GGDC RESEARCH MEMORANDUM *164*

Offshoring, Biased Technical Change and Labor Demand: New Evidence from Global Value Chains

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

October 2016

university of groningen

groningen growth and development centre

Offshoring, Biased Technical Change and Labor Demand: New Evidence from Global Value Chains

Laurie S. M. Reijnders, Marcel P. Timmer and Xianjia Ye*

October 2016

Abstract

Until now, it has not been possible to identify factor bias in technical change in the presence of offshoring. We present a novel approach to measure such biases in global value chains. In this approach, final output is mapped to labor and capital employed at any stage of production, in any country. We analyze changes in factor cost shares and find robust evidence of a bias in favor of college-educated workers and capital, and against non-college educated workers. Simulations suggest that offshoring and biased technical change contribute equally to the decline in employment of non-college educated workers in advanced countries.

JEL: J21, F66, E23, O47

*Reijnders, Timmer and Ye: Groningen Growth and Development Centre, Faculty of Economics and Business, University of Groningen, P.O. Box 800, 9700 AV Groningen, The Netherlands; l.s.m.reijnders@rug.nl, m.p.timmer@rug.nl and x.ye@rug.nl. Financial support from the Dutch Science Foundation (NWO) for Reijnders and Timmer is gratefully acknowledged (grant number 453-14-012). We are grateful to Ingvild Almås, Angus Deaton, Erwin Diewert, Giovanni Dosi, Robert Feenstra, Maarten Goos, Jonathan Haskel, Dale Jorgenson, Robert Johnson, C.A. Knox Lovell, Filip Matějka, Branko Milanović, Peter Neary, D.S. Prasada Rao, Robin Sickles and many seminar participants at University of California at Davis, Princeton University, Royal Economic Society Meeting in Brighton, Scuola Superiore Sant'Anna in Pisa, Tor Vergata Rome, University of Maastricht, Higher School of Economics Moscow, European Central Bank, University of Gent, University of Göttingen, CERGI-EI Prague, ETSG 2016 in Helsinki and University of Queensland for stimulating comments and discussion on an earlier version of this paper

I. Introduction

There is a general consensus among economists that biased technical change and offshoring are two important drivers of increasing skill premia and job polarization in advanced economies. At the same time there is considerable uncertainty about their relative importance as they are typically not separately observed. To see this, suppose that a firm's production technology does not change, but it decides to relocate unskilled production stages abroad. As a result, the use of unskilled workers at home declines. Alternatively, suppose that there is no offshoring, but a change in technology biased against the use of unskilled work, for example through automation. The impact on demand for domestic labor is comparable in both cases such that the effects of offshoring and biased technical change are observationally equivalent. However, for many theoretical as well as empirical questions we would like to be able to distinguish between these two drivers of factor demand (Feenstra and Hanson 2003).

The aim of this paper is to solve the observational equivalence problem. It builds upon the key insight that in the presence of offshoring, biases in technical change can only be observed when analyzing all stages of production, both at home and abroad. Following Antràs and Chor (2013) we refer to a vertically integrated production process that spans multiple countries as a global value chain (GVC from hereon). To frame our empirical work, we develop a basic model where GVC production needs several types of tasks. Each type requires the input of a single factor and can take place at home or abroad. We define a task price as the price paid for the factor that carries out the task, averaged across all countries that participate in a particular GVC. Given task prices, a firm chooses the intensity with which each of the tasks is performed within the GVC. We derive the optimal task demands and the corresponding factor cost shares and show how these are affected by the interplay of task allocation across countries, national factor prices and biases in technology.

To bring the model to the data we use newly available information from the World Input-Output Database (WIOD, see Timmer et al. 2015). We show how the WIOD data can be used to measure the factor content of domestic as well as offshored stages of production. We document changes in factor cost shares and task prices for a set of 291 GVCs of manufacturing goods during the period from 1995 to 2007. This new type of information is critical for our analysis. We use a system of GVC cost share equations to estimate task price elasticities and biases in technical change. In contrast to traditional analyses based on data for domestic stages of production only, we do not need to control for the effects of offshoring in our regressions as both domestic and foreign factor uses are already accounted for. We find robust evidence for a strong bias in technical change in favor of capital and college educated workers, and decidedly against non-college educated workers. This is our key finding and we show that it is robust to various alternative specifications. We also show that use of information technology in a GVC can explain a major part of the bias against less educated workers. This confirms the routinization hypothesis by Autor, Levy and Murnane (2003) which states that information technology substitutes for workers performing routine tasks. Finally we use our estimation results to analyze the effects of technical change and offshoring on the use of labor from advanced countries in GVC production. Based on a simple simulation exercise, we find that both forces had quantitatively similar effects on driving down demand for non-college educated workers.

Our approach builds upon an extensive literature that studies the effects of offshoring and biased technical change (BTC from hereon) on domestic factor demand.[1] In recent research Goos, Manning and Salamons (2014) exploited new data on the occupational structure of the labor force and claimed that the effects of technical change on labor demand were stronger than the effects of offshoring. They found evidence in favor of the routinization hypothesis for a wide set of advanced countries. In related cross-country work, Michaels, Natraj and Van Reenen (2014) used information on educational attainment levels of workers and showed that medium-educated workers were most affected by technical change. In particular, they found a limited role for offhshoring. Firpo, Fortin and Lemieux (2011) estimated an empirical wage setting model and found that automation of routine-tasks (as well as de-unionization) drove the wage distribution in the US in the 1980s and 1990s, while offshoring became an important driver only from the 1990s onwards.

To overcome the observational equivalence problem, the typical strategy in these studies is to add indicators that measure the potential for jobs to be offshored and the potential for them to be replaced by technology. However, these proxy indicators appear to be strongly positively correlated such that econometric identification of their separate effects is hampered. This is well known since many of the jobs that are potentially prone to be affected by technical change, are often also more likely to be offshored (Blinder and Krueger 2013). Based on data for US multinationals, Oldenski (2012) provided direct evidence that

1. See Acemoglu and Autor (2011) and Harrison, McLaren and McMillan (2011) for discussions of the literature.

routine-task intensive jobs are indeed more likely to be outsourced to a foreign affiliate. Rather than organising a "horse race" between indicators of *potential* offshoring and BTC, we will control for *actual* offshoring and thus provide a clean route to measure the labor demand effects of *actual* BTC.

Our econometric framework is closest to that of Michaels, Natraj and Van Reenen (2014) and Hijzen, Görg and Hine (2005). We follow them in employing a flexible translog cost function in which the price elasticities and BTC are unknown parameters that can be estimated from observable data on factor prices and cost shares. We also follow them by adding an indicator for the use of information technology in order to speak to the routinization hypothesis. We extend their approach and solve the observational equivalence problem by analyzing global value chains rather than single production stages. Put otherwise, we will investigate BTC in a final good production function including all stages of production, and not through a value added production function that only captures a single stage of production. In addition, we explicitly model the demand for capital as well as for labor. Typically, past studies on BTC rely on variation in demand across labor types as the main channel for identification, with no explicit role for capital inputs. At the same time there is abundant evidence on the strong decline in the relative price of investment goods and associated substitution of capital for labor, as studied in Krusell et al. (2000) and Karabarbounis and Neiman (2014). As both jobs and machines are prone to be shifted across borders, we develop an empirical framework that encompasses labor as well as capital.

Naturally, while trying to generalize the study of technical change in the presence of offshoring, we have to restrict ourselves in other dimensions. These are worth stressing at this point. Firstly, we take observed factor prices as given. To assuage possible concerns about endogeneity, we also provide alternative estimations based on instrumental variable techniques and show that the main results on the biases in technical change are robust. Secondly, our analysis only includes employment in the production of final manufacturing goods. Averaged across our set of advanced countries, this makes up about a quarter of the labor force in advanced countries. We are thus not able to account for various general equilibrium effects that may determine overall labor demand (see Goos, Manning and Salamons 2014). Thirdly, we characterize workers by educational attainment. Autor, Dorn and Hanson (2015), in a study of local labor markets in the US, found that the impact of imports from China and technology shocks differs across subnational, occupational, sectoral as well as demographic groups.

The remainder of this paper is organized as follows. Section II describes data construction and sources. Section III documents the changing characteristics of GVC production, and illustrates the richness of data we have to quantify BTC. Section IV outlines a simple model of GVC production and introduces the final good production function which motivates our econometric approach to measure BTC. In section V we present our main results and show their robustness to various estimation alternatives. Equipped with the new estimates, we compare the effects of offshoring and BTC on labor demand in advanced countries in section VI. Section VII concludes.

II. Data Construction and Sources

To derive the contribution of domestic and foreign factors to the production of final goods we build upon a method developed earlier in Valentinyi and Herrendorf (2008) and Los, Timmer and de Vries (2015).[2] Valentinyi and Herrendorf (2008) distinguished between a value-added production function and a final goods production function. The value-added function describes the technology of a single stage of production whereas the final goods function describes the technology encompassing all stages of production. The general idea in deriving the final goods production function is to net out intermediate inputs using information on the input-output structure of the world economy. Valentinyi and Herrendorf (2008) applied this idea in a domestic setting, and Los, Timmer and de Vries (2015) generalized this to an international setting such that one can map final output into value added generated domestically as well as abroad. Here, we extend the approach even further and break down value added into the contribution of various production factors such that we can analyze factor substitution and BTC in GVCs.

Cost shares and factor prices in GVCs are two key variables in our framework. They are not directly observable in primary data and we will construct a synthetic dataset by mapping final goods to value added by labor and capital in any country in the world. This ex-post accounting framework is based on backward tracing through the production chain of final products to identify the sources of value added. More formally, consider a world with countries $c = 1, \ldots, C$ and sectors $s = 1, \ldots, S$ such that there are CS country-sector pairs. The GVC of a final product, indexed by v, is identified by the country and sector where the last stage of production takes place. We start by finding the levels of gross

2. In turn, this is grounded in the older literature on input-output accounting with multiple regions going back in particular to work by Miller (1966), and surveyed in Miller and Blair (2009).

output in all country-sectors that are associated with the production of one US dollar of final output of v ($\mathbf{y}_v$). This is given by (see, e.g. Miller and Blair 2009):

$$\mathbf{y}_v = (\mathbf{I} - \mathbf{A})^{-1}\mathbf{z}_v, \tag{1}$$

where $\mathbf{A}$ is the matrix of global intermediate input coefficients with element (a, b) describing the intermediate inputs sourced by country-sector b from country-sector a as a share of b's gross output, and $\mathbf{I}$ is an identity matrix of the same size ($CS \times CS$).[3] $(\mathbf{I} - \mathbf{A})^{-1}$ is the so-called Leontief inverse, the use of which ensures that factor contributions in upstream suppliers are taken into consideration. $\mathbf{z}_v$ is a column vector ($CS \times 1$) with the element corresponding to GVC v equal to one while all other elements are set to zero.

In a second step, the gross output requirements are translated into factor demands. Let $\mathbf{f}_j$ be a column vector ($CS \times 1$) with elements indicating the payments to factor j per dollar of gross output for each of the country-sectors. Then:

$$\mathbf{g}_{jv} = \mathrm{diag}(\mathbf{f}_j)\mathbf{y}_v. \tag{2}$$

Here, $\mathbf{g}_{jv}$ is the vector of factor costs with elements $\mathbf{g}^{cs}_{jv}$, indicating the payment to factor j in each country-sector (c, s) that is involved in value chain v, expressed as a share of overall costs of v. The cost share of factor j in v (s_{jv}) is a simple summation of its payments in contributing country-sectors:

$$s_{jv} = \sum_c \sum_s g^{cs}_{jv}. \tag{3}$$

This procedure is repeated for each of the production factors to determine their cost share in a given GVC.

The same method can be used to derive the quantities, rather than the value, of factor j needed in the production of v, which we denote by q^{cs}_{jv}. Let the elements of $\mathbf{f}_j$ in equation (2) refer to the quantities of factor j required per dollar of output in a country-sector. Again summing across all country-sectors, we can derive the total quantity of factor j needed in the production of one dollar of v:

$$q_{jv} = \sum_c \sum_s q^{cs}_{jv}. \tag{4}$$

3. Matrices are indicated by bold capital symbols and vectors by bold lowercases.

Finally, we define the price paid for work carried out by factor j by dividing cost through quantity:

$$p_{jv} = \frac{s_{jv}}{q_{jv}}. \tag{5}$$

We will refer to these prices as GVC task prices from hereon as they reflect the average price paid for tasks carried out by factor j in a particular GVC, assuming tasks are factor-specific (see section IV). Task prices will differ across GVCs and over time, due to changes in factor prices in each country as well as reallocation of production stages across countries. This variation will allow us to identify elasticities and BTC in our econometric framework, to be introduced in section V.

