LUND UNIVERSITY
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Master in Economic Development and Growth

Job Creation in Global Value Chains: An Assessment for the Period of 2000-2014

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Abstract: Globalization has led to the emergence of global value chains (GVCs) and most of the world's trade is now in intermediate inputs. This has raised questions about employment in GVCs and attracted the interest of researchers and policymakers alike, but is difficult to study empirically. This paper investigates job creation in simple and complex GVCs for 43 economies between 2000 and 2014 on the basis of world input-output tables and a decomposition analysis. GVC activities were found to have grown by an estimated 37.5 million jobs by 2014, approximately the same increase as in traditional international trade employment for the period analyzed. China, Germany and the United States especially seem to have benefitted, in terms of both jobs and value added. Labor intensity, however, has fallen by half or more for both GVC activities and international trade for all 43 economies. For future studies, new datasets are crucial for a better understanding of the impacts of GVCs on employment.

Key words: Global Value Chains, Job Creation, Input-Output Analysis

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1 Introduction

The nature of trade has changed over the past decades and most of world trade is now in intermediate goods. Fueled by improved modes of transportation, falling trade tariffs and the information and communication technology (ICT) revolution, the production networks of firms have become increasingly internationally fragmented. This has led to a strong increase in the trade of intermediate inputs and the rise of global value chains (GVCs) where firms coordinate the production of goods across borders with individual stages of production spread out over multiple countries. These GVCs have received increased interest from researchers and policymakers alike over recent years (Jiang, 2013). Academic interest in GVCs has been both theoretical and empirical in nature as researchers have tried to develop trade models which could integrate intermediate input trade and sought to study the workings and impacts of GVCs (Timmer, Erumban, Los, Stehrer & de Vries, 2014). Policymakers meanwhile see both opportunities and threats in GVCs. In emerging economies, policymakers are urging their countries to join GVCs, seeing a potential to gain access to new technologies, boost exports and create jobs (Farole, 2016). At the same time, there are also fears that GVC participation would lead developing countries to become trapped in low-skilled activities. High income economies on the other hand worry about losing jobs to offshore locations (Dollar, 2017).

However, investigating the impact of GVCs empirically has been difficult. While various case studies exist, systematic empirical investigations from a macroeconomic perspective which would provide a more comprehensive picture are scarce (Koopman, Wang & Wei, 2014; Timmer et al., 2014; Shingal, 2015). A key obstacle to the systematic study of GVCs is the struggle of trade statistics to accommodate the intermediate input trade development. Most trade statistics are focused on measuring trade in gross output values, which leads to double counting in the presence of trade in intermediate inputs, and therefore do not provide an accurate picture of trade relations (Borin & Mancini, 2015; Koopman, Wang & Wei, 2014). To capture GVCs more accurately, the focus has to be placed on value added instead. Unfortunately, the datasets which can provide this kind of information, and further also include the relevant data on employment, are few (Shingal, 2015). Moreover, it is not just the empiricists who struggle with GVCs, trade theory is also up against a challenge in the face of intermediate input trade, as will be discussed later on in this paper. Despite, or rather because of, the difficulties to predict the effects of GVCs on employment, insights into jobs in GVCs are of high political and academic importance given their prevalence in world trade (Jiang, 2013). The aim of this study is to provide researchers and policymakers with such insights by making use of new data and methods. It investigates how many jobs were created by GVC activities and in which countries on the basis of 43 economies between 2000 and 2014. The period itself was marked by important events for international trade, with the Chinese accession to the World Trade Organization in 2001, the expansions of the European Union into Eastern Europe, and the financial crisis of 2008. The financial crisis caused a notable dip in trade activities and they have since recovered, though growth in GVC trade has slowed in the years after the crisis along with global economic growth (Degain, Meng & Wang, 2017; Los, Timmer & de Vries, 2015).

1.1 Definitions and Research Question

Global value chains (GVCs) have no universally agreed upon definition (Taglioni & Winkler, 2016:12) and the phenomenon is known by a variety of names apart from GVCs, including offshoring, international production fragmentation, and vertical specialization. The term global value chain itself paints a slightly misleading picture of these production networks. Activities are not necessarily carried out in a straight line with production moving from one step to the next as the word 'chain' would imply. Rather, the production networks can take many different complex forms (Baldwin & Venables, 2013; Timmer et al., 2014). The 'global' aspect of GVCs also requires additional qualification, since GVCs have been found to be still a largely regionally driven phenomenon for many industries; splitting into interconnected European, Northern American and East Asian systems, centered around Germany, the United States, and China. However, this has begun to change over recent years, with value chains becoming increasingly global since the 2000s (Baldwin & Lopez-Gonzalez, 2015; Diakantoni, Escaith, Roberts & Verbeet, 2017; Los, Timmer & de Vries, 2015). Despite these shortcomings, this study uses the term global value chain, as it is the most commonly used one (Taglioni & Winkler, 2016:12; Timmer et al., 2014). Definitions of the term global value chain have been proposed in various disciplines, including from strands of GVC research in sociology and business. Some definitions require production processes to span across at least two borders to be considered a GVC activity (e.g. Grossman & Rossi-Hansberg, 2012), others have defined GVCs as broadly as "sectors producing for global markets" (Gereffi, Humphrey & Sturgeon, 2005:79).

However, the complexities of GVCs in the broad definition of the term cannot be captured in the calculations of this paper. Instead, GVC activities are defined as production that involves cross-border trade of intermediate goods, which can further be divided into simple and complex GVC activities. The first refers to intermediate products crossing borders only once before leaving the production network (Wang, Wei, Yu & Zhu, 2017), for example, cocoa beans which are harvested and processed in Ghana, turned into chocolate in Switzerland and sold to Swiss consumers. In complex GVC activities, intermediate goods cross borders at least twice (Wang, Wei, Yu & Zhu, 2017), for example, a phone might be developed in the United States, components then produced in South Korea, assembled in China and eventually sold to U.S. consumers. The complexity of GVCs which can be captured in this analysis is further limited by a lack of information on ownership of firms. This leads, for example, foreign-owned firms producing for foreign markets with domestically sourced inputs to be classified as traditional international trade rather than as a GVC activity (Wang, Wei, Yu & Zhu, 2017). This may affect especially the labor-intensive textile and footwear sectors which often fall into this category (Los, Timmer & de Vries, 2015). Traditional international trade is therefore defined as final goods export production with purely domestic inputs, even though some activities which fall under this classification would be considered GVC activities by broader definitions (Borin & Mancini, 2015; Wang, Wei, Yu & Zhu, 2017). Value added is defined as the factor contents (e.g. labor and capital) which an economy adds to the production of a good (Los, Timmer & de Vries, 2015). With the definitions of the main concepts outlined, the research question of this paper is as follows:

How many jobs were directly and indirectly created by simple and complex GVC activities between 2000 and 2014 and where were they created?

There are a number of elements in the research question which require further definition and explanation. The paper covers 43 economies which account for over 85 percent of the world gross domestic product (GDP) (Stehrer, Foster & de Vries, 2012), a list is provided in Section 3. The number of jobs includes both full-time and part-time jobs, details on this data is provided in Section 3. Ideally, the number of jobs would be supplemented by information on the number of hours worked as these likely differ across the 43 economies, but this data is not available for all the economies included in the analysis and thus is taken into consideration. The analysis is focused on both directly and indirectly created jobs combined. This means it does not only count jobs which were created in the firms participating in GVCs themselves, but also jobs created at domestic suppliers and the domestic suppliers of those suppliers as a result of the demand of GVC firms for goods, services and intermediate inputs. In other words, it includes jobs created throughout the domestic production network as a result of GVC activities. The 'where' meanwhile refers to geographic locations defined by national borders. Because GVCs have led to what is called a trade in tasks across different industries (Grossman & Rossi-Hansberg, 2012), as will be explained in the next section, the focus is at the country aggregate level rather than individual industries. The use of the term 'activities' throughout this paper also ties into this discussion. The job creation between 2000 and 2014 is further defined as the difference in the number of jobs between 2014 and 2000. Consequently, the paper does not consider jobs which were created after 2000, but had disappeared again by 2014. Lastly, to derive more relevant and informative insights from the number of jobs created by GVCs, the question is approached in the context of job creation and value added across different categories of trade, including not just GVC activities but also traditional international trade as defined above.

1.2 Preview of Findings and Outline of the Thesis

The paper finds that simple and complex GVC activities created a total 37.5 million jobs between 2000 and 2014, approximately the same number of jobs as created in traditional international trade over the same time period. Emerging economies accounted for most of the GVC jobs created, with especially China driving a large share. In general, the main beneficiaries in terms of both GVC jobs and value added increase were China, Germany and the United States, the economies at the centers of the main GVC hubs. Labor intensity has fallen sharply across all categories of trade for both emerging and high income economies, raising a number of points for discussion.

The remainder of this paper is structured as follows. Section 2 discusses the related trade theory and previous studies, Section 3 outlines the data, including a brief introduction to Input-Output tables. This is then followed by the methodology in Section 4. Findings are presented and discussed in Section 5. Section 6 concludes and outlines avenues for future research.

2 Theory

2.1 How Globalization has Changed the Relationship Between Trade and Employment

In traditional economic trade theory, trade drives economies to specialize in sectors where they have a comparative advantage, leading to the classical cloth for wine example (Inomata, 2017). Driven by factor endowments, as in the Heckscher-Ohlin model for example, economies with a relative labor abundance would specialize in labor-intensive industries and relatively capital abundant economies would focus on capital-intensive industries (Shingal, 2015; Timmer et al., 2014). As countries specialize, jobs would move to produce goods where a country has a comparative advantage and away from industries where there is a comparative disadvantage (Shingal, 2015). Other key assumptions of traditional trade theory included constant returns to scale and homogeneity within industries, but empirical evidence challenged these models as high levels of intra-industry trade between countries with similar endowments and technology were observed, which did not fit with the cloth for wine narrative. In response, the New Trade Theory was developed (Inomata, 2017). Krugman (1979; 1980) and Helpman and Krugman (1985) devised a new model which could provide an explanation for the occurrence of intra-industry trade based on increasing returns to scale and a love of variety (Inomata, 2017). Empirical studies also found that most labor market effects occurred at the intra-industry level, rather than in the form of moving jobs from one industry to another (Jansen & Turrini, 2004). This then challenged the assumption of homogenous producers within industries (Shingal, 2015) and empirical evidence in the 1990s, notably Bernard, Jensen and Lawrence (1995), found that within the same industry the productivity of firms engaged in export differed from that of firms only active domestically. This within-industry firm heterogeneity gave rise to new trade models, among them Melitz (2003). Melitz (2003) assumes certain fixed costs associated with engaging in export and even higher fixed costs to engage in more complex forms of trade, such as subsidiaries and GVCs. This leads to only firms with higher productivity levels engaging in trade activities. At this point in the history of trade theory the focus is still on trade in final goods, but with globalization, the improvements in transportation and information and communication technologies (ICT) have led to an increase in trade in intermediate inputs and thus the emergence of GVCs. Trade in intermediate inputs is not a feature of traditional trade theory and efforts are currently made to develop new models which can account for it (Inomata, 2017).

