identify a global supply 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 GSCs 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 GSC of German cars then this includes employees in the UK financial services sector when they provide financial business services to this supply chain.

22. 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 favour of demand for non-routine jobs (see Appendix Figure D.2).

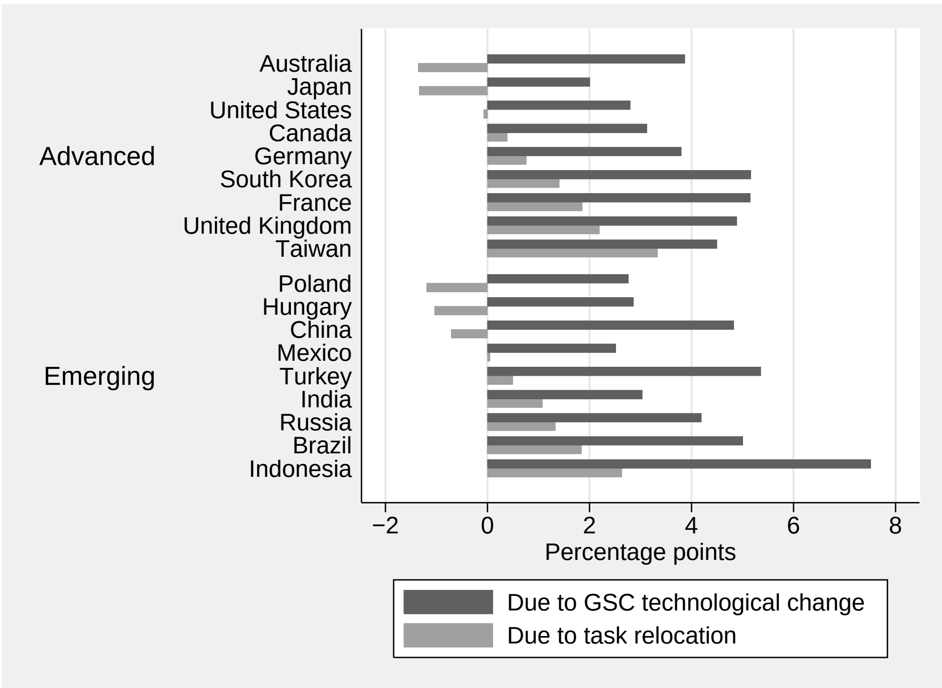
Figure 7: Percentage change in routine and non-routine jobs in manufacturing GSCs



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

Figure 7 is the counterpart of Figure 5 but restricts attention to employment in manufacturing GSCs. By comparing panel (b) in the two figures we see that task relocation plays indeed a more important role in manufacturing GSCs: 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? Figure 8 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 GSCs.

Figure 8: The contribution of task relocation and GSC technological change to changes in the employment share of non-routine jobs in manufacturing GSCs



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.

6 Concluding remarks

In many countries, there has been an increase in the share of non-routine jobs in the labour force. For advanced countries these changes in occupational employment have been widely documented and analysed (e.g. Autor et al. 2003; Goos et al. 2014). This paper uses a cross-country harmonised occupations database and shows that the employment share of non-routine jobs increased in thirty-seven advanced *and* emerging countries during the period 1999-2007. We examine these changes through the lens of a global supply chain model. In particular, for each supply chain we look at changes in the use of occupational labour per dollar of output (defined as 'GSC technology') and shifts in the share captured by each country ('task relocation'). Our findings suggest that technological change within global supply 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 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 supply chain, but it may also affect the ease at which a routine task can be relocated. One approach to better understand these type of interactions is by using detailed firm level data as in Fort (2017).

The harmonised occupations database presented in this paper opens up avenues for future research. First, it is possible to determine in what type of tasks countries specialise within global supply chains and how these specialisation patterns change over time. Another interesting research area to explore are complementarities between different activities in GSCs. So far researchers have looked at complementarities between production factors, such as capital and skilled labour, but there might also exist complementarity between certain tasks, for example between production and R&D activities (Defever 2012). Finally, an important open research question is the extent to which the employment changes documented here are helpful for understanding changes in wage inequality.

