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An Analysis of Cost Shares in Vertically Integrated Production

Marcel P. Timmer (University of Groningen, the Netherlands)

Xianjia Ye (University of Groningen, the Netherlands)

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Marcel P. Timmer and Xianjia Ye

Groningen Growth and Development Centre, Faculty of Economics and Business, University of Groningen, P.O. Box 800, 9700 AV Groningen, The Netherlands.

E-mail: m.p.timmer@rug.nl; x.ye@rug.nl

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Abstract

Current estimates of factor bias in technical change (FBTC) suffer from the observational equivalence of FBTC and increasing use of intermediates inputs. In this paper we model vertically integrated production which nets out intermediate inputs using information on their factor content, and derive factor cost shares and prices. We estimate translog cost functions for 280 chains of manufacturing products and find strong evidence of FBTC against low-skilled labour and in favour of high-skilled labour and capital. This finding is found to be robust in various alternative settings.

Introduction

Since long, economists recognize the importance of technological change as a driver of economic growth. There is increasing evidence that its effect on factor incomes is not neutral, favouring demand for some factors more than others. In particular there is long-standing empirical support for the 'Skill-Biased Technological Change" (SBTC) hypothesis which states that demand is shifting in favour of more educated workers. More recently, this hypothesis has been refined, stating that technological change is biased against jobs that are routine and can be easily automated. This "Routine-Biased Technological Change" hypothesis fits the observed polarisation of the job-market where employed shares of medium-skilled workers decline relative to high- and low-skilled workers as it is especially medium-skilled jobs that can be most easily replaced by information technologies.[1]

Empirical studies of STBC typically employ a cross-industry regression set up in which changes in employment or wage cost shares for various types of workers are related to relative wages and an indicator for technological change, such as investments in IT. To account for the effects of international trade, an indicator for off-shoring, such as the share of imported intermediates following Feenstra and Hansen (1997), is added as there is likely a factor-bias in the tasks being offshored. Due to increased opportunities for international fragmentation, production activities are being relocated to countries where they can be carried out at lowest costs. Effects for offshoring need to be controlled for as it might be observationally equivalent to a factor-bias in technological change, for example when the offshored activities are particularly low-skill intensive (see Feenstra and Hanson 2003 for an overview). However, for both theoretical and empirical reasons the existing proxies for offshoring and factor-biased technological change appear to be strongly positively correlated compounding identification problems and obfuscating interpretation (Goos et al. 2014 and Autor et al. 2013).[2] More fundamentally, this approach presumes separability between value added and intermediate inputs in production, which is unlikely to hold (Diewert and Wales, 1995). Any bias in technical change derived within these frameworks relate to the use of labor within a domestic industry only. But nowadays production processes are fragmented across industries and countries and any test of possible factor-biases in technical change needs to take into all factors needed in production.

In this paper we model the production process as an array of tasks to be carried out anywhere in the world with any combination of factor inputs along the lines suggested by Acemoglu and Autor (2011). In these so-called vertically integrated production functions there are only factor inputs. This approach basically nets out intermediate inputs by using information on their factor-content. We estimate a standard translog cost function for vertically integrated production based on a panel across products and countries. We include time dummies interacted with factor inputs to measure possible factor-biased technical change (FBTC). Factor cost shares are derived using information from the World Input-Output Database and applying a basic input-output technique to account for factor content of intermediates, following the recent insights of Johnson and Noguera (2013), Koopman, Wang and Wei (2014) and Timmer et al. (2014).

The analysis is restricted to a study of production processes of manufacturing goods as these are heavily affected by international fragmentation and data is most abundant. We first show that cost shares of low- and medium-skilled workers have rapidly declined over the period 1995-2007, while the cost shares of high-skilled workers and capital have increased. At the same time we find a rapid decline in the relative price of low-skilled workers due to a global supply shock after the opening up of

[1] See Autor et al. (2008) for a first confirmation of this hypothesis for the US economy and more recent contributions by Michaels et al. (2014) and Goos et al. (2014) based on international data.

[2] An alternative is to study development at local, rather than national, labour markets and use variation in the industry-composition of regional economies (Autor et al. 2013).

China, India and other labour-abundant economies in the 1990s. On the other hand, relative prices of high- and medium-skilled workers were rising. Changes in factor shares are subsequently explained by changes in relative factor prices and technical change in a standard translog cost framework introduced by Diewert (1974). We find that the major decline in the price of low-skilled workers can only account for a small part of their declining cost shares as own price elasticities are found to be moderate. Instead, we find strong evidence of technical change being biased against the use of less-skilled workers and favouring the use of capital and high-skilled workers.

The remainder of this paper is organised as follows. Section 2 presents the econometric approach based on estimation of a system of cost-share equations for a large set of vertically integrated production functions. Section 3 describes the data, outlining the method to derive factor content of intermediate inputs, and presents major trends in cost shares of four factors: capital, low-, medium- and high-skilled workers. Section 4 discusses the main results and presents estimates of factor substitution elasticities as well as of factor biases in technical change. It also shows how the main results are robust to variations in the set of industries and countries included, as well as to various estimation alternatives. Section 5 concludes.

2. Econometric methodology

In order to investigate the possible factor-biased nature of technological change we will use a standard translog cost framework as introduced by Christensen et al (1973) and Diewert (1974). This framework has been used in the recent literature on the effects of outsourcing on skill-demand such as Hijzen et al. (2005), Foster-McGregor et al. (2013) and Michels et al. (2014), and in previous analyses of technical change, e.g. Binswanger (1974), Jorgenson, Gollop and Fraumeni (1987) and Baltagi and Rich (2005).

However, our empirical implementation departs in an important way from previous studies in order to measure factor-biased technical change (FBTC). Typically, the framework is applied at the industry level, using observations of output and input use in a particular industry (in a particular country) such that outsourcing of tasks is represented as an increase in the use of intermediate inputs. Instead we will apply the translog cost framework to data on the factor inputs directly and indirectly needed in production. These factor inputs are located in the industry-country in which the final product was produced, but also in other industries-countries that participated in production through the delivery of intermediate inputs (see next section). Hence the cost function will be based on a model of vertically integrated production with only capital and labour as inputs.

