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Reijnders, Laurie S.M.; Timmer, Marcel P.; Ye, Xianjia

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Labour demand in global value chains: Is there a bias against unskilled work?

Laurie S. M. Reijnders | **Marcel P. Timmer** | **Xianjia Ye**

University of Groningen, Groningen, the Netherlands

Correspondence
Marcel P. Timmer, Faculty of Economics & Business, University of Groningen, P.O. Box 800, 9700AV Groningen, the Netherlands.
Email: m.p.timmer@rug.nl

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1 | INTRODUCTION

Participation in global value chains (GVCs) is recently touted as a promising route to ignite the growth process in poor countries, and features prominently on the development policy agenda (World Bank, 2019). GVC participation eases entry into global markets such that poor countries can play out comparative advantage on a larger scale, creating employment opportunities for their abundant unskilled workers. Yet, some analysts are sceptical about the potential for job growth in GVCs in particular for less skilled workers (Baldwin & Forslid, 2020; Rodrik, 2018). They warn that adoption of modern machinery, such as computer-aided manufacturing and deployment of industrial robots, might dampen the positive effects of increasing scale. In this paper, we will provide for the first time a systematic analysis of the hypothesis that technical change in GVCs is biased against low-educated workers.

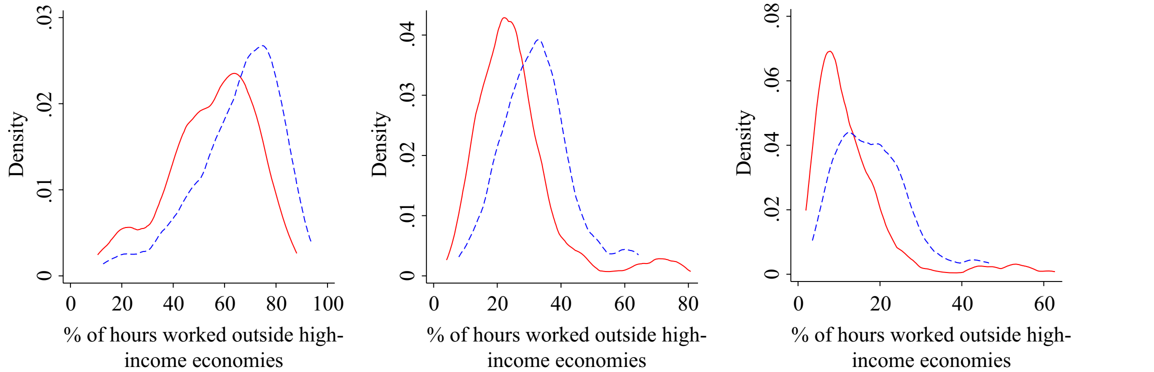
To this end, we will econometrically estimate parameters of what we refer to as a ‘GVC production function’. GVC production is characterised by the interlinking of various stages of production that are carried out in multiple countries (Baldwin & Lopez-Gonzalez, 2015). A GVC production function describes the production of a final product by the means of factor inputs used in all countries that participate in the GVC. In contrast, a traditional production function describes only one stage of production using factor inputs from a single country. More specifically, we use panel data to estimate parameters of a system of (translog) GVC cost functions for three worker types, distinguished by levels of schooling. These workers may come from any of the forty-one countries and regions in our data set. The data set covers countries at a wide range of (per capita) income levels and contains all major offshoring destinations including China, India and Mexico.[1] Our main finding is that technical change in GVCs of final goods during the period 1995–2007 was strongly biased against the use of low-educated workers (not having finished high school). The bias was neutral for middle-educated workers (up to college) and in favour of high-educated workers (college and above). Less surprisingly, we also find that demand for low-educated workers in lower income countries benefitted greatly from the reallocation of jobs in GVCs from high-income countries. And we find positive effects of substitution of low-skilled workers for middle- and high-educated workers in GVCs, as the relative price for low-educated work in GVCs has declined. But due to the low substitutability between low- and high-educated workers, its labour demand effect is much smaller compared to the effect from technical bias. These findings appear robust in a variety of alternative specifications.

Our analysis contributes to a growing literature that focuses attention on the distributional consequences of GVCs. There is mounting evidence that greater global fragmentation of production increases wage inequality in countries at all income levels (see Goldberg & Pavcnik, 2007 and Hummels et al., 2018 for overviews). Particularly, relevant is work on changing relative skill demand in countries that receive offshoring from advanced countries. In seminal work, Feenstra and Hanson (1997) found that growth of US FDI into Mexico in the 1980s was positively correlated with the relative demand for skilled labour. They hypothesised that inward FDI into Mexico consisted of production stages that were relatively unskilled compared to the stages that remained in the US. But the stages were relatively skilled compared to existing production in Mexico, thereby increasing the relative demand for skilled labour in Mexico as well as in the US. More generally, Feenstra and Hanson (2003) show that the impact of offshoring on local wage inequality depends amongst others on the technology and skill content of offshored stages relative to the structure of local labour demand. There is abundant evidence that foreign-owned firms in developing countries tend to adopt more skill- and capital-intensive techniques than comparable domestic firms. Modern technologies are likely to diffuse to local firms through multinational enterprise operations, for example by importing machinery (Javorcik, 2004).[2] Foreign-owned firms engage more in activities such as production of new goods and improvement of product quality, and possibly R&D activities and modern technology adoption that require skilled inputs (Crinò, 2012a; Verhoogen, 2008; Bernard, Moxnes, & Ulltveit-Moe, 2018). Using linked worker-firm data for five countries, Hijzen et al. (2013) conclude that the main effect of foreign ownership on the domestic wage structure is primarily by creation of high-skill (and high-wage) jobs. Our findings based on study of GVCs provide further support for the skill-bias in labour demand in global production. In particular, they highlight the role of technical change in lowering relative demand for the least skilled workers within GVCs over time.

For a proper interpretation of our results, it is important to note that our estimation strategy detects losses in demand for low-educated workers relative to other worker types. The results do not speak to the absolute level of employment, nor to possible improvements in the overall productivity with which inputs are being used. For example, Constantinescu et al. (2019) provide macro-evidence showing that

[1]The data set comprises 21 high-income, 7 upper-middle, 10 lower-middle and 2 low-income economies according to the World Bank Analytical Classification for 1995 (used in the World Development Indicators 1997). The rest-of-the-world region includes all other countries in the world, mostly other lower-middle and low-income countries.

[2]An illustrative example is provided by the Financial Times that reports: 'While Ericsson employs 22,000 people in India – more than in any other country – only about 1,000 will be involved in making products in its new factory. The rest are highly skilled roles hardly suitable for unskilled young workers. Much of that work will be done by robots' (Financial Times 2016, 23 February).



(a) Low-educated **(b)** Medium-educated **(c)** High-educated

FIGURE 1 Hours worked outside high-income countries in GVCs, by educational level. Notes: Density of share of hours worked outside the high-income countries in a GVC (in per cent). Kernel densities based on 273 observations of GVCs of goods that are finalised in the manufacturing sector in high-income countries. The distribution of 2007 is indicated by dash blue and 1995 solid red curves, see Section 3 for more information [Colour figure can be viewed at wileyonlinelibrary.com]

the use of imported inputs to produce for exports is important for productivity growth. Our finding implies that productivity growth in GVCs is decidedly not factor neutral, affecting relative skill demand. This result does not rule out that GVC participation may lead to enlarged scale of production and improved productivity, but it does indicate that potential for growth in unskilled jobs is dampened.

A particular novelty of our approach is in taking the GVC as a unit of observation, simultaneously considering factor demand in all countries that participate in the GVC. The main motive to do so is because an increasing part of value added in GVCs is generated abroad (Johnson & Noguera, 2012; Los et al., 2015). In particular, most of the unskilled work in GVC production of manufacturing goods is carried out outside high-income economies. In Figure 1, we show that on average 55 per cent of all low-educated hours used in GVC production in 1995 originated outside high-income countries (unweighted average over 273 GVCs). This share is much higher than the shares for middle- and high-educated hours worked. Moreover, the average share increased over time, to 65 per cent in 2007. These descriptive statistics indicate that study of a GVC production function is instrumental in analysis of technical change biases. To see this, suppose that a firm's production technology does not change, but it decides to relocate unskilled production stages abroad. Further suppose that the overall amount of unskilled workers in the production process remains unchanged. The traditional single country approach might detect a bias in technical change as the use of unskilled workers at home declines, while there is none.[3] Accounting for hours worked in all countries in a GVC thus helps to observe possible biases in technical change in the vertically integrated production function.