For empirical implementation we use the World Input-Output Database (WIOD) which contains annual information on interindustry flows of goods and services across 35 sectors and 40 countries for the period 1995-2011 (Timmer et al. 2015). All variables are in current US dollars based on official exchange rates. Sectors correspond to 2-digit industries in the International Standard Industrial Classification (ISIC, revision 3) and cover the whole economy; a detailed list is provided in Appendix C. It also contains an estimate for the "Rest-of-the-world" region such that all production and trade flows in the world are accounted for. This ensures that the mapping from final output to value added is exhaustive and includes all factors involved in production, which is crucial for our purposes.

We use additional information on the quantity and cost shares of factor inputs also provided in the WIOD at the country-sector level. Workers are characterized on the basis of educational attainment according to levels defined in the International Standard Classification of Education (ISCED).[4] In our baseline analysis we focus on the demand for two types of workers: college educated and above (ISCED categories 5 and 6), and below college (ISCED 0 to 4). In an additional analysis we split the latter into those without a high-school diploma (ISCED 0, 1 and 2) and those with at least a high-school diploma but no college degree (ISCED 3 and 4). Data on hours worked and wages is provided, including imputations for self-employed and family workers. Capital income is derived as a residual and defined as gross value added minus labor income. Defined this way, the sum

4. This procedure ensures that international comparability of worker categories is maximized. The implicit assumption is that cross-country wage differences for a worker with a given educational attainment type reflect factor price variation. Nevertheless, there may be differences in the quality of schooling within, or even across, ISCED levels. Differences in labor quality not related to formal education are notoriously hard to measure.

of factor incomes will be equal to value added in each sector as required for our mapping.[5] Capital quantity is measured as the stock of fixed reproducible capital at constant prices and covers machinery as well as buildings. Appendix C provides further detail on the data sources.

Throughout this paper we will provide analyses for GVCs of manufacturing products.[6] Production of manufacturing goods is characterised by strong international fragmentation trends, in particular in the 2000s as documented in Los, Timmer and de Vries (2015). Importantly, the GVC of a manufactured good contains value added from manufacturing industries, as well as from services and other sectors. For example, a T-shirt is a final product from manufacturing but contains value added that is produced in agriculture (e.g. the growing of cotton), in manufacturing (e.g. weaving), as well services (e.g. logistics).[7]

The WIOD (November 2013 release) contains data from 1995 up to 2011. We restrict our analysis to the period up to the global financial crisis as the identification of long-term trends might be obscured by the volatile trade patterns after 2007 (Bems, Johnson and Yi 2013). All in all, we have a panel of 291 global value chains of 14 final manufacturing products that end in 21 advanced countries, including fifteen European countries, Australia, Canada, Japan, South Korea, Taiwan and the US.[8] It should be kept in mind however that the factor inputs in these GVCs can come from *any* region in the world as the World Input-Output Database covers bilateral trade flows across all countries, including major emerging economies such as Brazil, China, India and Mexico (see Appendix C).

5. This implies that capital costs include possible mark up or pure profit components. Ideally these need to be separately evaluated and may contain trends, but they are notoriously hard to measure in particular at a disaggregated industry level needed for GVC analysis (see e.g. Karabarbounis and Neiman 2014).

6. Fragmentation of services production is generally much more difficult due to a higher customisation of the end product and the localized nature of many services delivery. Moreover, the data on services production in the WIOD is much less detailed than for manufacturing.

7. This mapping of final output of a product into value added from multiple sectors is also stressed in analyses by Johnson and Noguera (2012) and Herrendorf, Rogerson and Valentinyi (2013).

8. To be precise, we do not have data on individual products, but on the total output of final products from a particular manufacturing industry in a particular country (for example final output from transport manufacturing in Germany), see Appendix C for a list. For convenience we refer to these as "products". In principle we have data on 14 products times 21 countries which would correspond to 294 GVCs, but three industries in Luxembourg have zero final output so we have 291 GVCs left. We use annual data for the period 1995-2007, except 2003 (see Appendix C). 34 of the GVC observations have a negative return to capital, such that the actual number of observations that are used in the panel regressions is (at maximum) $3,496$.

III. The Changing Characteristics of Global Value Chain Production

Using the data constructed as discussed above, we document changes in the characteristics of GVC production for the period 1995-2007. We present trends in three sets of variables: foreign value added shares, relative task prices and factor cost shares. As annual trends have been largely monotonic throughout the period of investigation we report on changes over the full period 1995-2007 only (annual data is available upon request from the authors).

A. The Share of Foreign Value Added in GVCs

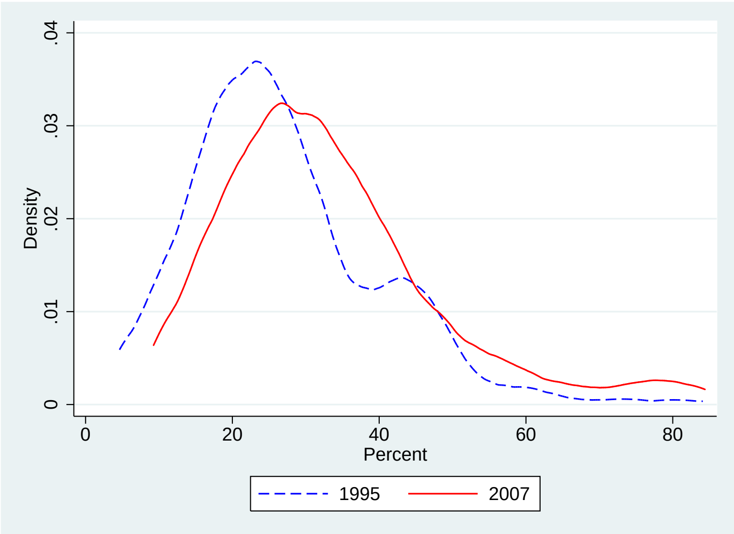

Figure 1: Foreign Value Added Share in GVCs,
1995 and 2007 (in percent)

Notes: Kernel density of foreign value added shares in final output of a GVC calculated according to equation (6). There are 291 observations for GVCs of manufacturing products.

Figure 1 provides evidence for the strong trend in offshoring by advanced countries in the production of manufacturing goods since 1995. We define offshoring as the amount of value added that is generated outside the country-of-completion (that is, the country were the final stage of production of a GVC takes place). Assuming that GVC v ends in country c we can define the foreign share as follows:

$$s_v^{\mathrm{FOR}} = 1 - \sum_j \sum_s g_{jv}^{cs}. \tag{6}$$

This share can be considered as a new measure of offshoring. It is a more general measure than the ratio of imported intermediates over gross output as suggested in Feenstra and Hanson (1999) as it also includes the imported content of domestically produced intermediates. The figure shows the Kernel density of the foreign shares in our set of GVCs for 1995 and 2007. Foreign value added is generally higher for products such as gasoline (as many countries have to rely on imports of crude oil) and electronics, the paragon of GVC production. It is also higher for GVCs ending in smaller countries, presumably as there is a lesser variety of domestic intermediates available for producers in these countries. But the offshoring trend is widely shared across products and countries, as evidenced by the shift of the distribution to the right. Foreign value added shares increased in 248 out of 291 GVCs. Across all GVCs the average share increased from 27.0 percent in 1995 to 33.0 percent in 2007, an increase of 6.0 percentage points. Weighted with log output, the mean increase is even higher at 6.5 percentage points, as offshoring was strongest for products finalised in major countries such as Germany, Japan and the US.

B. GVC Task Prices

For our analysis of factor biases in GVCs, we are interested in the average price paid for factor use across all production stages as defined in equation (5) which we called GVC task prices. Figure 2 shows the Kernel density plot for the (log) change in average task prices in our set of GVCs over the period 1995-2007. It plots the price changes of an hour of a non-college task (solid line) relative to capital, and similarly for a college task (dotted line). The prices paid for an hour of a non-college task have declined relative to prices for a college task by on average 8.4 log points (either unweighted or weighted by log output). The figure also shows that both labor tasks have become more expensive relative to capital tasks. The average price paid for capital tasks declined by 5.3 log points relative to non-college tasks and 13.7 log points relative to college tasks. This trend accords well with the finding of a rapid decline in prices of investment (in particular of equipment) relative to labor in many countries (both advanced and emerging).

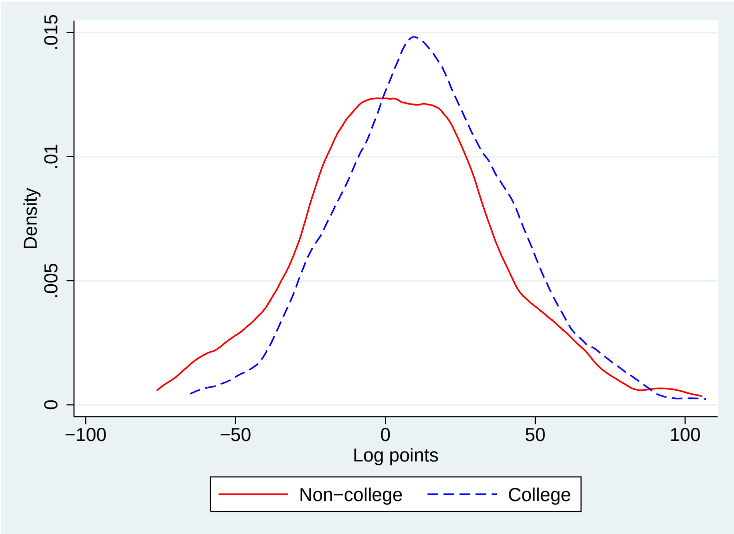

Figure 2: Change in Relative Task Prices in GVCs, 1995-2007 (in log points)

Notes: Kernel density of change in task prices of college and non-college educated labor in GVCs over the period 1995 to 2007, calculated according to equation (5). Changes are relative to price change of capital. There are 291 observations for GVCs of manufacturing products.

C. Factor Cost Shares in GVCs

Figure 3 shows changes in the factor costs shares of production factors in GVCs. The shares are expressed as a percentage of total value added in the GVC as in equation (3). The cost shares of college educated workers and of capital increased rapidly, while non-college educated workers' shares declined strongly. This is a pervasive pattern and found for 280 out of 291 GVCs in the case of non-college educated workers (on average 8.2 percentage points decline) and similarly in 280 GVCs for college educated workers (on average 4.4 percentage points increase). At the same time we find an increasing capital cost share in 223 GVCs, with on average a 3.8 percentage points increase.[9] Based on this we conclude that international production cannot be characterised by a Cobb-Douglas function with

9. It might be noted that by construction the costs for capital in a GVC include all residual profits (quasi-rents) in the chain irrespective of the territory where the profits are registered. In a situation of profit shifting across locations in a GVC, e.g. for tax reasons, analyses of production based on national data will be affected, but analyses based on GVC data will not. This is an advantage of a GVC-based analysis of factor biases in technical change. However, both types of analysis will be affected by situations of profit shifting to locations that are not actually involved in production.

constant factor shares. This finding complements Karabarbounis and Neiman (2014), who document a decreasing trend of the labor share across a large set of countries and sectors. We show here that this also holds true for GVCs that combine value added from many different sectors and countries.[10] In addition the figure shows that this decline is solely due to a declining cost share of non-college educated workers.

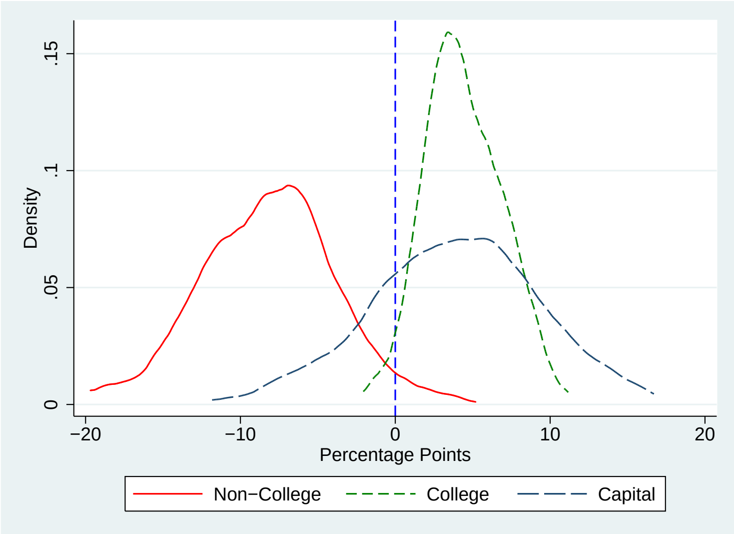

Figure 3: Change in Factor Cost Shares in GVCs, 1995-2007 (in percentage points)

Notes: Kernel density of change in cost shares in GVCs for three factors: college and non-college educated labor and capital. Change over the period 1995 to 2007, calculated according to equation (3). There are 291 observations for GVCs of manufacturing products..