Trade in intermediate inputs has a more complex relationship with employment (Jiang, 2013), as Baldwin and Evenett (2015) illustrate in a two-country model. Baldwin and Evenett (2015) provide a useful example in the form of a one-factor Ricardian model for trade between Britain and a foreign country which shows the effects of globalization on trade and the division of labor between the two. Starting from a traditional international trade situation, the model is depicted in Figure 1 (left) from British perspective and consists of sectors A to G. Britain and the foreign

country differ in terms of productivity and wages for each sector, which are plotted on the left and right axes. At the solid black line of w^{UK}/w^{For} wage levels are equal in Britain and the other country, this is the case for sector D. Consequently, neither country has a competitive advantage in the sector and it is not traded. Above the solid line, however, Britain is more productive which makes up for its higher wages and gives it a comparative advantage in sectors A, B and C. Below the solid line, the foreign country enjoys a comparative advantage in sectors E, F and G. While Britain might be more technologically advanced and thus more productive, it is outcompeted by the lower wages in the foreign country. Britain therefore exports products of sectors where it has a comparative advantage and imports from sectors where it has a comparative disadvantage. However, trade costs also need to be considered. While sectors C and E would be traded under zero trade costs, the current level of trade costs in the model cause the two sectors to be non-traded (Baldwin & Evenett, 2015). In this situation, Britain and the foreign country have what is also known as a latent comparative advantage (Chandra, Lin & Wang, 2013) in sectors C and E respectively. With the first wave of globalization, which Baldwin and Evenett (2015) call the first unbundling, the situation for sectors C and E changes. Improvements in transportation greatly decrease trade costs, leading both sectors now to become traded (Figure 1, right).

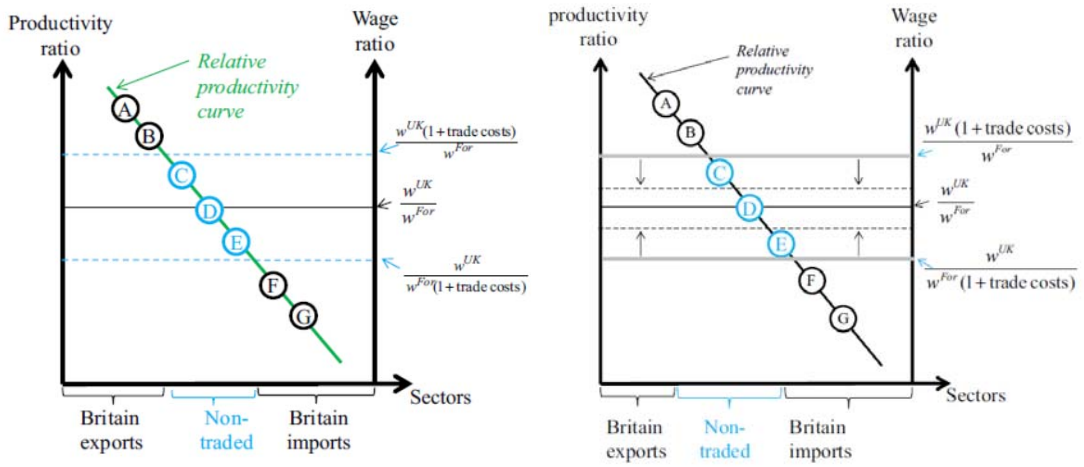

Figure 1: Trade before (left) and after (right) the first unbundling of globalization (Source: Baldwin & Evenett, 2015:39-40)

At this point trade is still focused around final goods. The emergence of GVCs comes with the second unbundling or wave of globalization driven by the ICT revolution (Baldwin & Evenett, 2015). With new technologies it becomes possible to split the production process into individual stages which can be spatially separated, leading to the rise in the trade of intermediate goods. Returning to the example of Britain, the high productivity sectors A and B may be composed of two production stages each, one more high-skill and the other low-skill intensive. Prior to the second unbundling, these two production stages were bound to the same place; the production was bundled as in Figure 1. With the unbundling, the lower-skill production stages migrate to the foreign country, following its comparative advantage while Britain retains the high-skill or technology intensive production stages as shown in Figure 2 (left), increasing overall efficiency (Baldwin & Evenett, 2015).

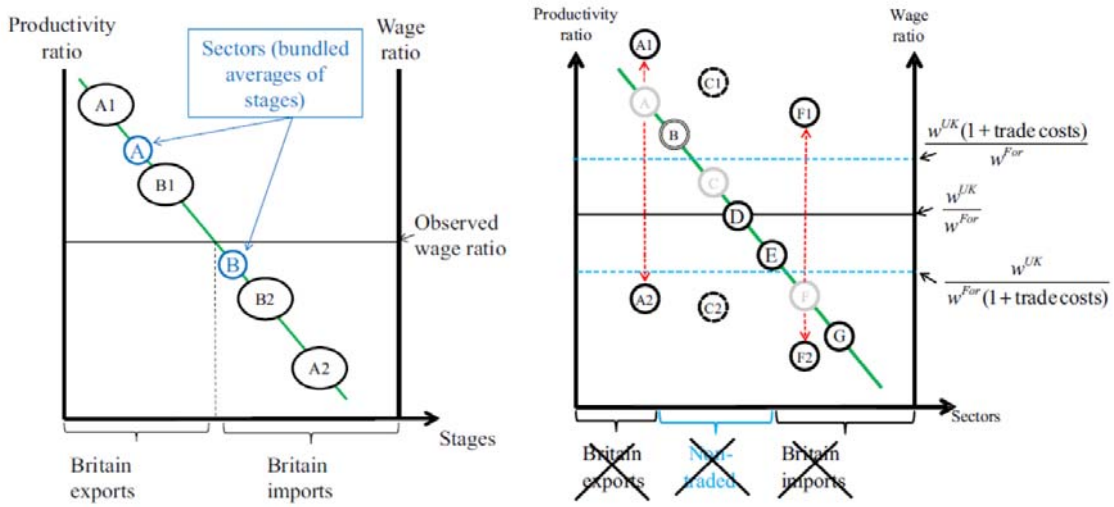

Figure 2: Trade after the second unbundling of globalization (left) and partial unbundling (right) (Source: Baldwin & Evenett, 2015:41-42)

However, Baldwin and Evenett (2015) noted that this new process of specialization for various reasons may not be smooth or could remain incomplete, which they call a partial unbundling. This is where traditional comparative advantage analysis starts to struggle and why the effects of GVC on employment are more difficult to predict. Figure 2 (right) shows such a scenario for Britain. Britain may lose jobs in sector A as the production unbundles and the low-skill stage moves abroad, but it may also gain jobs from sector F where it is now competitive in the high-skill production stages. As these production stages are themselves composed of various substages, Britain may lose higher and lower skilled jobs in the move of A2 abroad and gain jobs at both skill levels from F1. The fall in coordination costs as a result of new technology may also outweigh trade costs for some sectors, leading previously non-traded sectors to now become tradable, as is the case for sector C. Other sectors, such as B, may remain bundled because of any number of forces which are not yet well understood and potentially highly sector specific.

Comparative advantage analysis based on skill-intensity at the sectoral level as it is done in traditional trade theory therefore falls short when it comes to trade in intermediate inputs and anticipating how a sector might unbundle or how it will impact employment in the economies affected. Such predictions require more information about the specifics of tasks involved in an individual production process than is usually available to economists and policymakers (Baldwin & Eventt, 2015). There are a number of researchers which have taken up the challenge and sought to model the impact of GVCs on employment. While two are introduced below, there is a clear need for further empirical evidence to lay the groundwork (Inomata, 2017).

Based on studying maquiladoras in Mexico, Feenstra and Hanson (1997) proposed a model whereby offshoring can lead to an increased demand for skilled labor in both Britain and the foreign country (to reuse the example of Baldwin & Evenett, 2015), depending on the countries' skill levels in production prior to the offshoring. Britain may split its production into relatively high-skilled and relatively low-skilled components. The low-skilled components of production are then offshored to the foreign country and Britain specializes in the high-skilled activities. The production stage to be offshored which is considered relatively low-skill in Britain, may be

relatively high-skill in the foreign country and could thus also lead to an increased demand for skilled labor. Whether this occurs depends on the preexisting skill level of the foreign economy.

Grossman and Rossi-Hansberg (2012:593) argue that discussing GVCs in terms of industries has lost much of its usefulness, since the GVCs have led to "specialization in particular occupations and tasks" rather than specific industries. Based on a model on offshoring between countries of similar factor endowments, what kind of jobs are created where depends on external economies of scale, offshoring costs, and the size of aggregate output production which determine which tasks would be offshored (Grossman & Rossi-Hansberg, 2012).

Overall, the emergence of GVCs has made it more difficult to predict the impact of trade on employment (Jiang, 2013), even made it "unpredictable" as Baldwin and Evenett (2015:42) argue, and more empirical work is crucial to further our understanding (Shingal, 2015).

2.2 Previous Studies

As mentioned in the introduction, the topic has attracted the attention of various empirical researchers over recent years, but has mostly been studied in the form of case studies (Shingal, 2015). Systematic empirical studies are scarce (Jiang, 2013), but have increasingly become feasible with the availability of large new datasets, especially in the form of Input-Output tables (Shingal, 2015).

Focusing on factor content shares of labor and capital in the value chains of final manufacturing goods to see the impact of production fragmentation, Timmer and colleagues (2014) investigate trends and developments for 40 countries (the EU27 and 13 other major economies) over the period of 1995 to 2008. As in this paper, the study is conducted on the basis of Input-Output tables, which will be discussed in detail in the next section. Timmer and colleagues (2014) further supplement the tables with data on income by skill level for workers which allows them to break down developments by individual skill categories. They focus on four major trends in their data for the production of manufactures: 1. International fragmentation of production has increased sharply, with the average share of foreign value added in manufactures production increasing from 28 percent in 1995 to 34 percent in 2008. 2. In both, high income and emerging economies, the income shares of low and medium skilled workers are increasingly replaced by that of capital and high-skilled workers. 3. High income economies specialize more and more in high-skill work. 4. Emerging economies increasingly focus on capital-intensive production. They link their findings to a model by Rodrik (1998) which argues that the liberalization of capital markets has reduced the bargaining power of workers and increased the income share of capital. This international mobility of capital also helps to explain the increased specialization in capital-intensive industries by emerging economies according to Timmer and colleagues (2014:113) who connect it to the Lewis (1954) model, stating that while "there is a reservoir of unskilled labor that can be employed at wages well below their marginal productivity, rental-wage ratios will remain high. Thus, the income share of capital will increase in early stages of development, rather than decline."

A working paper for the ILO by Jiang (2013) also made use of Input-Output tables to analyze the period of 1995 to 2009 for the same countries as Timmer et al. (2014) (minus Luxembourg). Based on a decomposition similar to the one used in this paper, Jiang (2013) distinguished between five categories of trade activities as a source of job creation (measured as both full-time and part-time jobs) in a given country: domestic labor in export activities and foreign labor in imports (the traditional international trade components), as well as three GVC components (foreign labor in export, domestic labor in imports, labor of a third country in imports). The paper thereby takes the perspective of employment created through the labor demands of a country. In other words, it considers all employment associated with the production activities of a given country irrespective of whether jobs were created within the country itself or elsewhere. In total, the working paper arrives at close to 88 million jobs being involved in GVC activities in 2009, with Germany, the USA and China being the main job creators. This is in line with the previous discussion where Germany, the USA and China were identified as the main hubs around which GVC activities revolve. Taking a brief look at employment by skill shares, Jiang (2013) notes similar contradictions with the Heckscher-Ohlin model as Timmer and colleagues (2014) and highlights a need for future research on employment in GVCs.

The topic of employment in GVCs has further also been studied at the individual country and regional level, with studies having been conducted on India (e.g. Banga, 2016), Sub-Saharan Africa (e.g. Farole & Winkler, 2014), China (e.g. Los, Timmer & De Vries, 2012) and Bulgaria (Taglioni & Winkler, 2016) among others. This paper expands on the existing body of literature by making use of newly released, more recent data and considering GVC activities from all sectors to answer the research question of how many jobs (full-time and part-time) have been created by GVC activities over the period of 2000 to 2014 in 43 economies which account for over 85% of world GDP.