Following Christensen et al (1973) it is assumed that the product cost-functions can be approximated by a translog function, which is twice differentiable, linearly homogenous and concave in factor prices. For a particular product it is given by (product subscripts are omitted throughout for ease of presentation):

$$\begin{aligned}\ln C(\boldsymbol{p}_t, y_t, t) = \alpha + \sum_{i\in F}\beta_i \ln p_{it} + \frac{1}{2}\sum_{j\in F}\sum_{i\in F}\gamma_{ij}\ln p_{it}\ln p_{jt} \\ +\beta_Y \ln y_t + \frac{1}{2}\sum_{i\in F}\gamma_{iY}\ln p_{it}\ln y_t + \frac{1}{2}\gamma_{YY}(\ln y_t)^2 \\ +\beta_T t + \frac{1}{2}\sum_{i\in F}\gamma_{iT}t\ln p_{it} + \frac{1}{2}\gamma_{TT}t^2\end{aligned} \qquad (1)$$

where C represents total variable cost and is a function of prices p_i for factors i ($i \in F$, F refers to the set of factors) and output y. The parameters β_i and γ_{ij} will provide information on the factor demand elasticities, while β_Y and γ_{iY} indicate possible scale-bias in production. β_T represents the speed of Hicks-neutral technological change, and a positive γ_{iT} indicates a trend of technological change that complements factor i (or substitutes if γ_{iT}<0). These γ_{iT} parameters are our objects of main interest as they reveal possible FBTC.

If cost-minimization is assumed, Shephard's lemma can be used to derive the well-known factor cost-share equation for factor i

$$S_{it} = \beta_i + \sum_{j \in F} \gamma_{ij} \ln p_{jt} + \gamma_{iY} \ln y_t + \gamma_{iT} t \tag{2}$$

where $S_{it} = p_{it}Q_{it} / C_t$ with Q_{it} the quantity of factor i. We further impose constant returns to scale and other standard restrictions on the parameters in order to have a valid cost function system (see Berndt, 1991). Constant returns to scale requires that the cost function is linearly homogenous in factor prices which implies $\sum_{i \in F} \beta_i = 1$, and $\sum_{j \in F} \gamma_{ij} = 0$ for any i. Without loss of generality we also impose symmetry such that $\gamma_{ij} = \gamma_{ji}$. Finally, the summation of the cost shares of all factors by definition equals to one such that $\sum_{i \in F} \gamma_{iY} = \sum_{i \in F} \gamma_{iT} = 0$.

Given the cross restrictions in the share equations we can improve the efficiency of parameter estimates by estimating in a simultaneous equation system.[3] Berndt (1991) shows that this restricted equation system can be estimated by first dropping one cost-share equation and transforming the other equations accordingly. The cost share equation for capital is dropped and this choice is arbitrary as it does not affect the estimates since we iterate using Zellner's method (using ISUR).[4] The transformed unrestricted equation system to be estimated is as follows:

$$\begin{aligned} S_{Lt} &= \beta_L + \gamma_{LL} \ln(p_{Lt}/p_{Kt}) + \gamma_{LM} \ln(p_{Mt}/p_{Kt}) + \gamma_{LH} \ln(p_{Ht}/p_{Kt}) + \gamma_{LY} \ln y_t + \gamma_{Lt}\, \mathrm{t} \\ S_{Mt} &= \beta_M + \gamma_{ML} \ln(p_{Lt}/p_{Kt}) + \gamma_{MM} \ln(p_{Mt}/p_{Kt}) + \gamma_{MH} \ln(p_{Ht}/p_{Kt}) + \gamma_{MY} \ln y_t + \gamma_{Mt}\, \mathrm{t} \\ S_{Ht} &= \beta_H + \gamma_{HL} \ln(p_{Lt}/p_{Kt}) + \gamma_{HM} \ln(p_{Mt}/p_{Kt}) + \gamma_{HH} \ln(p_{Ht}/p_{Kt}) + \gamma_{HY} \ln y_t + \gamma_{Ht}\, \mathrm{t} \end{aligned} \tag{3}$$

Note that in this model biases in technical change are modelled as linear trends. Given our interest we also estimate a system with a more general modelling of FBTC. Baltagi and Griffin (1988) proposed a general index approach in which the time trend t is replaced by year dummies using the first year as base. For a factor i, $\gamma_{it} t$ is replaced by $\sum_{t=2}^{12} \lambda_{it} D_t$ where D_t are year dummies. The parameter restrictions $\sum_{i \in F} \gamma_{iT} = 0$ are subsequently replaced by $\sum_{i \in F} \lambda_{it} = 0$ for all t.

In addition to reporting parameter estimates of the cost function the elasticities of substitution and of factor demand will be presented. The coefficients γ_{ij} in system (3) are the second order derivatives with respect to factor prices. A positive γ_{ij} can be roughly interpreted as a net-substitution between factor i and j, since it means that a price increase of factor j would increase the cost share paid to factor

[3] Surprisingly, this is not often done in recent studies of labor demand, see e.g. Michels et al (2014). Hijzen et al. (2005) is a positive exception.

[4] Berndt and Wood (1975). The simultaneous equation system can be estimated via Zellner's seemingly unrelated regression (SUR), either in one-step or using iterated SUR (ISUR). The one-step SUR combines multiple equations into one stack form, and the stack form is estimated via ordinary least square (OLS), while the iterated method is equivalent to maximum likelihood (ML) estimates. We use the latter and although it might not always converge, it did in all our applications. Also, it appeared to be empirically close to the one-step SUR.

i which implies that the usage of i must have increased. Formally, the relationship between the γ parameters and substitution elasticities between factors i and j (σ_{ij}) are given by the so-called Allen-Uzawa partial elasticities of substitution[5]:

$$\sigma_{ij} = \frac{\gamma_{ij}}{S_i S_j} + 1, \qquad \text{(for } i \neq j\text{)} \tag{4}$$

And the price elasticity of demand of factor i with respect to price of j (ε_{ij}) is given by:

$$\varepsilon_{ij} = \sigma_{ij} S_j \qquad \text{(for } i \neq j\text{)} \tag{5}$$
$$\varepsilon_{ii} = \frac{\gamma_{ii}}{s_i} + s_i - 1$$

As is clear from these definitions, elasticities depend on cost shares and can vary across observations. We follow common practice and evaluate the elasticities on the basis of the simple average cost shares across all observations. In the next section we will outline our empirical strategy in identifying the direct and indirect factor inputs needed in production.

3. Factor cost shares: data sources and exploration

In this section we first outline our empirical strategy in identifying factor cost shares in output relying on the concept of a vertically integrated production function. Section 3.2 discusses data sources and section 3.3 provides trends in factor costs shares in the global production of manufacturing goods.