We will exploit our new information on GVC production to jointly estimate price elasticities and biases in technical change in a flexible econometric framework that allows for non-constant factor shares in section V. We will show that the large changes in relative task prices can only explain a minor part of the changes in factor cost shares, such that there must have been sizeable biases in technical change. To motivate this approach we will first outline a simple model of international production.

10. The finding by Karabarbounis and Neiman (2014) does not imply this as long there are differences in the *level* of the capital share across countries (and sectors). Capital shares might increase in each stage of the GVC, but the capital share in the overall GVC will also depend on possible shifts in value added between stages such that it may be non-increasing at the aggregate.

IV. A Task-Based Model of GVC Production

We model a representative cost-minimizing firm that faces the possibility to offshore production tasks along the lines suggested by Grossman and Rossi-Hansberg (2008). Assume that the production process of a (single final product) firm makes use of three types of tasks. Each of these requires the input of a single production factor, either capital (indexed by a subscript K), non-college labor (N) or college-educated labor (H). The set of tasks of each type is given by a continuum that is normalized to unity. We assume that each task requires the same amount of the corresponding production factor, irrespective of where they are performed. The firm chooses the total amount of factor j that is used for each task, which we denote by I_{jv} (Grossman and Rossi-Hansberg (2008) refer to this as the 'task intensity'[11]). The unit cost of I_{jv} is given by:

$$p_{jv} = \sum_c x^c_{jv} p^c_{jv}. \tag{7}$$

We refer to p_{jv} as the 'task price' for factor j in GVC v. The task price is a weighted average of the corresponding factor prices in each country p^c_{jv}, where the weights x^c_{jv} reflect a given task division across countries. That is, x^c_{jv} is the share of the continuum of tasks performed in country c so that $\sum_c x^c_{jv} = 1$. Importantly, task prices will vary across GVCs as well as over time. As tasks move to lower-cost locations, the task price faced by the firm will decline (ceteris paribus country-specific factor price developments). In order to avoid cluttering notation, we refrain from using a time index at this stage.

Taking the task price vector $\mathbf{p}_v = \{p_{Kv}, p_{Nv}, p_{Hv}\}$ as exogenously given, the cost-minimization problem of the firm for a given level of output Y_v is given by:

$$\min\left[p_{Kv}I_{Kv} + p_{Nv}I_{Nv} + p_{Hv}I_{Hv}\right] \quad \text{subject to} \quad F_v(I_{Kv}, I_{Nv}, I_{Hv}, A) = Y_v, \tag{8}$$

where the production function F_v depends on the level of technology A and features constant returns to scale with respect to task intensities. The cost-minimizing choice of factor

11. To be precise, Grossman and Rossi-Hansberg (2008) define the task intensity a_{jv} as the factor use per unit of output. Hence $I_{jv} = a_{jv} Y_v$ where Y_v is the level of output.

inputs should satisfy the following first-order conditions:

$$\frac{F_{vN}(I_{Kv}, I_{Nv}, I_{Hv}, A)}{F_{vK}(I_{Kv}, I_{Nv}, I_{Hv}, A)} = \frac{p_{Nv}}{p_{Kv}}, \tag{9a}$$

$$\frac{F_{vH}(I_{Kv}, I_{Nv}, I_{Hv}, A)}{F_{vK}(I_{Kv}, I_{Nv}, I_{Hv}, A)} = \frac{p_{Hv}}{p_{Kv}}, \tag{9b}$$

$$F_v(I_{Kv}, I_{Nv}, I_{Hv}, A) = Y_v. \tag{9c}$$

where $F_{vj} \equiv \partial F_v / \partial I_{jv}$ denotes the marginal product of factor j. The first two conditions equate the marginal rate of technical transformation to the ratio of prices for each of the three production factors, while the last condition restates the production constraint. After loglinearizing these equations we can solve them for the relative changes in task intensities:[12]

$$d \ln I_{jv} = \sum_l \varepsilon_{jlv} d \ln p_{jv} + d \ln Y_v - \frac{\partial \ln F_v}{\partial \ln A} d \ln A + \sum_{l \neq j} \varepsilon_{jlv} \frac{\partial \ln [F_{vj}/F_{vl}]}{\partial \ln A} d \ln A, \tag{10}$$

where ε_{jlv} is the elasticity of the demand for factor j with respect to the task price of factor l. This equation shows that changes in task intensities are driven by changes in task prices (first term), the level of output (second term) and technology (the last two terms). The effect of technical change is twofold. First, it increases the Total Factor Productivity (TFP) of all production factors, which implies that for a given amount of output the firm needs less inputs (hence the negative sign in front of $[\partial \ln F_v / \partial \ln A] d \ln A$). This reduction is the same for all factors. Second, there might be a bias in the direction of technical change. According to the definition put forward by Acemoglu (2002), technical change is biased towards the use of factor j at the expense of factor l if it increases the marginal productivity of the former relative to the latter.[13] That is:

$$\frac{\partial [F_{vj}/F_{vl}]}{\partial A} > 0. \tag{11}$$

Equation (10) shows that the total bias in favor or against a given production factor is a weighted sum of the bilateral biases with respect to each of the other factors, with weights given by the cross-price elasticities. If the overall effect is positive then demand for this input increases with biased technical progress, otherwise it decreases.

12. For details see Appendix B.

13. Note that factor-biased technical change is different from factor-augmenting technical change (see Acemoglu 2002).

As before, we let $s_{jv} = p_{jv} I_{jv} / \sum_l p_{lv} I_{lv}$ denote the GVC cost share of factor j. It follows that:

$$d \ln s_{jv} = [1 + \varepsilon_{jjv} - s_{jv}] d \ln p_{jv} + \sum_{l \neq j} [\varepsilon_{jlv} - s_{lv}] d \ln p_{lv} + \sum_{l \neq j} \varepsilon_{jlv} \frac{\partial \ln[F_{vj}/F_{vl}]}{\partial \ln A} d \ln A. \quad (12)$$

Equation (12) shows that changes in cost shares depend on task price developments and possible biases in technical change. As we assume constant returns to scale, changes in output and TFP do not play a role (see Appendix B for derivation and proof). A bias in technical change, on the other hand, increases the cost share of the favored production factor at the expense of the others.

V. Estimating Substitution and Biased Technical Change in GVCs

The key to econometrically test for BTC is to choose a parsimonious but flexible functional form that includes all factors of production and admits a variety of (time-varying) substitution patterns. In line with our theoretical model we therefore choose a translog cost framework that allows for the joint identification of BTC and price elasticities. This general framework allows the substitution elasticities to vary across different pairs of production factors. This is an important advantage in empirical analysis with more than two factor types.[14] We outline this framework in section A. Exploiting time-series variation in factor cost shares and task prices in GVCs, we estimate the baseline model, presenting results in section B. In section C we provide various tests of robustness to alternative regression specifications. In section D we extend the baseline model to test for a specific instance of BTC motivated by the routinization hypothesis.

14. See Jorgenson (1986) for a survey on the standard econometric approach to modelling the rate and biases of technical change. The translog cost function set-up has also been used by Hijzen, Görg and Hine (2005) and Michaels, Natraj and Van Reenen (2014).

A. Econometric Setup

For a particular product v the (log) cost function is given by:

$$\ln C_v(\mathbf{p}_{vt}, Y_{vt}, t) = \alpha + \ln Y_{vt} + \sum_j \beta_{jv} \ln p_{jvt} + \frac{1}{2} \sum_j \sum_l \gamma_{jl} \ln p_{jvt} \ln p_{lvt} + \beta_T t + \frac{1}{2}\gamma_{TT} t^2 + \sum_j \gamma_{jT} t \ln p_{jvt}, \tag{13}$$

where C_v represents total variable cost and is a function of task prices p_{jvt} and output Y_{vt}.[15] We have imposed constant returns to scale which implies $\sum_j \beta_{jv} = 1$ and $\sum_l \gamma_{jl} = 0$ for any j. Symmetry necessitates that $\gamma_{jl} = \gamma_{lj}$. Note that the β_{jv} parameters are GVC-specific.[16] Using Shephard's Lemma, the corresponding cost share equation for task j is given by:

$$s_{jvt} = \frac{\partial \ln C_v(\mathbf{p}_{vt}, Y_{vt}, t)}{\partial \ln p_{jvt}} = \beta_{jv} + \gamma_{jj} \ln p_{jvt} + \sum_{l \neq j} \gamma_{jl} \ln p_{lvt} + \gamma_{jT} t. \tag{14}$$

Since the cost shares sum to one $\sum_j \gamma_{jT} = 0$. Given that we have three types of tasks ($j = K, N, H$) this forms a system of three linear equations, which we estimate using Zellner's iterated seemingly unrelated regression (ISUR). One equation is redundant such that we drop the equation for capital and transform the other equations accordingly, that is, using task prices relative to the price of capital when we perform the estimation. We use the cost share equation restrictions to derive the parameters for capital that are also reported in the regression result tables.[17]

We can compare the empirical specification in (14) directly with its theoretical counterpart in equation (12). Recall that the latter is given in terms of relative changes $d \ln s_{jvt} = ds_{jvt}/s_{jvt}$. We can therefore derive the following relationship between the model parameters

15. We imposed constant returns to scale such that there are no cross-terms of the level of output with factor prices.

16. The constant term $\beta_{jv} = \beta_j + \beta_v$ is the sum of a product and a country fixed effect. Thus we allow for differences in production technologies across GVCs as well as for differences across countries where the last stage of production is located. These dummies are jointly significant at a high level in all regressions.

17. Note that the choice which equation to drop is arbitrary: it does not affect the estimates as we use ISUR.

and estimated coefficients on task prices:

$$\varepsilon_{jlvt} = \frac{\gamma_{jl}}{s_{jvt}} + s_{lvt} \text{ for } j \neq l, \tag{15a}$$

$$\varepsilon_{jjvt} = \frac{\gamma_{jj}}{s_{jvt}} + s_{jvt} - 1. \tag{15b}$$

Hence, from the estimates of γ_{jl} and given the GVC-specific cost shares s_{jvt} we can compute the price elasticities of the demand for factor j with respect to the task price of factor l. The effects of biases in technical change on cost shares are captured by the time trends γ_{jT}:

$$\gamma_{jT} = s_{jvt} \sum_{l \neq j} \varepsilon_{jlvt} \frac{\partial \ln[F_{vj}/F_{vl}]}{\partial \ln A} \frac{d \ln A}{dt}. \tag{16}$$

Note that the γ_{jT} coefficients capture the (weighted) bilateral biases in technical change. To understand the nature of technical change in situations with more than two production factors, it is useful to also separately identify the bilateral terms $[\partial \ln[F_{vj}/F_{vl}]/\partial \ln A] d \ln A$. We will do so using our estimates of the cross-price elasticities.

Finally, we check whether the estimated cost function is consistent with cost minimization behaviour. Cost functions are well-behaved if they are quasi-concave in task prices. This implies that the so-called Hessian matrix of second-order derivatives with respect to task prices must be negative semi-definite. The Hessian matrix is given by $\mathbf{\Gamma} - \mathrm{diag}(\mathbf{s}_v) + \mathbf{s}_v \mathbf{s}_v{}'$, where $\mathbf{\Gamma}$ refers to the symmetric matrix containing all γ_{jl} parameters, and $\mathbf{s}_v$ is a column vector of cost shares of each factor (which is specific for each GVC). When evaluating the eigenvalues at the simple average of the cost shares, we find that they are non-positive for all regression alternatives such that we can be confident that the estimation of our model for GVC production generates economically meaningful results.[18]

B. Baseline Results

In column (1) of Table 1 we report on the baseline regression. All coefficients are significantly different from zero at the 1% level and the model performs well in explaining cost

18. 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 20 out of 3,496 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.

shares for all factors as shown by the high R-squares. The γ_{jl} coefficients can be used to derive prices elasticities according to equations (15a)-(15b). 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. The implied own-price and cross-price elasticities have the expected signs: negative for the former and positive for the latter. In addition, the Morishima elasticities of substitution reveal that capital appears to be a complement for both college and non-college educated workers as elasticities are well below one, which is in line with the general findings in the literature, see Chirinko (2008).[19]

The effect of BTC on cost shares is summarized by the time trends γ_{jT}. The estimates reveal a highly significant bias in the overall effects of technical change against non-college educated labor, and in favor of college-educated labor and in particular capital. This is the total bias, which is a weighted average of the bilateral biases. Given our estimates of the time trend and the price elasticities we can use equation (16) to determine the extent to which technical change is biased towards one type of task at the expense of another.[20] We find that the marginal product of capital tasks has increased yearly by 5.1% relative to non-college tasks and by 0.9% relative to college tasks. Both bilateral biases are positive and contribute to the total positive bias effect. In contrast, for college tasks the two bilateral biases work in opposite directions. The marginal product ratio relative to capital has gone down, but relative to non-college tasks it has gone up by 4.2% each year. The total effect is positive as evidenced by the positive and significant value of $\gamma_{HT.}$ For non-college labor both bilateral biases are negative, as is the overall effect.