3 Data

To answer the research question, this paper makes use of the 2016 release of the World Input-Output Database (WIOD) which was constructed by the Groningen Growth and Development Center and originally created for the European Commission (Timmer, Dietzenbacher, Los, Stehrer & de Vries, 2015). The dataset consists of a series of World Input-Output Tables (WIOT) for the years 2000 to 2014 and covers the 43 economies listed in Table 1, plus an aggregate for the rest of the world. The countries are grouped into high income and emerging economies for the analysis and combined, the 43 economies capture over 85% of the world GDP (Stehrer, Foster & de Vries, 2012). For each economy, data is available at an aggregated level of 56 industries and in million USD at current prices (a list of all industries is available in Appendix A).

Information on employment (number of full-time and part-time jobs) stems from the 2018 satellite account release of the same database, the Socio-Economic Accounts (SEA). The main underlying data source for the SEA is Eurostat, data for countries not included in this database was constructed according to Eurostat methods to ensure consistency and comparability. The indicator of interest is the number of persons engaged, a measure of the number of jobs involved in the production activities of a given industry. The indicator includes all workers above the age of 15 and does not distinguish between full-time and part-time employment. More detailed information on the construction of the SEA and on the specific data construction for each economy is available in Gouma, Chen, Woltjer and Timmer (2018). The construction of the WIOTs themselves is based on national Supply and Use Tables and international trade data from statistical offices, results are in line with National Accounts (Dietzenbacher, Los, Stehrer, Timmer & de Vries, 2013). For additional information on the construction of the database, see Dietzenbacher, Los, Stehrer, Timmer and de Vries (2013).

Table 1: Economies included in the WIOD database 2016 release with high income economies classified according to the World Bank (2018) income classification of 2014 and remaining designated as emerging economies

High income economies (n = 33)
Australia (AUS), Austria (AUT), Belgium (BEL), Canada (CAN), Cyprus(CYP), Czech Republic (CZE), Denmark (DNK), Estonia (EST), Finland (FIN), France (FRA), Germany (DEU), Greece (GRC), Hungary (HUN), Ireland (IRL), Italy (ITA), Japan (JPN), Latvia (LVA), Lithuania (LTU), Luxembourg (LUX), Malta (MLT), Netherlands (NLD), Norway (NOR), Poland (POL), Portugal (PRT), South Korea (KOR), Slovakia (SVK), Slovenia (SVN), Spain (ESP), Sweden (SWE), Switzerland (CHE), Taiwan (TWN), United Kingdom (GBR), United States (USA)
Emerging economies (n = 10)
Brazil (BRA), Bulgaria (BGR), China (CHN), Croatia (HRV), India (IND), Indonesia (IDN), Mexico (MEX), Romania (ROU), Russia (RUS), Turkey (TUR)

Input-Output tables are in essence an accounting framework (Timmer et al., 2015) from which insights into the interdependencies of economies can be derived with the help of linear algebra (Miller & Blair, 2009:1). In the case of this study, this allows for the separation of purely domestic, traditional international trade, and GVC activites. The basic layout of a WIOT is presented in a stylized version in Figure 3 and features four main elements which are briefly discussed here to provide a short introduction to readers who are less familiar with Input-Output (IO) analysis. The paper follows common matrix notation as discussed in Miller and Blair (2009), using bold upper-case letters for matrices, bold lower-case for column vectors and italics lower-case for scalars. Primes ‘ and hats ^ are further used to indicate a transpose and diagonalized matrices respectively. The size and dimensions of a matrix are shown as *N* x *M*, indicating that the matrix has *N* rows and *M* columns (matrix dimensions are capitalized despite being scalars for readability). Summation vectors consist of elements of 1s and are used to sum matrices along rows (postmultiplication) or columns (premultiplication), they are denoted by **i**. An additional concept used in the next section of the methodology are block matrices, whereby a matrix contains submatrices.

		Country A		Country B		ROW		Country A	Country B	ROW	Gross
		Industry 1	Industry 2	Industry 1	Industry 2	Industry 1	Industry 2	FD	FD	FD	Output
Country A	Industry 1										
	Industry 2										
Country B	Industry 1										
	Industry 2										
ROW	Industry 1										
	Industry 2										
Value Added											
Gross Output											

Figure 3: Stylized World Input-Output Table, adapted from Los, McCann, Springford & Thissen (2017)

The first matrix, **Z**, contains information on intermediate input sales with element z_{ij} representing intermediate inputs sold by industry *i* to industry *j*, in other words interindustry sales (as well as intra-industry). The *GN* x *GN* matrix covers *G* countries with *N* industries. **F** is the final demand matrix which tracks the value of products that have left the production process for final consumption. It is a *GN* x *GM* matrix, where *M* refers to the number of demand categories. WIOD distinguishes between five categories of final demand: final consumption of households, non-profit organizations, and the government respectively, as well as gross fixed capital formation and changes in inventory and valuables. For the purpose of this study, however, the categories are aggregated into total final demand for each economy. The production of goods and services also requires labor and capital among other items on top of the intermediate inputs captured in **Z**. These are covered in **v**’, a *1*x*GN* row vector. Finally, the total output of each industry is shown in **x**, a *GN*x*1* vector. Total output can be either summed along the rows of the table as $\mathbf{x} = \mathbf{Zi} + \mathbf{f}$, where f is the total final demand aggregated across demand categories and countries, or along the columns as $\mathbf{x}' = \mathbf{iZ} + \mathbf{v}'$. Summing along the columns reflects sector’s inputs (giving the distribution of where inputs are sourced from) and along the rows the output of a sector (giving the distribution of an industry’s output). The tables thus capture all production and consumption in the world economy within a year.

The four elements of **Z**, **F**, **x** and **v** then allow the computation of a number of other identities which are used in this paper. By dividing z_{ij}/x_j, information on how much of a given input

from industry *i* needs to be used by industry *j* per one dollar of output of industry *j*. This is also known as a direct input coefficient or a_{ij}. In a similar vein, employment coefficients e_{ij} and value added coefficients v_{ij} can be obtained by dividing data on employment and value added in each industry by industry output. With the input coefficient matrix $\mathbf{A}$, ($\mathbf{A} = \mathbf{Z}\hat{\mathbf{x}}^{-1}$), the overall output of an economy can then be defined as $\mathbf{x} = \mathbf{A}\mathbf{x} + \mathbf{f}$. Rearranging the equation into $\mathbf{x} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{f}$ yields the Leontief inverse $\mathbf{B} \equiv (\mathbf{I} - \mathbf{A})^{-1}$ or total requirements matrix. As the name implies, the total requirements matrix captures not only the input of industry *i* required for the output of industry *j*, but also inputs required by industry *i* to produce the input for industry *j* and the inputs required to produce those inputs and so on. In other words, the Leontief inverse captures both direct and indirect effects (Miller & Blair, 2009:11-13/21).

As a result, it is possible in the context of this study to not only calculate the number of jobs created by GVC activities directly, but also indirectly. The key advantage of using Input-Output tables, and specifically the WIOD database, lies in its ability to address the changes which globalization has brought to global production structures, because it sheds light on interdependencies and linkages within and across economies. The WIOD database was specifically designed to study the increased international fragmentation of production and trace the trade in tasks (Dietzenbacher, Los, Stehrer, Timmer & de Vries, 2013).

However, the mapping of economic linkages across multiple economies in a comparable fashion across time and the aggregation into 56 industries necessarily require a number of simplifications and a degree of compromise (Dietzenbacher et al., 2013). Lack of disaggregated data and inconsistencies across countries mean WIOD assumes one product per industry and thus does not allow for heterogeneity in technology or production structures across firms within an industry (Timmer et al., 2015). A similar issue arises in linking the use of imports to industries and countries of origin. Because data availability is limited, import use is allocated based on a proportionality assumption. In other words, for example, if Switzerland as a whole were to import 20% of its electronics from Japan, then for every Swiss industry which uses electronics in its production or also for electronics purchases by final consumers 20% is assumed to stem from Japan. The WIOD thereby improves on previous IO datasets by distinguishing between three different use categories (intermediate inputs, final consumption and investments) within which the proportionality assumption is applied instead of applying the assumption uniformly to the entire economy. This is still a far from reality (Feenstra & Jensen, 2012; Timmer et al., 2015), even under the improved version of WIOD, since, for example, "if 60% of Czech imports of electronics for intermediate use is sourced from Germany, then 60% of use of electronics by any Czech industry is assumed to originate from Germany" (Timmer et al., 2015:592). All of these assumptions will necessarily gloss over any systematic differences in the way firms operate depending on whether they are involved in traditional international trade or GVC activities (such as higher import use in GVC firms, see e.g. Chen et al., 2012; De la Cruz, Koopman, Wang & Wei, 2011; Koopman, Wang & Wei, 2012).

Another concern is the reliability of the data. While WIOD uses only official statistical data which is publicly available and generally more thoroughly vetted, the quality of data still varies across countries. Especially, data on trade in services was difficult to obtain as there is to date no comprehensive database available. Services are difficult to capture because of their intangibility and the quality of the data on trade in services is still far below that of other goods. While the WIOD includes the highest quality of data on trade in services currently available (Dietzenbacher et al., 2013), this presents a clear limitation for the paper at hand. The poorer

data quality for services along with the necessary simplifications in the construction of the dataset reduce the accuracy of the employment calculations which has to be kept in mind in the interpretation of results. The limitations of the dataset discussed in this section are the ones most relevant to the present study, further information on limitations of the WIOD can be found in Timmer et al. (2015).

4 Methods

To determine the number of full-time jobs created by GVC activities and traditional international trade, a decomposition equation from a working paper on GVC participation by Wang, Wei, Yu and Zhu (2017) is used. The equation was developed based on the earlier works on decomposition equations for value added in GVCs (e.g. Borin & Mancini, 2015; Hummels, Ishii & Yi, 2001; Johnson & Noguera, 2012; Koopman, Wang & Wei, 2014). All calculations were made in MATLAB.

		Intermediate Use						Final Demand			Total
		Country 1	Country 2	Country 3	Country 4	...	Country G	Country 1	...	Country G	Output
Intermediate Input	Country 1	**Z**						**F**			**X**
	Country 2										
	Country 3										
	Country 4										
	⋮										
	Country G										
Value Added		**V'**									
Total Output		**X'**									

Figure 4: Inter-country IO table, adapted from Wang, Wei, Yu and Zhu (2017)

For simplicity and ease of notation, the equation is discussed based on an inter-country IO table (ICIO). Figure 4 provides a stylized version of the ICIO which is similar to the stylized WIOT in Figure 3, but does not feature the same level of disaggregation. Instead, the elements **Z**, **F**, **V** and **X** are block matrices. For example, element $\mathbf{Z}_{rs}$ in the **Z** matrix of the ICIO contains a *N*x*N* submatrix on intermediate sales and use for *N* industries between country *r* and country *s*. $\mathbf{f}_{rs}$ in the final demand matrix **F** contains a *N*x*1* vector of total final demand by country *s* for *N* industries of country *r*. **V**' holds $\mathbf{v}'_s$, a *1*x*N* vector with value added by *N* industries in country *s*, and **X** contains $\mathbf{x}_r$, a *N*x*1* vector with total outputs by *N* industries in country *r*. As in the introduction to the WIOT in the previous section, the input coefficient matrix can then be defined as $\mathbf{A} = \mathbf{Z}\widehat{\mathbf{X}}^{-1}$, the value added and employment coefficients as $\mathbf{V} = \mathbf{W}\widehat{\mathbf{X}}^{-1}$ and $\mathbf{E} = \mathbf{S}\widehat{\mathbf{X}}^{-1}$, and the Leontief inverse as $\mathbf{B} = (\mathbf{I} - \mathbf{A})^{-1}$. With all the necessary identities calculated, the total number of jobs in the world economy can be derived as $\widehat{\mathbf{E}}\mathbf{B}\widehat{\mathbf{F}}$, a *GN*x*GN* block matrix (Wang, Wei, Yu & Zhu, 2017). In order to derive the total employment involved in international trade and GVC activities, $\widehat{\mathbf{E}}\mathbf{B}\widehat{\mathbf{F}}$ is decomposed into three components: domestic activities, international trade, and GVC activities. Disentangling the three components starts with a breakdown of the previously discussed equation $\mathbf{X} = \mathbf{A}\mathbf{X} + \mathbf{F}$ in equation 1.

