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Jobs and Productivity Growth in Global Value Chains: New Evidence for Twenty-five Low- and Middle-Income Countries

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Abstract

Using newly developed data, the evolution of job and productivity growth in global value chains (GVCs) is analyzed for 25 low- and middle-income countries. GVC jobs are found to be more productive than non-GVC jobs. Their share in the total labor force is small, in particular for low-income countries. Growth in GVC jobs varies widely across countries in the period 2000–2014. Part of this can be accounted for by differences in the type of consumer market served. A bigger part is accounted for by the speed with which countries expand activities within supply chains, measured by their shares in GVC value added. Expansion in GVCs is positively correlated with labor productivity across countries as well as over time within GVCs.

JEL classification: J2, F16, F66, O1

Keywords: labor demand, global value chains, productivity, structural change

1. Introduction

Participation in global value chains (GVCs) is frequently highlighted as a promising route to industrialization and poverty reduction in low-income countries (World Bank 2020). At the same time, the potential of job growth through GVC participation is heavily debated. Industrialization trends in many countries in Africa and Latin America appear to be worryingly weak, especially compared to trends in some Asian countries (McMillan, Rodrik and Verduzco–Gallo 2014). A main concern is that technological change in GVCs is biased against the use of unskilled labor, leading to productivity growth but insufficient absorption of workers (Rodrik 2018). In this paper, new cross-country data on GVC jobs are presented

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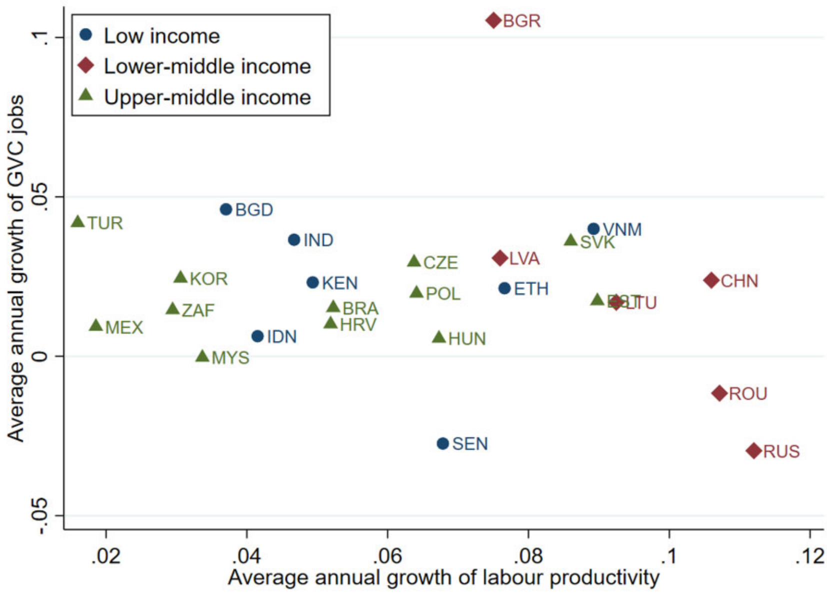
Figure 1. Productivity and Employment Growth in GVCs



Source: Authors' analysis based on World Input-Output Database (WIOD 2016 release, see Timmer et al. 2015) extended with data for seven other countries (see table 1). The U.S. CPI for final manufactured goods is used as deflator for value added.

Note: Average annual growth of workers and labor productivity (deflated value added per worker) in GVCs over period 2000–2014. Results are shown for 7 low-income (Bangladesh, Ethiopia, Indonesia, India, Kenya, Senegal, and Vietnam), 6 lower-middle income (Bulgaria, China, Lithuania, Latvia, Romania, and Russia), and 12 upper-middle income countries (Brazil, Croatia, Czech Republic, Estonia, Hungary, South Korea, Malaysia, Mexico, Poland, Slovakia, South Africa, and Turkey).

that provide some grounds for this concern (see fig. 1). GVC jobs are defined as the jobs in a country that participate in production of goods for consumption abroad.[1] Some countries, including the well-known examples of China and Vietnam, couple rapid labor productivity growth in GVCs (value added per GVC job) with high growth in jobs. Other countries, including Ethiopia, Romania, Russia, and Senegal also feature high productivity growth, but relatively weak job growth. Interestingly, Bangladesh, India, and Turkey are countries that feature relatively weak productivity growth yet above average job growth.

The main aim of this paper is to account for these diverging country experiences. GVC jobs growth in a country is decomposed as the sum of changes in three components: global consumer demand for goods, country activities in associated supply chains (as measured by shares in GVC value added), and labor intensity of production.[2] Using the results from the decomposition, three major findings are presented. First, cross-country variation in GVC job growth can partly accounted for by differences in consumer market integration. Consumer markets may differ in the type of products demanded and in expenditure growth (Kaplinsky and Farooki 2011; World Bank 2020). It is found, for example, that GVC job growth in Brazil and Ethiopia benefitted from being linked into faster-growing African and Asian consumer markets, whereas Mexico and Bangladesh were linked into slower-growing European, Japanese, and North American consumer markets. Second, differences in capturing shares in GVC value added accounted for a major part of cross-country differences in GVC job growth. A country's share in GVC value added can rise by increasing scale and/or scope of activities in the chain. Bangladesh, China, Ethiopia, and Vietnam were able to quickly increase activities in GVCs relative to other countries participating in the same chains.

1 GVC jobs are thus defined in analogue to exports of value added (Johnson and Noguera 2012). Method and data used are explained in section 2.

2 This is inspired by the accounting framework of trade flows in the presence of GVCs as in Bems, Johnson, and Yi (2011).