The overall bias effects of TC are not only statistically, but also economically highly significant. In fact, the cumulative effect of BTC on the cost share of non-college educated workers in manufacturing GVCs over the twelve year period, calculated as $12 \times \gamma_{NT}$, accounts for an 8.9 percentage point decline from its initial share of 49.7 percent in 1995 (so an 18 percent decline). The largest effect of BTC is found for college tasks, driving up the cost share by 4.3 percentage points from its initial level of 13.7 percentage points (31 percent increase). BTC increased the cost share of capital by 4.5 percentage points (12

19. Compared to the well-known Allen-Uzawa (partial) elasticities, the Morishima elasticities are more general (Blackorby and Russell 1989). They are asymmetric and for a pair of factors j and l it is given by $\varepsilon_{jl} - \varepsilon_{ll}$. Elasticity of non-college educated versus college is 0.919 and versus capital 0.541; for college educated versus non-college 0.888 and versus capital 0.741; and finally for capital versus non-college 0.394 and versus college 0.363.

20. Note also that the technical bias terms will be GVC-specific as γ_{jT} is the same for all GVCs but the price elasticities (and factor shares) are not. We evaluate at the simple average of the cost shares across GVCs and make use of the price elasticities given in Table 2.

Table 1: Explaining Cost Shares of Three Factors in Global Value Chains, 1995-2007: ISUR estimates

Dependent variables: Annual cost shares in GVCs

	(1) Baseline	(2) Non-linear BTC	(3) Lagged factor prices	(4) Predicted task allocation	(5) Long difference	(6) Last production stage
γ_{NN}	0.0860	0.0859	0.0742	0.0648	0.1190	0.0977
	(0.0029)	(0.0029)	(0.0033)	(0.0046)	(0.0085)	(0.0063)
γ_{NH}	0.0174	0.0182	0.0181	0.0297	−0.0224	−0.0133
	(0.0025)	(0.0025)	(0.0028)	(0.0044)	(0.0074)	(0.0060)
γ_{NK}	−0.1033	−0.1041	−0.0924	−0.0944	−0.0966	−0.0844
	(0.0022)	(0.0022)	(0.0027)	(0.0026)	(0.0055)	(0.0019)
γ_{HH}	0.0242	0.0234	0.0174	0.0081	0.0722	0.0463
	(0.0029)	(0.0029)	(0.0032)	(0.0047)	(0.0085)	(0.0060)
γ_{HK}	−0.0416	−0.0416	−0.0356	−0.0378	−0.0498	−0.0330
	(0.0014)	(0.0014)	(0.0016)	(0.0015)	(0.0040)	(0.0009)
γ_{KK}	0.1449	0.1458	0.1279	0.1322	0.1464	0.1174
	(0.0027)	(0.0027)	(0.0033)	(0.0031)	(0.0059)	(0.0023)
γ_{NT}	−0.7392		−0.7489	−0.7478	−8.5500	−0.9070
	(0.0145)		(0.0180)	(0.0159)	(0.1976)	(0.0307)
γ_{HT}	0.3610		0.3544	0.3769	3.5391	0.4119
	(0.0088)		(0.0105)	(0.0096)	(0.1491)	(0.0148)
γ_{KT}	0.3782		0.3945	0.3710	5.0109	0.4950
	(0.0168)		(0.0214)	(0.0185)	(0.1994)	(0.0358)
Obs	3,496	3,496	2,912	3,496	291	3,452
R^2_N	0.8532	0.8540	0.8295	0.8294	0.5449	0.7406
R^2_H	0.8496	0.8510	0.8416	0.8416	0.3564	0.7854

Notes: Estimation of parameters determining factor costs shares in system of equations as given in formula (14). First six explanatory variables refer to (cross) task price effects and last three to biases in technical change. Subscripts refer to college educated labor (H), non-college educated labor (N), capital (K) and time (T). In baseline model we assume a linear trend in the biases in technical change. In column (2) year dummy interactions are added. In column 3 task prices based on GVC task allocation in previous year are used. Column (4) reports second stage results from 2SLS estimation using predicted task prices through off-shoring propensity of other industries and countries. Column (5) is based on long-difference (2007 minus 1995) instead of annual. Column (6) reports on regression using information on cost shares and task prices in last stage of GVC production only. All regressions include 291 GVC product dummies and 21 country (last stage of production) dummies, and are estimated in a system with iterative seemingly unrelated regression (ISUR). R^2 are reported for college and non-college labor equations. Parameters involving K are implicitly derived using the parameter restrictions discussed in the main text. Parameters referring to time are multiplied by 100.

Table 2: Price Elasticities of Tasks in GVCs

	p_K	p_N	p_H
K	−0.2384	0.1858	0.0526
N	0.1550	−0.3548	0.1998
H	0.1240	0.5647	−0.6886

Notes: Own- and cross-price elasticities of tasks in GVCs based on equations (15a) and (15b), using the estimated coefficients on task prices from the baseline in Table 1. Prices (p) for college educated labor (H), non-college educated labor (N) and capital (K) tasks. Elasticities are evaluated at the average cost shares across all GVCs and years, which are $s_K = 0.3812$, $s_N = 0.4570$ and $s_H = 0.1617$.

percent increase from its initial level). These effects are much bigger than the effects of relative task price changes. Combining the actual task price changes as given in section III with the estimated coefficients on relative prices from column (1) in Table 1, we find that price developments can only explain 0.7, 0.4 and −1.1 percentage points of the respective cost share changes for college, non-college and capital. The overriding importance of BTC in driving factor demand in GVCs is our major finding that appears to be robust to various alternative specifications as will be shown below.

C. Robustness Analysis

In Table 1, we provide a series of tests to check for the robustness of the baseline results. In the baseline model biases in technical change are modelled as linear trends, but this might be overly restrictive. For example, both Firpo, Fortin and Lemieux (2011) and Autor, Dorn and Hanson (2015) suggested that the impact of technical change on US labor markets was stronger in the 1980s and 1990s than in the 2000s. The model of directed technical change by Acemoglu, Gancia and Zilibotti (2015) also points to the possibility that the factor bias might change over time. In particular they show that when technical change is endogenous with respect to factor abundance, increasing opportunities for offshoring to low-wage countries might direct innovation towards (unskilled) labor-using technologies. To capture the potential non-linearity of changes in BTC in our empirical model, we follow Baltagi and Griffin (1988) who proposed a general index approach in which the time trend t is replaced by year dummies using the first year as a reference. For a task j, $\gamma_{jT}t$ is replaced by $\sum_{t=2}^{12} \lambda_{jt} D_t$ where D_t are year dummies. The parameter restriction $\sum_j \gamma_{jT} = 0$

is subsequently replaced by $\sum_j \lambda_{jt} = 0$ for all t. As shown in column (2), the elasticity estimates are barely affected, and more importantly, for all tasks, a strong linear trend in BTC is found (see Appendix Figure A.1). Consequently further results in this paper are shown for the linear bias model only.[21]

A major worry in our current set-up might be the assumed exogenous nature of task prices. These prices are a weighted average of the factor prices around the world, with weights determined by the locations of the various production stages. Exogeneity might be defended in an admittedly extreme model of global production where offshoring is costless but technically constrained. An improvement in offshoring possibilities then leads to a reallocation of tasks towards a lower-cost location and a corresponding decline in the task price, which is exogenous to individual firms. In reality location choices are likely to respond to differences in factor prices at home and abroad (including non-zero offshoring costs), thus making the task prices (at least partly) endogenous.[22] In addition, offshoring might affect local factor demand and therefore factor prices. This channel of reverse causality is muted however as we analyze only a subset of the labor force in advanced countries, namely those employed in GVC production of manufacturing goods. Summed across all our GVCs, GVC employment makes up 23.1 percent of the labor force (averaged across our 21 countries).

We provide two alternative estimation strategies to assuage these endogeneity concerns. First we simply instrument by previous year factor prices. That is, we construct the task prices in year t using national factor prices in year $t-1$ in combination with the task allocation across countries in year t. Results are given in column (3) and are highly comparable to the baseline results. Column (4) reports on a more sophisticated instrumenting approach in the vein of Autor, Dorn and Hanson (2013). In the first stage we predict the share of the tasks that are offshored, that is, the share of working hours of a particular factor that will be undertaken in labor-abundant countries (defined as all countries in the world except the 21 advanced nations studied here). This prediction is based on a weighted average of the offshoring propensity of all other sectors in the country, as well as on the offshoring propensity of the same sector in other countries. Thus we take account of possible country-specific as well as sector-specific circumstances that determine offshoring. The

21. In additional work, we also relaxed the constraint on returns to scale. There appears to be a minor scale-bias against non-college tasks and in favor of capital. This moderates the estimates on BTC for these factors, albeit to a limited extent. We also weighted each observation with the final output of the GVC and similarly found little effect.

22. See Antràs and Yeaple (2014) for an overview of the literature on location choice in GVCs.

sector-specific and the country-specific propensities are both highly significant in predicting offshoring. For non-college educated workers, the first-stage weights for the country and sector effect are 0.568 and 0.432, respectively (R-square of 0.593), while for college educated workers they are 0.462 and 0.538, respectively (R-square of 0.702). In the second stage we use the predicted share of offshored tasks to predict task prices, and use these to estimate the system of cost share equations as in (14). Reassuringly, the differences compared to the baseline results are minor and in particular the estimates of the biases in technical change are of a similar magnitude.

Another concern might be that our baseline regression is affected by non-random measurement error driven by the use of volatile annual data, obscuring long-run trends. In particular the rental rate of capital can be influenced at high frequency, for example by short-run changes in interest rates or more generally, by adjustment costs following investment booms. Following Michaels, Natraj and Van Reenen (2014), we therefore estimate a long-difference model of 12 years which brings down the number of observations to 291 GVCs. The results reported in column (5) show that the parameter estimates differ somewhat from the baseline, but the BTC time trends are in the same direction and the overall bias in favor of capital is even more pronounced.

A main contention of this paper is that the GVC approach is a conceptually attractive alternative to the standard approach for quantifying BTC which focuses only on the last stage of production. Following Denny and May (1977) we test for the parametric restrictions corresponding to a homothetically separable production function. These tests strongly reject homothetic weak separability of the last stage. Put otherwise, when measuring biases in technical change one should treat factor inputs in the last stage together with inputs in other stages of production, as in the GVC approach.[23] But is it also empirically relevant in terms of the estimated BTC trends? One might expect that because of observational equivalence, ignoring offshored stages would lead to overestimated biases. In the last column of Table 1 we provide parameter estimates using data on factor cost shares and prices used in the last stage only.[24] Biases in TC appear to be overestimated compared to our baseline regression. The total bias effect of technical change is estimated to be even more negative for non-college work, while the positive bias for college work and in particular for

23. Results available upon request. This finding fits earlier work that investigated the existence of value added functions in US industries, as surveyed in Jorgenson (1986). Gross output production functions were typically found to be non-separable in value added.

24. In 2007, value added in the last stage made up only 32.4% of final output on average across our 291 manufacturing GVCs.

capital is estimated to be much higher. Importantly, the overestimation of the labor biases remains also after including an indicator for offshoring as is typically done in single-stage studies.[25] We conclude that the GVC approach is an attractive alternative to measuring BTC in global production, both conceptually as well as empirically.

D. The Role of Information and Communication Technology

So far, we have found evidence for biases in technical change without specifying what type of technology might be responsible for this. Much of the recent research on technical change has revolved around testing the "routinization hypothesis" put forward by Autor, Levy and Murnane (2003). It states that new information technology capital complements workers engaged in abstract tasks, substitutes for workers performing routine tasks, and has little effect on workers performing manual and services tasks. This hypothesis has been corroborated by Goos, Manning and Salamons (2014) using data on changes in occupational employment structures in industries for a large set of advanced countries. But we showed in section C that analyses such as these that rely on single-stage data are likely to overestimate the bias in technical change towards non-college educated workers, and this finding might carry over to analyses of the routinization hypothesis. Unfortunately, we cannot directly test this in the context of our multi-stage GVC model as there is no comparable data on workers and wages by occupation that cover a large set of advanced as well as emerging economies. We follow Michaels, Natraj and Van Reenen (2014) and rely on our educational attainment data instead and split non-college educated workers into medium-educated (ISCED classes 3 and 4: high school and above but below college) and low-educated workers (ISCED 0,1 and 2: up to high school), implicitly assuming that jobs carried out by medium-educated workers provide a good, albeit imperfect, proxy for the number of routine-intensive jobs.