3.1 Vertically integrated production functions

In this section we will outline our empirical strategy in identifying factor cost shares in output relying on the concept of a vertically integrated production function. In this conceptualization production takes place in various stages where value is being added by the use of capital and labour in each particular stage. The output value of a final product can thus be expressed as the sum of value added by factors in the industry performing the final stage, as well as by factor inputs needed in earlier production stages. Importantly, the latter can be located inside or outside the domestic economy. Typically statistical data is only available at the industry level, providing data on factor inputs in one stage of production only. Leontief (1936) suggested a simple empirical technique based on input-output relationships that provides a solution. This approach has proven to be useful in recent applications in a variety of related settings.[6]

Assume that there are S sectors, F production factors and N countries. Each country-sector produces one good, such that there are SN products. We use the term country-sector to denote a sector in a country. Let **y** be the vector of production of dimension (SNx1), which is obtained by stacking output levels in each country-sector. Define **f** as the vector of dimension (SNx1) that is constructed by stacking world final demand for output from each country-sector $f_i(s)$. World final demand is the summation of demand from any country. We further define a global intermediate input coefficients matrix **A** of dimension (SNxSN) which elements describe the output from sector s in country i used as intermediate input by sector t in country j as a share of output in the latter sector. **I** is an (SNxSN)

[5] See Berndt (1991) for details.

[6] See Herrendorf et al. (2013) who map consumption structures into value added structures; Johnson and Noguera (2012) measuring vertical specialisation in international trade; Koopman, Wang and Wei (2014) providing a decomposition of gross exports and Antràs et al. (2012) who compute the average number of 'transactions' a dollar will go through before final use.

identity matrix. We define $v_i(s)$ as the factor cost share of say capital per unit of gross output produced in sector s in country i and create the stacked SN-vector $\mathbf{v}$ containing these 'direct' factor coefficients. To take 'indirect' contributions into account, we derive the SN-vector of factor input levels $\mathbf{w}$ as generated to produce a final demand vector $\mathbf{f}$ by pre-multiplying the gross outputs needed for production of this final demand by $\mathbf{v}$:

$$\mathbf{w} \quad = \hat{\mathbf{v}}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{f} \qquad (6)$$

in which a hat-symbol indicates a diagonal matrix with the elements of $\mathbf{v}$ on the diagonal. We can now post-multiply $\hat{\mathbf{v}}(\mathbf{I}-\mathbf{A})^{-1}$ with a vector of global demand for a particular product and derive a set of factor inputs needed in its production. When done for all four factor inputs (which together exhaust value added), it will be the case that their summed costs is equal to the output value of the product.[7]

We would like to stress that the decomposition methodology outlined above is basically an ex-post accounting framework based on repeated application of a proportionality assumption and hence does not rely on an underlying economic model. It basically only assumes that intermediates and factor inputs in an industry are used in fixed proportions for all outputs of the industry. To see this, let z_n be a column vector with the nth element representing an euro of global consumption of goods from country-sector n, while all the remaining elements are zero. The production of z_n requires intermediate inputs given by Az_n. In turn, the production of these intermediates requires the use of other intermediates given by A^2z_n, and so on. As a result the increase in output in each sector is given by the sum of all direct and indirect effects (= $1+Z+Z^2+Z^3+\ldots$). This geometric series converges to $(\mathbf{I}-\mathbf{A})^{-1}\mathbf{z}_n$.

3.2 Data sources

Throughout the paper we will focus on GVC income in the production of final manufacturing goods. We denote these goods by the term "manufactures". Production systems of manufactures are highly prone to international fragmentation as activities have a high degree of international contestability: they can be undertaken in any country with little variation in quality. Some activities in the manufacturing sector are geared towards production of intermediates for final non-manufacturing products and are not part of manufactures GVCs. On the other hand, GVCs of manufactures also include value added outside the manufacturing sector, such as business services, transport and communication and finance, and in raw materials production. These indirect contributions will be explicitly accounted for through the modelling of input-output linkages across sectors.

The World Input-Output Database, which is freely available at www.wiod.org, has been specifically constructed for this type of analyses, see Timmer et al. (2014) for more detail. It provides world input-output tables for each year since 1995, covering forty countries, including all twenty-seven countries of the European Union (as of 1 January 2007) and thirteen other major economies:

[7] If $\mathbf{w}$ is indeed to give the distribution of the value of final output as attributed to sectors in the value chain of product n, the elements of $\mathbf{w}$ should add up to the elements of $\mathbf{f}$. Intuitively, this should be true, since the Leontief inverse takes an infinite number of production rounds into account, as a consequence of which we model the production of a final good from scratch. The entire unit value of final demand must thus be attributed to country-sectors. We can show also mathematically that this is true. Let $\mathbf{e}$ an SN summation vector containing ones, and a prime denotes transposition, then using equation (3) the summation of all value added related to a unit final demand $(\mathbf{e}'\mathbf{w}_n)$ can be rewritten as $\mathbf{e}'\mathbf{w}_n = \mathbf{e}'\hat{\mathbf{v}}(\mathbf{I}-\mathbf{A})^{-1}\mathbf{z}_n = \mathbf{v}'(\mathbf{I}-\mathbf{A})^{-1}\mathbf{z}_n$. By definition, value added is production costs minus expenditures for intermediate inputs such that $\mathbf{v}' = \mathbf{e}'(\mathbf{I}-\mathbf{A})$. Substituting gives $\mathbf{e}'\mathbf{w}_n = \mathbf{e}'(\mathbf{I}-\mathbf{A})(\mathbf{I}-\mathbf{A})^{-1}\mathbf{z}_n = \mathbf{e}'\mathbf{z}_n$. The value of final demand is thus attributed to value added generation in any of the SN country-sectors that could possibly play a role in the global value chain for product n.

Australia, Brazil, Canada, China, India, Indonesia, Japan, Mexico, Russia, South Korea, Taiwan, Turkey and the United States. In addition, a model 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 industries covering the overall economy, including agriculture, mining, construction, utilities, fourteen manufacturing industries and seventeen services industries. Output is measured at basic prices. Final demand consists of household and government consumption and investment.

One also needs information on quantities and incomes of labor and capital used in production. Three types of workers are identified on the basis of educational attainment levels as defined in 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. Workers include self-employed and family workers and an imputation for their income is made. Capital income is derived as a residual and defined as gross value added minus labor income. It represents remuneration for capital in the broadest sense, including tangible and intangibles. Defined this way, the sum of the four factor incomes will be equal to value added in each industry such that our decomposition given in (6) is complete.

In our analysis we focus on the overall factor quantities used in vertically integrated production chains, assuming that factors of the same type are perfect substitutes across countries. Prices are derived by dividing value by the quantities summed across countries. One might argue that despite our use of an international educational classification, quality differences within a given skill-category across countries might exist. In a robustness analysis we will also provide an alternative based on correction for possible productivity differences across countries.