$$\mathbf{X} = \mathbf{A}\mathbf{X} + \mathbf{F} = \mathbf{A}^{\mathrm{D}}\mathbf{X} + \mathbf{F}^{\mathrm{D}} + \mathbf{A}^{\mathrm{F}}\mathbf{X} + \mathbf{F}^{\mathrm{F}} = \mathbf{A}^{\mathrm{D}}\mathbf{X} + \mathbf{F}^{\mathrm{D}} + \mathbf{T} \quad (1)$$

, where superscripts D and F signify domestic and foreign, $F = [\sum_r^G F^{1r} \sum_r^G F^{2r} \cdots \sum_r^G F^{Gr}]$, a *GN*x*1* total final demand block vector, $\mathbf{A}^{\mathrm{D}}$ = *GN*x*GN* domestic input coefficient block matrix, $F^D = [F^{11} F^{22} \cdots F^{GG}]$, a GNx1 domesitc final demand block vector, $\mathbf{A}^{\mathrm{F}}$ = *GN*x*GN* foreign input coefficient block matrix, $F^F = Y - Y^D$, a *GN*x*1* foreign final demand block vector, $T = A^F X +$

$F^F = [\sum_{r\neq 1}^{G} T^{1r} \sum_{r\neq 2}^{G} T^{2r} \cdots \sum_{r\neq g}^{G} T^{gr}]$ and captures exports. $\mathbf{A}^{\mathrm{D}}$ only contains values on the diagonal with zeros elsewhere, in other words, $A^D = \begin{bmatrix} \mathbf{A}_{11} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{A}_{22} & \cdots & \mathbf{0} \\ \vdots & \cdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{A}_{GG} \end{bmatrix}$; for $\mathbf{A}^{\mathrm{F}}$ the values are off-diagonal with zeros on the diagonal.

Equation 1 is then rearranged to separate domestic activities from international trade and GVC activities as

$$\begin{aligned} \mathbf{X} &= (\mathbf{I} - \mathbf{A}^D)^{-1}\mathbf{F}^D + (\mathbf{I} - \mathbf{A}^D)^{-1}\mathbf{T} = \mathbf{L}\mathbf{F}^D + \mathbf{L}\mathbf{T} \\ &= \mathbf{L}\mathbf{F}^D + \mathbf{L}\mathbf{F}^F + \mathbf{L}\mathbf{A}^F\mathbf{X} = \mathbf{L}\mathbf{F}^D + \mathbf{L}\mathbf{F}^F + \mathbf{L}\mathbf{A}^F\mathbf{B}\mathbf{F} \end{aligned} \quad (2)$$

, where $\mathbf{L} = (\mathbf{I} - \mathbf{A}^D)^{-1}$ refers to the local Leontief inverse, as opposed to the global Leontief inverse B. This local Leontief inverse is needed to calculate the international trade component as proposed by Borin and Mancini (2015). To summarize the rearranging in equation 2 in words, after deriving the production for domestic demand and exports, E is split into its two components of exports for foreign final demand and foreign intermediate use. In a last step, **X** is swapped for **BF**, since $\mathbf{X} = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{F} = \mathbf{B}\mathbf{F}$. In order to obtain information on the employment involved in producing the output in the three different categories, the terms in equation 2 are premultiplied by the employment coefficients E which yields equation 3.

$$\hat{\mathbf{E}}\mathbf{B}\hat{\mathbf{F}} = \hat{\mathbf{E}}\mathbf{L}\hat{\mathbf{F}}^D + \hat{\mathbf{E}}\mathbf{L}\hat{\mathbf{F}}^F + \hat{\mathbf{E}}\mathbf{L}\mathbf{A}^F\mathbf{B}\hat{\mathbf{F}} \quad (3)$$

To distinguish between simple and complex GVC activities, the third term in equation 3 is further split into two parts as shown in equation 4. A formal derivation of the two terms can be found in the appendix of Wang, Wei, Yu and Zhu (2017). The intuition behind the two terms can be gained by looking at their components. The third term, $\hat{\mathbf{E}}\mathbf{L}\mathbf{A}^F\mathbf{L}\hat{\mathbf{F}}^D$, calculates the employment involved in simple GVC activities as the labor a country needs to produce intermediate inputs for another country ($\hat{\mathbf{E}}\mathbf{L}\mathbf{A}^F$), which the other country then uses produce output to satisfy its domestic final demand ($\mathbf{L}\hat{\mathbf{F}}^D$). Hence the intermediate inputs only cross borders once before leaving the production process. In the fourth term, $\hat{\mathbf{E}}\mathbf{L}\mathbf{A}^F\left(\mathbf{B}\hat{\mathbf{F}} - \mathbf{L}\hat{\mathbf{F}}^D\right)$, the second half has changed to $\left(\mathbf{B}\hat{\mathbf{F}} - \mathbf{L}\hat{\mathbf{F}}^D\right)$. In other words, intermediate inputs cross borders at least twice before leaving the production process as the subtraction of $\mathbf{L}\hat{\mathbf{F}}^D$ excludes inputs which are used to satisfy final demand after crossing borders only once.

$$\hat{\mathbf{E}}\mathbf{B}\hat{\mathbf{F}} = \hat{\mathbf{E}}\mathbf{L}\hat{\mathbf{F}}^D + \hat{\mathbf{E}}\mathbf{L}\hat{\mathbf{F}}^F + \hat{\mathbf{E}}\mathbf{L}\mathbf{A}^F\mathbf{L}\hat{\mathbf{F}}^D + \hat{\mathbf{E}}\mathbf{L}\mathbf{A}^F\left(\mathbf{B}\hat{\mathbf{F}} - \mathbf{L}\hat{\mathbf{F}}^D\right) \quad (4)$$

To further illustrate how the decomposition works, consider a world economy which consists of the two countries *s* and *r* with N sectors that are traded. Decomposing the employment involved in the production of output for domestic activities, international trade, simple, and complex GVC activities then takes the form of equation 5 in block matrix notation for the two countries.

$$\begin{aligned} \hat{\mathbf{E}}\mathbf{B}\hat{\mathbf{F}} = &\begin{bmatrix} \hat{\mathbf{E}}^s\mathbf{L}^{ss}\hat{\mathbf{F}}^{ss} & \mathbf{0} \\ \mathbf{0} & \hat{\mathbf{E}}^r\mathbf{L}^{rr}\hat{\mathbf{F}}^{rr} \end{bmatrix} + \begin{bmatrix} \hat{\mathbf{E}}^s\mathbf{L}^{ss}\hat{\mathbf{F}}^{sr} & \mathbf{0} \\ \mathbf{0} & \hat{\mathbf{E}}^r\mathbf{L}^{rr}\hat{\mathbf{F}}^{rs} \end{bmatrix} + \begin{bmatrix} \mathbf{0} & \hat{\mathbf{E}}^s\mathbf{L}^{ss}\mathbf{A}^{sr}\mathbf{L}^{rr}\hat{\mathbf{F}}^{rr} \\ \hat{\mathbf{E}}^r\mathbf{L}^{rr}\mathbf{A}^{rs}\mathbf{L}^{ss}\hat{\mathbf{F}}^{ss} & \mathbf{0} \end{bmatrix} \\ &+ \begin{bmatrix} \hat{\mathbf{E}}^s\mathbf{L}^{ss}\mathbf{A}^{sr}(\mathbf{B}^{rs}\hat{\mathbf{F}}^{ss} + \mathbf{B}^{rr}\hat{\mathbf{F}}^{rs}) & \hat{\mathbf{E}}^s\mathbf{L}^{ss}\mathbf{A}^{sr}[(\mathbf{B}^{rr} - \mathbf{L}^{rr})\hat{\mathbf{F}}^{rr} + \mathbf{B}^{rs}\hat{\mathbf{F}}^{sr})] \\ \hat{\mathbf{E}}^r\mathbf{L}^{rr}\mathbf{A}^{rs}(\mathbf{B}^{ss} - \mathbf{L}^{ss})\hat{\mathbf{F}}^{ss} + \mathbf{B}^{sr}\hat{\mathbf{F}}^{rs})] & \hat{\mathbf{E}}^r\mathbf{L}^{rr}\mathbf{A}^{rs}(\mathbf{B}^{sr}\hat{\mathbf{F}}^{rr} + \mathbf{B}^{ss}\hat{\mathbf{F}}^{sr}) \end{bmatrix} \end{aligned} \quad (5)$$

Equation 5 further demonstrates that summing individual terms along rows yields the domestic employment involved in the production of output for the given category. Summing along the columns, on the other hand, provides information on all employment – both domestic and foreign – involved in the production of sectoral output. For the purpose of this study, the focus is placed on the summation along rows, taking a producer's perspective (Wang, Wei, Yu & Zhu, 2017). To gain further insight into the distribution of jobs involved and created in the different categories over the period of 2000 to 2014, summation vectors are added to create variations of equation 4. Included are summation vectors with ones and zeros which distinguish between agricultural, manufacturing and service sectors, as well as a distinction by continent and income level of the country. For example, the summation vector for the agricultural sector includes ones in places corresponding to agricultural industries and zeros elsewhere.

5 Empirical Analysis

5.1 Results

In total, GVC activities and traditional international trade created an approximately equal absolute number of jobs across the 43 economies during the timeframe of 2000 to 2014 as shown in Table 2 as the delta for Columns 1 and 2. Employment in international trade increased from 130 million to 168.5 million jobs, which amounts to an increase of 38.5 million or 29.5 percent. GVC activities saw an increase of 37.5 million or 39.1 percent over the same period of time, rising from 95.5 million to 133 million employed. Breaking down GVC activities further into simple and complex shows that the increase in job creation was especially marked for jobs in complex GVC activities in both absolute and relative terms. 15.5 million jobs created in simple GVC activities and 22 million in complex GVCs, corresponding to a 26.0 percent increase from 59.5 million to 75 million and a 60.5 percent increase from 36 million to 58 million respectively. In relative terms, this leads GVC activities to account for 44.1 percent of all jobs in trade activities in 2014. With regards to the value added generated by the different trade activities over the period of 2000 to 2014, all trade categories more than doubled in size. In 2014, trade activities created 12 trillion USD in value added, of which GVC activities constituted 61.8 percent. The largest relative increase occurred in complex GVC activities which grew from one to three trillion USD by 2014, a more than 200 percent increase. GVC activities seem to have grown in importance in both the number of jobs and value added over the time period considered.

Table 2: Number of jobs (in thousands) and value created (in million USD, current prices) by trade activity in 2000 and 2014 for the 43 countries of the WIOD database combined

Employment (in thousands)						
		International trade	GVC activities	Simple GVC	Complex GVC	Total
	2014	168,527	132,992	74,878	58,115	301,519
		55.9%	44.1%	24.8%	19.3%	100%
	2000	130,108	95,636	59,435	36,201	225,744
		57.6%	42.4%	26.3%	16.0%	100%
Delta		38,419	37,356	15,443	21,913	75,775
Delta %		29.5%	39.1%	26.0%	60.5%	33.6%

Value added (million USD)						
		International trade	GVC activities	Simple GVC	Complex GVC	Total
	2014	4,583,310	7,413,517	4,348,471	3,065,047	11,996,827
		38.2%	61.8%	36.2%	25.6%	100%
	2000	1,829,109	2,630,486	1,648,596	981,890	4,459,595
		41.0%	59.0%	37.0%	22.0%	100%

Delta	2,754,201	4,783,031	2,699,874	2,083,157	7,537,233
Delta %	150.6%	181.8%	163.8%	212.2%	169.0%

Having answered the question of how many jobs were created by GVC activities overall, the next step is focused on where the jobs were created. Table 3 shows the geographic distribution of the over 75 million trade-related jobs created from 2000 to 2014.