Shares of Indonesia, Senegal, and Kenya grew only slowly, or even declined, accounting for their moderate or even declining GVC job growth. Third, a robust positive correlation is found between productivity in a country and its share in GVC value added, both in the cross-section and over time for detailed GVCs (characterized by reporter country, product group, and end-market). This finding fits the implications of a (partial equilibrium) model of firms trading off increasing (fixed and variable) costs of undertaking more production stages in the chain and paying lower prices for inputs and/or receiving higher prices for their output as outlined in Chor, Manova, and Yu (2021). Central to this process are internal returns to scale that make complementary investments that are subject to fixed costs more attractive to firms (Bustos 2011). An exogenous positive shock to productivity would induce the firm to both span more production stages and to operate on a bigger scale due to the complementarity between the two, ultimately leading to higher profits. GVC participation might deliver such a productivity shock as it may provide access to cheaper inputs from abroad and new technologies through the operations of multinational lead firms (Antràs 2020). The paper does not aim for, nor claim, causal analysis of GVC participation and growth. The goal in this paper is to bring new data and a first exploration of cross-country patterns in GVC job growth that might help uncover the key economic mechanisms at work.

The findings contribute to several strands of research. An important development debate is whether GVC participation stimulates structural transformation in poorer countries or entrenches them in low employment growth activities. This debate pivots around the possible biased nature of technologies spread through global production lines. Country regressions suggest that participation in GVCs is a significant driver of labor productivity (Constantinescu, Mattoo, and Ruta 2019), but not necessarily of employment growth (Pahl and Timmer 2020). Using firm data, Diao and colleagues (2021) find that larger firms in Tanzania and in Ethiopia recently engaging in exports exhibit superior productivity performance but do not expand employment much. Rodrik (2018) conjectures that this is due to the biased nature of multinational technology transfer, as it mostly concerns automated production techniques, raising output per worker but driving down relative demand for less skilled labor.[3] Reijnders, Timmer, and Ye (2021) find indeed a significant fall in relative demand for low-skilled workers (below high school) during 1995–2007 in GVCs of manufacturing goods.[4] Yet, declining relative demand for labor in GVCs does not necessarily imply weak employment growth overall. Chor, Manova, and Yu (2021) provide causal evidence that suggests that Chinese firms increase the scale and scope of activities in GVCs when they become more productive, increasing productivity as well as employment. It is found that some of the countries in the data set, like China, have been able to increase productivity, scale, and job growth in GVCs. Yet, job growth in some other countries is disappointing despite rapid productivity growth in their GVC activities.

The second contribution is to the literature on structural change and aggregate productivity growth (Gollin, Lagakos, and Waugh 2014; McMillan, Rodrik, and Verduzco–Gallo 2014). It is well known from both theory and empirics that exporting firms are generally more productive than non-exporting firms (Alessandria, Arkolakis, and Ruhl 2021). Firms in manufacturing that both export and import show higher labor productivity than one-way traders (import or export only) or nontraders (World Bank 2020, fig. 3.3). McCaig and Pavcnik (2018) find that the reallocation of labor from informal firms toward formal firms during the export boom following the 2001 United States–Vietnam Bilateral Trade Agreement appears to have raised aggregate productivity economy-wide. In line with this, it is found in this paper that GVC jobs are generally more productive than non-GVC jobs, in particular in the manufacturing sector. The potential for GVC job reallocation to raise aggregate productivity appears to be especially high in low-income countries.

3 Schulte (2021) finds international technology diffusion to be statistically and economically important in explaining the skill-biased technical change in a country.

4 Using occupational data, Reijnders and de Vries (2018) suggest this is related to a decline in relative demand for routine tasks within GVCs.

Finally, the newly assembled data add to the scarce cross-country data on GVC employment and productivity for poorer countries. New data for 25 low- and middle-income countries are developed based on national input-output tables that are linked together with bilateral trade data for the period 2000–2014. The multiregional dimension of the dataset is exploited to link production in GVCs to demand of consumers in end-markets, extending the accounting framework for trade flows with multinational production developed in Bems, Johnson, and Yi (2011).[5] The new data track GVC jobs in the manufacturing sector (formal and informal) as well as in other sectors of the economy (including agriculture and services) that are linked to it by delivering inputs.[6] The data are made public at the Dataverse repository at https://doi.org/10.34894/NJR5EB. The remainder of this paper is organized as follows. Section 2 outlines the measurement of GVC jobs and presents data-construction methodology. Section 3 compares the productivity of GVC jobs with other jobs in the economy. Section 4 zooms in on the role of consumer market linkages and increasing scale of operations for GVC job growth. Section 5 offers concluding remarks.

2. Measurement and Data

In this section the concept of GVC jobs is introduced as well as the data sources that have been used to measure it.

The Concept of GVC jobs

GVC jobs are defined in analogy to exports of value added (Johnson and Noguera 2012). GVC jobs include all jobs in a country involved in the production of goods that are ultimately consumed abroad. These jobs can be jobs in an exporting manufacturing industry or in industries participating in upstream stages of goods export production.[7] The concept of "GVC jobs" is different from the concept of "labor content of exports" used in, for example, Cali et al. (2016). The latter contains double counts that arise since part of the exports might be imported again for domestic use, as pointed out by Koopman, Wang, and Wei (2014). More importantly, the "labor content of exports" perspective provides no possibility to investigate the link between jobs and demand growth in consumer end-markets as it only considers backward linkages. Take for example the following GVC: cotton yarn produced in Ethiopia that is exported as input for production of T-shirts in China that are ultimately sold to European consumers. Demand for jobs in Ethiopia in this GVC will ultimately depend on final consumption of textiles in Europe. The present study follows Johnson and Noguera (2012) and relates production in countries to final demand abroad through forward linkages that may span multiple countries. Information on the labor required per unit of value added in a country-industry is added to measure the number of jobs involved in the production for a particular GVC. Further details of the actual calculations are provided in S1 of the Supplementary Online Appendix, available with this article at *The World Bank Economic Review* website. Information on international input-output linkages is a key ingredient in the analysis, together with national industry-level data on employment.[8]

The analysis is restricted to activities in the production chains of final manufactured goods. Production systems of manufactures are prone to cross-border fragmentation as activities have a high degree

5 See Johnson (2018) for an overview of GVC measurement.

6 Pahl and Timmer (2020) study developments of GVC jobs in the formal manufacturing sector for a set of 58 countries for 1970 to 2008.