3.3 Trends in factor cost shares in production of manufacturing goods

Changes in factor income shares in global value chains have been plotted in Figure 1. The value of final manufacturing goods from twenty advanced countries is decomposed into value added by four factors: capital, low-, medium- and high-skilled labor. (In our approach, value added and income of factors are equivalent, so these terms will be used interchangeably.) The twenty countries are: all old EU-15 countries plus Australia, Canada, Japan, South Korea, Taiwan Region and the United States. For each factor we show on the horizontal axis the income share in 1995 and on the vertical axis the share in 2008. Points above the 45 degree line indicate global value chains in which the factor has increased its share. We have in total 280 value chains: 14 manufacturing product groups with 20 possible countries of completion. It illustrates major trends: cost shares of capital and in particular high-skilled labour are increasing in many chains, while the cost shares of low-skilled labour are decereasing (see also Timmer et al., 2014).

[Figure 1about here]

Table 1 reports summary statistics. The S_L, S_M, S_H, and S_K represent the share of cost paid to low, medium, high-skilled labour and capital in the whole global value chain. Capital captures around 37% of cost share in the value chain (unweighted average across all years and country-industries). The medium-skilled labour have the largest labour share in production which is around 30% of the total cost (around 50% of the total labour cost), and low- and high-skilled labour's cost shares are around 17%. Standard deviations indicate sizeable variation in cost shares across product chains.

Table 2 further reports the changes in cost shares, prices and input quantities of each factor (unweighted across industries-countries). It confirms the trends depicted in Figure 1. The decrease of low-skilled workers' wage share was 6.9 percentage points in the 12-year period. This is substantial given its average cost share of only 17 percent over the period. There is also a decrease in the income share of medium-skilled workers, but the average magnitude is limited to only 2.5 percentage points in 12 years. In contrast, cost shares of capital and high-skilled workers increased with 3.4 and 4.7 percentage points. At the same time, there was a major change in the relative prices of factor inputs. The opening up of Asian economies led to a shock in the global supply of unskilled workers and their relative price rapidly declined. Prices of medium- and high-skilled workers increased, also relative to capital. Surprisingly, the quantity of low-skilled workers used grew only slowly with 9 percent. Use of high-skilled workers grew the fastest. Juxtaposing price and quantity growth rates suggest a strong role for technical change biased against low-skilled workers and in favour of high-skilled. This will be formally tested in the next section.

[Table 1 about here]
[Table 2 about here]

Section 4 Results

Table 3 reports the results of estimating the system of equations with different econometric techniques. The first specification uses the pooled iterative Zellner or seemingly unrelated regression estimator (Pooled ISUR). The second specification accounts for country- as well as product-fixed effects (fixed-effect ISUR). It is estimated with time trends in (column 2) and year dummies in (col 3) to allow for non-linear trends in factor-biased technological change. In seemingly unrelated regression an R^2 is calculated for each regression equation and reported below. Both country and product group dummies show jointly significance at high level. They are not reported to save space. A Hausman test clearly rejects the pooled regression. This is not surprising given that there are strong differences across countries and product groups in the intensity of task-offshoring (see Los, Timmer and de Vries 2014). In the remainder of the paper we will therefore use the fixed-effects alternative throughout.

Before one can start interpreting the results, it is necessary to check whether the estimated cost function is consistent with economic theory and cost minimization behaviour. Cost functions are well-behaved if they are quasi-concave in factor prices. This implies that the so-called Hessian matrix of second-order derivatives with respect to factor prices must be negative semi-definite. A test for this is rather complex and Diewert and Wales (1987) provide a simpler alternative namely whether the matrix $(H - \mathrm{Diag}(s) + ss')$ is negative semi-definite, where H refers to the symmetric matrix containing all σ_{ij} of factors, and s is a column vector of cost shares of each factor. The eigenvalues of this matrix should be evaluated for each observation, and it is unlikely that negative semi-definity holds for all observations. Nevertheless, we have checked the quasi-concavity for each observation in the baseline model (col 2), and only 184 out of 3258 observations have positive eigenvalue, which suggests that the Hessian matrix associated with the estimated translog cost function is negative semi-definite in most of the cases.[8]

Our main variables of interest are the estimated parameters on FBTC which is captured by the time trends γ_{iT} in the first specifications. The fixed-effects model in column 2 shows highly significant biases in technological change against low- and medium-skilled labour, while being complementary to high-skilled labour. The cost share equation for capital is dropped and since the restriction requires

[8] Typically, an even simpler method is used in the literature by investigating the eigenvalues evaluated at the simple average of the cost shares. Doing this, we find that all eigenvalues are non-positive (-0.1875, -0.1164, -0.0807, 0), which satisfies the requirement.

that $\sum_i \gamma_{ij} = 0$ for all factors j, it follows that $\gamma_{iK} = -(\gamma_{iL} + \gamma_{iM} + \gamma_{iH})$. The trend for capital is found to be positive as well. In order to test for possible non-linear effects of FBTC we also estimated a model with year dummies (column 3). The results for the year dummies can be found in Appendix Table 1. For low- and high-skilled labour, the accumulated FBTC are highly significantly different from 0 throughout the period. Accumulated FBTC is significant for capital in all years except the first two. Only for medium-skilled labour the bias in technical change is insignificant in the period up to 2001, but highly significant afterwards. For all factors, a strong linear trend is found. This is illustrated in Figure 2 which shows the cumulative effect of the linear trend estimates from the trend specification as well as the yearly estimates based on the year-dummy specification for each factor. The cumulative effect shows the economic significance of FBTC in explaining changes in factor shares given in Table 2. For all factors, a major part of the change in factor shares over the period 1995-2007 can be explained by FBTC. This is our major finding that appears to be robust over various alternative specifications as shown later on.

Table 3 about here
Figure 2 about here

The role of price changes is not negligible however, and can be inferred from the other parameter estimates. The interpretation of these is not straightforward since the factor price variables on the right-hand side are in natural logarithms, whereas the dependent variables are not. Instead, results are discussed on the basis of estimated elasticities derived as in equations (4) and (5). Table 4 represents the price elasticities (left part) and elasticities of substitution between each factor (right part), all evaluated at the average of the cost shares. The implied own-price elasticities are negative for all factors, as expected given the concavity of the cost functions, and strongest for unskilled labour, while weakest for capital. For low-skilled labour, the self-price elasticity is as low as -0.64, which means that 1 per cent decrease in the wage of low-skilled worker corresponds to the 0.64 per cent increase in the number of low-skilled hours worked in the value chain. This high elasticity suggests that the rapid decline in the price of low-skilled work will only have a modest impact on its cost share. Indeed we found above, that the majority of the falling cost-share is attributable to biased technical change.
Cross price elasticities are positive otherwise but rather small, in particular with respect to the price of capital. Rising capital prices will lead to only a small increase in the quantities of labour used. This is suggestive of low elasticities of substitution between capital and labour as confirmed in the right part of the table. It is particularly low between high-skilled work and capital albeit still positive, suggestive of capital being more complementary to high-skilled labour than to other labour. Elasticities between labour types are much higher, in particular between low- and medium-skilled workers.