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A Data sources

Table A.1: Sources of occupational data by country

Country	Source(s)	Years
Australia	Labour Force: Employed Persons Quarterly Large Source Dataset	1999-2007
Brazil	National Household Sample Survey (PNAD)	1999-2007
Canada	Canadian Labour Force Survey	1999-2007
China	Population census	2000, 2010
EU members*	Labour force survey	1999-2007†
India	National Sample Survey	2000, 2004-2006, 2008
Indonesia	National Labour Force Survey (Sakernas)	2000-2007‡
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	Labour force survey	2007
United States	Population census American community surveys	2000 2000-2007

Notes:
* We examine the 27 countries that are a member of the EU (per January 2007).
† Bulgaria and Malta from 2000 onwards; Poland from 2004 onwards.
‡ We drop 2000-2002 because of anomalies in the data.

B Methodology

B.1 World input-output tables

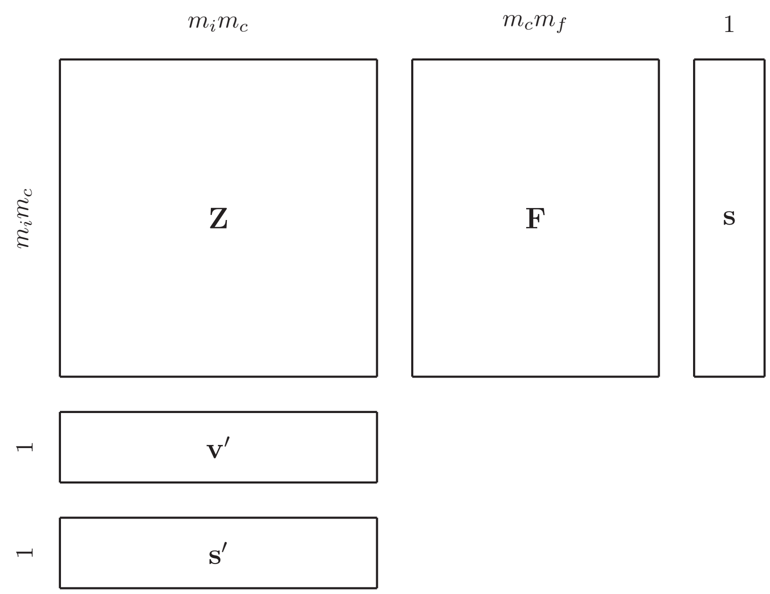
The World Input-Output Database (WIOD, November 2013 release) provides data on $m_i = 35$ industries and $m_c = 41$ countries, including one that captures 'the rest of the world'. The basic structure of the world input-output table for a given year is given in Figure B.1. The units of observations are 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 organisations 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:

$$\mathbf{s} = \mathbf{Z}\mathbf{1}_{m_i m_c} + \mathbf{F}\mathbf{1}_{m_c m_f}, \tag{B.1}$$

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 that 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.

We use this data to construct two new matrices. The first is the $m_i m_c \times m_i m_c$ matrix $\mathbf{A} = \mathbf{Z}\text{diag}(\mathbf{s})^{-1}$ of intermediate use coefficients, where diag($\mathbf{s}$) is the $m_i m_c \times m_i m_c$ matrix with the successive elements of the output vector $\mathbf{s}$ on the diagonal. A typical element of $\mathbf{A}$ 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 $\mathbf{f} = \mathbf{F}\mathbf{1}_{m_c m_f}$ of final demand. The identity given in (B.1) can then be

Figure B.1: Structure of a World Input-Output Table



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

rewritten as:

$$\mathbf{s} = \mathbf{A}\mathbf{s} + \mathbf{f}. \tag{B.2}$$

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

$$\mathbf{s} = \mathbf{B}\mathbf{f}, \tag{B.3}$$

where $\mathbf{B} = [\mathbf{I} - \mathbf{A}]^{-1}$ is the so-called Leontief inverse with $\mathbf{I}$ the $m_i m_c \times m_i m_c$ identity matrix. A given column of $\mathbf{B}$ 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 supply chain as a country-industry pair that delivers a product for final use. This means that each GSC corresponds to a column of the matrix $\mathbf{B}$ and that we can think of each cell within a column as the task output that the corresponding industry delivers to this GSC. The dollar value of final demand for each GSC ($p_v Y_v$ in the main text) is given by the elements of the vector $\mathbf{f}$.