7 This study uses the general concept "industry" as it is used in the national accounts statistics, referring more specifically to, e.g., manufacturing industry or services industry when needed.

8 To calculate "labor content in exports," only information on national input-output linkages is needed, as shown by Los, Timmer, and de Vries (2016) for the case of "value added in exports." Alternatively, one may be interested in jobs consumed abroad as well as jobs that cater to domestic demand. This can also be measured in this paper's data by judicious choice of the final demand vector; see S1 in the supplementary online appendix.

of international contestability. This contestability is a possible reason for GVC jobs to be more productive than other jobs in the economy, a hypothesis investigated in the next section. It is also important to note that the value chains of final agricultural goods and services are not considered in the analysis. Yet the production of final manufacturing goods requires not only manufacturing activities but also upstream activities in other sectors. Most agricultural goods (with the notable exception of fresh products) are processed further in the manufacturing sector and hence are part of manufacturing GVCs studied in this paper. This is also true for various business services that are intermediate to goods production. Final services production is mostly domestic with generally much less international fragmentation and shorter chains than final goods production (Timmer et al. 2021).

Data Sources

For the purpose of this paper, new data are developed according to the methodology of the World Input-Output Database (WIOD). The WIOD provides information on intercountry and interindustry flows of goods and services. The latest (2016) release contains information for 43 mostly high- and middle-income countries (Timmer et al. 2015). The present study has added new information for seven low- and middle-income countries in Africa and Asia according to the methodology of the WIOD such that it can be used in conjunction, namely Ethiopia, Kenya, Senegal, South Africa, Bangladesh, Malaysia, and Vietnam. The choice of these countries was determined by the aspiration to study the experience of low-income countries that are active participants in GVCs, while striking a balance between the economic relevance of the countries and the suitability of available official statistics for GVC and employment measurement. The new data are combined with the existing data in the WIOD such that growth of GVC jobs can be analyzed for 25 low- and middle-income countries. The final data set includes 7 low-income (Bangladesh, Ethiopia, Indonesia, India, Kenya, Senegal, and Vietnam), 6 lower-middle income (Bulgaria, China, Lithuania, Latvia, Romania, and Russia), and 12 upper-middle income countries (Brazil, Croatia, Czech Republic, Estonia, Hungary, South Korea, Malaysia, Mexico, Poland, Slovakia, South Africa, and Turkey).[9]

Data construction for the seven newly added countries is discussed extensively in S3 in the supplementary online appendix, and only key characteristics are highlighted here. For each country, annual supply and use tables (SUTs) were linked over time using the most recent statistics on final demand categories, gross output, and value added by industry from the UN (2018) *National Accounts Statistics*. The national SUTs were subsequently linked to SUTs of other countries using detailed international bilateral trade data classified by end-use category. This is the so-called BEC classification that maps COMTRADE products into intermediate use, consumption use, or investment use. SUTs were combined to create a symmetric world input-output table of an industry-by-industry type.[10] This study's strategy for solving particular issues such as missing or inconsistent trade data is discussed in the country-specific sources in S3 of the supplementary online appendix.

A general qualification is in order as aggregated input–output tables require assumptions in construction. In particular, available data sets typically have no survey information on which domestic industries buy which imports, and a homogeneity assumption is used in construction of the input-output table such that all firms in the same industry use the same bundle of inputs. Yet input use may vary with output because firms may export to different countries and industries and face, for example, different rules of origin (de Gortari 2019). As of yet there is no alternative, as available surveys do not trace firm-to-firm

9 Income classes are according to the World Bank country classification as of 2000, which is the starting year in this study's data.

10 In the analysis a new country was added individually to the existing WIOT: that is, bilateral trade flows between the new countries were not separately identified but remained part of the "rest of the world" region.

transactions across countries. This would require linking data from customs offices and firm identifiers across the world (Johnson 2018).[11]

To implement this study's measurement framework, information on employment by sector in each country is also needed. This is available at www.wiod.org for the original set of WIOD countries. For the seven newly added countries, employment accounts are built, as they are not readily available from official sources.[12] Importantly, the employment data need to be consistent with the value added series in order to derive meaningful estimates of labor productivity. Therefore, the study makes sure it is based on the same classification and concepts.[13] For detailed manufacturing industries, UNIDO's *Indstat* (2018) is used, which is the only widely available source (across countries and over time) with detailed information on the manufacturing sector. A major advantage of UNIDO's Indstat is that it provides gross output and employment figures, which are internally consistent with the value added accounts, because the entries generally come from the same establishments sampled within a given ISIC classification. Importantly, the same vintages of UNIDO's Indstat (2018) are used and extrapolated if needed to assure internal consistency with the value added and output accounts. This study distinguishes between 18 manufacturing industries consisting of 2-digit industries (ISIC rev.4 code) or groups thereof (see table S2.4). Data on manufacturing industries for low-income countries are typically only available from surveys that cover the formal part of the economy. The study refers to this as "formal manufacturing" and also makes an estimate for nonformal manufacturing when analyzing trends in the overall economy. This is done by subtracting formal employment from total manufacturing employment; see section S3 in the supplementary online appendix for details. The coverage of the formal manufacturing firms differs per country. For Bangladesh and Ethiopia, the data for formal manufacturing cover all establishments with 10 or more employees. For Kenya, data pertain to establishments with 5 or more persons engaged. For Senegal, South Africa, Malaysia and Vietnam, the scope of the data is all registered establishments. Table 1 provides a summary of the data sources used for each country.

3. Productivity of GVC jobs

Participation in global value chains may facilitate a process of productive reallocation of workers in the economy. The productivity of workers in GVC jobs is compared with the productivity of other workers in the economy. A finding of large productivity gaps between the two sets of workers might suggest that the allocation of labor is inefficient and reallocation might contribute to macroeconomic productivity growth.