Table 4 about here

So far, we have pooled observations of all manufacturing products together, but there might be substantial differences in the substitution elasticities and FBTC across various product groups. We therefore allocated the 14 manufacturing products into three groups based on similarities in factor cost shares: light manufacturing, heavy manufacturing and machinery. Regression results for each group together with the pooled results (model2 from Table 3) are given in Table 5. Elasticities are given in Appendix Table 2. All implied cost-functions are well behaved as the Hessian matrices, i.e. $H - \mathrm{Diag}(s) + ss'$, have non-positive eigenvalues throughout (see Appendix Table 2)

We find for all industry subgroups that the substitution elasticities between labour and capital is relatively low. But the substitution elasticities between different labour types differ substantially across groups. In light manufacturing, substitution between various types of labour is high. But in heavy industries and machinery and electronics high-skilled workers are difficult to substitute for, suggesting that they perform distinct activities that are difficult to perform without tertiary education. Most striking however is the uniformity in the degree of FBTC across all industries given in the lower panel. The coefficients on the time dummies are highly significant and have similar signs and magnitudes across all products groups. Technical change is heavily biased against low-skilled labour in all product groups and in particular in light manufacturing. On the flip side, it favours use of high-skilled workers and capital in all product groups. Interestingly technical change was only slightly biased against medium-skilled workers in heavy manufacturing, albeit still positive at 0.1% significance level.

Table 5 about here

Robustness analysis

In order to comment on the robustness of the results we present a number of alternative estimates. First, we modify the set-up of the cost-share framework. Following Hijzen et al. (2005) capital is now assumed to be quasi-fixed so that both output and capital can be treated as exogenous in the short run. In this alternative, the dependent variables are the shares of each type of labour in overall labour costs. With three variable inputs, we drop the high-skilled cost share equation and estimate the two equations systems with linear time-trends and fixed effects as before. The results for the various product groups are given in in Table 6. The interpretation of the results is slightly different from that in the baseline model. By keeping capital quasi-fixed, biases in technical change refer to labour types only. As a result, the magnitude of FBTC estimates from the quasi-fixed version are not directly comparable with the baseline version. But the results are qualitatively the same: technical change is heavily biased against low-skilled workers and in favour of high-skilled workers, while neutral with respect to medium-skilled work.

Table 6 about here

A second set of alternative regressions is given in Table 7. One might argue that wage levels across countries do not fully reflect differences in the marginal productivity of workers. We classify workers by three levels of educational attainment, but these might not fully reflect international differences in the quality of workers. A common way to correct for this is to transform actual number of workers into effective numbers by adjusting for cross-country productivity differences. Similarly, effective factor prices can be derived by dividing total factor cost by effective labour rather than actual. To control for possible differences in quality, all factors in a country are adjusted by the MFP level of the country as given in Penn World Table 8.0 (Feenstra, Inklaar and Timmer, 2013). These levels differ across countries and over time, but not across industries. The results are given in column 3. The adjustment has minimal impact on the parameter estimates and the estimates of FBTC are nearly identical to the ones in the base model (column 1).

So far, we only considered production chains that end in twenty rich countries. We expand the set of countries to include all forty countries for which there is data in WIOD. These countries, which are typically much poorer, were initially not included as one might argue that cost-minimizing behaviour underlying our modelling strategy is less compatible with production chains in which they contribute the majority of value added. Results are given in column 4. Parameter estimates differ significantly, but interestingly the estimates of FBTC are close to our baseline model.

Lastly, we extend our base model by including a particular technology indicator in addition to the time trend. It has been frequently argued that the development of information- and communication technologies (ICT) is an important driver of FBTC and nearly all studies have included an indicator for this. We follow common practice and include the stock of ICT capital per worker as an independent variable. This indicator differs across industries, countries and over time and is interacted with skill types ($\gamma_{I,ICT}$). Results are given in column 2. Estimates are barely affected, except for the interaction of time with medium-skilled labour which becomes insignificant. ICT technology seems to be heavily biased against medium-skilled labour providing further evidence for the RBTC hypothesis. According to the "routinization hypothesis" put forward by Autor, Levy and Murnane (2003), information technology capital complements highly educated workers engaged in abstract tasks, substitutes for moderately educated workers performing routine tasks, and has little effect on less-skilled workers performing manual tasks and tasks that require personal interactions, such as in many services.

5. Concluding remarks

In this paper we modelled vertically integrated production which nets out intermediate inputs using information on their factor content, and derive factor cost shares and prices. We estimated translog cost functions for 280 chains of manufacturing products (14 product groups which last stage of production took place in any of twenty rich countries). We found strong evidence of FBTC against low-skilled labour and in favour of high-skilled labour and capital. The FBTC trends were found for manufacturing product sub-groups as well as for the overall pooled set. These findings are found to be robust in various alternative settings such as treating capital input as quasi-fixed and adjusting for possible factor quality differences across countries. In a next step, we will seek to find indicators of specific technologies that might explain part of the FBTC trends, such as ICT technologies.

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Table 1. Average cost shares, 1995-2007

Var	Obs	Mean	Std. Dev.	Min	Max
Low	3258	16.9	8.5	1.8	50.1
Medium	3258	29.6	7.6	10.0	52.9
High	3258	16.7	4.7	6.5	39.7
Capital	3258	36.7	7.0	4.3	70.0

Note: Shares of capital, low-, medium- and high-skilled labour income in value added. Pooled across 20 countries, 14 manufacturing product groups and 12 years.

Table 2. Cost Share, Price and Input Quantity Changes between 1995 and 2007

	Factor	Mean	Std. Dev	5% pct	25% pct	Median	75% pct	95% pct
Cost Shares (% points)	Low	-6.87	3.88	-13.77	-9.22	-6.77	-3.90	-0.94
	Medium	-1.24	4.68	-9.24	-4.70	-1.13	2.15	6.97
	High	4.71	2.42	1.20	2.96	4.31	6.45	8.85
	Capital	3.40	5.60	-6.13	0.15	3.89	6.77	12.25
Price (%)	Low	5.15	28.29	-34.26	-15.17	0.20	23.72	56.39
	Medium	38.14	31.15	-11.00	18.72	35.42	54.57	89.44
	High	40.20	29.02	-13.39	22.79	36.23	62.17	89.01
	Capital	21.27	33.01	-31.07	1.04	20.46	40.80	72.42
Input Quantity (%)	Low	9.21	92.36	-60.46	-30.71	-7.99	26.89	115.88
	Medium	24.27	124.12	-56.85	-21.08	6.76	38.00	133.76
	High	65.00	153.81	-33.75	6.72	41.31	86.10	189.52
	Capital	56.10	141.56	-40.86	8.73	32.98	71.64	170.41

Table 3 Regression results, 1995-2007.