B.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 $\mathbf{q}_j$ of labour with occupation j employed per dollar of gross output in each industry-country pair. It follows that $\mathbf{Q}_j = \text{diag}(\mathbf{q}_j)\mathbf{B}$ is the matrix that gives for each GSC (columns) the amount of labour 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 $\mathbf{N}_j$, of which the element in row c and column v corresponds to $N^c_{jv}/[p_v Y_v]$: the demand for occupational labour in country c by GSC v per dollar of final output.

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

$$L_j^c = \sum_v \frac{N_{jv}^c}{p_v Y_v} p_v Y_v = \mathbf{i}_c' \mathbf{N}_j \mathbf{f}, \tag{B.4}$$

where $\mathbf{i}_c$ is a $m_c \times 1$ selection vector which equals 1 for country c and 0 otherwise.

B.3 Decomposition

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

$$L_j^c = \sum_v \frac{N_{jv}^c}{p_v Y_v} \frac{p_v Y_v}{W} W = \mathbf{i}_c' \mathbf{N}_j \mathbf{d} W. \tag{B.5}$$

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

$$\begin{aligned} L_{j,t+1}^c - L_{j,t}^c &= \mathbf{i}_c' \mathbf{N}_{j,t+1} \mathbf{d}_{t+1} W_{t+1} - \mathbf{i}_c' \mathbf{N}_{j,t} \mathbf{d}_t W_t \\ &= \underbrace{\mathbf{i}_c' [\mathbf{N}_{j,t+1} - \mathbf{N}_{j,t}] \mathbf{d}_{t+1} W_{t+1}}_{\text{within}} \\ &\quad + \underbrace{\mathbf{i}_c' \mathbf{N}_{j,t} [\mathbf{d}_{t+1} - \mathbf{d}_t] W_{t+1}}_{\text{between}} + \underbrace{\mathbf{i}_c' \mathbf{N}_{j,t} \mathbf{d}_t [W_{t+1} - W_t]}_{\text{income}}. \end{aligned} \tag{B.6}$$

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 C and discussed in the main text.

C Decomposition results for all countries

Table C.1 and Table C.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’, ‘GSC technology’ and ‘location’, see Section 4.