The productivity of GVC jobs (value added per worker) relative to the economy-wide average in 2014 is reported for the set of 25 countries (table 2). It reports on GVC jobs in the manufacturing sector as well as GVC jobs outside manufacturing. In development debates, attention is often focused on the former as manufacturing activity is believed to be more susceptible to capital and scale-intensification than other activities and as such more conducive for productivity growth (Rodrik 2013, 2016). Empirically, a large body of observational evidence suggests that formal firms also pay premium wages, especially large, foreign-owned or exporting firms.[14] It is found in table 2 that for low-income countries the productivity of GVC jobs in manufacturing is indeed much higher than the economy-wide productivity level. For example,

11 See Dhyne et al. (2021) for a firm-to-firm analysis at the domestic level.

12 Ideally, one would like to investigate changes in the extensive margin (jobs) as well as the intensive margin (hours per job). Unfortunately data on hours worked in low income countries are sparse and highly incomplete.

13 In particular, ILO employment statistics cannot be relied on to adhere to this consistency as they are sometimes based on surveys with biased samples (e.g., urban areas only); see Timmer, de Vries, and de Vries (2015).

14 The literature is reviewed in Blattman and Dercon (2018). They also provide the results of an experiment that suggests that workers may have a revealed preference for self-employment over industry when barriers to self-employment are eased.

Table 1: Overview of Main Sources Used

Country	Input-output table	Value added and output	Trade	Employment
Bangladesh (BGD)	2011 (ADB/NSO)	UN OCD; UNIDO Indstat	COMTRADE; adjustment for THA-BGD flows	LFS (NSO); UNIDO Indstat
Ethiopia (ETH)	2006 (IFPRI/EDRI)	GGDC 10-Sector Database; UN OCD; UNIDO Indstat	COMTRADE; large re-exports in 2013 & 2014	LFS (NSO); UNIDO Indstat
Kenya (KEN)	2003 and 2013 (IFPRI/KIPPRA)	GGDC 10-Sector Database; UN OCD; UNIDO Indstat	COMTRADE	LFS & Establishment surveys (NSO); UNIDO Indstat
Malaysia (MYS)	2010 (ADB/NSO)	GGDC 10-Sector Database; UN OCD; UNIDO Indstat	COMTRADE	LFS (NSO); UNIDO Indstat
Senegal (SEN)	2005 (UN DESA)	GGDC 10-Sector Database; UN OCD; UNIDO Indstat	COMTRADE; large adjustment for re-exports	ESPS-I & ESPS-II (LFS/NSO); UNIDO Indstat
Vietnam (VNM)	2012 (ADB/NSO)	UN OCD; UNIDO Indstat	COMTRADE	Population census & LFS (NSO); UNIDO Indstat
South Africa (ZAF)	2013 (NSO)	GGDC 10-Sector Database; UN OCD; UNIDO Indstat	COMTRADE; missing commodities before 2011	Population census & LFS (NSO); UNIDO Indstat
Eighteen other countries	World Input-Output Database (WIOD, 2016 release)			

Note: New data for seven countries is developed that can be used in conjunction with the data for other countries in the World Input-Output Database (WIOD, 2016 release; see Timmer et al. 2015). NSO refers to national statistical office; IFPRI is International Food Policy Research Institute; ADB is Asian Development Bank; UN DESA is United Nations Department of Economic and Social Affairs; KIPRA is Kenya Institute of Public Research; EDRI is Ethiopian Development Research Institute; LFS is labor force survey. UN OCD is UN Official Country Data (UN 2018), GGDC 10-Sector Database from Timmer, de Vries, and de Vries (2015), UNIDO Indstat from UNIDO (2018). For details, see country-specific notes in section S3 in the supplementary online appendix.

labor productivity in GVCs is more than double the economy-wide average in Kenya and Vietnam, and even five times as high in Ethiopia and Senegal. These findings are in line with other studies that found large productivity differentials across sectors in the economy in low-income countries (Gollin, Lagakos and Waugh 2014; McMillan, Rodrik and Verduzco-Gallo 2014; Timmer, de Vries, and de Vries 2015; Diao, Harttgen, and McMillan 2017). Also in middle-income countries GVC jobs have generally a productivity advantage, albeit smaller than in low-income countries. The productivity of GVC jobs in manufacturing is respectively 10 and 21 percent higher than the economy-wide average (unweighted averages within lower- and upper-middle income groups).

The productivity of GVC jobs outside the manufacturing industry is generally lower than of GVC jobs within manufacturing. In low-income countries such as Kenya, Senegal, and Vietnam, more than 50 percent of the GVC workers is employed in agriculture, and even 95 percent in Ethiopia (in 2014).[15] In middle-income countries, the share of GVC jobs outside manufacturing is typically around half, or higher as in Brazil (mainly jobs in agriculture), Russia, and South Africa (mainly in services). For low-income countries the productivity of all GVC workers (in and outside the manufacturing industry) is on average 14 percent above the economy-wide level (unweighted country average in the group), up to 40 percent in Vietnam and 70 percent in Senegal. For the groups of lower- and upper-middle countries the relative productivity of all GVC jobs is respectively 5 and 10 percent higher than the economy-wide level.