	Pooled ISUR			Fixed Effect ISUR			Fixed Effect with year dummies		
Variable	Coef	std. E		coef	std. E		coef	std. E	
β_L	0.1972	0.0115	***	0.1566	0.0103	***	0.1602	0.0103	***
β_M	-0.0006	0.0132		-0.0623	0.0121	***	-0.0765	0.0122	***
β_H	0.0036	0.0110		-0.2065	0.0099	***	-0.2049	0.0100	***
γ_{LL}	0.1310	0.0033	***	0.0316	0.0024	***	0.0275	0.0024	***
γ_{LM}	-0.1125	0.0028	***	0.0109	0.0024	***	0.0116	0.0024	***
γ_{LH}	-0.0002	0.0022		-0.0047	0.0018	**	-0.0016	0.0019	
γ_{MM}	0.2514	0.0053	***	0.0743	0.0047	***	0.0771	0.0049	***
γ_{MH}	-0.0693	0.0046	***	-0.0096	0.0038	**	-0.0121	0.0039	**
γ_{HH}	0.0809	0.0051	***	0.0655	0.0038	***	0.0650	0.0038	***
γ_{LY}	-0.0007	0.0007		-0.0005	0.0006		-0.0012	0.0005	*
γ_{MY}	-0.0024	0.0006	***	-0.0022	0.0006	***	-0.0017	0.0006	**
γ_{HY}	0.0045	0.0004	***	0.0020	0.0005	***	0.0022	0.0005	***
γ_{LT}	-0.0026	0.0003	***	-0.0052	0.0001	***	-		
γ_{MT}	-0.0043	0.0003	***	-0.0016	0.0001	***	-		
γ_{HT}	0.0037	0.0002	***	0.0032	0.0001	***	-		
Country Dummies		NO			YES			YES	
Product Dummies		NO			YES			YES	
Year Dummies		NO			NO			YES	
Number of observations		3258			3258			3258	
R^2 *- LS*		0.4237			0.9437			0.9467	
R^2 *- MS*		0.4320			0.9193			0.9215	
R^2 *- HS*		0.1650			0.8733			0.8748	

Notes. Standard errors in column next to parameter estimates. ***,** and * refer to 0.1%, 1% and 5% significance levels. Subscripts refer to high-skilled labor (H), medium-skilled labor (M), low-skilled labor (L) and Y to output. In Seemingly unrelated regression R^2 are calculated for each regression equation. The reported R^2 is the simple average of the R^2 of the three regression equations. Both country and product group dummies show jointly significance at high level and are not reported to save space. Hausman test comparing pooled and fixed effect gives χ^2=3178 at significance level .0000, which favours fixed effect model. See Appendix Table 1 for the estimates of year dummies in last regression.

Table 4 Factor demand elasticities

	Implied Price Elasticity				Implied Elasticity of Substitution			
	w_L	w_M	w_H	r	L	M	H	K
L	-0.644	0.361	0.140	0.143	-	1.218	0.834	0.390
M	0.205	-0.453	0.135	0.112	1.218	-	0.807	0.306
H	0.141	0.239	-0.442	0.062	0.834	0.807	-	0.168
K	0.066	0.091	0.028	-0.184	0.390	0.306	0.168	-

Note: the elasticities are based on equations (4 and 5) and correspond to the regression results in Table 3 (fixed effects with time trend). *w* refers to wages of high-skilled labor (H), medium-skilled labor (M), low-skilled labor (L) and *r* to the price capital (K). See Appendix 2 for underlying Hessian Matrix.

Table 5 Regression results for product groups, 1995-2007.

Variable	Light manufacturing	Heavy manufacturing	Machinery and electronics	All manufacturing
β_L	0.1544	0.1075	0.1589	0.1566
	0.0173***	0.0191***	0.0183***	0.0103***
β_M	-0.1633	-0.0718	0.0453	-0.0623
	0.0199***	0.0249**	0.0197*	0.0121***
β_H	-0.1326	-0.1648	-0.1590	-0.2065
	0.0177***	0.0174***	0.0146***	0.0099***
γ_{LL}	0.0331	0.0247	0.0314	0.0316
	0.0033***	0.0045***	0.005***	0.0024***
γ_{LM}	0.0027	0.0347	0.0199	0.0109
	0.0032	0.0046***	0.0051***	0.0024***
γ_{LH}	0.0056	-0.0209	-0.0201	-0.0047
	0.0028*	0.0032***	0.0034***	0.0018**
γ_{MM}	0.0695	0.0764	0.0833	0.0743
	0.0069***	0.0088***	0.009***	0.0047***
γ_{MH}	0.0148	-0.0361	-0.0400	-0.0096
	0.0058**	0.0068***	0.0063***	0.0038**
γ_{HH}	0.0268	0.1009	0.1081	0.0655
	0.0062***	0.0069***	0.0059***	0.0038***
γ_{LY}	-0.0023	-0.0030	0.0005	-0.0005
	0.001*	0.0011**	0.0011	0.0006
γ_{MY}	-0.0003	-0.0025	-0.0025	-0.0022
	0.0011	0.0014*	0.0011*	0.0006***
γ_{HY}	-0.0013	-0.0002	-0.0020	0.0020
	0.0009	0.0009	0.0008**	0.0005***
γ_{LT}	-0.0056	-0.0047	-0.0054	-0.0052
	0.0002***	0.0002***	0.0002***	0.0001***
γ_{MT}	-0.0018	-0.0008	-0.0015	-0.0016
	0.0002***	0.0002***	0.0002***	0.0001***
γ_{HT}	0.0038	0.0026	0.0031	0.0032
	0.0002***	0.0001***	0.0001***	0.0001***
Obs.	1079	1090	1089	3258
R^2 - LS	0.9495	0.9572	0.9472	0.9437
R^2 - MS	0.9373	0.9216	0.9223	0.9193
R^2 - HS	0.9006	0.8945	0.9004	0.8733
Implied FBTC over 12 years (% points)				
L	-6.73	-5.66	-6.43	-6.28
M	-2.21	-0.98	-1.76	-1.89
H	4.54	3.08	3.69	3.87
K	4.39	3.56	4.50	4.29

Note: Results based on fixed-effects regressions with time-trends. Standard errors are given below estimates. ***,** and * refer to 0.1%, 1% and 5% significance levels. Subscripts refer to high-skilled labor (H), medium-skilled labor (M), low-skilled labor (L) and Y to output. Appendix Table 2 shows Hessian matrices and implied elasticities for each model. *Light Manufacturing* includes products from 3. Food, beverages, and tobacco, 4. Textiles, 5. Leather and footwear, 7. Pulp, paper, printing and publishing; *Heavy manufacturing* includes 8. Coke, refinery of petroleum and nuclear fuel, 9. Chemicals, 10. Rubber and plastics, 11. Other non-metallic mineral, 12. Basic and fabricated metals. *Machinery and electronics* includes 14. Electrical equipment, 15. Transportation equipment, 13. Other machinery and 16. Other manufacturing products (Industry numbers correspond to the codes in WIOD).