Appendix Figure A.2 provides the changes in task prices and cost shares in GVCs for our new four-factor split in analogy to the three-factor split presented in section III. The comparison reveals major differences in price and cost share trends: the price of low-educated work in GVCs declined on average with 15.5 log points, whereas the price of medium-educated work actually increased, almost in line with the price increase of high-

25. For example, when we include foreign value added as a percentage of total output as a measure of offshoring (as defined in equation (6)), the implied biases towards capital, non-college and college educated workers are 0.343, −0.814 and 0.471, respectively.

skilled work. This finding supports the offshoring model presented in Feenstra and Hanson (1997) that showed how FDI from advanced countries might increase demand for above-average skilled labor in the host economy. Cost shares of low- and medium-skilled diverged in similar fashion with the largest declines found for the least skilled workers.

We re-estimate our baseline model with a system of three cost equations (again dropping the equation for capital) and find a sizeable difference in the bias in TC towards low- and medium-educated labor. The first column in Table 3 shows that TC is strongly biased against low-educated labor with an implied bias of 7.4 percentage points over the twelve-year period. We also find a significant bias against medium-educated workers, but this one is much smaller at 0.77 percentage points. Compared to the model with three factors, the estimated biases in favor of high-educated workers and capital are somewhat smaller but still sizeable.

To test specifically for the routinization hypothesis we need to include an indicator that captures the use of information technologies. We follow Michaels, Natraj and Van Reenen (2014) and include the (log) stock of ICT capital per worker as an independent variable, derived from the EU KLEMS database (O'Mahony and Timmer 2009) and comprised of software, computer hardware and communication equipment stocks. This indicator is based on annual ICT use in the last stage only as this type of information is not available for most less advanced countries. 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 chain. Note that the ICT indicator differs across products and countries as well as over time, as we have annual data. We have ICT use data for 12 advanced countries and some countries do not have a full coverage for all years, such that the number of observations that can be used drops from $3,496$ to $1,999$.[26] As this sub-sample is not likely to be random, we re-estimate the baseline model for the subset of observations. Results in column (2) show that the estimated biases in TC are in the same direction as for the full data set, albeit with some differences in magnitudes. Based on this restricted data set we subsequently test the routinization hypothesis and add the ICT indicator as one of the explanatory variables in the cost share equation system.

The results given in the last column of Table 3 provide strong evidence in support of the

26. These countries are Australia, Austria, Denmark, Finland, Germany, Italy, Japan, Netherlands, Spain, Sweden, United Kingdom and USA.

Table 3: Explaining Cost Shares of Four Factors in Global Value Chains, 1995-2007: ISUR estimates

Dependent variables: Annual cost shares in GVCs

	(1) Baseline	(2) Restricted sample	(3) Including ICT
γ_{LT}	−0.6160	−0.5186	−0.5138
	(0.0133)	(0.0136)	(0.0174)
γ_{MT}	−0.0640	−0.1489	0.0872
	(0.0142)	(0.0191)	(0.0244)
γ_{HT}	0.3323	0.3428	0.3790
	(0.0098)	(0.0116)	(0.0147)
γ_{KT}	0.3478	0.3247	0.0476
	(0.0172)	(0.0194)	(0.0253)
$\gamma_{L,ICT}$			−0.0005
			(0.0009)
$\gamma_{M,ICT}$			−0.0183
			(0.0013)
$\gamma_{H,ICT}$			−0.0029
			(0.0008)
$\gamma_{K,ICT}$			0.0217
			(0.0014)
Obs	3,496	1,999	1,999
R^2_L	0.9118	0.9349	0.9347
R^2_M	0.8774	0.8661	0.8794
R^2_H	0.8495	0.8793	0.8798

Notes: Estimation of parameters determining factor costs shares in system of equations as given in formula (14). Showing only results for possible biases in technical change. Subscripts refer to college educated labor (H), high-school and above, but below college, educated labor (M), and up-to-high-school educated labor (L), capital (K), time (T) and ICT use, which is measured as amount of ICT capital per worker in the last stage of production. Column (1) reports on baseline model including all GVC observations and column (2) on sample which is restricted to those GVCs for which there is data on ICT use. Column (3) includes ICT use as explanatory variable. All regressions include a GVC product dummy and country dummy, and are estimated in a system with iterative seemingly unrelated regression (ISUR). R^2 is reported for each labor factor equation. Parameters involving K are implicitly derived using the parameter restrictions. Parameters referring to time are multiplied by 100.

routinization hypothesis in the context of GVC production. By far the biggest impact of information technology is found on the demand for medium-educated workers: the coefficient on ICT use is negative and highly significant. The time coefficient on medium-educated work turns mildly positive, which indicates that much of the bias in TC against medium-educated workers is explained by the use of ICT. This is in line with the findings of the study by Michaels, Natraj and Van Reenen (2014) that used data on single-stage production only. Interestingly, ICT use also explains almost all of the effects of BTC on the capital cost share. The significance of γ_{KT} falls and the remaining bias in TC, not related to the use of ICT, is small.[27] Also in accordance with the hypothesis, we find that ICT use does not impact the use of low-educated work in GVC production. More surprisingly, ICT does not seem to be a major driver of BTC in favor of high-educated work: $\gamma_{H,ICT}$ is quantitatively small and even negative in sign, while γ_{HT} remains highly significant after including ICT use and, if anything, increases.

All in all, we conclude that our finding of a bias in TC against medium-skilled labor and in favor of capital can for a large part be explained by ICT use in the last stage of the production chain. This is in line with the routinization hypothesis put forward by Autor, Levy and Murnane (2003). Additional analysis based on the task content of GVC production is needed for providing more direct tests, and might shed further light on the possible complements between high-skilled tasks and ICT use.

VI. The Impact of Offshoring and BTC on Domestic Labor Use in GVC Production

The main problem posed by the observational equivalence of offshoring and BTC is in quantifying their separate effects on domestic labor demand. Our GVC approach solved the observational equivalence problem and provided a clean estimate of BTC in production. This offers the opportunity to revisit the debate on the relative strength of the two labor demand drivers in advanced countries. We will do so using a simulation exercise rooted in our GVC production model. We assume that the bias in technical change towards a

27. It should be noted that this finding is not the obvious result of our capital measure. The correlation between our ICT capital indicator and the price of capital is low (0.14) such that this finding is not due to collinearity. In general, ICT capital is only a small part of the capital stock as machinery and buildings have much longer life times and lower depreciation rates than computers and software. On average ICT capital makes up only 15.2 percent of the capital stock (based on EU KLEMS database, see O'Mahony and Timmer 2009).

particular factor affects domestic and foreign factors in the GVC alike. Then we simulate the effects of BTC, as measured in the previous section, on domestic labor demand keeping the task allocation in the GVC constant. Alternatively, we simulate the effects of the actual change of the task reallocation in the GVC under a scenario of no BTC.

As before, this analysis pertains to employment related to GVC production of manufacturing goods. This obviously comprises only a subset of the active labor force in an economy. Summed across all our GVCs, GVC employment makes up 23.1 percent of the labor force in 1995 (averaged across our 21 countries). We refer to this as GVC employment. We thus do not claim to provide an assessment of the overall impact on labor demand in each country. Moreover, we fully realize that changes in prices, production location and technology most often do not take place in isolation and therefore do not want to suggest that we are able to parse them out completely. This would require a full general equilibrium set up of global demand and production which is outside the scope of this paper. Nevertheless, we do believe this simple exercise contributes to a better understanding of what drives domestic labor demand.

Appendix Figure A.3 shows the Kernel density of the foreign share of hours worked in GVCs for 1995 and 2007. Panel (a) depicts the density function for non-college educated workers and (b) similarly for college educated workers. The foreign share is defined as one minus the domestic share, where domestic refers to hours worked in the country where the last stage of production takes place. It thus can be considered as an indicator of the amount of work that is offshored within a particular GVC. There is a clear trend for both types of labor: the foreign share increased in 263, respectively 235, out of the 291 GVCs. As expected the increase is much larger for non-college work than for college work: the unweighted mean share increased 10.4 percentage points for non-college and 5.7 for college (median increased by 14.4 and 7.9 percentage points). In 2007, 86 percent of the offshored non-college hours was carried out in non-advanced countries. In contrast, only 57 percent of the offshored college hours was carried out in non-advanced countries, indicating that almost half of the hours was relocated to other advanced countries.[28] The latter finding is particular relevant for quantifying the overall effects of offshoring on local labor demand, as it is the 'net' effect of GVC production reallocation across all GVCs that should be considered. Our findings suggest that in particular in the case of college-educated work, the negative effects of offshoring on labor demand in the domestic economy will be moderated by offshoring

28. 54.3 out of 63.4 percentage points of foreign non-college hours was carried out in non-advanced countries, and 25.3 out of 44.3 percentage points for college, see Appendix Table A.1.

from other advanced economies. In the simulation we will thus measure the 'net' effects of reallocation of tasks across all GVCs.

Our goal is to analyze changes in the demand for a particular factor j in a given country c related to GVC production of manufacturing goods. To do so, we start with the expression for the change in demand for tasks associated with factor j in a particular GVC v (I_{jv}), repeated from (12):

$$d\ln I_{jv} = \sum_{l} \varepsilon_{jlv} d\ln p_{jv} + d\ln Y_v + \left[\sum_{l\neq j} \varepsilon_{jlv} \frac{\partial \ln[F_{vj}/F_{vl}]}{\partial \ln A} - \frac{\partial \ln F_v}{\partial \ln A} \right] d\ln A. \tag{17}$$

We simplify in order to focus on a comparison of the effects of GVC reallocation and BTC. More specifically, we keep final demand levels Y_v constant[29] and assume that TFP growth $[\partial \ln F_v/\partial \ln A] d\ln A$ is zero, such that:

$$d\ln I_{jv} = \sum_{l} \varepsilon_{jlv} d\ln p_{jv} + \sum_{l\neq j} \varepsilon_{jlv} \frac{\partial \ln[F_{vj}/F_{vl}]}{\partial \ln A} d\ln A. \tag{18}$$

For a given country c, total GVC employment of factor j (E_j^c) is the sum of employment of j across all global value chains v:

$$E_j^c = \sum_{v} x_{jv}^c I_{jv}, \tag{19}$$

where x_{jv}^c is the share of factor-j tasks in GVC v carried out by country c, as defined in section IV. The change in employment at the country level is then a weighted average of changes in GVCs, with weights given by the national employment shares:

$$\begin{aligned} d\ln E_j^c &= \sum_{v} \frac{x_{jv}^c I_{jv}}{E_j^c} [d\ln x_{jv}^c + d\ln I_{jv}] \\ &= \sum_{v} \frac{x_j^c I_{jv}}{E_j^c} \Bigg\{ \underbrace{d\ln x_{jv}^c}_{\text{task shares}} + \underbrace{\sum_{l} \varepsilon_{jlv} d\ln p_{lv}}_{\text{task prices}} + \underbrace{\sum_{l\neq j} \varepsilon_{jl} \frac{\partial \ln[F_{vj}/F_{vl}]}{\partial \ln A} d\ln A}_{\text{biased technical change}} \Bigg\}. \end{aligned} \tag{20}$$

29. Goos, Manning and Salamons (2014) showed that there are important final demand effects that determine aggregate employment patterns, alongside within-industry developments. Similar effects might play a role here, as BTC and task reallocation leads to changes in relative prices of final goods. This requires a full general equilibrium set up for multiple countries and interlinked sectors which is outside the boundary of this paper and left for future work.

This equation shows that we can simulate three demand drivers for a particular factor j in country c. The first two are related to reallocation of tasks across countries within GVCs. This first term, denoted by 'task shares', picks up the net effect of offshoring by domestic and foreign GVCs. The second term, 'task prices', captures the effect of changes in task prices within GVCs, moderated by the various price elasticities. When the price of a particular task declines this will, ceteris paribus, increase use of the task throughout the GVC, that is, increase demand for this factor in all countries that participate. Note that in principle task price change is determined by changes in national factor prices as well as by task reallocation across countries within GVCs, see equation (7). We keep the national factor prices constant such that it only simulates the effect of task reallocation. For example, when in a GVC v more tasks by factor l are offshored to lower wage countries, the corresponding task price p_{lv} will decline. The last element picks up the effects of BTC, again moderated by the task price elasticities. It will vary across factors, but it is assumed to affect domestic and foreign factors symmetrically.