Table 3: Geographic distribution of the jobs and value added created by trade activities over the period of 2000 to 2014. Percentages may not add up to one hundred due to rounding. A table with individual country contributions is provided in Appendix B

	International trade		Simple GVC		Complex GVC		Total	
	Jobs	Value	Jobs	Value	Jobs	Value	Jobs	Value
Asia-Pacific	85.1%	42.9%	48.6%	42.9%	45.6%	34.5%	67.3%	40.6%
Europe	10.8%	43.2%	17.3%	32.3%	43.5%	49.2%	21.6%	41.0%
Americas	2.1%	13.9%	34.1%	24.8%	10.8%	16.3%	11.2%	18.5%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%
Emerging economies	88.0%	41.2%	85.6%	40.1%	50.2%	32.7%	76.6%	39.1%
High income economies	12.0%	58.8%	14.4%	59.9%	49.8%	67.3%	23.4%	60.9%
	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%

In terms of regional distribution, the majority of 67.3 percent across all trade activities was created in Asia-Pacific. This was almost entirely driven by China and India which account for 43.8 percent and 20.5 percent of all trade jobs created. Europe contributed 21.6 percent of all jobs created, with Germany creating the most (4.3 percent) followed by Turkey (4.2 percent). The remaining 11.2 percent were created in the Americas, led by the USA with 4.5 percent. The distribution in value added is more balanced with Europe and Asia-Pacific accounting each for slightly above 40 percent. In Europe the main contributors were Germany and France who generated 8.3 percent and 4.2 percent of the total increase in value added by trade activities. Asia-Pacific was again driven by China and India with 24.9 percent and 4.0 percent respectively. The Americas generated 18.5 percent of the value added created over the period of 2000 to 2014, mainly through the USA with 11.7 percent.

Breaking trade jobs down into the different categories, the lead of Asia-Pacific is especially substantial in traditional international trade where it accounts for 85.1 percent of all traditional international trade jobs created. This is led again by China (52.1 percent) and India (34.4 percent). The key contributors in the smaller shares of Europe and the Americas were Turkey (4.1 percent) and Mexico (2.2 percent). The bulk of value added in traditional trade is again shared between Asia-Pacific and Europe with 42.9 percent and 43.2 percent respectively. The main contributors were China (31.7 percent), India (3.7 percent), and Germany (11.1 percent), France (3.6 percent). In the Americas 13.9 percent of the total change in value added for international trade was generated, 9.6 percent of which in the USA. In simple GVC activities, 48.6% of all jobs were created in Asia-Pacific and 34.1% in the Americas. The main contributors in the two regions where China (41.8 percent), India (8.6 percent), USA (14.4 percent), and Brazil (10.5 percent). Europe created 17.3 percent of all simple GVC jobs, with most created in Russia (9.2 percent) and Turkey (5.5 percent). The increase in value added involved in simple GVC stems 42.9 percent from Asia-Pacific, 32.3 percent from Europe and 24.8 percent from the Americas. This was driven by China (22.5 percent), Japan (6.2 percent), Germany (4.5 percent), France (4.4 percent), and the USA (15.2 percent) in the respective regions. In complex GVC activities, the number of created jobs was approximately evenly split between Asia-Pacific and Europe with 45.6 percent and 43.5 percent. Top contributors were China (30.8 percent), South Korea (5.2 percent), Germany (8.7 percent), and Turkey (3.5 percent). The Americas constituted the remaining 10.8 percent of the total complex GVC jobs created with the USA experiencing the greatest increase at 4.5 percent. The increase in value added in complex GVC activities is mainly captured by Europe (58.3 percent), driven by Germany (9.3 percent) and France (4.6 percent). Asia-Pacific accounted for 34.5 percent of the increase, with China again capturing the largest share (18.9 percent) and South Korea the second largest (4.5 percent). A share of 16.3 percent was created in the Americas, the USA contributing 9.9 percent.

However, while all 43 economies experienced an increase in value added across all types of trade from 2000 to 2014, this is not the case for jobs. Japan, Taiwan and Greece experienced an overall decrease in the number of jobs in trade activities for the period studied. In traditional international trade, Australia, Canada, Denmark, Finland, France, Hungary, Indonesia, Ireland, Netherlands, Norway, Romania, Russia, Sweden and Taiwan all had fewer jobs in the category in 2014 than in 2000. The largest drops were experienced by Russia and Indonesia. In simple GVC activities, it was Bulgaria, Spain, the UK, Greece, Croatia, Hungary, Italy, Japan, Lithuania, Luxembourg, Latvia, Slovakia and Slovenia which saw a decrease in the number of jobs. The largest decrease by far in simple GVC jobs was experienced by Japan which lost the equivalent of nearly 18% of all simple GVC jobs created over the period studied or 2.7 million jobs. In complex GVC activities only Taiwan saw a decrease in the number of jobs involved, dropping by 139’000 jobs.

Grouping countries by income level rather than geographic location shows that the majority of jobs accrued to emerging economies while high income economies carried greater shares in value added. In both traditional international trade and simple GVC activities, emerging economies accounted for over 80% of all jobs created and approximately 40% of the increase in value added. In complex GVC activities job creation is evenly split between emerging and high income countries while value added is again carried by high income economies which command a share of over 65%.

So far, the size of the economy has not been taken into consideration, making it difficult to compare results across countries and trade categories. To enable such comparisons, the focus is next placed on labor intensity which provides information on productivity to gain a better understanding of how many jobs were created by the different types of trade activities, how this has changed over the period studied and how the different categories compare. First, the labor intensities of international trade and GVC activities (simple and complex combined) are compared. Figure 5 shows the labor intensity of international trade and GVC activities by country measured as thousand jobs per million USD in value added. In other words, Figure 5 provides information on how many thousand jobs are needed to generate one million USD in value added in a country.

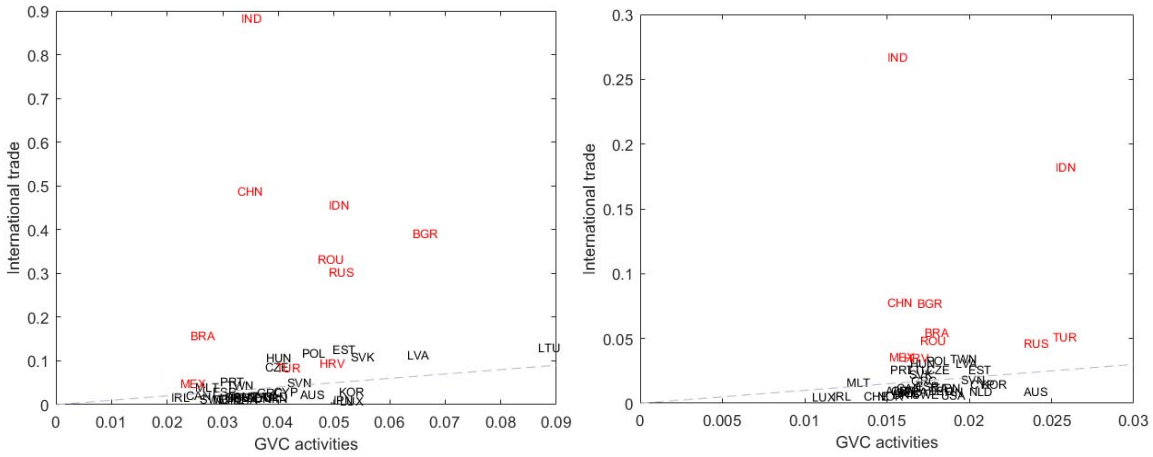

Figure 5: Labor intensity of international trade and GVC activities in 2000 (left) and 2014 (right) for the 43 economies of the WIOD database. Labor intensity is calculated as number of jobs in thousands divided by value added in million USD. Emerging economies are displayed in red, labor intensity of international trade and GVC activities is equal on the grey dotted line. (Author's calculations)

Labor intensity in both traditional international trade and GVC activities fell over the period considered. India recorded the highest labor intensity in international trade activities with 885 jobs per one million USD in value added in 2000. By 2014, India was still the most labor intense in international trade, but with only 268 jobs per one million USD value added. In GVC activities, Lithuania was the most labor intense with 89 jobs in 2000. The most labor intensive GVC activities in 2014 were in Indonesia with 26 jobs. The difference in labor intensity between emerging and high income economies in international trade is evident in Figure X for 2000 and 2014. In the year 2000, international trade involved on average 326 jobs per million USD value added (stdv 252.7) in emerging economies. By 2014, the number of jobs needed in emerging economies for international trade had dropped to on average 88 jobs (stdv 76.3). High income economies required on average 44 jobs in international trade in 2000 (stdv 39.8) and 16 jobs in 2014 (stdv 9.1). For GVC activities it is more difficult to clearly distinguish between emerging and high income economies. Emerging economies averaged 43 jobs per one million USD value added in 2000 (stdv 13.0) for GVC activities and 19 jobs in 2014 (stdv 4.2). For high income economies the 2000 average was at 40 jobs (stdv 12.9) and at 18 jobs in 2014 (stdv 2.7). The largest relative decreases in labor intensity in international trade and GVC activities accrued mainly to the newer EU members, both emerging and high income economies as shown in Table 4. Other large decreases in labor intensity were experienced in China, India, Japan,

Luxembourg, and Russia. High income economies saw on average a 53.7% decrease in international trade labor intensity with a standard deviation of 16.2 percentage points, GVC activities experienced an average 53.9% decrease with a standard deviation of 10.1 points. In emerging economies labor intensity in international trade decreased by an average 65.9% at a standard deviation of 19.7 points and GVC activities by 52.2% with a standard deviation of 13.8 points.

Table 4: Highest relative decreases in labor intensity among high income and emerging economies in international trade and GVC activities

High income economies				Emerging economies			
International trade	2000	2014	% Change	International trade	2000	2014	% Change
Lithuania	133	26	80.1%	Romania	335	49	85.3%
Slovakia	111	23	79.4%	Russia	305	47	84.6%
Estonia	128	27	79.0%	China	489	79	83.9%
Latvia	117	32	72.8%	Bulgaria	393	78	80.2%
Poland	120	34	72.1%				
GVC activities	2000	2014	% Change	GVC activities	2000	2014	% Change
Lithuania	86	17	80.9%	Bulgaria	67	18	73.5%
Luxembourg	53	11	79.0%	Croatia	50	17	66.2%
Latvia	65	20	69.6%	Romania	50	18	64.1%
Slovakia	55	17	69.1%	India	35	16	55.6%
Japan	51	19	63.5%				

In a next step, GVC activities are separated into simple and complex to compare their labor intensity and how it has developed. Figure 6 displays the measure of thousand jobs per one million USD value added for simple and complex GVC activities with the 45-degree dotted line marking equal labor intensity in the two categories.