15 See table S2.1 in the supplementary online appendix for sector shares in GVC jobs.

Table 2: GVC Jobs Relative to All Jobs in the Economy, 2014

	Productivity of GVC jobs (relative to all jobs in the economy)		GVC jobs (as share of all jobs in the economy, in %)	
	GVC jobs in all sectors	GVC jobs in manufacturing	GVC jobs in all sectors	GVC jobs in manufacturing
Low-income countries	*1.14*	*2.84*	*7.6*	*2.3*
Bangladesh*	1.06	1.18	10.1	5.0
Ethiopia*	0.71	5.54	4.0	0.03
Indonesia	1.24	1.57	7.8	2.9
India	1.03	1.13	5.4	1.9
Kenya*	1.09	2.09	2.9	0.67
Senegal*	1.70	5.55	2.3	0.17
Vietnam*	1.40	2.82	20.8	5.6
Lower-middle-income countries	*1.05*	*1.10*	*12.9*	*5.5*
Bulgaria	0.86	0.82	17.8	7.2
China	1.10	1.26	10.6	4.9
Lithuania	1.07	1.21	15.5	7.4
Latvia	0.95	0.90	12.8	5.8
Romania	0.90	1.05	14.1	6.1
Russia	1.44	1.36	6.4	1.6
Upper-middle-income countries	*1.10*	*1.21*	*14.7*	*7.7*
Brazil	0.88	1.11	5.5	1.3
Czech Republic	1.04	1.06	24.2	14.9
Estonia	0.99	0.81	15.2	8.9
Croatia	0.91	0.80	15.2	7.7
Hungary	1.14	1.26	20.5	11.6
Korea	1.40	2.11	13.6	6.2
Mexico	1.30	1.31	8.5	4.5
Malaysia*	1.31	1.39	15.0	6.1
Poland	0.97	0.95	17.1	8.6
Slovakia	1.04	0.99	19.3	12.7
Turkey	0.95	0.88	13.8	7.7
South Africa*	1.25	1.81	9.0	2.0

Source: Authors' calculation based on described data in table 1.

Note: Productivity is measured as value added per worker in GVCs. Unweighted averages for groups of countries are given.

*Manufacturing covers formal manufacturing data only. For Bangladesh and Ethiopia, data pertains to all establishments with 10 or more employees; for Kenya to establishments with 5 or more persons engaged; for Senegal, South Africa, Malaysia, and Vietnam to all registered establishments. Informal manufacturing is reported with services for these countries. Manufacturing sector data for other countries includes all manufacturing firms (formal and informal).

The potential for reallocation towards GVC jobs appears to be large. The share of GVC jobs in the overall economy is only 4.0 percent or less in Ethiopia, Kenya, and Senegal compared to 10.1 and 20.8 percent in Bangladesh and Vietnam in 2014 (as shown in third column of table 2). GVC jobs in (formal) manufacturing make up only 0.67 percent of the jobs in Kenya, 0.17 percent in Senegal, and an abysmal 0.03 percent in Ethiopia, compared to 5.0 percent in Bangladesh and 5.6 percent in Vietnam (fourth column in table 2). The potential for aggregate productivity growth through a reallocation towards GVC jobs seems to be particularly large for the low-income countries in Africa covered in this study.[16]

For a proper interpretation of these empirical findings, it is important to be wary of the nature of the data. There are various reasons why the presented levels are under- or overestimations of the true productivity gaps. On the one hand, the productivity gaps shown in table 2 are based on aggregate sectoral data and hence do not capture possible within-sector heterogeneity in productivity levels. It is well known

16 See Diao et al. (2021) for in-depth firm-level evidence for Tanzania and Ethiopia.

that trading firms are generally more productive than nontrading firms in the same industry (Alessandria, Arkolakis, and Ruhl 2021; World Bank 2020; Diao et al. 2021). This would indicate that the presented productivity gaps are underestimations of the true gaps. On the other hand, GVC jobs might attract higher-ability individuals. Lagakos and Waugh (2013) and Gollin, Lagakos, and Waugh (2014) show that the productivity gap between agriculture and nonagriculture shrinks considerably when labor use is adjusted for differences in hours worked as well as a number of observable dimensions of human capital. Productivity gaps could also reflect systematic differences in the capital-intensity of GVC production versus other production activities (World Bank 2020; Diao et al. 2021). In that case, large differences in average labor productivity are not necessarily indicative of similar large differences in the marginal products of labor.[17] Better measurement can clarify the extent to which the observed productivity advantages of GVC jobs are real and the extent to which they are driven by differences in physical and/or human capital intensities (Hamory et al., 2021).

4. Accounting for GVC Job Growth

A large variation in the actual growth rates of GVC jobs across countries is documented (fig. 1). In this section a decomposition framework is presented to quantify proximate sources for these cross-country differences. In accordance with the insights from Bems, Johnson, and Yi (2011) and Johnson and Noguera (2012) GVC job growth in a country is related to demand growth in consumer end-markets as well as growth in a country's activity in associated supply chains.

Decomposition Framework

Let $L_{i,z}$ indicate the number of jobs in country i that participate in the GVC of final good z.[18] And let $L_i = \sum_z L_{i,z}$ be the total number of GVC jobs in country i. It is shown in S1 in the supplementary online appendix that the growth of GVC jobs in country i can be decomposed as follows:

$$\underbrace{\Delta \ln L_i}_{\text{Country growth of GVC jobs}} = \sum\nolimits_Z \bar{w}_{i,z} \left(\underbrace{\Delta \ln C_z}_{\text{Global demand growth for GVC output}} + \underbrace{\Delta \ln \left[\frac{v_{i,z}}{C_z}\right]}_{\text{Country growth in GVC value added share}} - \underbrace{\Delta \ln \left[\frac{v_{i,z}}{L_{i,z}}\right]}_{\text{Country growth in GVC productivity}} \right), \tag{1}$$

with $\bar{w}_{i,z} = \frac{1}{2}\left(\frac{L^t_{i,z}}{\sum_z L^t_{i,z}} + \frac{L^0_{i,z}}{\sum_z L^0_{i,z}}\right)$ the period average share of GVC workers in country i working in GVC z. Each element in the decomposition has a straightforward economic intuition.[19] The first term picks up the effects due to the growth of world demand for output of GVC z (C_z). Growth of GVC jobs will be faster in a country that is better positioned relative to global demand growth or, put otherwise, a country that has a larger share of its jobs in GVCs of final products for which demand is growing faster (as reflected in $\bar{w}_{i,z}$). This article will refer to it in short as the "global demand" effect. For example Bems, Johnson, and Yi (2011) showed likewise the important knock-on effects of the global downturn in final demand in 2008/2009 on production further down the supply chains. The second term captures the contribution of changes in a country's shares in GVC value added ($\frac{v_{i,z}}{C_z}$, with $v_{i,z}$ indicating the value added in country i in the GVC of final good z). For example, a country's share is growing when it starts to produce intermediates at home that were imported before as documented for China (Kee and Tang 2016;

17 Under a Cobb-Douglas production function, the marginal value product of labot is equal to the labot share in value added times the average product of labor.