In our simulation exercise we will substitute in the actual change in one particular element for the period 1995-2007, while keeping all other elements constant at their 1995 level. Results are given in Table 4 separately for non-college educated workers (first three columns) and college educated workers (last three columns) for each of our 21 countries. We find a clear asymmetry in the effects on demand for both labor types. The average across countries, given in the last row, suggests that task-reallocation within GVCs and biases in technical change have comparable effects on domestic demand for non-college educated workers. The negative bias in TC alone would drive down demand by 16.4 log points. With only task reallocation, demand would decline by 16.8 log points due to strong task share effects (-20.9), basically reflecting offshoring to low-wage countries as shown in Appendix Table A.1. Reallocation leads to declining relative task prices for non-college work in GVCs. The implied substitution effects due to task price changes are positive but relatively small: ceteris paribus, it would add on average 4.8 log points to non-college labor demand in advanced countries. This is a general pattern across countries, although there is some variation in the effects of task share reallocation. This is likely to be related to the timing and strength of the offshoring process, for example, the effect is lowest for Japan which had its peak in offshoring already before 1995 (Feenstra 1998).

In contrast, demand for college educated workers is clearly driven by the positive bias in TC, increasing demand by 39.5 log points on average. In all countries the positive effect of BTC was much larger than the negative effect of GVC task reallocation. While we

Table 4: Simulation of Change in GVC Employment in Advanced Countries, 1995-2007

	Non-college educated			College educated		
	Reallocation		BTC	Reallocation		BTC
	Task shares	Task prices		Task shares	Task prices	
Australia	−20.2	4.9	−15.8	−12.9	−3.3	51.7
Austria	−18.1	4.4	−13.8	6.4	−9.3	47.3
Belgium	−18.5	4.7	−15.7	−14.5	−4.5	37.6
Canada	−25.0	6.5	−17.8	−3.0	−5.8	40.7
Denmark	−15.9	3.2	−15.6	−11.7	−2.0	39.5
Finland	−25.3	5.1	−17.0	−20.6	−4.7	28.9
France	−26.3	5.2	−16.0	−9.6	−6.2	28.1
Germany	−22.5	4.9	−15.8	−19.6	−3.4	26.5
Greece	−23.7	3.1	−17.5	−5.2	−4.1	58.6
Ireland	−33.2	8.7	−17.5	−9.8	−5.5	39.9
Italy	−13.3	3.9	−13.9	6.1	−7.0	71.6
Japan	−4.5	2.3	−17.9	−3.2	1.4	35.7
Luxembourg	−16.1	2.1	−16.1	−20.7	−0.7	38.1
Netherlands	−12.6	4.1	−15.8	18.0	−6.4	36.8
Portugal	−7.3	2.3	−14.4	−7.8	−0.6	56.4
South Korea	−33.3	7.3	−16.3	−4.3	−9.5	22.7
Spain	−25.2	5.8	−17.2	−1.5	−6.4	34.3
Sweden	−30.4	6.2	−15.8	−6.4	−8.2	41.2
Taiwan	−12.4	2.4	−17.3	5.8	0.4	36.5
United Kingdom	−30.2	7.1	−17.0	−10.4	−7.4	31.5
United States	−24.0	7.2	−19.6	−15.4	−3.7	25.9
Average	−20.9	4.8	−16.4	−6.7	−4.6	39.5

Notes: Change in hours worked for workers (non-college and college educated) in a particular country due to task reallocation, change in task prices and biased technological change in 291 GVCs of manufacturing products. Calculated on the basis of equation (20) imputing the actual change in the period 1995-2007 for one element, while keeping the other elements constant at the 1995 levels. Estimated task substitution elasticities and biases in technological change in GVCs from baseline regression results in Table 1, combined with data on GVC reallocation and GVC task prices as described in section II. Unweighted average across all 21 countries given in last row.

documented strong offshoring tendencies also for college educated work (see section III), the overall quantity effects are limited at the country level (-6.7 log points on average across all countries). This is because in contrast to non-college work, much of the offshoring is done to other advanced countries. For some countries, like Austria and the Netherlands, the net effect is even positive. Finally, increases in the relative price of college educated workers in most GVCs led to substitution towards other factors, but with limited effects on demand (-4.6 log points on average).

We conclude that biased technical change and GVC reorganization have quantitatively comparable effects driving down demand for non-college educated workers in almost all advanced countries. In contrast, for college educated workers, we find that the negative effects of GVC reorganization are more than outweighed by the positive bias in technical change. This is partly because much of the offshoring of high-skilled work is to other advanced countries, compensating the negative impact of domestic offshoring.

VII. Concluding Remarks

This paper offers a new empirical approach to measure factor biases in technical change in the presence of offshoring. A key feature of this approach is the mapping of output of final products to value added by labor and capital employed in any stage of production at home as well as abroad. We showed the final output (GVC) production function to be a conceptually and empirically relevant alternative to the standard single-stage value added function. In particular it solves the observational equivalence problem that hinders clear identification of possible biases in technical change. Using the new approach, we found strong and robust evidence of technical change being biased against non-college educated workers, and in favor of college educated workers and capital. In a further simulation exercise, we quantified the impact of these biases in technical change on employment of domestic labor in GVCs and compared this to the effects of offshoring. We found that task reallocation within GVCs and biased technical change drove down employment of non-college educated workers in advanced countries in equal measure during 1995-2007. In contrast, Goos, Manning and Salamons (2014) and Michaels, Natraj and Van Reenen (2014) found technical change to be (much) more important. This might be related to their use of indicators for offshoring potential, while we use actual offshoring data. We have also shown that their use of single stage production data is likely to overestimate the effects of BTC.

The analysis in this paper is limited to GVC production of manufacturing goods. It can be readily extended to include other types of products such as final business services, once more detailed data on this becomes available. Given its intangible nature, technical change in services production might have different characteristics. Extending coverage to all products in the economy would also open up possibilities for general equilibrium modelling and allow for endogenous responses of demand, final output and factor prices. Other extensions are possible. So far, we analyzed changes in demand for workers who are characterized by levels of educational attainment. A promising next step is in developing a more complex task-based framework that models the shifting comparative advantage of different production factors in different locations carrying out particular tasks, as in Acemoglu and Autor (2011). One might hypothesize that technical change is not symmetric across all tasks and locations of the GVC. Innovations in assembly production are likely to differ from technologies in, say, headquarter activities. This will await new information on the occupational structure of GVC production and on workers task sets. And looking forward, if technical change is directed by factor abundance as in Acemoglu, Gancia and Zilibotti (2015), will global abundance be more relevant for future technology developments than local abundance? We hope that our GVC approach will be helpful for further thinking on these important issues.

Appendix A: Additional results

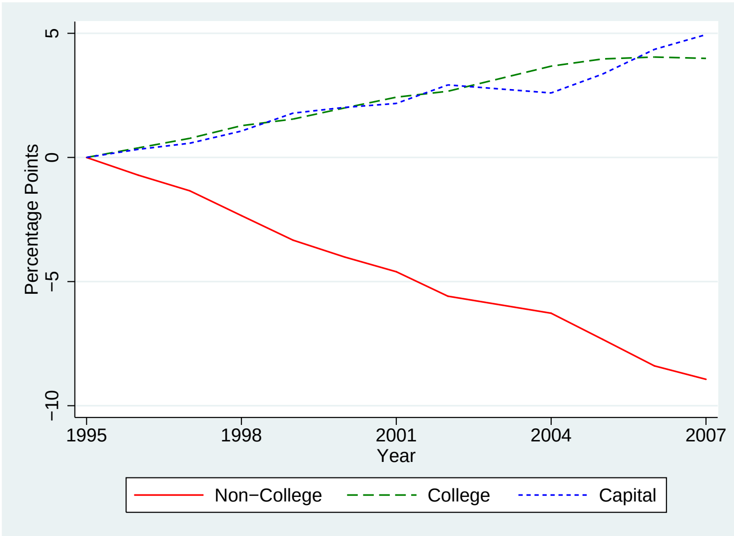

Figure A.1: Cumulative Annual Change in Bias in Technical Change

Notes: Based on regression with non-linear BTC reported in column (2) of Table 1.

Table A.1: Descriptive Statistics for Foreign Value Added and Foreign Hours Worked in Global Value Chains, 1995-2007

	Foreign value added in final manufacturing output (%)		Foreign share in total hours worked (%)				Share in total hours worked by non-advanced countries (%)	
			non-college		college		non-college	college
	1995	2007	1995	2007	1995	2007	2007	2007
Australia	15.7	18.5	42.8	52.5	31.2	40.0	48.3	27.6
Austria	26.1	38.2	49.8	64.6	53.1	57.0	52.6	31.7
Belgium	45.5	51.8	77.9	81.7	69.4	74.1	68.2	38.1
Canada	32.1	30.8	49.1	61.3	39.2	41.6	51.7	19.0
Denmark	26.0	34.0	67.7	71.7	40.4	49.9	60.4	27.9
Finland	26.6	35.6	59.4	73.3	30.0	49.6	64.0	35.1
France	21.7	29.8	51.3	64.7	27.8	35.0	53.9	19.1
Germany	18.1	28.8	56.4	67.5	26.9	43.4	59.5	27.7
Greece	20.9	34.6	26.5	46.8	17.6	26.6	42.7	18.6
Ireland	40.0	50.0	56.7	78.9	47.0	63.6	59.2	23.2
Italy	20.5	27.4	44.0	52.3	49.1	49.2	46.7	30.0
Japan	6.5	16.6	41.2	45.6	14.2	19.3	42.2	12.8
Luxembourg	43.0	52.0	73.2	74.8	56.1	69.5	53.4	32.7
Netherlands	36.1	41.8	83.5	85.4	72.2	65.7	79.1	48.0
Portugal	30.5	36.5	32.7	39.8	45.3	51.9	34.1	26.2
South Korea	26.0	33.6	43.1	60.8	9.6	15.9	56.1	10.8
Spain	22.1	32.8	44.7	61.4	21.6	28.7	53.3	17.7
Sweden	28.8	37.2	53.7	68.7	49.9	57.3	56.5	32.6
Taiwan	33.2	44.3	46.0	55.5	25.5	29.1	49.6	16.2
United Kingdom	21.9	24.1	49.3	63.3	25.1	32.8	54.2	18.2
United States	12.3	18.0	46.2	59.9	14.1	25.9	55.3	18.0
Average	26.4	34.1	52.1	63.4	36.4	44.1	54.3	25.3

Notes: Own calculations based on November 2013 release of World Input-Output Database (WIOD, Timmer et al. 2015). Foreign value added is defined in equation (6). For each country a (weighted) average is given across 14 GVCs of manufacturing products that are finalized in the country. Total hours worked in a GVC is calculated according to equation (4). The foreign share is defined as one minus the domestic share, where domestic refers to hours worked in the country where the last stage of production takes place. Average in last row refers to unweighted average across all 21 countries. Non-advanced countries are all countries in the world not listed in this table.

Panel (a): Change in Relative Task Prices, in GVCs 1995-2007 (in log points)

Panel (b): Change in Factor Cost shares in GVCs 1995-2007 (in percentage points)

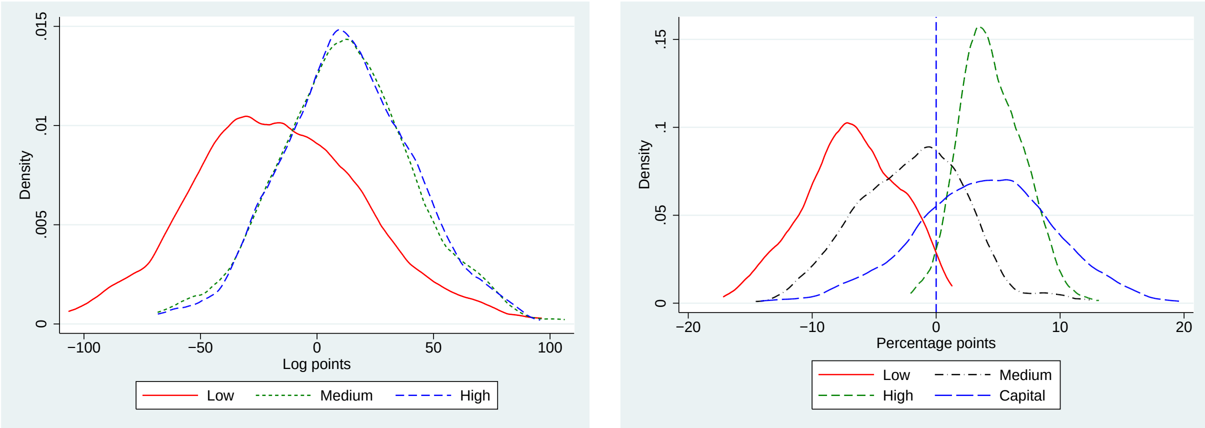

Figure A.2: Change in Task Prices and Factor Cost Shares in GVCs, Four Factors, 1995-2007

Notes: Kernel densities as in Figures 2 and 3 based on four factors: low-, medium- and high-educated labor and capital.