Our study is also related to a vast literature about possible channels through which technical change affects relative labour demand. The consensus finding is that the introduction of information and communication technologies (ICT) over the past decades led to a major bias in demand in favour of high-skilled workers, as surveyed in Acemoglu and Autor (2011). This finding was refined by Autor

[3]The typical strategy to overcome this so-called observational equivalence problem is to include indicators that measure the potential for jobs to be offshored from advanced countries, and the potential to be replaced by technology. Unfortunately, these indicators appear to be strongly positively correlated such that econometric identification of the separate effects is considerably weakened (Blinder & Krueger 2013).

et al. (2003) who found that introduction of ICT in the US mainly replaced workers carrying out jobs with substantial routine task content, in particular middle-educated workers. Goos et al. (2014) found wider evidence in a panel of industries in sixteen Western European countries. We include the (log) stock of real ICT capital per worker as an additional independent variable in our GVC cost share regressions and find ICT to be biased in favour of high-educated and against middle-educated labour. Interestingly, we find no significant impact on demand for low-educated work in GVCs. This suggests that the bias in demand arises from other factors beyond the mere use of ICT capital in the GVC. To probe this question, more specific measures of technology adoption such as computer-aided manufacturing and robot adoption in GVCs are needed.

The plan of the paper is as follows. Section 2 outlines the empirical model and econometric strategy. We employ a standard system of translog cost functions in which substitution elasticities and factor demand biases are unknown parameters that can be estimated from observable data on wages and wage bill shares. Section 3 describes the construction of the data set and offers some preliminary descriptive statistics. We focus on the developments in GVCs of manufacturing goods between 1995 and 2007, which is a period that is characterised by sizeable offshoring and international production fragmentation (Johnson & Noguera, 2017). Section 4 provides a discussion of the main regression results for the baseline model, as well as various robustness analyses. In section 5, we use the estimated parameters to compare the effects of reallocation, factor substitution and biased technical change on labour demand within GVCs for individual countries. We show that the bias in technical change is not only statistically significant, but also quantitatively important. Section 6 concludes.

2 | EMPIRICAL MODEL: THE GVC COST FUNCTION

Our empirical modelling follows the cost share approach that has a long tradition in labour demand studies, see, for example, Berman et al. (1994) and Hijzen et al. (2005). The approach needs to be adapted however as we consider inputs from multiple countries rather than a single country. In addition, we need to carefully outline the measurement of technical bias and substitution elasticities in the context of a three-factor, multi-country cost function as we will use them later on to compare the quantitative effects of technical change, substitution and reallocation in GVCs.

We consider a representative cost-minimising firm that produces a final consumer good and faces the possibility to offshore production tasks along the lines suggested by Grossman and Rossi-Hansberg (2008). Assume that the production process makes use of three types of tasks. Within each type, there is a continuum of tasks requiring the input of a single type of worker. In the empirical exercise, we will distinguish between low-educated (indexed by L), middle-educated (M) and high-educated (H) workers. We assume that each task requires the same amount of the corresponding production factor, irrespective of where the task is performed.[4] Let n_c^E denote the total number of workers with education E in the GVC that is employed in country c, and n^E the total across all countries. Then, the average wage for type E worker in the GVC is given by:

$$W^E = \sum_C \frac{n_c^E}{N^E} w_c^E, \quad \text{for} \quad E \in \{L, M, H\}. \tag{1}$$

The GVC wage W^E is a weighted average of the wages for type E across countries (w_c^E) where the weights reflect a given task division across countries. As in the model of Grossman and Rossi-Hansberg

[4]This assumption might be too strong and will be relaxed in the empirical exercise in Appendix E.

(2008), we think of the firm as restricted in her choice where to perform a task due to frictions in the economic environment. These may be standard frictions like prohibitive trade costs, but also costs related to coordination of cross-border activities. Exogenous change in these frictions allows a re-organisation of the employment mix across countries to take benefit from cross-country wage differences. These frictions may vary by type of work as some tasks are easier to offshore than the others. For example, tasks that follow explicit codifiable procedures will be easier to offshore because they can be performed at a distance without substantial loss of quality. If L-type tasks are easier to offshore to lower-cost locations than H-type tasks, then the relative wage paid to L-type workers in the GVC decreases, ceteris paribus. We exploit the associated wage variation over time (and across GVCs) to identify the structural parameters of the model and to measure biases in technical change in GVCs.

Further, let Y be the desired amount of final output and assume capital (K) to be quasi-fixed. Then, the short-run variable cost is given by $C\,(W^L, W^M, W^H; K, Y, t)$. The role of technical progress, which allows the firm to produce the same amount of output at a lower level of costs, is captured by the inclusion of time t.[5] We approximate the short-run variable cost function by a transcendental logarithmic (translog) specification.[6] There are various reasons to favour the use of a translog rather than the traditional CES (or Cobb-Douglas) specification. In particular, it allows substitution elasticities to vary across different pairs of factors when there are more than two factor inputs. In fact, we find the elasticities to differ significantly across different labour pairs, some being larger and others smaller than one.

The translog GVC cost function is given by:

$$
\begin{aligned}
d\ln C = {} & \alpha + \sum_E \beta^E \ln W^E + \beta^K \ln K + \beta^Y \ln Y + \beta^T t \\
& + \frac{1}{2}\sum_E \sum_D \gamma^{ED} \ln W^E \ln W^D + \frac{1}{2}\gamma^K (\ln K)^2 + \frac{1}{2}\gamma^Y (\ln Y)^2 + \frac{1}{2}\gamma^T t^2 \\
& + \sum_E \delta^{EK} \ln W^E \ln K + \sum_E \delta^{EY} \ln W^E \ln Y + \sum_E \delta^{ET} t \ln W^E \\
& + \delta^{KY} \ln K \ln Y + \delta^{KT} t \ln K + \delta^{YT} t \ln Y.
\end{aligned}
\tag{2}
$$

Symmetry requires that $\gamma^{ED} = \gamma^{DE}$ for any pair $E, D \in \{L, M, H\}$, while linear homogeneity of the cost function in factor prices implies that.

$$
\sum_E \beta^E = 1, \quad \sum_E \gamma^{ED} = \sum_E \gamma^{ED} = 0, \quad \sum_E \delta^{EK} = \sum_E \delta^{EY} = \sum_E \delta^{ET} = 0. \tag{3}
$$

Using Shephard's Lemma, we can derive the share of labour with education E in the total wage bill (the 'cost share' for short) as:

$$
s^E = \frac{\partial \ln C}{\partial \ln W^E} = \beta^E + \sum_D \gamma^{ED} \ln W^D + \delta^{EK} \ln K + \delta^{EY} \ln Y + \delta^{ET} t. \tag{4}
$$

[5] One might also be interested in a specification, which includes individual country wages rather than the average in the GVC. Yet, it appears that increasing the number of factor inputs leads to a rapid decline in the degrees of freedom making parameter identification infeasible.

[6] A translog cost function provides a second order approximation to any twice-differentiable production function. It has a long tradition in production analysis (Christensen, Jorgenson and Lau 1973) and applications in the context of labour demand including Berman, Bound and Griliches (1994), Hijzen et al. (2005), Crinò (2012b), Foster-McGregor, Stehrer and de Vries (2013), and Michaels, Natraj and Van Reenen (2014). It is also used in studies that estimate substitution elasticities of imports for domestic factors, including Aw and Roberts (1985) and Tombazos (1998).

In line with Stevenson (1980) and Jorgenson et al. (1987), we define the technical bias with regard to labour with education E as the derivative of the cost share with respect to time:

$$\frac{\partial s^E}{\partial t} = \delta^{ET}. \tag{5}$$

A value $\delta^{ET} > 0$ (<0) implies that technical change induces firms to use labour type E more (less) intensively. Under the assumption of constant returns to scale ($\delta^{EY} = 0$ for all E), technical change is neutral in the sense of Hicks if $\delta^{ET} = 0$ for all E. This means that it leaves the marginal rate of technical substitution (the ratio of the marginal products) between each pair of inputs unchanged so that the cost shares are unaffected and only the level of expenditure changes. In the case of more than two inputs, δ^{ET} is equal to a weighted average of the bilateral bias terms.[7] Hence, δ^{ET} shows whether 'on average' labour with education E gains in productivity from technical change relative to the other labour types.[8]

Apart from the technical bias, we are also interested in the price elasticities implied by the translog model. These will help us to compare the substitution effects induced by relative wage changes in the GVCs, relative to the effects of technical change. The price elasticities will also help us to check the validity of the cost minimisation framework.[9] They can be derived from the coefficients in the estimating equations as follows:

$$\eta^{EE} = \frac{\gamma^{EE}}{s^E} + s^E - 1, \quad \eta^{ED} = \frac{\gamma^{ED}}{s^E} + s^D \quad \text{if} \quad D \neq E. \tag{6}$$

In addition, we can compute the Allen-Uzawa elasticities of substitution between production factors:

$$\sigma^{ED} = \frac{\eta^{ED}}{s^D}. \tag{7}$$

If the model is well-specified, then the own-price elasticity η^{EE} should be negative for all E and the cost function's Hessian matrix of second-order derivatives with respect to wages must be negative semi-definite. The Hessian matrix is given by $\Gamma - \text{diag}\,(\mathbf{s}) + \mathbf{ss}'$, where Γ refers to the symmetric matrix containing all γ^{ED} parameters, and $\mathbf{s}$ is a column vector of cost shares of each factor.