18 A GVC is characterized by product group and end-market as discussed later on.

19 Note that the decomposition results cannot be used as a basis for evaluating counterfactuals, as conceptually each of the three terms is ultimately an endogenous object of a general equilibrium system with many countries and industries.

Chor, Manova, and Yu 2021).[20] The first two terms are proximate sources for growth in GVC production in a country. The third term captures the attenuating effect of labor productivity growth on job growth, given growth in GVC production. Productivity is measured as value added per worker ($\frac{v_{i,z}}{L_{i,z}}$).[21] For example, a bias in technical change against labor will drive down the amount of labor needed for unit of output (the inverse of labor productivity).

Main Findings

For each country, the (log-point) change in the number of GVC jobs is calculated during the period from 2000 to 2014, which are the first and last year for which data are available. Large differences in GVC job growth across the 25 countries are found (fig. 1). Results of the decomposition according to equation (1) are given in table 3.[22] Contributions of global demand growth to GVC job growth range from a mere 0.10 log points or less in Bangladesh and Mexico to more than 0.50 log points in Senegal, South Africa, and various other middle-income countries (column 1). These differences relate partly to the type of end-markets that are served by the GVCs in which countries participate (Kaplinsky and Farooki 2011; World Bank 2020). For example, Bangladesh and Mexico are heavily linked into final markets in Europe and North America with relatively slowly growing demand (see table S2.2 in the supplementary online appendix). In contrast Brazil, Ethiopia, and South Korea are examples of countries that were more heavily linked to fast-growing final demand from China, boosting growth in GVC jobs. Vietnam participates in GVCs that have a wide range of end-markets likely making demand for Vietnamese jobs more robust to demand shocks that are local in character. Overall, the results in column (1) demonstrate that differences in consumer market integration may account for a substantial fraction of differences in GVC job growth between some country pairs.

The second finding is that countries differ in particular in the expansion of their activities in GVCs. The cross-country variation in the contributions of expanding shares (as given in column 2, with variance across all countries is 0.24) is much larger than variation in the contributions of end-market growth (in column 1, variance 0.02). Interestingly, all countries in the sample (with the exception of Senegal) have increased their shares in GVC value added. Note that this share term is measuring the value added of a country in a GVC relative to value added contributions of other countries in the same chain. It indicates that collectively the sample set of 25 low- and middle-income countries is gaining bigger shares in GVCs at the expense of countries outside the sample, mostly high-income countries in Europe, North America, and Japan. In particular this finding is not supporting the notion that GVC activities are mainly concentrating in China (Haraguchi, Cheng, and Smeets 2017) as shares of many other countries are increasing at well. Yet, large differences exist. Low-income countries Bangladesh, Ethiopia, and Vietnam were able to rapidly increase their shares in GVC value added whereas shares of Indonesia, Senegal, and Kenya grew only slowly. Additional sector analysis reveals that Vietnam entered many new manufacturing activities in GVCs alongside more traditional agricultural activities. For example, it quadrupled its share of value added in textiles chains ultimately destined for the U.S. end-market, and made similar advances in the GVCs of electronics. Senegal on the other hand was losing value added shares in food GVCs, not only in those GVCs for traditional consumer markets in Western Europe but also in GVCs serving markets in

20 A higher share in GVC value added can be related to increased scale of existing activities in the chain and/or enlarged scope of activities, such as producing more upstream intermediate inputs (Chor, Manova, and Yu 2021), all relative to other participants in the chain. The actual change in the share is a combination of both scale and scope changes.

21 It should be noted that the decomposition is stated in volume terms using the U.S. CPI deflator for final manufactured goods. Hence growth in labor productivity is measured as change in the volume of value added per worker.

22 As noted in section S1 in the supplementary online appendix, an approximation error arises in the decomposition as higher-order terms are ignored. In practice higher-order terms, reported in the fourth column in the table, are minor and are not further discussed.

Table 3: Sources of Job Growth in GVCs of Final Manufactured Goods, 2000–2014

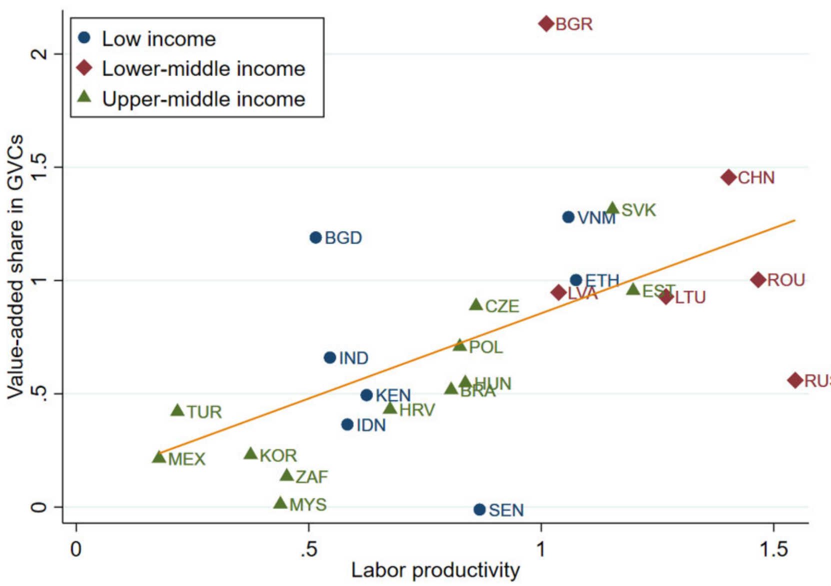
	Change in				
	Global demand for GVC output (1)	Country share in GVC value added (2)	Country productivity in GVC (3)	Approximation error (4)	Total GVC job growth (5)
Low-income					
Bangladesh	0.01	1.19	−0.51	−0.04	0.65
Ethiopia	0.45	1.00	−1.07	−0.08	0.30
India	0.42	0.66	−0.55	−0.03	0.51
Indonesia	0.32	0.36	−0.58	−0.01	0.09
Kenya	0.47	0.49	−0.62	−0.01	0.32
Senegal	0.53	−0.01	−0.87	−0.03	−0.38
Vietnam	0.42	1.28	−1.06	−0.09	0.56
Lower-middle-income					
Bulgaria	0.37	2.13	−1.01	−0.01	1.48
China	0.29	1.46	−1.40	−0.01	0.33
Latvia	0.51	0.95	−1.04	0.01	0.43
Lithuania	0.52	0.93	−1.27	0.06	0.24
Romania	0.29	1.00	−1.47	0.01	−0.16
Russia	0.57	0.56	−1.55	0.00	−0.41
Upper-middle-income					
Brazil	0.54	0.52	−0.81	−0.04	0.21
Croatia	0.39	0.43	−0.67	0.00	0.14
Czech Republic	0.39	0.89	−0.86	−0.01	0.41
Estonia	0.49	0.96	−1.20	−0.01	0.24
Hungary	0.35	0.55	−0.84	0.02	0.08
Korea	0.49	0.23	−0.37	−0.01	0.34
Malaysia	0.41	0.01	−0.44	0.01	−0.01
Mexico	0.10	0.21	−0.18	−0.01	0.13
Poland	0.35	0.71	−0.82	0.04	0.28
Slovakia	0.38	1.31	−1.15	−0.04	0.50
South Africa	0.52	0.14	−0.45	0.00	0.20
Turkey	0.42	0.42	−0.22	−0.03	0.59