D Changes in employment shares for all countries

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

Table C.1: Decomposition for non-routine occupations

	Initial	Change	Within			Between	Income
			TFP	GSC technology	Location		
Australia	5,108	1,320	−400	487	−367	136	1,464
Austria	2,224	368	−131	42	57	−210	612
Belgium	2,535	436	−36	91	−74	−228	683
Bulgaria	1,762	228	−38	−347	−59	215	457
Brazil	34,743	16,659	−1,459	5,667	1,215	76	11,160
Canada	9,049	1,819	−58	−425	−211	0	2,514
China	190,511	54,368	−73,363	−51,645	5,498	119,145	54,733
Cyprus	182	56	−19	2	10	9	53
Czech Republic	2,913	367	−852	267	61	127	764
Germany	23,710	2,217	−1,899	1,727	121	−4,024	6,293
Denmark	1,751	260	−53	69	−99	−129	472
Spain	8,715	3,919	367	489	−242	615	2,690
Estonia	376	54	−122	7	−6	77	99
Finland	1,467	254	−179	118	−55	−31	402
France	14,294	2,741	−702	967	−386	−1,111	3,973
United Kingdom	18,446	3,360	−2,138	1,133	−672	−100	5,137
Greece	2,241	587	−280	3	−107	341	630
Hungary	2,310	166	−429	102	−2	−114	610
Indonesia	28,270	8,334	−3,586	−1,279	1,958	3,819	7,422
India	89,130	23,801	−14,207	−18,106	2,798	26,516	26,800
Ireland	996	355	−63	−15	−10	147	296
Italy	12,970	2,903	723	332	−197	−1,622	3,667
Japan	30,822	221	−989	−1,033	−744	−4,669	7,655
South Korea	10,923	2,321	−1,565	−273	39	1,037	3,082
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	18,304	7,227	345	2,391	−722	−337	5,550
Malta	86	14	1	−5	−7	2	23
Netherlands	5,497	653	−314	−74	−11	−415	1,468
Poland	7,254	911	−1,259	248	−20	86	1,856
Portugal	2,408	430	1	159	−30	−365	665
Romania	3,237	528	−1,343	248	−40	806	857
Russia	40,041	6,671	−16,532	3,565	275	8,408	10,955
Slovakia	1,244	133	−355	61	28	71	326
Slovenia	452	109	−96	48	2	26	128
Sweden	2,828	423	−461	275	−13	−151	773
Turkey	7,589	1,843	−1,407	−596	192	1,492	2,163
Taiwan	4,671	934	−575	92	262	−128	1,283
United States	88,315	10,499	−7,969	−112	−2,672	−2,213	23,465

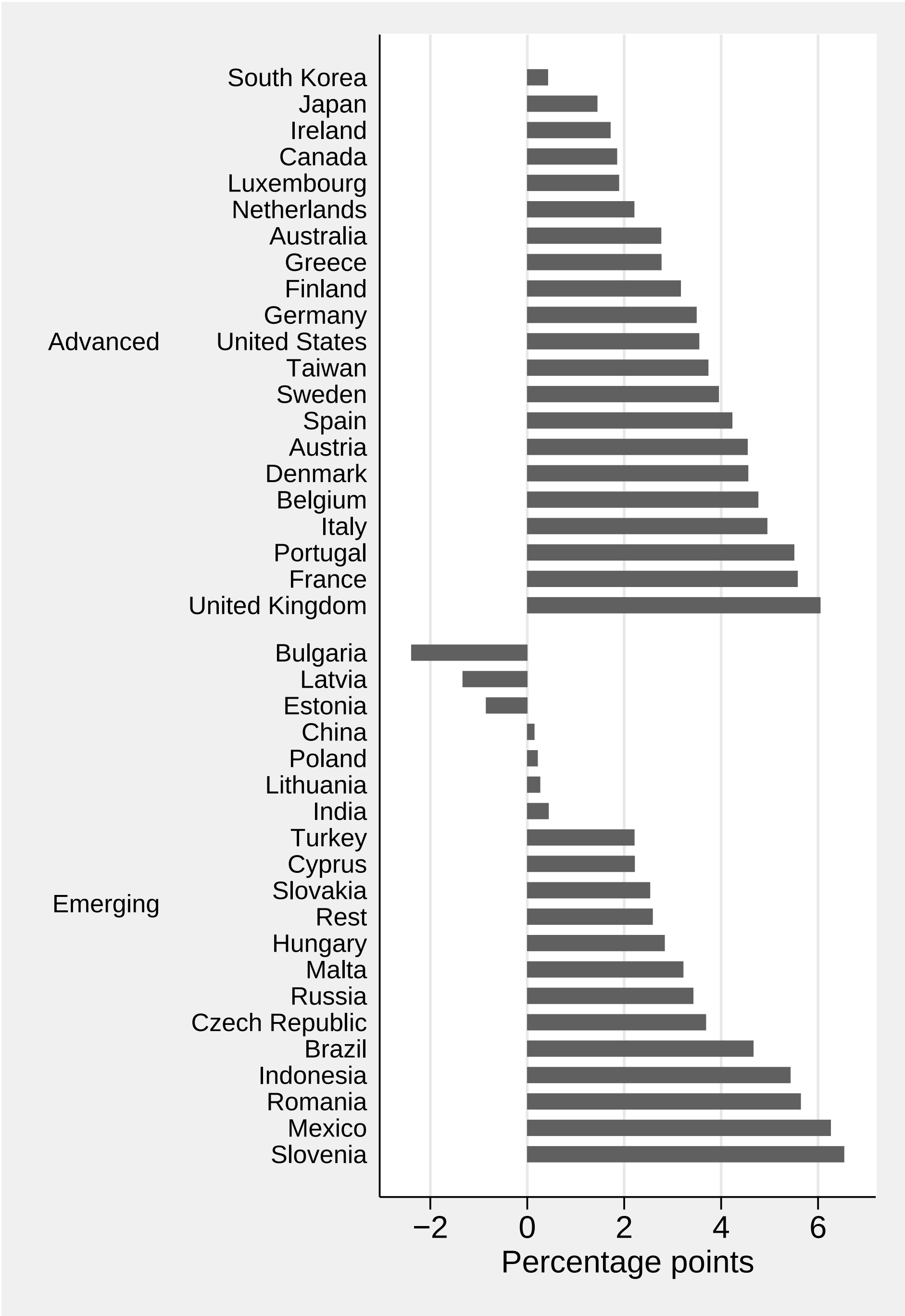
Notes: In thousands of jobs.