Table 6 Alternative regression results with capital as quasi-fixed, 1995-2007.

Variable	Light Manufacturing	Heavy Manufacturing	Machinery and Electronics	All Manufacturing
β_L	0.5823	0.4734	0.4745	0.5355
	0.0189^{***}	0.0161^{***}	0.0133^{***}	0.0094^{***}
β_M	0.3016	0.4839	0.4476	0.4137
	0.0146^{***}	0.0171^{***}	0.0137^{***}	0.0089^{***}
γ_{LL}	0.0348	0.0420	0.0411	0.0402
	0.0051^{***}	0.0065^{***}	0.0067^{***}	0.0033^{***}
γ_{LM}	-0.0298	0.0198	0.0014	-0.0187
	0.0041^{***}	0.0067^{**}	0.0070	0.0032^{***}
γ_{MM}	0.0840	0.1227	0.1058	0.0984
	0.009^{***}	0.0138^{***}	0.013^{***}	0.0068^{***}
γ_{LK}	-0.0057	0.0041	-0.0146	-0.0049
	0.0053	0.0044	0.0045^{***}	0.0027^{*}
γ_{MK}	0.0267	0.0095	0.0146	0.0152
	0.0042^{***}	0.0046^{*}	0.0046^{***}	0.0026^{***}
γ_{LY}	-0.0015	-0.0052	0.0145	0.0034
	0.0052	0.0041	0.0043^{***}	0.0026
γ_{MY}	-0.0203	-0.0109	-0.0126	-0.0161
	0.004^{***}	0.0043^{**}	0.0044^{**}	0.0025^{***}
γ_{LT}	-0.0073	-0.0065	-0.0066	-0.0068
	0.0003^{***}	0.0002^{***}	0.0003^{***}	0.0001^{***}
γ_{MT}	0.0000	0.0012	0.0003	0.0001
	0.0002	0.0002^{***}	0.0003	0.0001
Obs.	1079	1090	1089	3258
R^2 - LS	0.9586	0.9699	0.9638	0.9603
R^2 - MS	0.9645	0.9542	0.9422	0.9480
Implied FBTC over 12 years (% pts)				
L	-8.79	-7.82	-7.90	-8.21
M	-0.04	1.45	0.31	0.11
H	8.83	6.38	7.60	8.11

Note: Results based on fixed-effects regressions with time-trends, high-skilled labor (H), medium-skilled labor (M) and low-skilled labor (L) as variable inputs and capital (K) as quasi-fixed input. Y is output. Standard errors are given below estimates. ***,** and * refer to 0.1%, 1% and 5% significance levels. See Table 5 for definition of product groups.

Table 7 Alternative regression model results, 1995-2007.

Variable	Base Model	Include ICT	MFP adjusted	Expanding products
β_L	0.1566 0.0103^{***}	0.1376 0.0121^{***}	0.1429 0.0108^{***}	0.1001 0.0081^{***}
β_M	-0.0623 0.0121^{***}	-0.0530 0.0164^{***}	-0.0784 0.0124^{***}	0.0331 0.0081^{***}
β_H	-0.2065 0.0099^{***}	-0.1874 0.0125^{***}	-0.1941 0.0100^{***}	-0.0592 0.0054^{***}
γ_{LL}	0.0316 0.0024^{***}	0.0309 0.0027^{***}	0.0274 0.0029^{***}	0.0385 0.0021^{***}
γ_{LM}	0.0109 0.0024^{***}	0.0094 0.0029^{***}	0.0138 0.0030^{***}	0.0163 0.0017^{***}
γ_{LH}	-0.0047 0.0018^{**}	-0.0009 0.0021	-0.0028 0.0023	-0.0101 0.0012^{***}
γ_{MM}	0.0743 0.0047^{***}	0.0832 0.0057^{***}	0.07 0.0060^{***}	0.0269 0.0028^{***}
γ_{MH}	-0.0096 0.0038^{**}	-0.0171 0.0043^{**}	-0.0063 0.0047	0.0179 0.0022^{***}
γ_{HH}	0.0655 0.0038^{***}	0.0650 0.0043^{***}	0.0595 0.0046^{***}	0.0222 0.0022^{***}
γ_{LY}	-0.0005 0.0006	-0.0005 0.0007	-0.0008 0.0006^{***}	0.0036 0.0005^{***}
γ_{MY}	-0.0022 0.0006^{***}	-0.0026 0.0009^{**}	-0.0028 0.0006^{***}	-0.0061 0.0005^{***}
γ_{HY}	0.0020 0.0005^{***}	0.0017 0.0006^{**}	0.0014 0.0005^{***}	-0.0005 0.0003^{*}
γ_{LT}	-0.0052 0.0001^{***}	-0.0045 0.0001^{***}	-0.0056 0.0001^{***}	-0.0045 0.0001^{***}
γ_{MT}	-0.0016 0.0001^{***}	-0.0001 0.0002	-0.0017 0.0001^{***}	-0.0018 0.0001^{***}
γ_{HT}	0.0032 0.0001^{***}	0.0037 0.0001^{***}	0.0033 0.0001^{***}	0.0024 0.0001^{***}
$\gamma_{L,ICT}$		-0.0035 0.0008^{***}		
$\gamma_{M,ICT}$		-0.0145 0.0010^{***}		
$\gamma_{H,ICT}$		-0.0024 0.0007^{***}		
Obs.	3258	2003	3258	6184
R^2 - LS	0.9437	0.9512	0.9421	0.9145
R^2 - MS	0.9193	0.9172	0.9169	0.9224
R^2 - HS	0.8733	0.9019	0.8711	0.9018

Notes: Results based on country and industry fixed-effects ISUR regressions with time-trends. ***,** and * refer to 0.1%, 1% and 5% significance levels. Subscripts refer to high-skilled labor (H), medium-skilled labor (M), low-skilled labor (L) and Y to output. In first column the base regression from Table 3 is given. The *ICT* model includes the stock of ICT capital per worker as an independent variable (from EU KLEMS database, O'Mahony and Timmer 2009). In the *MFP-adjusted* model all factors in a country are adjusted by the multi-factor productivity level of the country as given in Penn World Table 8.0 (Feenstra, Inklaar and Timmer, 2013). In column with *Expanding products* we also include observations of manufactures GVCs of which final stage of production takes place in twenty rich as well as twenty poor countries.