We use the variation in wage bill shares, average wages, capital stocks and real output between global value chains to estimate the parameters in (4) for $E, D \in \{L, M, H\}$. The restrictions in (3) in combination with the fact that the wage bill shares add up to 1, allow us to drop one of the cost share equations and to use only relative wages. We choose to drop the cost share equation for high-educated labour (but this choice does not affect the results, see Berndt, 1991). This means that our estimating equations are given by:

$$\begin{aligned} s^L_{pct} = {} & \beta^L_p + \beta^L_c + \gamma^{LL} \ln\left(\frac{W^L}{W^H}\right)_{pct} + \gamma^{LM} \ln\left(\frac{W^M}{W^H}\right)_{pct} + \delta^{LK} \ln\left(\frac{K}{Y}\right)_{pct} \\ & + \left(\delta^{LY} + \delta^{LK}\right) \ln Y_{pct} + \delta^{LT} t + \varepsilon^L_{pct}, \end{aligned} \tag{8}$$

[7]See Appendix A for an exposition.

[8]If there are scale effects this is not necessarily true. For this reason, Stevenson (1980) refers to the definition in (5) more generally as 'factor-input-share bias' instead of 'technical bias'. This also underlines the fact that the bias can arise from other factors beyond technological change. We follow the literature and use the shorthand 'technical bias' throughout.

[9]More details on the calculations can be found in Appendix A.

$$s^M_{pct} = \beta^M_p + \beta^M_c + \gamma^{ML} \ln\left(\frac{W^L}{W^H}\right)_{pct} + \gamma^{MM} \ln\left(\frac{W^M}{W^H}\right)_{pct} + \delta^{MK} \ln\left(\frac{K}{Y}\right)_{pct} + \left(\delta^{MY} + \delta^{MK}\right) \ln Y_{pct} + \delta^{MT} t + \varepsilon^M_{pct}, \tag{9}$$

where p denotes the product and c the country of completion that together identify a GVC, and t indicates time. Note that β^E_p and β^E_c (with $E \in \{L, M\}$) are fixed-effect dummies for product and country of completion, respectively. These capture systematic differences in wage bill shares between different product groups and countries of completion. Coefficients might be heterogeneous across countries and products, so we test for this as well in an extension.

All coefficients in the system defined in (8) and (9) are estimated in a simultaneous equation system with the constraints in (3) imposed, using maximum likelihood (as in Hijzen et al., 2005 and Crinò, 2012b). In cost share systems with more than two variable factor inputs, it is recommended to use a system estimator, which yields more efficient results than single equation estimations. A system estimator is more efficient as it takes the cross-equation restrictions in the cost share equations into consideration. This in contrast to the estimation of separate regressions, which does not necessarily ensure similarity of coefficients that should theoretically be the same. The right-hand side of the equations includes common variables, and there are cross-equation restrictions such that disturbances are likely to be correlated across equations (Berndt, 1991).

3 | GLOBAL VALUE CHAINS: DATA AND DESCRIPTIVES

Empirical studies of cross-border production are scarce due to the fact that GVCs cannot be directly observed. Firm production surveys typically only contain information on the type of intermediate inputs purchased, with little information on the supplier. To resolve this, various proxy approaches have been developed as surveyed in Johnson (2018). Recent prominent studies of global production chains such as Hummels et al. (2001), Johnson and Noguera (2012, 2017) and Johnson (2014) focus on the contribution of domestic factors to a country's exports. For this study, we need the factor input of all countries that contribute to production. We follow the method of Los et al. (2015) to vertically integrate across stages in a GVC and trace for each GVC the factor inputs used in any of the 41 countries and regions in the data set. It covers workers employed in manufacturing as well as services sectors, thus accounting for the increasing importance of service linkages in the world economy (Francois et al., 2015).

3.1 | Data construction

Our method relies on information about inter-industry and inter-country flows of goods and services as summarised in world input–output tables. A world input–output table contains for each country industry information on the use of value added and intermediate inputs, sourced from any other country industry in the world. Consider for example the global value chain of cars that are finalised in Germany. The input–output table shows that the German car industry imports intermediate inputs from the machinery industry in Poland. It also shows that the latter industry, in turn, sources from the steel industry in China. Combining this information allows us to determine the output of the steel industry in China needed for the final output of cars in Germany. More generally, let $\mathbf{f}$ be a vector of final demand and $\mathbf{y}$ a vector of gross output in all country-industries, then $\mathbf{y} = \mathbf{Bf}$ with $\mathbf{B}$ the so-called Leontief inverse matrix

(Leontief, 1953). A typical element b_{ji} in row j and column i of **B** gives the amount of output from country industry j required to produce one dollar's worth of output for final use by country industry i. We combine this with information on the labour input needed per unit of output in each country industry. Thus, we can determine the amount of Chinese, Polish as well as German workers used in the production of a car that is finalised in Germany. A formal discussion is provided in Appendix B.[10]

To apply this method, we use information on the input–output structure of the global economy from the world input–output database (WIOD), 2013, release (Timmer et al., 2015). World input–output tables record the flows of goods and services for intermediate use between 35 different industries in 40 economies as well as a region that represents the rest of the world (Timmer et al., 2015).[11] Industries are distinguished at the 2-digit level of the International Standard Industrial Classification (ISIC, revision 3) together spanning the whole economy, see Appendix Table C.1 for a list. We study the GVCs of manufacturing goods that are finalised in twenty-one advanced economies, including fifteen European countries, Australia, Canada, Japan, South Korea, Taiwan and the US.[12] We distinguish between output from thirteen manufacturing industries, so all in all, we will study the production structure of 273 (=13 × 21) GVCs.

Labour input in the GVCs can come from any of the 40 economies and the rest-of-world region covered in the WIOD. The Socio-Economic Accounts (SEA) of the WIOD provide additional information on compensation and total hours worked by type of worker in each country industry. Workers are characterised on the basis of educational attainment according to levels defined in the International Standard Classification of Education (ISCED). We distinguish workers that are college educated and above (ISCED categories 5 and 6, which we refer to as high-educated), workers with at least a high-school diploma but no college degree (ISCED 3 and 4, middle-educated) and workers without a high-school diploma (ISCED 0, 1 and 2, low-educated). Although the national statistics are harmonised through a common international classification, one might still have a concern about the comparability of educational attainment levels across countries. Ideally, we would like to adjust for differences in the quality of schooling across countries, but there is no systematic information that can be used.[13] Arguably, cross-country schooling quality differences matter the most for highly educated workers. Therefore, we test robustness of our results assuming international price equalisation of workers with college degree and above in additional analysis.

[10]This is inspired by a long tradition in using input–output (I-O) tables to measure the factor content of trade going back to Leontief (1953). In related line of work Pasinetti (1973) provides an early treatise of vertically integrated production chains. A caveat is in order as reliance on I-O tables comes with strong assumptions. In particular, I-O tables aggregate out well-documented firm-level heterogeneities in cross-border trade (Johnson 2018). Feenstra and Jensen (2012) assess the imported input 'proportionality' assumption that underlies the U.S. I-O table construction against information from firm-level data. For Mexican trade, De Gortari (2019) documents heterogeneities in firm input use by output destination. Using rich data for Belgium, Bems and Kikkawa (2020) find that sectoral aggregation leads to understated import content of gross exports. To deal with this issue in the context of this paper, a wider availability of micro-level evidence on cross-border transactions for a broader set of countries is needed.

[11]The database covers the 27 members of the European Union (per January 2007), Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey, the United States and a rest-of-the-world region. It follows that all production and trade flows in the world are accounted for, which is crucial for our purposes. See Appendix C for a list of countries and regions.

[12]These are all high-income economies in 1995 according to the World Bank Analytical Classification (used in the World Development Indicators 1997) with the exception of Greece that became high-income in 1996. Cyprus is also classified as high-income by the World Bank, but due to its very small economic size, it is not included in our high-income sample.

[13]A notable exception is provided by Schoellman (2012) who derives estimates inferred from wages of immigrants in the U.S. His estimates are based on years of schooling however, and cannot be used to adjust the levels of education.