Panel (a): Non-college Educated Workers

Panel (b): College Educated Workers

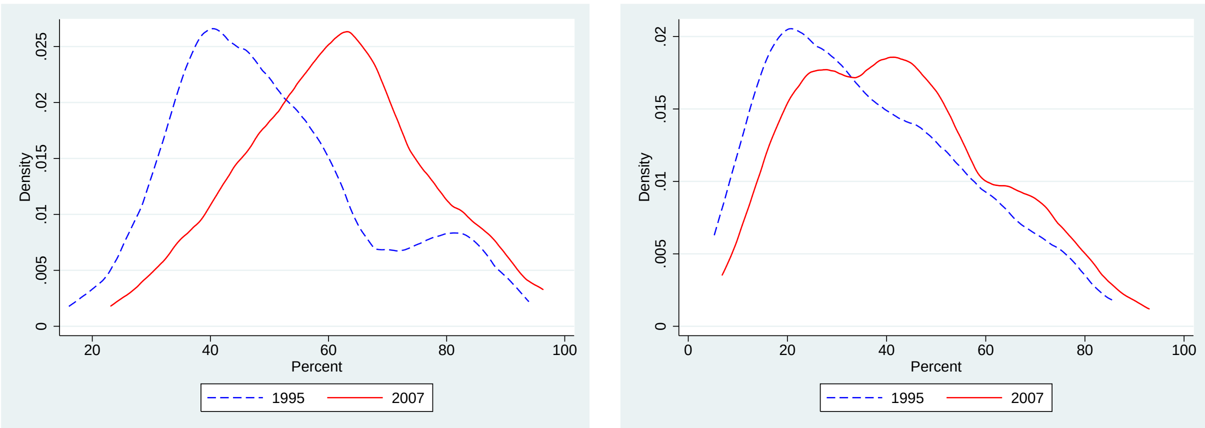

Figure A.3: Foreign Share in Hours Worked in GVCs, 1995 and 2007 (in percent)

Notes: Kernel densities of foreign shares in total hours worked in GVC. Total hours worked in a GVC is calculated according to equation (4). The foreign share is defined as one minus the domestic share, where domestic refers to hours worked in the country where the last stage of production takes place. The number of observations is 291, see notes to Figure 1.

References

Acemoglu, Daron. 2002. “Directed Technical Change.” *Review of Economic Studies* 69 (4): 781–809.

Acemoglu, Daron, and David Autor. 2011. “Skills, Tasks and Technologies: Implications for Employment and Earnings.” In *Handbook of Labor Economics,* edited by David Card and Orley Ashenfelter, vol. 4(B), 1043–1171. Elsvier.

Acemoglu, Daron, Gino Gancia and Fabrizio Zilibotti. 2015. “Offshoring and Directed Technical Change.” *American Economic Journal: Macroeconomics* 7 (3): 84–122.

Antràs, Pol, and Davin Chor. 2013. “Organizing the Global Value Chain.” *Econometrica* 81 (6): 2127–2204.

Antràs, Pol, and Stephen R. Yeaple. 2014. “Multinational Firms and the Structure of International Trade.” In *Handbook of International Economics,* edited by Gita Gopinath, Elhanan Helpman and Kenneth Rogoff, 4:55–130. Elsevier.

Autor, David H., David Dorn and Gordon H. Hanson. 2013. “The China Syndrome: Local Labor Market Effects of Import Competition in the United States.” *American Economic Review* 103 (6): 2121–2168.

Autor, David H., David Dorn and Gordon H. Hanson. 2015. “Untangling Trade and Technology: Evidence from Local Labour Markets.” *The Economic Journal* 125 (584): 621–646.

Autor, David H., Frank Levy and Richard J. Murnane. 2003. “The skill content of recent technological change: An empirical exploration.” *Quarterly Journal of Economics* 118 (4): 1279–1333.

Baltagi, Badi, and James Griffin. 1988. “A General Index of Technical Change.” *Journal of Political Economy* 96 (1): 20–41.

Bems, Rudolfs, Robert C. Johnson and Kei-Mu Yi. 2013. “The Great Trade Collapse.” *Annual Review of Economics* 5 (1): 375–400.

Blackorby, Charles, and R. Robert Russell. 1989. "Will the Real Elasticity of Substitution Please Stand Up? (A Comparison of the Allen/Uzawa and Morishima Elasticities)." *American Economic Review* 79 (4): 882–888.

Blinder, Alan S., and Alan B. Krueger. 2013. "Alternative Measures of Offshorability: A Survey Approach." *Journal of Labor Economics* 31 (2): S97–S128.

Chirinko, Robert S. 2008. "σ: The long and short of it." *Journal of Macroeconomics* 30 (2): 671–686.

Denny, Michael, and Doug May. 1977. "The Existence of a Real Value-added Function in the Canadian Manufacturing Sector." *Journal of Econometrics* 5 (1): 55–69.

Diewert, Walter E., and Terence J. Wales. 1987. "Flexible Functional Forms and Global Curvature Conditions." *Econometrica* 55 (1): 43–68.

Feenstra, Robert C. 1998. "Integration of Trade and Disintegration of Production in the Global Economy." *The Journal of Economic Perspectives* 12 (4): 31–50.

Feenstra, Robert C., and Gordon H. Hanson. 1997. "Foreign direct investment and relative wages: Evidence from Mexico's maquiladoras." *Journal of International Economics* 42 (3-4): 371–393.

Feenstra, Robert C., and Gordon H. Hanson. 1999. "The Impact of Outsourcing and High-technology Capital on Wages: Estimates for the United States, 1979–1990." *Quarterly Journal of Economics* 114 (3): 907–941.

Feenstra, Robert C., and Gordon H. Hanson. 2003. "Global Production Sharing and Rising Inequality: A Survey of Trade and Wages." In *Handbook of International Trade,* edited by Kwan E. Choi and James Harrigan, 119–145. Blackwell Publishing.

Firpo, Sergio, Nicole M. Fortin and Thomas Lemieux. 2011. *Occupational Tasks and Changes in the Wage Structure.* Discussion Paper 5542. IZA.

Goos, Maarten, Alan Manning and Anna Salamons. 2014. "Explaining Job Polarization: Routine-Biased Technological Change and Offshoring." *American Economic Review* 104 (8): 2509–2526.

Grossman, Gene M., and Esteban Rossi-Hansberg. 2008. "Trading Tasks: A Simple Theory of Offshoring." *American Economic Review* 98 (5): 1978–1997.

Harrison, Ann, John McLaren and Margaret McMillan. 2011. "Recent perspectives on trade and inequality." *Annual Review of Economics* 3:261–289.

Herrendorf, Berthold, Richard Rogerson and Ákos Valentinyi. 2013. "Two Perspectives on Preferences and Structural Transformation." *American Economic Review* 103 (7): 2752–2789.

Hijzen, Alexander, Holger Görg and Robert C. Hine. 2005. "International Outsourcing and the Skill Structure of Labour Demand in the United Kingdom." *Economic Journal* 115 (506): 860–878.

Jin, Hui, and Dale W. Jorgenson. 2010. "Econometric Modeling of Technical Change." *Journal of Econometrics* 157 (2): 205–219.

Johnson, Robert, and Guillermo Noguera. 2012. "Accounting for Intermediates: Production Sharing and Trade in Value Added." *Journal of International Economics* 86 (2): 224–236.

Jorgenson, Dale W. 1986. "Econometric Methods for Modeling Producer Behavior." In *Handbook for Econometrics,* edited by Zvi Griliches and Michael D. Intriligator, 3:1841–1915. Noord-Holland.

Karabarbounis, Loukas, and Brent Neiman. 2014. "The Global Decline of the Labor Share." *Quarterly Journal of Economics* 129 (1): 61–103.

Krusell, Per, Lee E. Ohanian, José-Víctor Ríos-Rull and Giovanni L. Violante. 2000. "Capital-skill complementarity and inequality: A macroeconomic analysis." *Econometrica* 68 (5): 1029–1053.

Los, Bart, Marcel Timmer and Gaaitzen J. de Vries. 2015. "How Global Are Global Value Chains? A New Approach to Measure International Fragmentation." *Journal of Regional Science* 55 (1): 66–92.

Michaels, Guy, Ashwini Natraj and John Van Reenen. 2014. "Has ICT Polarized Skill Demand? Evidence from Eleven Countries over 25 Years." *Review of Economics and Statistics* 96 (1): 60–77.

Miller, Ronald E. 1966. "Interregional feedback effects in input-output models: Some preliminary results." *Papers of the Regional Science Association* 17 (1): 105–125.

Miller, Ronald E., and Peter Blair. 2009. *Input-Output Analysis Foundations and Extensions.* 2nd ed. Cambridge University Press.

Oldenski, Lindsay. 2012. "The Task Composition of Offshoring by US Multinationals." *International Economics* 131:5–21.

O'Mahony, Mary, and Marcel P. Timmer. 2009. "Output, Input and Productivity Measures at the Industry Level: The EU KLEMS Database." *The Economic Journal* 119 (538): F374–F403.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer and Gaaitzen J. de Vries. 2015. "An Illustrated User Guide to the World Input-output Database: The Case of Global Automotive Production." *Review of International Economics* 23 (3): 575–605.

Valentinyi, Akos, and Berthold Herrendorf. 2008. "Measuring Factor Income Shares at the Sector Level." *Review of Economic Dynamics* 11 (4): 820–835.

Appendix B: Analytical Derivations

FOR ONLINE PUBLICATION

A Factor Demand in a GVC

For a given GVC, the system of first-order conditions for cost-minimization is given by (dropping the v subscript for convenience):

$$\begin{aligned}
\frac{F_N(I_K, I_N, I_H, A)}{F_K(I_K, I_N, I_H, A)} &= \frac{p_N}{p_K}, \\
\frac{F_H(I_K, I_N, I_H, A)}{F_K(I_K, I_N, I_H, A)} &= \frac{p_H}{p_K}, \\
F(I_K, I_N, I_H, A) &= Y.
\end{aligned}$$

Loglinearization gives the following expressions:

$$\mathbf{\Phi}\begin{pmatrix} d\ln I_K \\ d\ln I_N \\ d\ln I_H \end{pmatrix} = \begin{pmatrix} d\ln p_N - d\ln p_K - \frac{\partial \ln[F_N/F_K]}{\partial \ln A} d\ln A \\ d\ln p_H - d\ln p_K - \frac{\partial \ln[F_H/F_K]}{\partial \ln A} d\ln A \\ d\ln Y - \frac{\partial \ln F}{\partial \ln A} d\ln A \end{pmatrix},$$

where the matrix of coefficients is defined as:

$$\mathbf{\Phi} = \begin{pmatrix} \frac{\partial \ln[F_N/F_K]}{\partial \ln I_K} & \frac{\partial \ln[F_N/F_K]}{\partial \ln I_N} & \frac{\partial \ln[F_N/F_K]}{\partial \ln I_H} \\ \frac{\partial \ln[F_H/F_K]}{\partial \ln I_K} & \frac{\partial \ln[F_H/F_K]}{\partial \ln I_N} & \frac{\partial \ln[F_H/F_K]}{\partial \ln I_H} \\ \frac{\partial \ln F}{\partial \ln I_K} & \frac{\partial \ln F}{\partial \ln I_N} & \frac{\partial \ln F}{\partial \ln I_H} \end{pmatrix}.$$

If the production function F is homogeneous of degree 1 (so that the technology features constant returns to scale) then its partial derivatives F_N, F_K and F_H are homogeneous of degree 0 and so are the ratios F_N/F_K and F_H/F_K. In that case, the first two rows of $\mathbf{\Phi}$ add up to zero, while the last row sums to unity. We write the solution to this system of equations as:

$$\begin{pmatrix} d\ln I_K \\ d\ln I_N \\ d\ln I_H \end{pmatrix} = \begin{pmatrix} \varepsilon_{KN} & \varepsilon_{KH} & \varepsilon_{KY} \\ \varepsilon_{NN} & \varepsilon_{NH} & \varepsilon_{NY} \\ \varepsilon_{HN} & \varepsilon_{HH} & \varepsilon_{HY} \end{pmatrix} \begin{pmatrix} d\ln p_N - d\ln p_K - \frac{\partial \ln[F_N/F_K]}{\partial \ln A} d\ln A \\ d\ln p_H - d\ln p_K - \frac{\partial \ln[F_H/F_K]}{\partial \ln A} d\ln A \\ d\ln Y - \frac{\partial \ln F}{\partial \ln A} d\ln A \end{pmatrix}.$$

The coefficient matrix on the right-hand side equals the inverse of $\mathbf{\Phi}$ and its elements consist of price and output elasticities, which are defined as:

$$\varepsilon_{jl} = \frac{\partial \ln I_j}{\partial \ln p_l}, \quad \varepsilon_{jY} = \frac{\partial \ln I_j}{\partial \ln Y}.$$

With constant returns to scale $\varepsilon_{jY} = 1$ for each production factor j.[30] Changes in factor demands can then be written as:

$$d \ln I_j = \sum_l \varepsilon_{jl} d \ln p_j + \varepsilon_{jY} d \ln Y + \left[\sum_{l \neq j} \varepsilon_{jl} \frac{\partial \ln [F_j / F_l]}{\partial \ln A} - \varepsilon_{jY} \frac{\partial \ln F}{\partial \ln A} \right] d \ln A$$

The cost share of production factor j is defined as $s_j = p_j I_j / \sum_l p_l I_l$. Hence we find:

$$\begin{aligned} d \ln s_j = d \ln s_{jv} &= (1 - s_{jv}) \left[d \ln p_{jv} + d \ln I_{jv} \right] - \sum_{l \neq j} s_{lv} \left[d \ln p_{lv} + d \ln I_{lv} \right] \\ &= [1 + \varepsilon_{jj} - s_j] d \ln p_j + \sum_{l \neq j} [\varepsilon_{jl} - s_l] d \ln p_l + \eta_{jY} d \ln Y \\ &\quad + \left[\sum_{l \neq j} \varepsilon_{jl} \frac{\partial \ln [F_j / F_l]}{\partial \ln A} - \eta_{jY} \frac{\partial \ln F}{\partial \ln A} \right] d \ln A. \end{aligned}$$

where:

$$\eta_{jY} = (1 - s_j) \varepsilon_{jY} - \sum_{l \neq j} s_l \varepsilon_{lY}$$

This corresponds to equation (12) in the main text under the assumption of constant returns to scale so that $\eta_{jY} = 0$.