Table C.2: Decomposition for routine occupations

	Initial	Change	Within			Between	Income
			TFP	GSC technology	Location		
Australia	3,234	383	−234	−141	−204	114	849
Austria	1,355	−60	−68	−147	−86	−81	322
Belgium	1,400	−77	−17	−205	−128	−77	351
Bulgaria	932	236	−20	−284	−13	302	251
Brazil	21,366	4,430	−760	−165	201	−714	5,867
Canada	5,065	543	−37	−627	−202	54	1,353
China	162,521	45,163	−59,261	−56,734	11,002	105,883	44,274
Cyprus	109	20	−11	−7	4	5	29
Czech Republic	1,919	−71	−518	−242	25	197	466
Germany	13,774	−856	−1,003	−1,077	−122	−1,941	3,286
Denmark	835	−63	−22	−87	−96	−52	194
Spain	5,906	1,252	231	−640	−362	358	1,665
Estonia	175	33	−59	−20	−2	66	47
Finland	647	4	−73	−53	−38	6	162
France	8,366	−589	−393	−1,158	−679	−411	2,052
United Kingdom	10,345	−1,051	−1,039	−1,491	−809	−134	2,421
Greece	1,265	148	−154	4	−90	51	338
Hungary	1,573	−76	−276	−188	20	−14	383
Indonesia	22,605	801	−2,823	−5,505	601	2,868	5,662
India	74,525	18,241	−11,103	−22,828	−500	31,055	21,616
Ireland	591	153	−37	−48	−12	84	166
Italy	8,545	−85	419	−1,082	−632	−938	2,147
Japan	29,216	−1,445	−921	−2,408	−357	−4,911	7,152
South Korea	7,124	1,361	−1,033	−376	−55	790	2,035
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	12,943	902	196	−1,599	−861	−170	3,336
Malta	55	1	0	−7	−4	−2	14
Netherlands	2,222	5	−119	−287	43	−185	553
Poland	4,385	506	−736	−295	208	243	1,086
Portugal	1,911	−116	5	−175	−30	−385	468
Romania	2,966	−220	−1,133	−448	−73	722	711
Russia	15,827	−335	−6,009	−2,497	−601	4,809	3,963
Slovakia	772	−6	−200	−122	−40	170	186
Slovenia	337	−19	−58	−60	−6	26	80
Sweden	1,248	−66	−180	−144	−45	6	298
Turkey	5,655	762	−953	−1,624	220	1,637	1,482
Taiwan	4,025	126	−441	−339	−7	−97	1,010
United States	54,580	−2,185	−4,610	−6,056	−2,204	−2,632	13,316