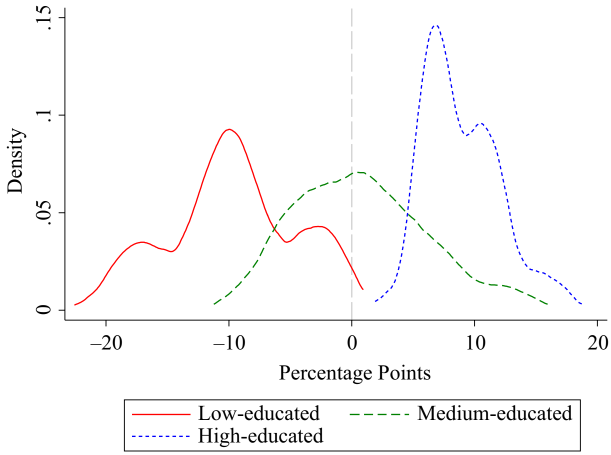


FIGURE 2 Changes in wage bill shares in GVCs of manufacturing goods, 1995–2007. Notes: Kernel density of change in labour cost shares for low-, middle- and high-educated workers. Change over the period 1995–2007 (in percentage points) [Colour figure can be viewed at wileyonlinelibrary.com]

The WIOD (2013 release) contains data on factor inputs for the period 1995–2009. We restrict our analysis to the period 1995–2007 as the identification of trends might be obscured by the volatile trade and output movements in the global economic crisis in 2008–09.

3.2 | GVC production characteristics

We are now in the position to provide an exploratory, non-parametric, characterisation of GVC production. We do so by providing some initial descriptives on changes in wages and wage bill shares in our set of GVCs over the period from 1995 to 2007. Let n_c^E the amount of labour with education E in the GVC that is employed in country c with associated wage w_c^E. Adding up wage bills across workers from all country-industries in a particular GVC gives the total payments to labour within the chain. The wage bill share of labour with education E for a given GVC is then given by.

$$s^E = \frac{\sum_c n_c^E w_c^E}{\sum_E \sum_c n_c^E w_c^E}, \quad \text{for} E \in \{L, M, H\}\,. \tag{10}$$

Figure 2 shows the kernel density plot for changes in the wage bill shares in GVCs for low-, middle- and high-educated workers, expressed in percentage points. In 1995, the (unweighted) average shares were 32.3, 46.0 and 21.7 per cent for low-, middle- and high-educated workers. The figure shows that the wage bill share of the high-educated increased rapidly, on average by 8.9 percentage points. It increased in virtually all GVCs. On the other hand, the share of the low-educated declined in almost all GVCs, on average by 9.7 percentage points. The share of the middle-educated increased slightly by 0.8 percentage points on average, but with a large variance across GVCs.

Figure 3 shows the kernel density plot for the (log) change in average GVC wages (as defined in Equation 1). It plots the changes of low-educated wages relative to high-educated (solid line), and similarly for middle-educated relative to high-educated (dotted line). The relative wages of low-educated workers in GVCs have declined by 18 log points over the period 1995–2007 (unweighted average across GVCs). This is of course related to the continuous offshoring of unskilled-intensive

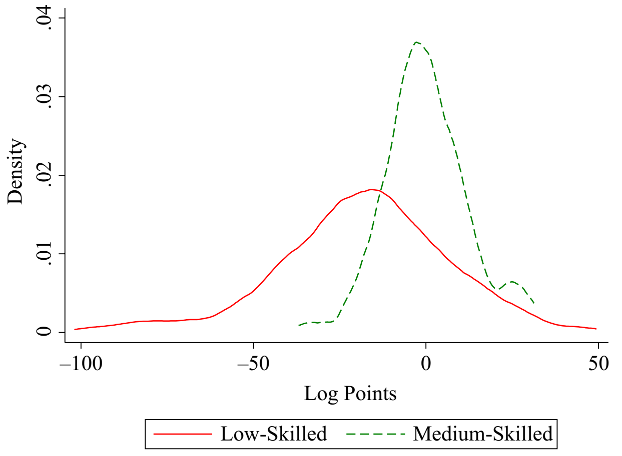


FIGURE 3 Changes in relative wages in GVCs of manufacturing goods, 1995–2007. Notes: Kernel density of change in average prices of low-educated and middle-educated workers relative to high-educated workers. Change over the period 1995–2007 (in log points) [Colour figure can be viewed at wileyonlinelibrary.com]

stages to low-wage countries illustrated in Figure 1. There is sizable variance in wage changes across GVCs. For example, the decline was strongest for GVCs of leather products (minus 35.5 log points, unweighted average across 21 GVCs of leather) and textiles (minus 29.1 log points), but much less so for GVCs of food products and metal products (minus 10.0 log points each). Wages of middle- and high-educated work in GVCs moved in step on average, although the variation across GVCs is sizable also in this case, varying from minus 5.2 log points in GVCs of electronics to plus 2.6 log points in GVCs of metal products. The variation in wage changes across GVCs is the key in our identification strategy of biases in technical change.

In the econometric estimation, we will make use of the panel structure of the data containing annual data for 273 GVCs for the period from 1995 to 2007. Twenty GVCs have zero or negative final output in some years, such that we have 3,256 observations left for our panel regressions.[14] Appendix Table D.1 provides descriptive statistics of this set.

4 | ECONOMETRIC RESULTS

4.1 | Baseline results

In this section, we report on the baseline regressions. Before discussing the results, we first check whether the estimated GVC cost function is consistent with cost minimisation behaviour. Cost functions are well-behaved if they are quasi-concave in factor prices. When evaluating the eigenvalues of

[14]This is true for Leather products in Luxembourg (all years), Non-metallic mineral (Australia, 2005), Wood (Finland, 1998, 2000; Luxembourg, 1997), Machinery (Greece 1995, 1996, 1997) and Metal (Luxembourg, 2002). Negative final output arises in cases where a decline in inventories is bigger than the output of the industry. In addition, we exclude the data for the year 2003. The reason is that for a number of European countries wages by level of educational attainment data in the EU labour Force Survey was miscoded such that the share of low-educated workers jumped up from 2002 to 2003 and down again from 2003 to 2004. Including this (erroneous) data would not quantitatively change the main results of this paper however (available upon request).

the Hessian matrix at the simple average of the cost shares, we find that they are non-positive for all regression alternatives.[15] This is important to ensure that the estimation of our model for GVC production generates economically meaningful results. This also confirms that the parameters can be used in a simulation exercise described in the next section.

Our first set of results for the system of wage bill share regressions, given in Equations (8) and (9), is reported in Table 1. The dependent variables are annual wage bill shares of the low-educated in panel A, and of middle-educated in panel B. All coefficients are multiplied by 100 to ease interpretation. Standard errors are in parentheses and derived with bootstrapping (1,000 draws).[16] All regressions contain country (21) and product (13) fixed effects, which are jointly highly significant. For convenience, we report the coefficients for high-educated as implied by the parameter restrictions from Equation (3) in panel C.

Column (1) reports on the baseline regression results. The coefficients on quasi-fixed capital are positive for both low- and middle-educated, but only significant for the former. It is significantly negative for the high-educated skill share, suggesting that capital-intensive production processes are more (less) intensive in the use of low- (high-) educated workers. Scale effect is unlikely in all cases as coefficients on output are not significantly different from zero. The coefficients on the relative wages are positive and highly significant for all wage bill shares. The coefficients are hard to interpret by themselves, but can be used to derive price elasticities and elasticities of substitution according to Equations (6) and (7). We follow common practice and evaluate the elasticities on the basis of simple average cost shares across all observations. Results are given in Table 2 together with bootstrapped standard errors. The implied own-price and cross-price elasticities have the expected signs: negative for the former and positive for the latter. In addition, the elasticities of substitution indicate that middle-educated and low-educated work are substitutes, while both are complements to high-educated work.[17]

The effect of biased technical change on cost shares is captured by the coefficients on the time trend. The baseline estimates reveal a highly significant bias in the overall effects of technical change against low-educated workers (−0.792), a mildly positive effect in favour of middle-educated (0.082) and a strong bias in favour of high-educated workers (derived from the cross-equation restriction of Equation 3 as $0.792 - 0.082 = 0.710$).[18] The latter echoes earlier findings on the skill-biased nature of technological change for local labour markets in advanced countries (Acemoglu & Autor, 2011). The overall effects of technical change are not only statistically, but also economically highly significant. In fact, the cumulative effect of biased technical change on the cost share of low-educated

[15]Ideally, the eigenvalues of this matrix should be evaluated for each observation as suggested by Diewert and Wales (1987) although this is rarely done. We find that for the baseline specification merely 17 out of 3,256 observations have positive eigenvalues, which suggests that the Hessian matrix associated with the estimated translog cost function is indeed negative semi-definite in almost all cases.