Source: Authors' calculation based on described data in table 1.
Note: Decomposition of (log) growth rates of number of GVC jobs based on equation (1). Approximation error is given in column (4) and arises as only first-order terms are taken into account in the decomposition. Total in last column is sum of entries in first four columns.

China and India. Equally wide variation can be found among middle-income countries. China provides a telling example as it boosted growth in GVC jobs by 1.46 log points through increasing shares in GVC value added. This macro finding is consistent with evidence from firm-level studies. Chor, Manova, and Yu (2021) show that Chinese firms successfully competed for upstream stages in the production of their exports, locating more and more stages of the production chain within the domestic economy (see also Kee and Tang 2016). Also the Czech Republic, Estonia, and Slovakia rapidly improved their GVC shares contributing respectively 0.89, 0.96, and 1.31 log points to domestic GVC job growth. In contrast, activity expansion in GVCs was slow in Malaysia, Mexico, and South Africa, contributing respectively only 0.01, 0.21 and 0.14 log points to GVC job growth.

This study delves deeper into the relation between productivity growth and value added share growth of a country, given the large variation documented above. This relation is governed by opposing forces. Over time, countries may follow their (static) comparative advantage, concentrating on their most productive

Figure 2: Cross-Country Relation between Productivity and Value Added Shares in GVCs



Source: Based on results given in table 3.
Note: Cross-country correlation between improvements in productivity of GVC workers in a country (horizontal axis) and changes in a country's shares in GVC value added (vertical axis) during 2000–2014. Regression line included (slope 0.75 with $p = 0.001$, robust standard errors).

stages in the chain, while stepping out of less productive (noncore) stages. Offshoring of noncore activities will, *ceteris paribus*, show up as a negative correlation between productivity growth and the share in GVC value added. On the other hand, productivity improvements in a country may drive down production costs relative to other countries that are potential competitors in the chain. This will raise demand for a country's output as lead firms in GVCs substitute towards cheaper inputs and result in a positive correlation between productivity and GVC shares. First evidence for a positive correlation in the aggregate data is presented in fig. 2: countries that have larger improvements in productivity are also more successful in capturing larger shares in GVC value added.

Aggregation in the data might actually obscure the true strength of the relationship between productivity and shares in GVC value added. For example, there might be product-specific demand factors that lead to changing concentration of production across countries within a product GVC over time, unrelated with productivity. This may obscure the productivity-value added share relationship in analysis of aggregate data. Therefore the detailed information in the data are exploited in further panel data analysis.[23] A GVC is characterized in the data by final product group p destined for end-market j, indicated by GVC (p, j), e.g., the production chain of wearing apparel consumed in Germany. The (log) share of country i in value added of GVC (p, j) at time t is regressed on country i's (log) labor productivity in GVC (p, j) at time t. The data include observations for all GVCs for 18 product groups[24] and 43 end-markets, with each of the 25 countries as reporters, annually during the period 2000–2014. The sample has about 296,000 observations. In the baseline regression reporter country dummies are added to control for general country differences in GVC shares (e.g., size of a country), dummies for product groups and for end-markets to control for heterogeneity, as well as year dummies to control for global time effects. The relationship between productivity and value added shares appears to be significant and strongly positive

23 Thanks go to a reviewer for suggesting this approach.
24 See table S2.4 in the supplementary online appendix.

(column 1 in table 4). This finding appears to be robust in additional tests. Restricting the sample to the manufacturing sector does not affect the conclusion (column 2). Broadening the sample by including data for 17 high-income countries suggests that the relationship is even stronger for GVC jobs in high-income countries (column 3). Within-GVC specifications allow inclusion of a thorough set of fixed effects to absorb potential omitted variables (columns 4 to 7). In these regressions, the coefficient of interest is identified from the variation within GVCs over time. Annual data are used to compare changes within the cross-sectional units (reporter country—product group—end-market combinations) in a panel fixed effects model. This setup controls for several time-invariant country-product-market specific variables, such as trade costs related to distance.[25] The coefficient is again found to be strongly positive (column 4). Restricting the sample to only the manufacturing sector leads to a smaller, but still highly significant positive coefficient (column 5). Broadening the sample with high-income reporter countries leads to an even higher coefficient, as before (column 6). Lastly, long-run effects (using data for 2000 and 2014 only) in the detailed panel data are regressed and find again that the estimated coefficient is strongly positive (column 7). Overall, it can be concluded that the positive correlation between labor productivity and value-added shares in GVCs holds across countries as well as over time in a country within detailed GVCs. The results are OLS estimates and should therefore be viewed as informative partial correlations only. Further analysis is needed to clearly identify possible causality.