B Factor Demand in a Country

The demand for factor j in country c coming from GVCs is given by:

$$E_j^c = \sum_v x_{jv}^c I_{jv}$$

30. This can be proved by deriving $\mathbf{\Phi}^{-1}$ and imposing the restrictions on $\mathbf{\Phi}$ that are valid when the production function is linear homogeneous.

where the subscript v denotes a particular GVC. This expression can be loglinearized as:

$$d \ln E_j^c = \sum_v \frac{x_{jv}^c I_{jv}}{E_j^c} \left[d \ln x_j^c + d \ln I_{jv} \right]$$

Substituting in for $d \ln I_{jv}$ we obtain:

$$\begin{aligned} d \ln E_j^c = \sum_v \frac{x_{jv}^c I_{jv}}{E_j^c} \Bigg\{ & d \ln x_{jv}^c + \sum_l \varepsilon_{jlv} d \ln p_{lv} + d \ln Y_v \\ & + \sum_{l \neq j} \varepsilon_{jlv} \frac{\partial \ln [F_j / F_l]}{\partial \ln A} d \ln A - \frac{\partial \ln F}{\partial \ln A} d \ln A \Bigg\}, \end{aligned}$$

This corresponds to equation (20) in the main text under the assumption of constant demand ($d \ln Y_v$) and no change in total factor productivity ($[\partial \ln F / \partial \ln A] d \ln A = 0$).

Appendix C: Data Sources

FOR ONLINE PUBLICATION

The data for this study is taken from the World Input-Output Database (WIOD), which is freely available at `www.wiod.org`. It has been specifically constructed for the analysis of global value chains, see Timmer et al. (2015). It provides world input-output tables for each year since 1995, covering 40 countries, including all 27 countries of the European Union (as of 1 January 2007) and 13 other major economies in the world (see Table C.1). In addition, an estimate for the remaining non-covered part of the world economy is provided such that the value-added decomposition of final output is complete. It contains data for 35 sectors covering the overall economy, including agriculture, mining, construction, utilities, 14 manufacturing industries and 17 services industries (see Table C.2).

A couple of issues need highlighting. First, the WIOD input-output data is given in so-called basic prices, which means that trade margins as well as (net) taxes on products are not included in the final output value of products. Put differently, we decompose the value of a product at "the gate of the factory" which excludes domestic retailing activities. Second, we analyze cost shares in final output. Due to net taxes paid on intermediate products, factor costs do not add up to final output value. These taxes (in most GVCs less than 2 percent of the final output value) cannot be allocated to specific factors. We therefore subtract these from final output before calculating the factor cost shares such that they sum to one.

Apart from the input-output tables, an important input into our analysis is information on quantities and prices of labor and capital used in production. These can be found in the Social-economic accounts from WIOD (WIOD-SEA). These series are not part of the core set of national accounts statistics reported by National Statistical Institutes and have been constructed in the WIOD-SEA. We briefly describe the methods and sources used in this construction. For a full discussion, see Erumban et al. (2012).

A Wages and Employment by Educational Attainment Levels

Data on wages and employment by skill types are not part of the core set of national accounts statistics; at best only data on total hours worked and wages by industry are included. Therefore, additional material has been collected from employment and labor

Table C.1: Countries Covered in the World Input-Output Database (WIOD)

Advanced countries	Other countries
Australia	Brazil
Austria	Bulgaria
Belgium	China
Canada	Cyprus
Denmark	Czech Republic
Finland	Estonia
France	Hungary
Germany	India
Greece	Indonesia
Ireland	Latvia
Italy	Lithuania
Japan	Malta
Luxembourg	Mexico
Netherlands	Poland
Portugal	Romania
South Korea	Russian Federation
Spain	Slovak Republic
Sweden	Slovenia
Taiwan	Turkey
United Kingdom	Rest-of-World region
United States	

Notes: List of countries covered in the WIOD, November 2013 release. We study the global value chains from countries listed in the first column which we refer to in the main text as "advanced countries". Value added in these GVCs can come from any of the 41 countries in this table.

force statistics. For each country covered, a choice was made of the best statistical source for consistent wage and employment data at the industry level. In most countries this was the labor force survey (LFS). In most cases this needed to be combined with an earnings surveys as information wages are often not included in the LFS. In other instances, an establishment survey, social-security database, industry or population census was used. Care has been taken to arrive at series which are time consistent, as most employment surveys are not designed to track developments over time, and breaks in methodology or coverage frequently occur. For most countries data on hours worked was taken from the EU KLEMS database (O'Mahony and Timmer 2009), revised and updated. For countries not in EU KLEMS new sources have been used which are described in the detailed country notes (Erumban et al. 2012).

Table C.2: Sectors in the World Input-Output Database (WIOD)

	Code	Sector name
	AtB	Agriculture, Hunting, Forestry and Fishing
	C	Mining and Quarrying
⋆	15t16	Food, Beverages and Tobacco
⋆	17t18	Textiles and Textile Products
⋆	19	Leather, Leather Products and Footwear
⋆	20	Wood and Products of Wood and Cork
⋆	21t22	Pulp, Paper, Printing and Publishing
⋆	23	Coke, Refined Petroleum and Nuclear Fuel
⋆	24	Chemicals and Chemical Products
⋆	25	Rubber and Plastics
⋆	26	Other Non-Metallic Mineral
⋆	27t28	Basic Metals and Fabricated Metal
⋆	29	Machinery, Not elsewhere classified
⋆	30t33	Electrical and Optical Equipment
⋆	34t35	Transport Equipment
⋆	36t37	Manufacturing, Not elsewhere classified; Recycling
	E	Electricity, Gas and Water Supply
	F	Construction
	50	Sale and Repair of Motor Vehicles and Motorcycles; Retail Sale of Fuel
	51	Wholesale Trade, Except of Motor Vehicles and Motorcycles
	52	Retail Trade and Repair, Except of Motor Vehicles and Motorcycles
	H	Hotels and Restaurants
	60	Inland Transport
	61	Water Transport
	62	Air Transport
	63	Other Supporting Transport Activities
	64	Post and Telecommunications
	J	Financial Intermediation
	70	Real Estate Activities
	71t74	Renting of Machinery & Equipment and Other Business Activities
	L	Public Administration and Defence; Compulsory Social Security
	M	Education
	N	Health and Social Work
	O	Other Community, Social and Personal Services
	P	Private Households with Employed Persons

Notes: List of sectors covered in the WIOD (November 2013 release) by ISIC revision 3 industry code. Each of these sectors can potentially contribute to a GVC. In this study we focus on GVCs of manufacturing products, that is final output of manufacturing industries indicated by ⋆.

Labor compensation of self-employed is not registered in the National Accounts, which as emphasised by Angrist and Krueger (1999) leads to an understatement of labor's share. This is particularly important for less advanced economies that typically feature a large share of self-employed workers in industries like agriculture, trade, business and personal services. Imputations have been made instead. For advanced countries, the compensation per hour of self-employed is assumed equal to the compensation per hour of employees. For emerging countries this assumption is not plausible as a large part of informal workers earns much less than the average wage of low-skilled workers. Instead, additional information was used which differs by country (Erumban et al. 2012).

In the WIOD-SEA three skill types of labor are being distinguished, based on the level of educational attainment of the worker. Three types of workers are identified following the International Standard Classification of Education (ISCED). Low skilled (ISCED categories 0, 1 and 2) roughly corresponds to less than secondary schooling. Medium skilled (3 and 4) means secondary schooling and above, including professional qualifications, but below college degree. High skilled (5 and 6) includes those with a college degree and above.

Typically, data on wages is scarcer than for number of workers, both in terms of industry coverage and time such that imputations have to be made. For each country relative wages for at least one year in the period 1995-2007 are available which ensures that country-specific skill-premia are reflected in the data. For most countries there are at least three observations across the period such that changes in skill premia over time are reflected. Wages for years in between are linearly interpolated. The level of industry detail also varies across countries and depends crucially on the sample sizes of the surveys on which the estimates are based. If needed, shares of aggregate sectors were applied to more detailed underlying industries. Details on various country-specifics can be found in Erumban et al. (2012).

Two additional points are worth mentioning. First, in the main analysis of our study we excluded 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 Labor Force Survey was miscoded such that the share of low-skilled workers jumped up from 2002 to 2003 and down again from 2003 to 2004. This data was used in the WIOD-SEA as well, and we therefore excluded it in the main analysis. Including this (erroneous) data would not quantitatively change the main results of this paper however. Second, the WIOD-SEA does not provide data for the Rest of the world region. We used shares based on Indonesia.

B Capital Stocks

The WIOD SEAs contain capital stock series by industry at constant prices. The series cover all fixed assets as defined in the SNA 1993. As for labor, for most countries data was taken from the EU KLEMS database (O'Mahony and Timmer 2009). For other countries, capital stocks have been constructed on the basis of the Perpetual Inventory Method (PIM) in which the capital stock in year t is estimated as the sum of the depreciated capital stock in year $t-1$ plus real investment in year t. The depreciation rates are industry-specific rates and assumed to be the same for all countries. For many countries long time-series of investments are available and there is no need to have information on an initial stock estimate. For countries with no investment data before 1995 (mainly Eastern European countries), industry specific ratios of value added to capital stocks were used of a country at a similar stage of development. For countries for which investment series were available for a number of years before 1995, an initial capital stock for the year in which investment series start was estimated using the Harberger method which can be written as: $K_0 = (i/(g+d)) \times GO$, where K_0 is the initial capital stock in constant 1995 prices, GO is gross output by industry in constant 1995 prices, i is the investment rate, g is the average growth rate of output, and d is the total depreciation rate by industry. For the Rest of the world region, a ratio of the capital price relative to the US was estimated from the Penn World Tables (Feenstra, Inklaar and Timmer 2015). This was applied to the value added in each industry (which is in US dollars) times the capital share (one minus the labor share) to back out the capital stock in each industry.

References Online Appendix

Angrist, Joshua D., and Alan B. Krueger. 1999. "Empirical Strategies in Labor Economics." Chap. 23 in *Handbook of Labor Economics,* edited by David Card and Orley Ashenfelter, vol. 3(A), 1277–1366. North Holland.

Erumban, Abdul Azeez, Reitze Gouma, Gaaitzen J. de Vries, Klaas de Vries and Marcel P. Timmer. 2012. *WIOD Socio-Economic Accounts (SEA): Sources and Methods.* http://www.wiod.org/publications/source_docs/SEA_Sources.pdf. University of Groningen.

Feenstra, Robert C., Robert Inklaar and Marcel P. Timmer. 2015. "The Next Generation of the Penn World Table." *American Economic Review* 105 (10): 3150–3182.

O'Mahony, Mary, and Marcel P. Timmer. 2009. "Output, Input and Productivity Measures at the Industry Level: The EU KLEMS Database." *The Economic Journal* 119 (538): F374–F403.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer and Gaaitzen J. de Vries. 2015. "An Illustrated User Guide to the World Input-output Database: The Case of Global Automotive Production." *Review of International Economics* 23 (3): 575–605.