[16]We use bootstrap because it allows us to determine the standard errors for the price and substitution elasticities. These are highly non-linear expressions in the regression coefficients. The (clustered) white robust standard errors do not differ much from the bootstrapped standard errors for the regression coefficients, and are available upon request.

[17]Allen-Uzawa (partial) elasticities are symmetric by definition. Alternatively, one might evaluate Morishima elasticities that are more general (Blackorby and Russell 1989). They are asymmetric, and for each pair of factors E and D it is given by $\eta^{ED} - \eta^{DD}$. Using this measure, elasticity of low-educated versus middle-educated is 0.989 and versus high-educated 0.871; for middle-educated versus low-educated 0.948 and versus high-educated 0.667; and finally for high-educated versus low-educated 0.591 and versus middle-educated 0.550.

[18]If we exclude the time trend capturing biased technical change from the regression, the R-squares drop from 0.961 to 0.918 for low-educated, from 0.945 to 0.944 for middle, and from 0.905 to 0.796 for high. The explanatory power of the price variables is much smaller: excluding them from the regression lowers the R-squares to 0.961, 0.940 and 0.899, respectively.

TABLE 1 Explaining changes in wage bill shares in global value chains of manufacturing goods, 1995–2007

	(1) Baseline	(2) ICT	(3) IV1	(4) IV2	(5) Long-dif	(6) C&P FE	(7) Country spec
A. Wage bill share low-educated							
ln (W^L/W^H)	1.041	1.937	0.099	−1.606	3.847	1.198	1.304
	(0.367)	(0.416)	(0.436)	(0.717)	(1.507)	(0.408)	(0.290)
ln (W^M/W^H)	1.316	0.126	2.107	0.434	−2.663	0.068	1.571
	(0.330)	(0.399)	(0.410)	(0.609)	(1.350)	(0.371)	(0.282)
ln (K/Y)	1.608	0.715	1.389	1.605	−0.818	1.187	1.884
	(0.351)	(0.445)	(0.381)	(0.346)	(1.104)	(0.420)	(0.353)
ln (Y)	−0.080	−0.007	−0.112	−0.142	−1.020	−0.703	0.030
	(0.076)	(0.124)	(0.080)	(0.076)	(0.491)	(0.189)	(0.061)
t	−0.792	−0.705	−0.766	−0.846		−0.779	
	(0.017)	(0.026)	(0.020)	(0.022)		(0.015)	
ICT		0.066					
		(0.108)					
B. Wage bill share middle-educated							
ln (W^L/W^H)	1.316	0.126	2.107	0.434	−2.663	0.068	1.571
	(0.330)	(0.399)	(0.410)	(0.069)	(1.350)	(0.371)	(0.282)
ln (W^M/W^H)	4.775	4.699	4.396	8.791	13.284	9.356	1.700
	(0.726)	(0.859)	(0.816)	(1.034)	(2.111)	(0.742)	(0.673)
ln (K/Y)	0.484	2.530	0.641	0.098	4.796	2.003	−0.592
	(0.333)	(0.564)	(0.365)	(0.350)	(1.046)	(0.416)	(0.301)
ln (Y)	0.014	−0.131	0.032	−0.021	1.156	0.763	−0.136
	(0.072)	(0.109)	(0.073)	(0.072)	(0.552)	(0.188)	(0.056)
t	0.082	0.088	0.060	0.063		0.050	
	(0.015)	(0.017)	(0.018)	(0.018)		(0.014)	
ICT		−0.809					
		(0.117)					
C. Wage bill share middle-educated							
ln (W^L/W^H)	−2.357	−2.063	−2.206	1.172	−1.184	−1.266	−2.875
	(0.282)	(0.379)	(0.363)	(0.510)	(0.774)	(0.274)	(0.273)
ln (W^M/W^H)	−6.091	−4.826	−6.503	−9.225	−10.621	−9.423	−3.271
	(0.653)	(0.852)	(0.725)	(0.855)	(1.672)	(0.588)	(0.652)
ln (K/Y)	−2.091	−3.245	−2.029	−1.703	−3.979	−3.190	−1.292
	(0.305)	(0.529)	(0.355)	(0.307)	(0.718)	(0.281)	(0.330)
ln (Y)	0.066	0.139	0.081	0.163	−0.136	−0.060	0.107
	(0.070)	(0.106)	(0.074)	(0.068)	(0.380)	(0.116)	(0.062)
t	0.710	0.616	0.706	0.782		0.729	

(Continues)

TABLE 1 (Continued)

	(1) Baseline	(2) ICT	(3) IV1	(4) IV2	(5) Long-dif	(6) C&P FE	(7) Country spec
	(0.012)	(0.020)	(0.014)	(0.014)		(0.009)	
ICT		0.743					
		(0.112)					
Country of completion (CoC) fixed effect	X	X	X	X			X
Product FE	X	X	X	X			X
CoC&Prod FE						X	
Country FE × t							X
Observations	3,256	1,856	2,713	3,256	271	3,256	3,256
$R^{2,L}$	0.961	0.961	0.963	0.962	0.032	0.979	0.975
$R^{2,M}$	0.945	0.947	0.949	0.945	0.256	0.971	0.966
$R^{2,H}$	0.906	0.920	0.906	0.899	0.255	0.973	0.919
Implied cumulative biases from 1995 to 2007 (% points)							
Low-educated	−9.51	−8.46	−9.19	−10.16	−8.81	−9.34	
Middle-educated	0.99	1.06	0.72	0.76	0.36	0.60	
High-educated	8.52	7.40	8.47	9.40	8.45	8.74	

Notes: Estimation of parameters determining wage bill shares in system of equations as given in formulas (8) and (9). Results for low-educated reported in Panel A, for middle-educated in Panel B, and for high-educated in panel C. First two explanatory variables in each panel refer to (cross) wage effects (W), and the second last variable the bias in technical change (t). Superscripts refer to low-educated (L), middle-educated (M) and high-educated (H) labour. Quasi-fixed capital (K) and output (Y) levels are included. Column (1) is the baseline model, and column (2) reports results when the log ICT capital per worker in the last production stage is included as a control variable. Column (3) reports the second-stage results from 2SLS estimation using factor prices weighted with previous year distribution of workers. Column (4) reports the results from estimation using predicted distribution of workers as described in main text. Column (5) reports on results for long-difference specification (1995–2007). Column (6) controls for a combined country of completion (CoC) and product pair fixed effect. Column (7) allows the time trend to be specific to the finalising country of each GVC. Coefficients are estimated with maximum likelihood and multiplied by 100. Bootstrapped standard errors (1,000 draws) are reported in parentheses.

workers over the 12-year period, calculated as 12 times δ^{ET}, is minus 9.5 percentage points. This is a large drop, given that the average initial cost share in 1995 was 32.3 per cent. The cumulative biases are reported at the bottom of Table 1.

An important issue is what mechanism is driving the biases in labour demand in GVCs. An obvious candidate is the use of ICT that plays a central role in driving relative labour demand in high-income countries (Acemoglu & Autor, 2011). We include the current (log) stock of real ICT capital per worker as an additional independent variable. This indicator is derived from the EU KLEMS database (O'Mahony & Timmer, 2009) and comprised of software, computer hardware and communication equipment stocks. It is based on ICT capital in the last production stage, as this type of information is only available for advanced countries (and hence not for stages carried out in non-advanced countries).

TABLE 2 Elasticities

	Price elasticities				Elasticities of substitution		
	L	*M*	*H*		*L*	*M*	*H*
Baseline							
w^L	−0.694	0.295	0.177	*L*	n.a.	1.105	0.665
	(0.014)	(0.007)	(0.011)			(0.027)	(0.040)
w^M	0.519	−0.429	0.239	*M*	1.105	n.a.	0.508
	(0.013)	(0.015)	(0.024)		(0.027)		(0.052)
w^H	0.175	0.134	−0.416	*H*	0.665	0.508	n.a.
	(0.011)	(0.014)	(0.025)		(0.040)	(0.052)	
IV							
w^L	−0.732	0.309	0.181	*L*	n.a.	1.169	0.685
	(0.017)	(0.009)	(0.014)			(0.033)	(0.052)
w^M	0.550	−0.436	0.225	*M*	1.169	n.a.	0.479
	(0.016)	(0.017)	(0.027)		(0.033)		(0.057)
w^H	0.181	0.127	−0.406	*H*	0.685	0.479	n.a.
	(0.014)	(0.015)	(0.028)		(0.052)	(0.057)	

Notes: The price elasticities are based on Equation (6), and Allen-Uzawa elasticities of substitution on (7), where the γ^{ED} coefficients are taken from either the baseline or IV regression reported in columns (1) and (3) of Table 1. The elasticities are evaluated at the mean shares across all years. Standard errors are derived from bootstrapping of 1,000 draws.