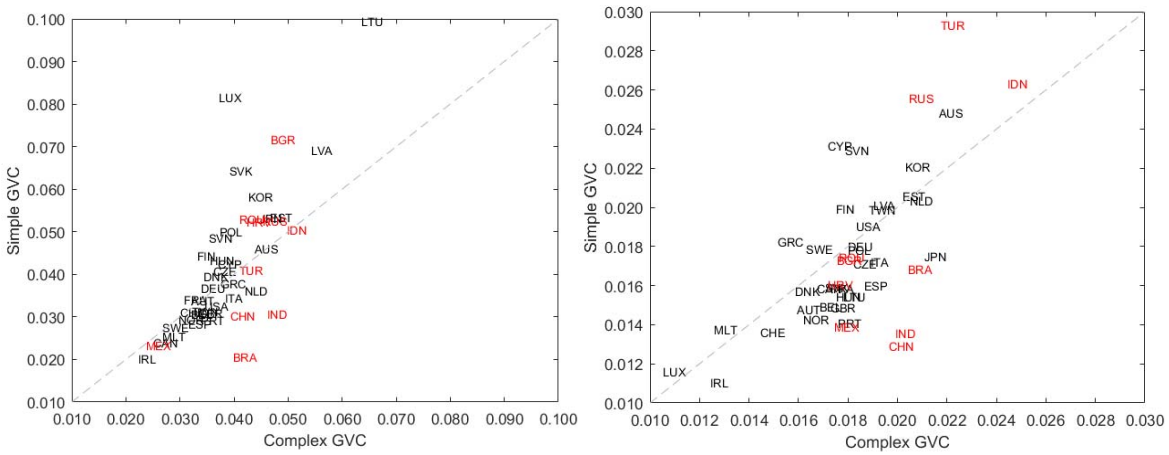

Figure 6: Labor intensity of simple and complex GVC activities in 2000 (left) and 2014 (right) for the 43 economies of the WIOD database. Labor intensity is calculated as number of jobs in thousands divided by value added in million USD. Emerging economies are displayed in red, labor intensity of simple and complex GVC activities is equal on the grey dotted line. (Author's calculations)

Lithuania had the highest labor intensity in both simple and complex GVC activities in 2000 with 100 and 65 jobs per million USD value added respectively. In 2014, the most labor intense simple GVC activities were in Turkey (29 jobs) and the highest complex GVC labor intensity was in Indonesia (25 jobs). On average, emerging economies used 43 jobs in simple GVC (stdv 16.2 jobs) and 44 jobs in complex GVC activities (stdv 7.0) in 2000. By 2014, labor intensity was reduced to on average 19 (stdv 5.9) and 20 jobs (stdv 2.3) respectively. High income economies required an average of 42 jobs in simple GVC (stdv 17.0) and 38 jobs in complex GVC activities (stdv 8.1) in 2000. In 2014, the average labor intensity was 17 jobs in simple GVC (stdv 3.3) and 18 jobs in complex GVC activities (stdv 2.4). The largest relative reductions are listed in Table 5 and focused in both categories around newer EU member states. The average reduction in simple and complex GVC activity labor intensity for high income economies amounted to 54.8% (stdv 12.4 points) and 52.4% (stdv 7.4 points) respectively. In emerging economies the labor intensity fell an average 51.2% (stdv 18.1 points) in simple and 52.9% (stdv 8.9 points) in complex GVC activities.

Table 5: Highest relative decreases in labor intensity among high income and emerging economies in simple and complex GVC activities

High income economies				Emerging economies			
Simple GVC	2000	2014	% Change	Simple GVC	2000	2014	% Change
Luxembourg	82	12	85.5%	Bulgaria	72	17	75.9%
Lithuania	100	16	84.5%	Croatia	53	16	69.4%
Slovakia	65	16	75.3%	Romania	53	18	67.1%
Latvia	69	20	71.0%	China	30	13	57.3%

Japan	53	18	67.1%				

Complex GVC	2000	2014	% Change	Complex GVC	2000	2014	% Change
Lithuania	65	18	72.1%	Bulgaria	49	18	63.2%
Luxembourg	39	11	72.0%	Croatia	45	18	60.4%
Latvia	56	20	65.4%	Romania	43	18	58.0%
Greece	40	16	60.6%	India	48	20	57.7%
Estonia	49	21	57.6%				

The previous paragraphs would suggest a fairly similar labor intensity between high income and emerging economies in GVC activities. However, to obtain more robust results, labor intensity is computed again on the one hand with changes in income classification taken into account and on the other without the mining sector. The countries which had changed their World Bank income classification status during the period are the Czech Republic, Estonia, Hungary, Latvia, Lithuania, Poland, and Slovakia (World Bank, 2018). Taking into account these changes in classifications had quantitative effects on the results, it did not change the findings from a qualitative point of view. The exclusion of the mining sector, however, had both quantitative and qualitative impacts on results and will be discussed in detail. The mining sector is generally not labor-intensive, but high in value added and prices in natural resources have risen over the period considered (Los, Timmer & de Vries, 2015). Since results are reported at the aggregate country level across all sectors, this may have led to a bias in the labor intensity analysis above. The effect is expected to mainly be felt in GVC activities, as mining is most likely an upstream sector. The analysis is thus repeated with all jobs and value added by the mining sector excluded, starting with the comparison between international trade and value added in Figure 7.

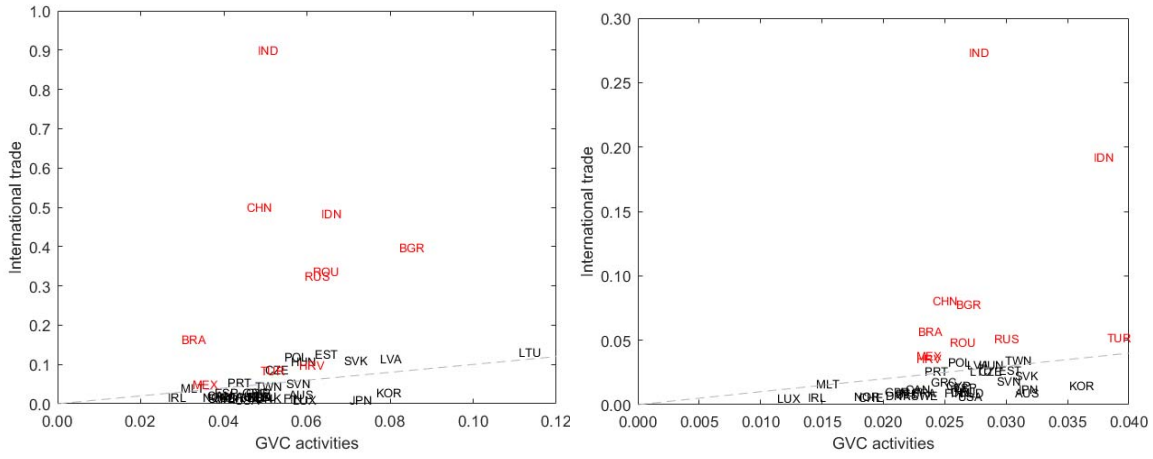

Figure 7: Labor intensity of international trade and GVC activities in 2000 (left) and 2014 (right) for the 43 economies of the WIOD database with the mining industry excluded. Labor intensity is calculated as

number of jobs in thousands divided by value added in million USD. Emerging economies are displayed in red, labor intensity of international trade and GVC activities is equal on the grey dotted line. (Author's calculations)

Excluding mining activities appears to have a mainly quantitative effect, but does not lead to any qualitative changes in the comparison of labor intensity in international trade and GVC activities. Labor intensity is generally higher without mining as was expected and mainly affects GVC activities. Average labor intensity in international trade without mining in emerging economies amounted to 336 jobs in 2000 (stdv 258.4 jobs) and fell to 91 jobs by 2014 (stdv 78.6). In high income economies the international trade labor intensity remained the same as with mining, dropping from an average 44 jobs (stdv 39.7) to 16 jobs (stdv 9.0). In GVC activities emerging and high income economies both show higher labor intensity when mining is excluded; emerging economies changed from 56 jobs in 2000 (stdv 15.5) to 29 jobs in 2014 (stdv 5.7), high income economies from 53 jobs in 2000 (stdv 16.4) to 25 jobs in 2014 (stdv 5.3). The countries with the highest relative decreases in labor intensity have remained the same as shown in Table 6 with the notable exception of Denmark which has replaced Slovakia in GVC activities.

Table 6: Highest relative decreases in labor intensity among high income and emerging economies in international trade and GVC activities excluding the mining sector

High income economies				Emerging economies			
International trade	2000	2014	% Change	International trade	2000	2014	% Change
Lithuania	133	26	80.1%	Romania	338	49	85.4%
Slovakia	111	23	79.4%	Russia	327	52	84.2%
Estonia	128	27	78.9%	China	501	81	83.8%
Latvia	116	32	72.6%	Bulgaria	398	79	80.2%
Poland	121	34	72.2%				
GVC activities	2000	2014	% Change	GVC activities	2000	2014	% Change
Luxembourg	59	12	79.3%	Bulgaria	85	27	68.3%
Lithuania	113	27	75.4%	Croatia	61	24	61.3%
Latvia	80	28	65.5%	Romania	64	27	59.0%
Denmark	50	21	58.2%	Russia	63	30	51.9%
Japan	72	31	56.5%				

Splitting GVC activities into simple and complex shows a clear difference in labor intensity between the two categories when mining is not considered, as indicated by the gray dotted line in Figure 8. While simple and complex GVC activities appeared to be approximately equally labor intensive in most countries in Figure 6, Figure 8 shows complex GVC activities were more labor intensive in all countries with the exception of Luxembourg in 2000.

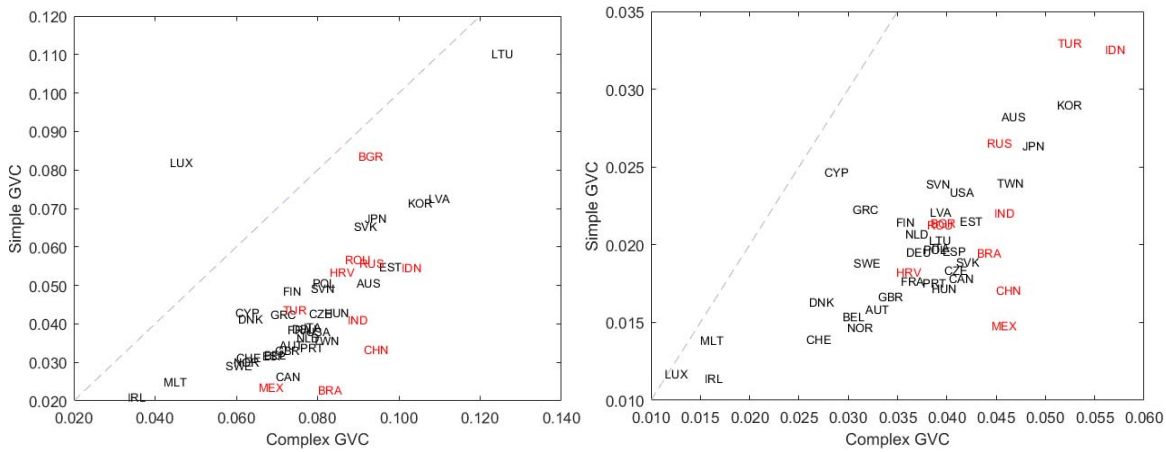

Figure 8: Labor intensity of simple and complex GVC activities in 2000 (left) and 2014 (right) for the 43 economies of the WIOD database with the mining sector excluded. Labor intensity is calculated as number of jobs in thousands divided by value added in million USD. Emerging economies are displayed in red, labor intensity of simple and complex GVC activities is equal on the grey dotted line. (Author's calculations)

The more robust version also shows that emerging economies are on average comparatively more labor intensive in complex GVC than high income economies activities than the previous analysis suggested. Without the mining sector included, emerging economies used on average 47 jobs in simple GVC activities (stdv 18.2 jobs) and 88 jobs in complex GVC activities (stdv 10.1) in 2000. During the same year, high income economies used 45 jobs in simple (stdv 18.8) and 77 jobs in complex GVC activities (stdv 18.1). By 2014, average labor intensity in GVC activities in emerging economies had fallen to 23 jobs in simple (stdv 6.2) and 45 jobs in complex activities (stdv 6.2). For high income economies, simple GVC activities used 20 jobs (stdv 4.3) and complex activities involved 36 jobs (stdv 8.9) on average in 2014. The largest relative decreases in labor intensity still accrued to newer EU members among both high income and emerging economies when not taking mining into account. Among the emerging economies, Russia has replaced China and India as the fifth largest decrease in both simple and complex GVC activities. For high income economies Malta and Switzerland have replaced Greece and Estonia as shown in Table 7.