Finally, interactions of the labor productivity variable with product-group dummies are included. Marginal effects on GVC value added shares for each product group are reported in fig. S2.1 in the supplementary online appendix. The relationship between productivity and share growth appears to be heterogeneous across product groups. Marginal effects are smallest in the chains of textiles and wearing apparel, of food and beverages, and of wood products, and the highest in chains of computers, of electrical equipment, of machinery, of motor vehicles and of other transport equipment.[26] These differences might relate to the cost types in GVCs: for example, higher productivity may be particularly important in GVCs in which countries compete on labor cost, whereas costs related to reliability or timeliness in delivery may be more important in other GVCs (Hummels and Schaur 2013). These results help to understand cross-country variation as observed in fig. 2. For example, given its productivity growth, growth in Senegalese shares in GVC value added is disappointing. This might be related to its specialization in GVCs of food and beverages (accounting for 76 percent of its GVC jobs in 2014). On the other hand, Bangladesh experienced faster increases in value-added shares than expected (see fig. 2) despite its high dependence on GVCs of textiles. The data do not allow for zooming in on specific value chain activities, but the product heterogeneity found suggests that this is an important avenue for future research.

5. Conclusion

There is potential for aggregate productivity growth through reallocation of labor towards GVC activities. Based on new data for 25 low- and middle-income countries, the study found a productivity advantage of GVC workers relative to other workers in the economy. The potential is particularly high for low-income countries such as Ethiopia, Kenya, and Senegal as only a small share of workers is employed in GVCs. Actual labor productivity growth within GVCs was found to be 2 percent or more per year during 2000–2014 in all countries. Yet, variation across countries in GVC job growth is large: China, Romania, Russia, Senegal and Vietnam all experienced rapid productivity growth in GVCs, but only China and Vietnam registered high GVC job growth. Indonesia, Malaysia, Mexico, and South Africa are other examples

25 The literature on GVC trade has shown that trade costs, proxied by trade agreements and distance, matter for a country's value-added exports to end markets (Johnson and Noguera 2017). Fernandes, Kee, and Winkler (2021) further investigate determinants of participation in GVCs and confirm the role of tariffs and distance to major GVC hubs.

26 The large differences in marginal effects across product groups are found to be robust across alternative cuts of the data (table S2.3 in the supplementary online appendix).

Table 4: Regression Results

	Dependent variable: Log share in GVC value added						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
VARIABLES	Baseline	Manufacturing only	Including high income	PFE, annual	PFE, manufacturing only	PFE, including high income	PFE, Begin and end year only
Log labor productivity	0.446***	0.421***	0.617***	0.610***	0.406***	0.846***	0.797***
	(0.00897)	(0.00778)	(0.00651)	(0.0106)	(0.00870)	(0.00800)	(0.0163)
Observations	296,524	296,493	592,956	296,524	296,493	592,956	39,516
Adjusted R-squared	0.801	0.801	0.816	0.402	0.385	0.277	0.564
Reporter country dummies	X	X	X	-	-	-	-
Product group dummies	X	X	X	-	-	-	-
End-market dummies	X	X	X	-	-	-	-
Reporter X Product X End-market dummies	-	-	-	X	X	X	X
Year dummies	X	X	X	X	X	X	X
Number of groups				19,782	19,782	39,557	19,782

Source: Authors' calculations based on described data and method.

Note: Regression of log share in GVC value added on log labor productivity. Baseline dataset includes 25 low- and middle-income countries as reporter countries (columns 1 to 3). Panel fixed effects (PFE) estimates in columns (4) to (7). Columns (2) and (5) include only productivity and value added in the manufacturing sector. Columns (3) and (6) also include high-income countries. Column (7) for observations of 2000 and 2014 only.

*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses.

of countries that have disappointing GVC job growth compared to other countries with comparable productivity growth rates. Part of these cross-country differences in GVC job growth can be accounted for by differences in the type of consumer market served. A bigger part is accounted for by differences in the speed with which countries expand activities within GVCs, as measured by their shares in GVC value added. In general, countries with rapid growth in GVC jobs also capture larger shares in the value added within the associated chains. This is indicative of increasing scale and scope of activities in the chain (Kee and Tang 2016; Chor, Manova, and Yu 2021). A robust positive correlation between productivity and value added shares was found across countries as well as over time within detailed GVCs. This result cannot be used directly as a basis for specific policy guidance, however, as causality between productivity growth and GVC shares increases can run in both directions. Multisector general equilibrium modeling in the vein of Caliendo and Parro (2015) and Antràs and de Gortari (2020) might help establishing causality, and the macro findings in this paper might provide valuable input. The findings do suggest that labor productivity growth appears not to be a sufficient condition for GVC job growth. More generally, GVC job growth might be the result of an overall improvement in production capabilities within a country (Fernandes, Kee, and Winkler 2021), raising productivity as well as increasing value added shares in a GVC in a cumulative process. An important role is for capability development in services sectors that appear to be relevant for growth of manufactured goods exports (Francois, Manchin, and Tomberger 2015; Miroudot and Cadestin 2017; Liu et al. 2020). The prime policy question is under what conditions GVC participation will play a role in structural transformation, and which type of activities in GVCs might be most likely to generate the more productive GVC jobs. A better understanding of the dynamics of productivity and scale expansion, the skill content of GVC activities and the biased nature of technology upgrading in GVCs is needed. This includes further study of the governance and durability of firm-to-firm relationships in the chain and associated flows of inputs, knowledge, and technologies (Gereffi, Humphrey, and Sturgeon 2005; Antràs 2020).

Data Availability

The data underlying this article are available in the Dataverse repository at https://doi.org/10.34894/NJR5EB.

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