Given the fact that many GVC headquarters are located in advanced economies, it is not implausible to assume that most of the ICT outlay within GVCs will take place there such that this indicator provides a reasonable proxy for ICT use throughout the value chain. Note that the ICT indicator differs across products and countries. We have data for 12 countries, so the number of observations drops to 1,856. As this subsample might not be random, we re-estimate the baseline model for this subset of observations first without ICT control. Estimated biases in technical change are as follows: −0.697, −0.014 and 0.711 (not shown in the table). Note that for this subsample there is a (small) bias against middle-educated.

The results including ICT as a control are shown in column (2) of Table 1. ICT use has a positive and significant effect on demand for high-educated. The average level of (log) ICT increased from 0.99 in 1995, to 2.56 in 2007. This translates into 1.16 percentage point increase in the high-educated cost share (1.57×0.743). This is in line with the common finding of skill-bias in technical change documented in the existing literature. Interestingly, the biggest impact of ICT in GVCs is on the demand for middle-educated labour. The coefficient is significantly negative and the increase in ICT drives down the cost share by 1.27 percentage point (1.57×-0.809). The coefficient on the time trend for middle-educated turned mildly positive again. This result is in line with the hypothesis of routine-replacing bias in technical change as in Autor et al. (2003) and congruent with the findings on the impact of ICT on demand for middle-educated workers in advanced countries by Michaels et al. (2014). Interestingly, we find that ICT use in GVCs does not impact the use of low-educated work. The estimated coefficient is small and not significant. This suggests that the bias in demand arises from other factors beyond the mere use of ICT capital in the GVC. Acemoglu and Restrepo (2018), Graetz and Michaels (2018) and Blanas et al. (2020) provide more detailed analysis of the types of technical change and find that in advanced countries robots reduce the employment share of low-skill workers in high-income countries. We will discuss possible channels in the concluding remarks.

4.2 | Robustness

Our major finding is the strong bias in technical change against low-educated work in GVCs. This finding appears to be robust to various alternative specifications. What follows in this section is the results from two instrumenting strategies for the wages, long-difference estimates, controlling for the product and country of completion pair fixed effect, and allowing for heterogeneity in the biases across GVCs. These results are reported in Table 1. We also tried various other specifications, using different weighting schemes, allowing for non-linear trends, and cross-country differences in schooling quality; the results can be found in Appendix E.

4.2.1 | Instrumenting for wages

Our empirical strategy requires that the classic simultaneity issue between cost shares and (relative) factor prices is minor. We are using disaggregated industry data assuming national wages to be exogenous, as in standard cross-country industry-level studies.[19] Yet, in our set-up there is a potentially more serious issue, as the average GVC wage is also dependent on the distribution of jobs across countries. In the task-offshoring model of Grossman and Rossi-Hansberg (2008), the firm is restricted in its choice where to perform a task due to frictions in the economic environment. Exogenous change in these frictions allows a re-organisation of the employment mix across countries to take full advantage of cross-country wage differences. One might argue that events such as China's joining of the WTO, or developments in international transport or communication technologies have an exogenous impact on the cross-country distribution of labour in GVCs. But on the other hand, it is also clear that firms have some room to choose production locations, even within given external constraints. We provide two alternative instrumental variable strategies to assuage possible endogeneity concerns.[20]

First, we construct an alternative set of GVC wages in year t using national wages in year t in combination with the labour allocation across countries in year $t-1$ (these are the weights in Equation 1). The intuition behind this instrument is straightforward: firms might control the allocation of labour across countries, but have no impact on national wages. The instrument has a first-stage F-statistic that is large for both $\ln(W^L/W^H)$ and $\ln(W^M/W^H)$ (p-value 0.000), and the sign of the first-stage regressions is positive as expected. The second-stage estimates for the instrumented equation system are given in column (3) of Table 1. The coefficients on relative wages in the regression for low-educated are

[19] One might argue that offshoring affects local factor demand and therefore local factor prices as well. This channel of reverse causality is muted however, as we analyse only a subset of the active labour force in advanced economies, namely those employed in GVC production of manufacturing goods. Summed across all our GVCs, GVC employment makes up 23.1 per cent of the labour force (averaged across the 21 advanced economies).

[20] In cross-country studies, it is common to replace the relative prices on the right-hand side of the cost share equations by country and year fixed effects. This is under the assumption of wage bargaining at the national level. However, it is unlikely that wage bargaining holds at the international level. As a result movements in GVC wages (that are averages of national wages, see Equation 1) will differ across industries of completion even when they are in the same country, for example as they will differ in the use of foreign labour in the cross-section and over time. Thus, the endogeneity issue cannot be resolved by incorporation of a set of fixed effects.

particularly affected. Reassuringly, the associated price elasticities are still well behaved, and are of the same signs and magnitudes as those of the baseline. Constant returns to scale is still not rejected, and the effects of quasi-fixed capital remain the same. Our main parameters of interest, the coefficients on the time trend, are somewhat smaller than in the baseline but still very significant. Over the 12-year period, the IV regression suggests a bias of 9.2 percentage points against low-educated, 0.7 points in favour of middle-educated and 8.5 points in favour of high-educated workers.

For further robustness check, we also employ an alternative instrumenting approach in the vein of Autor et al. (2015). In the first stage, we predict the share of working hours in a particular GVC that will be undertaken outside of the advanced economies (see Appendix Table C.1 for a list of these economies). The prediction is based on a weighted average of this share in other GVCs that end in the same country. We use these predictions as weights in Equation (1) to construct a new average GVC wage measure. This is a plausible strategy when offshoring decisions by firms in a particular country are likely to be driven by common exposure to international outsourcing opportunities. The results are given in column (4) in Table 1. As with the previous IV, it appears that the coefficients on relative wages in the regression for low-educated are particularly affected, even turning negative in the own wage bill regression (when relative to high educated). But even in this case, the associated price elasticities are still showing the proper signs, and the same magnitudes as in the baseline. Price elasticities for L relative to (W^L, W^M, W^H) are (−0.793, 0.486, 0.307), for M (0.276, −0.343, 0.067) and for H (0.311, 0.119, −0.431). Reassuringly, the results on the factor biases in technical change are still highly significant and if anything, suggest even larger biases than in the baseline.

4.2.2 | Long difference

So far, we estimated our regressions on annual data for the period 1995–2007. This greatly increases the number of observations and allows for more precise estimates of our model parameters. Yet, it might be the case that our baseline regression is affected by (possibly non-random) measurement error due to lower signal-to-noise ratios of the annual data. To investigate this, we estimate a long-difference model for the period 1995–2007 as in Michaels et al. (2014). This brings down the number of observations to 271. The results reported in column (5) in Table 1 show that the parameter estimates are quite different, typically larger, compared to the baseline and at the same time less significant as standard errors increase. Yet, the estimates for the biases in technical change are still similar in direction and magnitude when compared to the baseline. Note that in this cross-section set-up the intercept captures the time trend of our panel data model. These are reported in the bottom rows.

4.2.3 | Product – country of completion pair fixed effects

In the baseline, we use separate fixed effects for the country of completion (i.e. the country where the last stage of production takes place) and for the final product of the GVC (that depends on the industry where the last stage of production takes place). This approach implicitly assumes that initial factor intensities and technological characteristics of a particular product GVC do not differ across countries of completion. Put simply, we assume that factor use in the GVC of a car finalised in Germany does not differ from the GVC of a car finalised in France. The advantage of this approach is that we may infer patterns of substitution between factors over time. Alternatively, we may allow for across country heterogeneity in GVCs (as, e.g., in Crinò, 2012b) and include product-country of completion fixed effects. As a consequence the degrees of freedom drop substantially. Results are reported in column

(6) of Table 1. The results are quantitatively close to those obtained from estimation with long differences in (5) as is to be expected as both absorb the product-country variation.

5 | COMPARING THE QUANTITATIVE EFFECTS OF REALLOCATION, SUBSTITUTION AND BIASED TECHNICAL CHANGE IN GVCS

How large are the effects of biased technical change, reallocation and substitution in GVCs on the employment in individual countries? To compare the relative strengths of these effects, we perform a simulation analysis using the estimated parameters of the GVC production functions, combined with our information on the reallocation of workers across countries.