Table 7: Highest relative decreases in labor intensity among high income and emerging economies in simple and complex GVC activities excluding the mining sector

High income economies				Emerging economies			
Simple GVC	2000	2014	% Change	Simple GVC	2000	2014	% Change
Luxembourg	82	12	85.7%	Bulgaria	84	21	74.4%
Lithuania	110	20	81.6%	Croatia	53	18	65.9%
Slovakia	65	19	71.1%	Romania	57	21	62.6%
Latvia	73	22	69.6%	Russia	56	27	52.6%
Poland	51	20	61.2%				
Complex GVC	2000	2014	% Change	Complex GVC	2000	2014	% Change
Luxembourg	47	13	73.1%	Croatia	86	36	58.0%
Lithuania	125	39	72.0%	Bulgaria	93	40	57.4%
Latvia	110	39	64.2%	Romania	90	39	56.3%
Malta	45	14	63.9%	Russia	93	45	51.5%
Switzerland	63	27	57.1%				

What has so far not been considered is the importance of GVC activities relative to international trade for the individual countries. Table 8 shows the relative contribution of the three categories of international trade, simple, and complex GVC activities to the total trade activities of an economy in terms of employment and value added.

Table 8: Share of trade activity employment and value added by category in 2014 for the 43 economies of the WIOD database. Standard deviations are reported in percentage points

	Employment shares			Value added shares		
	International trade	Simple GVC	Complex GVC	International trade	Simple GVC	Complex GVC
AUS	10.9%	64.5%	24.6%	23.4%	53.7%	22.9%
AUT	29.7%	31.8%	38.5%	38.9%	29.2%	32.0%
BEL	22.0%	31.4%	46.6%	33.5%	29.1%	37.4%
BGR	64.9%	19.4%	15.7%	29.5%	39.7%	30.8%
BRA	46.2%	36.4%	17.4%	21.7%	56.5%	21.8%
CAN	26.3%	45.4%	28.3%	31.9%	43.3%	24.8%
CHE	30.1%	31.5%	38.4%	49.4%	24.0%	26.7%

CHN	81.2%	9.3%	9.5%	46.5%	32.4%	21.1%
CYP	30.2%	44.2%	25.6%	36.4%	36.2%	27.5%
CZE	43.2%	19.9%	36.9%	34.0%	24.4%	41.5%
DEU	35.2%	29.0%	35.8%	48.8%	23.2%	28.0%
DNK	24.2%	32.4%	43.4%	40.7%	25.9%	33.4%
ESP	36.2%	31.4%	32.4%	40.9%	31.7%	27.4%
EST	36.4%	26.0%	37.6%	30.5%	28.5%	41.0%
FIN	19.1%	47.3%	33.6%	31.4%	38.3%	30.3%
FRA	25.7%	39.3%	34.9%	37.0%	35.1%	27.9%
GBR	28.6%	41.9%	29.5%	38.1%	38.9%	23.0%
GRC	32.4%	43.5%	24.2%	31.5%	41.6%	26.9%
HRV	57.7%	22.6%	19.7%	38.9%	34.2%	27.0%
HUN	44.9%	16.0%	39.1%	30.6%	22.4%	47.0%
IDN	70.3%	19.9%	9.8%	25.1%	49.2%	25.7%
IND	89.6%	6.3%	4.1%	33.4%	46.4%	20.2%
IRL	23.1%	21.7%	55.2%	36.4%	19.9%	43.7%
ITA	35.3%	33.2%	31.5%	43.8%	30.4%	25.8%
JPN	26.3%	47.0%	26.7%	35.0%	44.4%	20.5%
KOR	29.6%	39.1%	31.3%	37.4%	33.9%	28.7%
LTU	57.5%	18.6%	23.9%	46.4%	25.6%	27.9%
LUX	15.5%	21.7%	62.7%	25.6%	18.4%	56.0%
LVA	45.9%	29.2%	24.9%	34.6%	34.7%	30.7%
MEX	54.5%	20.3%	25.2%	34.2%	33.5%	32.3%
MLT	33.1%	20.0%	47.0%	28.1%	20.7%	51.3%
NLD	21.9%	35.5%	42.7%	37.2%	28.9%	33.8%
NOR	14.2%	51.4%	34.4%	28.3%	45.6%	26.1%
POL	55.1%	22.5%	22.4%	39.9%	30.6%	29.5%
PRT	45.6%	26.6%	27.8%	33.2%	36.7%	30.1%
ROU	57.1%	24.6%	18.3%	32.4%	39.3%	28.2%
RUS	36.5%	45.6%	18.0%	22.8%	52.1%	25.1%
SVK	39.0%	17.0%	44.0%	32.2%	20.2%	47.6%
SVN	40.5%	27.6%	31.9%	42.0%	23.7%	34.2%
SWE	25.7%	39.1%	35.2%	43.1%	29.1%	27.8%
TUR	58.0%	24.0%	18.1%	40.6%	29.8%	29.6%
TWN	44.9%	29.3%	25.8%	31.4%	36.1%	32.6%
USA	15.1%	58.8%	26.1%	32.6%	46.5%	20.9%
High income (n = 33)						
Min	10.9%	16.0%	22.4%	23.4%	18.4%	20.5%
Max	57.5%	64.5%	62.7%	49.4%	53.7%	56.0%
Average	31.6%	33.8%	34.6%	35.9%	31.8%	32.3%
Stdv	11.5%	12.0%	9.4%	6.3%	8.8%	8.8%
Emerging Economies (n = 10)						
Min	36.5%	6.3%	4.1%	21.7%	29.8%	20.2%
Max	89.6%	45.6%	25.2%	46.5%	56.5%	32.3%
Average	61.6%	22.8%	15.6%	32.5%	41.3%	26.2%
Stdv	15.7%	11.5%	6.1%	8.0%	9.2%	4.2%

Employment in high income economies is on average approximately evenly distributed between trade activities with 31.6% of jobs in international trade, 33.8% in simple and 34.6% in complex value chains, but is cumulatively focused on GVC activities (68.4% of all jobs in trade activities). In emerging economies, the greater share of employment is in international trade with an average 61.6% and 38.4% in GVC activities. The share of employment in GVC activities is split into an average 22.8% in simple and 15.6% in complex GVC activities. In terms of value added, high income economies draw on average 64.1% of all value generated by trade from GVC activities and 35.9% from international trade. A similar picture presents itself for emerging economies where GVC activities create 67.5% of the value added in trade activities and international trade accounts for 32.5%.

5.2 Discussion

The question this paper aimed to answer was how many jobs (full-time and part-time) were directly and indirectly created by simple and complex GVC activities between 2000 and 2014 and where were they created. The decomposition analysis has shown that GVC activities are an important source of value added from trade for the 43 economies, but that their role in employment is more complex. In 2014, GVC activities involved an additional 37.5 million jobs compared to the beginning of the observed period, approximately the same as the increase in international trade jobs in the 43 economies studied. This leads to a total of 133 million jobs involved in GVC activities which accounts for 44% of all employment in trade. All categories of trade experienced double-digit growth in jobs and more than doubled in value added over the period studied, especially complex GVC activities saw strong growth in both jobs and value added. The number of jobs in trade activities increased for most countries, but a few benefitted especially. As mentioned in the theoretical framework, global value chains are not truly global, but cluster into three main GVC systems. The decomposition has shown that it is the economies at the centers of these systems, China, Germany and the United States, which were the main beneficiaries in terms of GVC jobs and value added. Job and value added created over the period in general was strongly driven by China and most GVC jobs accrued to Asia-Pacific. However, GVC activities do not seem to have the same labor absorption capacity as traditional international trade. Labor intensity has fallen by close to or more than half in all trade activities over the period observed for both emerging and high income economies. The low and falling labor intensity in GVCs for emerging economies shows that not only do these economies use far fewer workers than in international trade, but they catch up with high income economies fast. Especially in simple GVC activities is it difficult to distinguish between high income and emerging economies in absolute terms. The highest relative drops in labor intensity for all three trade categories were found in newer EU members across both emerging and high income economies; a finding likely linked to their quick value chain integration with older EU members (Los, Timmer & de Vries, 2015). It is also noteworthy that labor intensities seem to converge within the two groups as indicated by the standard deviations.

Overall, and although not every country saw an increase in the number of jobs involved in GVCs from 2000 to 2014, GVC activities were a major employer in most economies in 2014. On average, high income economies were very balanced, with approximately equal shares of total trade activity jobs and value added derived from international trade, simple, and complex

GVC activities. Emerging economies on the other hand were approximately balanced in value added, though slightly skewed towards simple GVC, but had most of their workers in international trade. The averages hide various different profiles for individual countries, on the one side among high income economies are the extremes of Australia and the USA which had over 80% of their trade labor force in GVC activities. On the other side among the emerging economies are China and India which followed the opposite pattern. Despite the large share of China in the number of GVC jobs created across all 43 economies, only around 20% of all Chinese trade jobs were in GVC activities (an observation in line with Los, Timmer & de Vries, 2015). This is second only to India, where only around 10% of the jobs in trade were in GVCs in 2014.

How well do the findings fit with the trade theory discussed and how do they compare to previous studies? On the surface, the findings of this study are largely in line with traditional trade theory. More than 85% of all simple GVC jobs created between 2000 and 2014 accrued to emerging economies, the assumed comparatively labor-abundant. The high income economies, which are assumed to be comparatively capital abundant, accounted for approximately 60% of all additional simple GVC value added. While the jobs created in complex GVC activities were approximately evenly split between high income and emerging economies, the labor intensity (once corrected for mining) shows that the complex GVC activities in emerging economies are more labor intense. However, as in the studies by Timmer et al. (2014) and Jiang (2013), this paper also seems to raise questions for traditional trade theoryxxxx. The key issue is the labor intensity of GVC activities. While the labor intensity in traditional international trade has also fallen, emerging economies are still clearly specialized in more labor intensive activities. In GVC activities the labor-capital specialization between emerging and high income economies is less obvious, but appears to be still present. In simple GVC activities, the average labor intensity of emerging economies is close to that of high income economies in absolute numbers. From a relative point of view, however, the gap in labor intensity has widened. In 2000, simple GVC activities in emerging economies were on average around 4.4% more labor-intensive than high income economies. By 2014, this difference had increased to 15.0% (corrected for mining). In complex GVCs, emerging economies started out 14.3 percent more labor-intense in 2000 and by 2014 the gap had grown to 25 percent. This does not contradict the findings of Timmer et al. (2014) and Jiang (2013), but questions whether their findings really are at odds with the Heckscher-Ohlin model as both studies note. The falling GVC labor intensity in emerging economies observed in this study would seem to fit well with the findings of Timmer et al. (2014) and Jiang (2013) as it indicates that emerging economies have become more capital and skilled labor intensive. However, while they may have become more skill and capital intensive, they would appear to still be comparatively more labor intensive than GVC activities in high income economies.