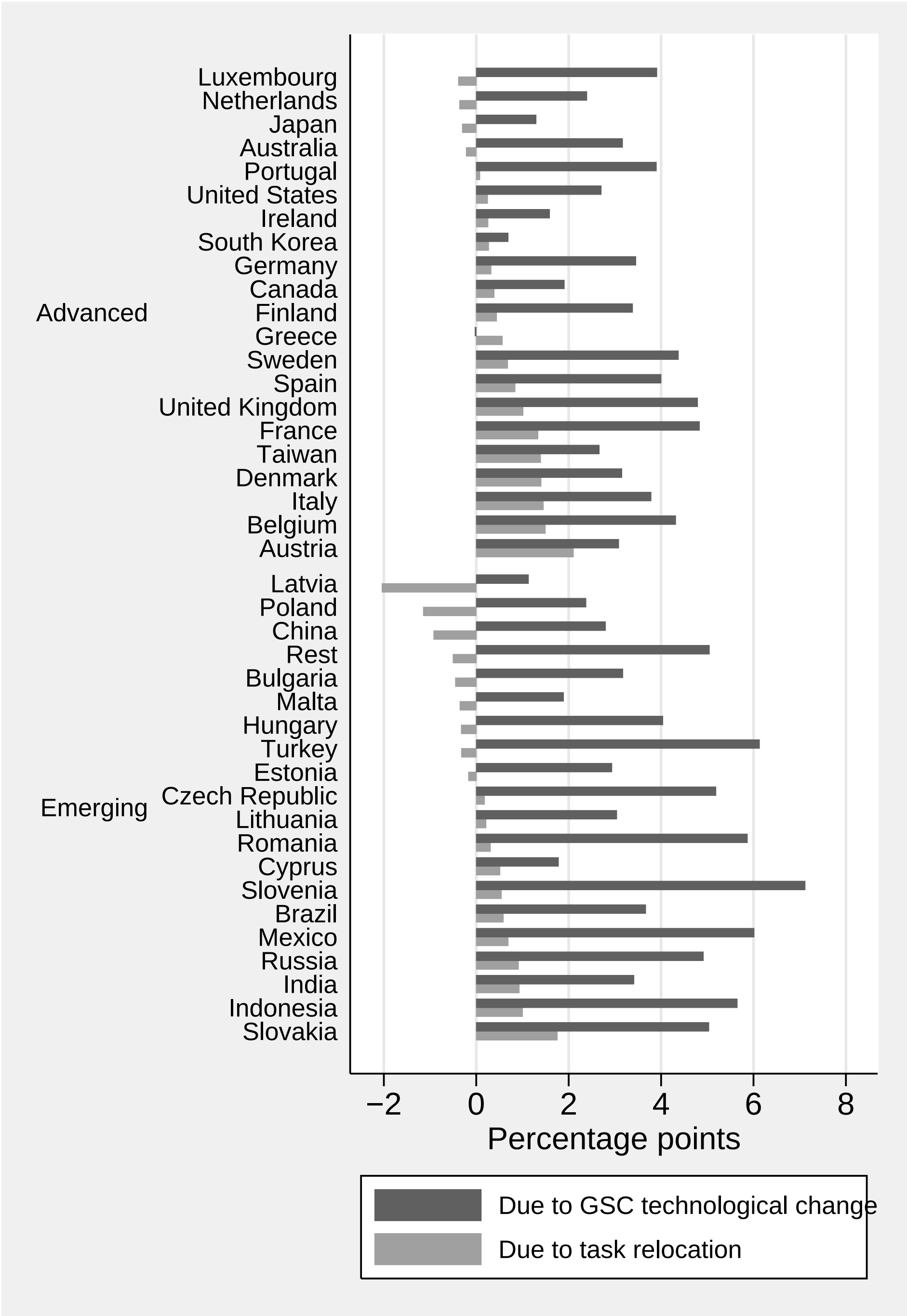
Notes: In thousands of jobs.

Figure D.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.

Figure D.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.