For a given GVC, the change in labour demand for type E can be written as:

$$d\ln N^E = \sum_D \eta^{ED} d\ln W^D + \eta^{EY} d\ln Y + \left[\sum_{D \neq E} \eta^{ED} \frac{\partial \ln \left[F^E / F^D \right]}{\partial t} - \eta^{EY} \frac{\partial \ln F}{\partial t} \right] dt, \tag{11}$$

where $F(.)$ is the production function and F^E denotes the marginal product of type E workers. This equation follows from the translog specification of the cost function (see Appendix A for derivation). The impact of technical change (in square brackets) consists of two elements: the last part captures the effect of TFP growth which is factor neutral, while the first part captures the effect of factor biases in technical change. We simplify in order to focus on the differential demand effect across worker types. Specifically, we keep final output levels in the GVC (Y) constant and assume that TFP growth is zero. In that case we can write the change in labour demand in a particular GVC (subscript p) as:

$$d\ln N_P^E = \sum_D \eta_p^{ED} d\ln W_p^D + A_p^E dt, \tag{12}$$

with $A_p^E = \sum_{D \neq E} \eta_p^{ED} \frac{\partial \ln \left[F_p^E / F_p^D \right]}{\partial t}$.

As we are interested in the effects for individual countries, we have to account for changes in the allocation of workers across countries in a GVC. Let x_{cp}^E be the share of country c workers in N_p^E such that $x_{cp}^E N_p^E$ is the number of country c workers employed in GVC p. The sum of type E employment in c across all global value chains is given by.

$$N_c^E = \sum_p x_{cp}^E N_p^E. \tag{13}$$

We refer to N_c^E as the total GVC employment of type E in country c. After log-linearisation, it follows that the change in GVC employment in c is proxied by.

$$d\ln N_c^E = \sum_p \frac{N_{cp}^E}{N_c^E} \left[d\ln x_{cp}^E + d\ln N_p^E \right]. \tag{14}$$

Substituting (12) into (14), we derive the following decomposition of the change in GVC employment in country c:

$$d\ln N_c^E = \sum_p \frac{N_{cp}^E}{N_c^E}\left[\underbrace{d\ln x_{cp}^E}_{\text{Reallocation}} + \underbrace{\sum_D \eta_p^{ED} d\ln W_p^D}_{\text{Substitution}} + \underbrace{A_p^E dt}_{\text{Bias}}\right]. \tag{15}$$

This equation shows that we can simulate three drivers of demand for GVC employment in a particular country c. The first term between brackets on the right-hand side picks up the (net) effect of changing employment shares across countries within GVCs. The reallocation effect is positive for countries that increased employment shares in GVCs relative to other countries. For example, offshoring of low-skilled jobs from advanced to low-income countries will show up as a negative reallocation effect for sending countries and a positive reallocation effect for receiving countries. In short, we refer to this as the 'reallocation' effect. The second term captures the effect of substitution of factor inputs in a GVC due to changes in relative wages in the GVC, moderated by the various wage elasticities (in short 'substitution' effect). Finally, the last element picks up the effects of factor biases in technical change in GVCs (in short 'bias' effect). As shown in the previous section, the biases vary strongly across worker types and this differentially affects the employment demand in GVCs, again moderated by the wage elasticities.

Our aim is to compare the magnitudes of the three effects on GVC labour demand for individual countries. We do this through simulating one effect at a time. More specifically, we simulate the growth in labour demand due to reallocation by imputing the actual changes in shares x_{cp}^E during the period 1995–2007, while keeping all other elements in the decomposition constant at their 1995 level. Similarly, we simulate the effects of substitution by imputing the actual changes in wages in the second term in (15), keeping the other elements constant. Finally, we simulate the effects of factor bias by imputing the biased technical change in the third term in (15), again keeping the other elements constant. We do this for employment in each GVC and sum across GVCs for each country with weights N_{cp}^E/N_c^E for 1995. The factor substitution elasticities η^{ED} and biases A_p^E in Equation (15) can be derived from the estimated γ and δ coefficients in our regressions using GVC specific (period average) cost shares, as shown in Appendix A. The parameters are taken from the regression allowing for heterogeneity across countries of completion as reported in column (7) in Table 1. Note that we simulate growth in labour input by keeping output levels and TFP of GVCs constant in all simulations; that is, the simulation results are solely due to the changes in the labour input requirements per unit of output. In this way, we can cleanly compare the three effects without the confounding effects of final output and factor neutral technology growth across GVCs.[21]

The three simulated effects are reported in Table 3 for low-, middle- and high-educated workers for each of the forty economies in our data set. The economies are ordered from poor to rich based on GDP per capita levels in 1995 (at current PPP from Feenstra et al., 2015). We discuss the results for each labour type in turn. The first three columns report the effects on GVC employment of low-educated workers. We have three findings. First, countries with a positive reallocation effect all rank amongst the lowest in income. Vice versa, most rich countries have negative reallocation effects in low-skilled employment (with the exception of Denmark). The negative effect for Mexico, Turkey

[21]Ideally, one would like to model the effects of substitution and technical change in GVCs on final output prices, and subsequently trace the effects on global demand for output of each GVC. This requires a full general equilibrium setting along the lines of, for example, Goos et al. (2014) extended through the inclusion of cross-country production linkages.

and the Baltic states is surprising, as they are relatively poor but did not appear to benefit from job reallocation within GVCs. Second, the factor bias effect negatively affected demand for low-educated workers in all countries and is quantitatively important, consistent with our finding of a strong bias in GVCs. The factor bias effects differ across countries as we use estimates of the bias that differ across GVCs, and countries differ in the weight of each GVC in their overall GVC employment (the N_{cp}^{E}/N_{c}^{E} weights in Equation 15). Third, the factor substitution effect is positive for almost all countries and regions (except Denmark, Portugal and Taiwan) as the relative wages of low-educated workers declined in most GVCs. The effect is typically small compared to the (absolute) effects of reallocation and technical change.

Taken together, the simulation results suggest that demand for low-educated GVC workers in rich countries was strongly reduced due to the effects of reallocation and of factor bias. The positive substitution effects are typically much smaller and cannot compensate. Heterogeneity in middle-income and low-income countries is high, however. China is the only country that benefitted massively from reallocation (49 per cent growth), reflecting its unique position as the prime offshoring location in the world economy in the period studied. This positive effect of reallocation more than compensated for the negative effects of the factor bias (−31 per cent). Brazil, Bulgaria and Indonesia also benefitted from job reallocation, but the positive effects of reallocation and substitution are greatly reduced by the negative effect of the factor bias. In India and Romania, the combined positive effects of reallocation and substitution are not even enough to compensate for the negative factor bias. In Mexico, Poland, Turkey and the Baltic states reallocation effects are even negative on top of the negative effects of the bias. It is important to note that this does not mean that the number of low-educated jobs in GVCs in a country like India has declined. It has actually increased because output of GVCs increased rapidly over this period, while the simulation assumes no output growth. The finding does indicate however that the number of jobs per unit of output declined strongly due to technical change bias. We conclude that the bias against low-educated work in GVCs is quantitatively important and is muting the potential of GVCs to generate demand for low-skilled jobs in low-income countries.

The last three columns of Table 3 report the effects on demand for high-educated workers in GVCs. The factor bias effect is strongly positive for all countries, consistent with our finding of a major bias in favour of high-skilled work in GVCs. The substitution effect is negative in most countries as the relative price of high-skilled work has increased in most GVCs, shifting demand to middle- and low-educated workers. The substitution effect is only small relative to the effect of factor bias. The effect of reallocation varies widely across countries depending on whether they are (net) receivers or senders of high-skilled jobs. The effect was negative for most advanced countries but not for all, consistent with the finding that firms in advanced countries relocate jobs for high-educated workers also towards other advanced economies (Fort, 2017). Most low-income countries benefitted greatly from the positive effects of the high-skill factor bias as well as reallocation, including India (31 and 74 per cent growth, respectively), China (39 and 54 per cent growth), Indonesia (32 and 53 per cent growth) and Brazil (31 and 56 per cent growth).