The falling labor intensity is no surprise to Farole (2016) who argues, based on his previous work on Sub-Saharan Africa (see Farole & Winkler, 2014), that a decrease in GVC labor intensity in emerging economies is to be expected, since firms in GVC activities are highly focused around economies of scale which allow them to reach the necessary productivity levels and quality standards for GVC participation. This also involves a lot of investment in better technologies (Farole, 2016). The decrease in GVC labor intensity may then also be an indicator that GVC activities during the period observed has indeed led to an increase in demand for skilled labor in high income and emerging economies as predicted by the model of Feenstra and

Hanson (1997) and as found the previous studies by Timmer et al. (2014) and Jiang (2013) based on skill share data. To further confirm this, however, data on skill shares would be needed which is currently not available for the more recent period under consideration and thus will have to be investigated in future studies. Additionally, the decrease in labor intensity in GVC activities may also raise some doubts about the explanation of Timmer and colleagues (2014) for the fall of low and medium skilled labor income share where they argue that the labor share has declined because of the reduced bargaining power of workers in light of the international mobility of capital. They support their theory by noting that the increase in manufactures production did lead to the creation of millions of jobs in emerging economies over 1995 to 2011. While this paper also found an increase in the number of GVC workers employed in emerging economies and is not completely comparable to the paper of Timmer et al. (2014) because the studies focus on different time periods and sectors, the findings on labor intensity in the study at hand would suggest that the declining income share of low- and medium-skilled workers could be less a matter of lost bargaining power and more of low and medium skill labor being replaced by fewer high-skilled workers.

5.3 Limitations

At this point, it is also important to repeat some of the limitations of this study. Limitations were generally discussed in the relevant passages throughout this paper, but a number of them bear reemphasizing and elaborating on. Overall, while decomposition methods and datasets have improved, many aspects of GVCs can still not be accurately captured (Borin & Mancini, 2015; Shingal, 2015). One caveat to the analysis conducted in this study which was already mentioned in this paper's definition of GVC activities relates to ownership. Just as the currently available IO data and thus this paper cannot distinguish between foreign and domestic ownership of firms and thus attributes jobs based on national borders, there is also no distinction made between profits which stay in the country they were generated in and profits which are repatriated. This is no issue for the analysis at hand, since the focus was on value added rather than income generated for the country (Los, Timmer & de Vries, 2015), but is nonetheless important to keep in mind when interpeting the results.

It is also important to note that this paper did not cover net job creation by GVCs in the different countries, in other words, the paper focused solely on jobs created or lost in GVC activities in a country without accounting for jobs that may have been lost in the same country because of the rise of GVCs. For example, jobs may have been lost because of GVCs in sectors which have newly become tradable or who were import-competing. It further also does not consider jobs which were created after 2000, but had disappeared again by 2014 as previously mentioned. What should further be considered and which does not just apply to this paper, but to other studies on job creation in GVCs as well, is that given the limited availability of datasets which allow the systematic empirical investigation of employment in GVCs (for a list of main IO databases, see Taglioni & Winkler, 2016:252-253), most studies are bound by the same limitations of the same datasets. The development of new datasets which overcome the weaknesses of existing databases mentioned in this paper is vital for more accurate analyses. As previously discussed theory and empirical evidence suggests (i.e. Chen et al., 2012; De la Cruz

et al., 2011; Koopman, Wang & Wei, 2012; Melitz, 2003), the ideal dataset would most likely be collected at firm-level to account for firm heterogeneity.

New data would also be needed to better understand specialization patterns under GVCs, since they follow tasks rather than industries (Grossman & Rossi-Hansberg, 2012). The paper at hand does not provide any insight into this matter and a better understanding rests on the development of datasets which would allow a distinction between different kinds of tasks (e.g. routine versus non-routine) (Grossman & Rossi-Hansberg, 2012).

6 Conclusion

The study has shown that GVC activities created approximately 37.5 million jobs between 2000 and 2014 and are an important employer for trade workers in most countries. Especially China, Germany and the United States, the economies at the centers of the major GVC systems, appear to have benefitted. At the same time, the analysis also showed that GVCs do not have the same labor absorption capacity as traditional international trade in emerging economies und their labor intensity has fallen sharply for both emerging and high income economies. Without data on the skill intensity of different activities, this study cannot do much to address fears of emerging economies of becoming trapped in low-skill labor-intense activities directly. However, previous studies as well as the lower and falling labor intensity in GVC activities observed in this paper would suggest that this is not the case. Rather, this paper echoes the conclusion of Farole (2016) that policymakers should see GVCs and GVC participation mainly as an opportunity for productivity gains, rather than widespread job creation. For most high income economies, GVC activities also saw an increase in the number of jobs involved, but no conclusions can be drawn about the change in net employment from this paper. The study further raised questions about whether findings by previous studies were actually at odds with traditional trade theory, providing important empirical input for the development of the next wave of trade models. To the best of the author's knowledge, this study would also seem to be the first which systematically evaluates GVC employment from a producer's perspective and across a time period beyond the financial crisis. The findings also highlight the need for further research into employment in GVCs and specialization patterns. But most importantly, while the use of input-output tables may have allowed this paper to produce a likely more accurate picture of the employment impacts of GVCs, because it considers both direct and indirectly created jobs, the discussion and limitations clearly show that the key to a better understanding of job creation in GVCs lies in the construction of better datasets.

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Appendix A

Table 9: List of all 56 industries included in the WIOD 2016 database

Crop and animal production, hunting and related service activities
Forestry and logging
Fishing and aquaculture
Mining and quarrying
Manufacture of food products, beverages and tobacco products
Manufacture of textiles, wearing apparel and leather products
Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
Manufacture of paper and paper products
Printing and reproduction of recorded media
Manufacture of coke and refined petroleum products
Manufacture of chemicals and chemical products
Manufacture of basic pharmaceutical products and pharmaceutical preparations
Manufacture of rubber and plastic products
Manufacture of other non-metallic mineral products
Manufacture of basic metals
Manufacture of fabricated metal products, except machinery and equipment
Manufacture of computer, electronic and optical products
Manufacture of electrical equipment
Manufacture of machinery and equipment n.e.c.
Manufacture of motor vehicles, trailers and semi-trailers
Manufacture of other transport equipment
Manufacture of furniture; other manufacturing
Repair and installation of machinery and equipment
Electricity, gas, steam and air conditioning supply
Water collection, treatment and supply
Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services
Construction
Wholesale and retail trade and repair of motor vehicles and motorcycles
Wholesale trade, except of motor vehicles and motorcycles
Retail trade, except of motor vehicles and motorcycles
Land transport and transport via pipelines
Water transport
Air transport
Warehousing and support activities for transportation
Postal and courier activities
Accommodation and food service activities
Publishing activities
Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
Telecommunications
Computer programming, consultancy and related activities; information service activities
Financial service activities, except insurance and pension funding
Insurance, reinsurance and pension funding, except compulsory social security
Activities auxiliary to financial services and insurance activities

Real estate activities
Legal and accounting activities; activities of head offices; management consultancy activities
Architectural and engineering activities; technical testing and analysis
Scientific research and development
Advertising and market research
Other professional, scientific and technical activities; veterinary activities
Administrative and support service activities
Public administration and defence; compulsory social security
Education
Human health and social work activities
Other service activities
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
Activities of extraterritorial organizations and bodies

Appendix B

Table 10: Individual country shares in jobs and value added created between 2000 and 2014

	Simple GVC		Complex GVC		International trade		Total	
	Jobs	*Value added*	*Jobs*	*Value added*	*Jobs*	*Value added*	*Jobs*	*Value added*
AUS	6.40%	2.28%	1.58%	1.29%	-0.25%	0.72%	1.63%	1.43%
AUT	0.17%	0.75%	0.96%	1.25%	0.27%	1.01%	0.45%	0.98%
BEL	1.31%	1.35%	1.74%	2.31%	0.01%	1.28%	0.78%	1.59%
BGR	-0.16%	0.20%	0.34%	0.25%	0.92%	0.20%	0.53%	0.21%
BRA	10.52%	3.83%	2.83%	1.97%	0.09%	1.24%	3.01%	2.37%
CAN	7.84%	3.86%	1.14%	2.04%	-0.68%	1.42%	1.58%	2.46%
CHE	0.42%	1.13%	1.39%	1.90%	0.51%	2.57%	0.75%	1.87%
CHN	41.80%	22.54%	30.75%	18.91%	52.12%	31.66%	43.84%	24.87%
CYP	0.01%	0.03%	0.01%	0.04%	0.02%	0.04%	0.01%	0.04%
CZE	0.42%	0.52%	2.19%	1.49%	0.64%	0.86%	1.05%	0.91%
DEU	0.10%	4.52%	8.73%	9.28%	3.54%	11.12%	4.34%	8.25%
DNK	0.10%	0.65%	0.49%	1.12%	-0.11%	0.81%	0.11%	0.84%
ESP	-0.65%	1.37%	2.09%	2.32%	0.78%	2.71%	0.87%	2.12%
EST	0.05%	0.06%	0.24%	0.15%	0.06%	0.09%	0.11%	0.10%
FIN	0.69%	0.58%	0.38%	0.56%	-0.10%	0.21%	0.20%	0.44%
FRA	2.18%	4.39%	3.22%	4.60%	-0.33%	3.60%	1.21%	4.16%
GBR	-0.66%	3.95%	0.99%	3.30%	0.31%	3.43%	0.31%	3.58%
GRC	-0.95%	0.17%	0.09%	0.33%	0.21%	0.27%	-0.06%	0.25%
HRV	-0.22%	0.11%	0.07%	0.14%	0.04%	0.14%	0.00%	0.13%
HUN	-0.26%	0.31%	1.05%	1.06%	-0.06%	0.50%	0.22%	0.59%
IDN	8.00%	2.35%	2.47%	1.57%	-2.47%	0.83%	1.09%	1.58%
IND	8.62%	5.15%	4.46%	3.04%	34.37%	3.66%	20.47%	4.02%
IRL	0.64%	0.65%	1.79%	2.16%	-0.08%	1.14%	0.61%	1.25%
ITA	-3.21%	1.92%	1.94%	3.30%	0.90%	3.47%	0.37%	2.87%
JPN	-17.81%	6.17%	1.79%	4.29%	1.44%	1.66%	-2.39%	4.00%
KOR	0.95%	3.53%	5.23%	4.49%	2.14%	4.03%	2.79%	3.98%
LTU	-0.31%	0.12%	0.23%	0.20%	0.19%	0.24%	0.10%	0.19%
LUX	-0.60%	0.22%	0.42%	1.00%	0.09%	0.31%	0.04%	0.47%
LVA	-0.01%	0.08%	0.13%	0.11%	0.12%	0.09%	0.10%	0.09%
MEX	1.33%	1.84%	2.33%	2.40%	2.20%	1.65%	2.06%	1.92%
MLT	0.00%	0.03%	0.14%	0.16%	0.05%	0.07%	0.06%	0.08%
NLD	1.01%	1.32%	2.73%	2.75%	-0.23%	1.60%	0.88%	1.82%
NOR	1.35%	0.89%	0.63%	0.64%	-0.14%	0.31%	0.38%	0.61%
POL	0.19%	1.22%	2.39%	1.88%	1.76%	1.92%	1.63%	1.66%
PRT	-0.74%	0.22%	0.15%	0.41%	0.23%	0.38%	0.01%	0.33%
ROU	1.06%	0.64%	0.81%	0.62%	-0.16%	0.53%	0.37%	0.60%
RUS	9.16%	2.52%	2.67%	1.63%	-3.10%	0.94%	1.06%	1.70%
SVK	-0.25%	0.24%	1.41%	0.97%	0.43%	0.49%	0.57%	0.53%
SVN	-0.09%	0.06%	0.18%	0.19%	0.05%	0.17%	0.06%	0.14%
SWE	1.08%	0.73%	0.43%	0.91%	-0.10%	0.94%	0.29%	0.86%
TUR	5.50%	1.37%	3.49%	2.17%	4.05%	1.77%	4.18%	1.74%
TWN	0.64%	0.87%	-0.64%	0.87%	-0.22%	0.37%	-0.17%	0.69%

USA	14.38%	15.23%	4.52%	9.94%	0.52%	9.56%	4.50%	11.70%
Total	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%	100.0%