The effects on demand for middle-educated workers in GVCs are reported in columns 4–6 of Table 3. The factor bias effect is mostly moderate, consistent with our result of not finding a significant bias for middle-educated work in GVCs. Also the substitution effects are typically small, and mostly negative as the price of middle-educated work increased relative to low-educated work (see Figure 3). The effect of reallocation is (much) bigger than the effects of substitution and factor bias in most countries. For example, it is strongly negative for Germany and the United States, reinforcing the negative factor bias effect. It is positive for most low-income countries, and strongly so, dwarfing the effects of substitution and factor bias. For example, the effect of reallocation on demand for middle-educated

TABLE 3 Simulated Growth of GVC employment in a country during 1995–2007 due to reallocation, substitution and biased technical change in GVCs (%)

	Low-educated			Middle-educated			High-educated		
	Reallo	Subst	Bias	Reallo	Subst	Bias	Reallo	Subst	Bias
India	6.2	8.1	−26.9	27.3	−3.3	0.9	73.5	−2.8	31.4
China	49.1	12.3	−31.3	28.2	−5.3	−1.5	54.3	−1.8	38.6
Indonesia	22.7	10.7	−30.4	42.6	−3.7	1.2	52.6	−2.4	31.7
Romania	6.9	10.2	−27.4	6.3	−6.3	7.4	−11.2	−1.5	37.6
Lithuania	−44.1	7.0	−26.6	−45.5	−4.5	2.7	−44.6	−2.1	37.9
Latvia	−26.9	12.1	−27.3	−29.3	−4.6	0.0	−43.5	−3.5	36.0
Brazil	23.8	7.5	−26.1	153.3	−2.9	0.7	55.5	−2.5	31.3
Bulgaria	23.7	9.5	−27.3	35.5	−6.4	8.6	38.1	−2.3	37.1
Estonia	−27.3	11.5	−27.4	−39.3	−4.5	0.3	−48.3	−3.0	36.1
Mexico	−5.0	7.0	−17.6	53.5	0.5	−4.3	3.7	−5.3	24.7
Turkey	−30.3	9.5	−24.7	75.0	−5.5	4.3	78.7	−3.2	34.6
Poland	−32.2	7.6	−23.0	9.4	−3.5	−0.4	67.5	−2.4	32.2
Russian Federation	−50.1	9.9	−27.9	−32.2	−4.4	3.3	−33.5	−2.1	33.6
Hungary	−3.1	9.1	−23.4	17.2	−4.4	1.8	13.0	−2.3	34.9
Slovakia	−39.8	8.7	−21.1	10.1	−3.8	0.4	0.6	−2.1	34.9
Malta	−47.1	9.1	−28.6	−33.1	−5.9	9.6	−34.6	−1.7	38.4
Portugal	−2.9	−3.7	−16.4	−1.7	9.4	11.8	−5.0	6.5	42.1
Czech Republic	−23.3	8.9	−19.8	−2.5	−3.0	−1.8	−15.9	−2.9	30.8
Republic of Korea	−58.4	31.9	−43.6	−19.0	−8.9	−4.4	−3.2	−6.9	40.4
Greece	−25.8	5.9	−34.6	−4.2	−11.2	30.5	−1.5	−2.2	41.0
Slovenia	−28.7	8.9	−23.7	−11.1	−5.4	4.7	1.3	−1.9	35.6
Spain	−22.9	3.7	−31.8	2.2	−4.6	25.2	1.7	−2.8	43.1
Cyprus	−5.8	13.3	−32.2	0.9	−6.2	2.9	−25.1	−3.5	36.7
Ireland	−21.3	4.5	−30.4	−27.8	−0.5	−7.8	−8.9	−5.9	55.8
Finland	−33.2	17.7	−32.4	−8.3	−5.7	5.3	−17.1	−6.7	26.2
Taiwan, China	−7.4	−1.0	−24.9	4.3	0.8	7.9	7.2	2.5	30.9
France	−28.8	6.4	−29.9	−16.5	−3.9	2.8	−7.2	−0.7	32.1
United Kingdom	−33.3	11.0	−34.6	−17.6	−3.6	2.3	−8.4	−5.8	38.9
Italy	−15.3	10.9	−33.8	5.1	−14.3	30.5	9.3	0.5	52.0
Sweden	−42.6	15.1	−32.0	−18.1	−6.3	1.2	−4.0	−1.0	43.5
Netherlands	−5.9	18.5	−25.1	14.5	−10.2	−5.2	21.8	−0.2	47.6
Belgium	−31.9	12.5	−33.2	10.1	−7.8	9.8	−11.0	−0.8	32.9

(Continues)

TABLE 3 (Continued)

	Low-educated			Middle-educated			High-educated		
	Reallo	**Subst**	**Bias**	**Reallo**	**Subst**	**Bias**	**Reallo**	**Subst**	**Bias**
Denmark	13.8	−9.1	−14.3	−19.2	3.7	−11.4	−9.2	1.0	50.0
Germany	−19.1	6.8	−12.6	−15.4	−0.9	−6.2	−17.0	−2.7	24.2
Australia	−18.7	3.0	−23.9	−9.5	−1.0	5.6	−11.3	−3.1	41.7
Austria	−24.5	11.8	−22.1	−11.0	−3.5	−6.1	5.2	−1.5	52.8
Canada	−57.3	37.6	−23.6	−14.3	−3.4	−4.1	−0.7	−2.0	27.4
Japan	−23.7	8.0	−45.0	0.2	−2.6	3.1	−1.3	−0.1	28.3
United States	−19.1	9.7	−13.6	−16.2	2.2	−7.1	−12.8	−7.0	20.3
Luxembourg	−29.0	11.3	−31.4	3.1	−5.7	7.3	−18.0	−4.8	38.4

Note: Simulation of growth in hours worked (%) by GVC workers of a particular type in a given country or region. Entries report the simulated growth due to the effects of reallocation of jobs of a given type across countries within a GVC (*Reallo*), the effects of substitution between worker types in a GVC (*Subst*), or the effects of bias in technical change (*Bias*). Based on 273 GVCs of manufacturing products. Calculated on the basis of Equation (15) imputing the actual change in the period 1995–2007 for one element, while keeping the other elements constant at the 1995 levels, as described in main text. Estimated substitution elasticities and biases in technical change in GVCs derived from regression (7) in Table 1, combined with data on GVC wages and employment across countries as described in subsection 3.A. Countries and regions are sorted from poor to rich on basis of real GDP per capita in 1995 (GDP(e) at current PPP from PWT, Feenstra et al., 2015).

workers in India is 27 per cent, compared to a bias effect of 1 per cent and a substitution effect of −3.3 per cent. A similar pattern is observed for Brazil, China, Indonesia, Mexico and Turkey.

6 | CONCLUDING REMARKS

In this paper, we analysed for the first time changes in labour demand in global value chains. We uncovered that technical change in the global production of manufacturing goods has a major factor bias, driving down relative demand for low-educated workers throughout the chain. We also showed that the effect of the unskilled bias in technical change is quantitatively important compared to the effects of substitution across worker types and reallocation of workers across countries within GVCs. To be clear, our findings do not deny that GVC participation and associated technology flows allow poor countries to increase productivity, the scale of production and demand for local employment. But they do suggest a limited capacity of industrialisation to absorb the abundance of low-educated workers in low-income countries, in line with the hypothesis of Rodrik (2018).

Our results carry various policy implications and suggest avenues for further research. First, the unskilled bias tempers hope to bring back unskilled jobs to rich countries through reshoring of manufacturing activities. Our results suggest that a sizeable part of the unskilled jobs that were offshored in the past decades have been substituted for by more skilled workers and capital. Baldwin 2019 suggest that rapidly increasing efficiency in automation drives the use of robots for production stages that are brought back in high-income countries. Graetz and Michaels (2018) find that introduction of robots reduced the employment share of low-skill workers in high-income countries, but only had a small effect on total employment. In a related work, Blanas et al. (2020) make explicit distinction between ICT hardware, software and robots. Their results are consistent with the view that ICT hardware makes humans more productive, while software and robots can render them redundant, at least in some occupations (Acemoglu & Restrepo, 2018). Deeper insights into patterns of substitution and complementarity in GVC production require more specific measures of technology adoption in low-income countries, such as use of computer-aided manufacturing and robots. We expect this to be a fruitful avenue for further research in particular when combined with information on the occupational structure of production in GVCs along the lines of Reijnders and de Vries (2018) and de Vries et al. (2020).

Second, our results suggests that lower income countries must upgrade their labour force to meet the requirements of today's global production systems. In GVCs, customised parts and components are exchanged across parties in different countries, often under incomplete contracting. As a result, GVCs typically involve longer-term relationships between firms that are particularly conducive for transfer of information and technology needed in making a product or providing a service. Putting the relational nature of firms in GVCs centre stage is instrumental in better understanding these dynamics (Antràs, 2020; Gereffi et al., 2005). To control production, multinational lead firms in a GVC may dictate product specifications and stringent requirements for flexibility, quality and speed of production (Gereffi, 1999; Nadvi, 2008; Verhoogen, 2008). In addition, there are increasingly demanding standards that relate to consumer health and safety as well as to wider social, environmental and ethical concerns about the production process. Case studies show that compliance with these international standards is nowadays crucial for successful participation in global production networks (An & Maskus, 2009; Medin, 2019; Nadvi, 2008). Meeting these standards might foster the adoption of technology that will drive down reliance on unskilled workers in favour of more tightly controlled activities by machines, robots and skilled operators. More generally, new technology might steadily erode the comparative advantage of poor countries, raising the need for alternative development strategies. Further research into the mechanisms that drive technical change in GVCs is warranted to properly gauge the potential of GVC participation for unskilled job growth in lower income countries.

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ORCID

Marcel P. Timmer https://orcid.org/0000-0001-6397-4417

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SUPPORTING INFORMATION

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