Appendix Table 1. Estimates on year-dummies in fixed effects model in Table 3

	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007
λ_{LT}	-0.0070	-0.0163	-0.0249	-0.0316	-0.0373	-0.0410	-0.0483	-0.0373	-0.0560	-0.0599	-0.0634	-0.0659
	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0018	0.0019	0.0019	0.0019
λ_{MT}	*-0.0001*	*0.0033*	*0.0020*	*-0.0001*	*-0.0001*	*-0.0029*	-0.0053	-0.0104	-0.0029	-0.0093	-0.0160	-0.0194
	0.0019	*0.0019*	*0.0019*	*0.0019*	*0.0019*	*0.0019*	0.0019	0.0019	0.0020	0.0020	0.0020	0.0021
λ_{HT}	0.0040	0.0080	0.0126	0.0147	0.0193	0.0231	0.0251	0.0250	0.0344	0.0369	0.0379	0.0372
	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0015	0.0016	0.0016	0.0016	0.0016
λ_{KT}	*0.0031*	*0.0051*	0.0103	0.0170	0.0181	0.0207	0.0285	0.0228	0.0245	0.0323	0.0415	0.0481
	0.0026	*0.0026*	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026	0.0026	0.0027	0.0027

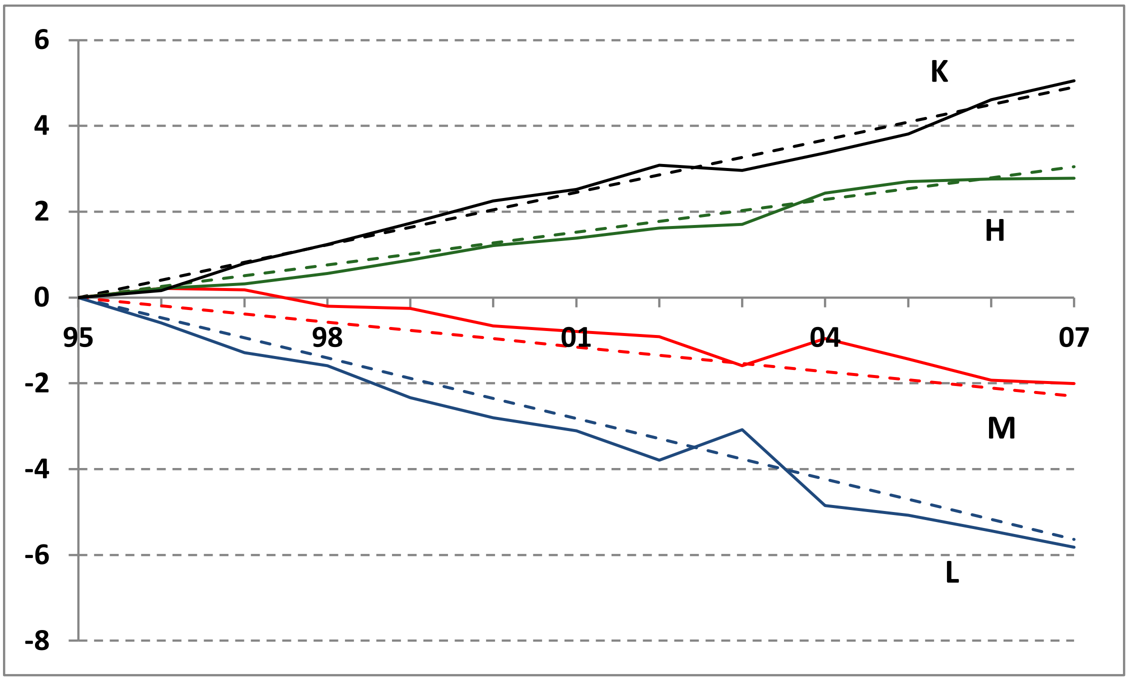
Note: Standard errors are given below. Those values that are not significant at 1% level are in italics.

Appendix Table 2 Hessian Matrices and Implied Elasticities

		Implied Price Elasticity				Implied Elasticity of Substitution				*H*-Diag(*s*)+*ss*' Matrix and Eigenvalues			
		w_L	w_M	w_H	*R*	L	M	H	K	L	M	H	K
Light Manufacturing	L	-0.636	0.315	0.197	0.124	-	1.05	1.185	0.351	-0.116	0.057	0.036	0.022
	M	0.191	-0.468	0.216	0.062	1.05	-	1.296	0.175	0.057	-0.141	0.065	0.019
	H	0.215	0.389	-0.672	0.068	1.185	1.296	-	0.194	0.036	0.065	-0.112	0.011
	K	0.064	0.053	0.032	-0.149	0.351	0.175	0.194	-	0.022	0.019	0.011	-0.052
										E-Vals: -0.2012, -0.1503, -0.0687, 0			
Heavy Manufacturing	L	-0.686	0.502	0.023	0.161	-	1.802	0.148	0.393	-0.107	0.078	0.004	0.025
	M	0.28	-0.447	0.028	0.139	1.802	-	0.179	0.34	0.078	-0.125	0.008	0.039
	H	0.023	0.05	-0.204	0.131	0.148	0.179	-	0.321	0.004	0.008	-0.032	0.021
	K	0.061	0.095	0.051	-0.206	0.393	0.34	0.321	-	0.025	0.039	0.021	-0.084
										E-Vals: -0.1956, -0.1121, -0.0399, 0			
Electronics and Machinary	L	-0.646	0.428	0.059	0.158	-	1.378	0.333	0.461	-0.109	0.073	0.010	0.027
	M	0.233	-0.421	0.049	0.139	1.378	-	0.276	0.406	0.073	-0.131	0.015	0.043
	H	0.056	0.086	-0.214	0.072	0.333	0.276	-	0.209	0.010	0.015	-0.038	0.013
	K	0.078	0.126	0.037	-0.242	0.461	0.406	0.209	-	0.027	0.043	0.013	-0.083
										E-Vals: -0.1960, -0.1145, -0.0505, 0			
All Manufacturing	L	-0.644	0.361	0.14	0.143	-	1.218	0.834	0.39	-0.109	0.061	0.024	0.024
	M	0.205	-0.453	0.135	0.112	1.218	-	0.807	0.306	0.061	-0.134	0.040	0.033
	H	0.141	0.239	-0.442	0.062	0.834	0.807	-	0.168	0.024	0.040	-0.074	0.010
	K	0.066	0.091	0.028	-0.184	0.39	0.306	0.168	-	0.024	0.033	0.010	-0.068
										E-Vals: -0.1875, -0.1164, -0.0807, 0			

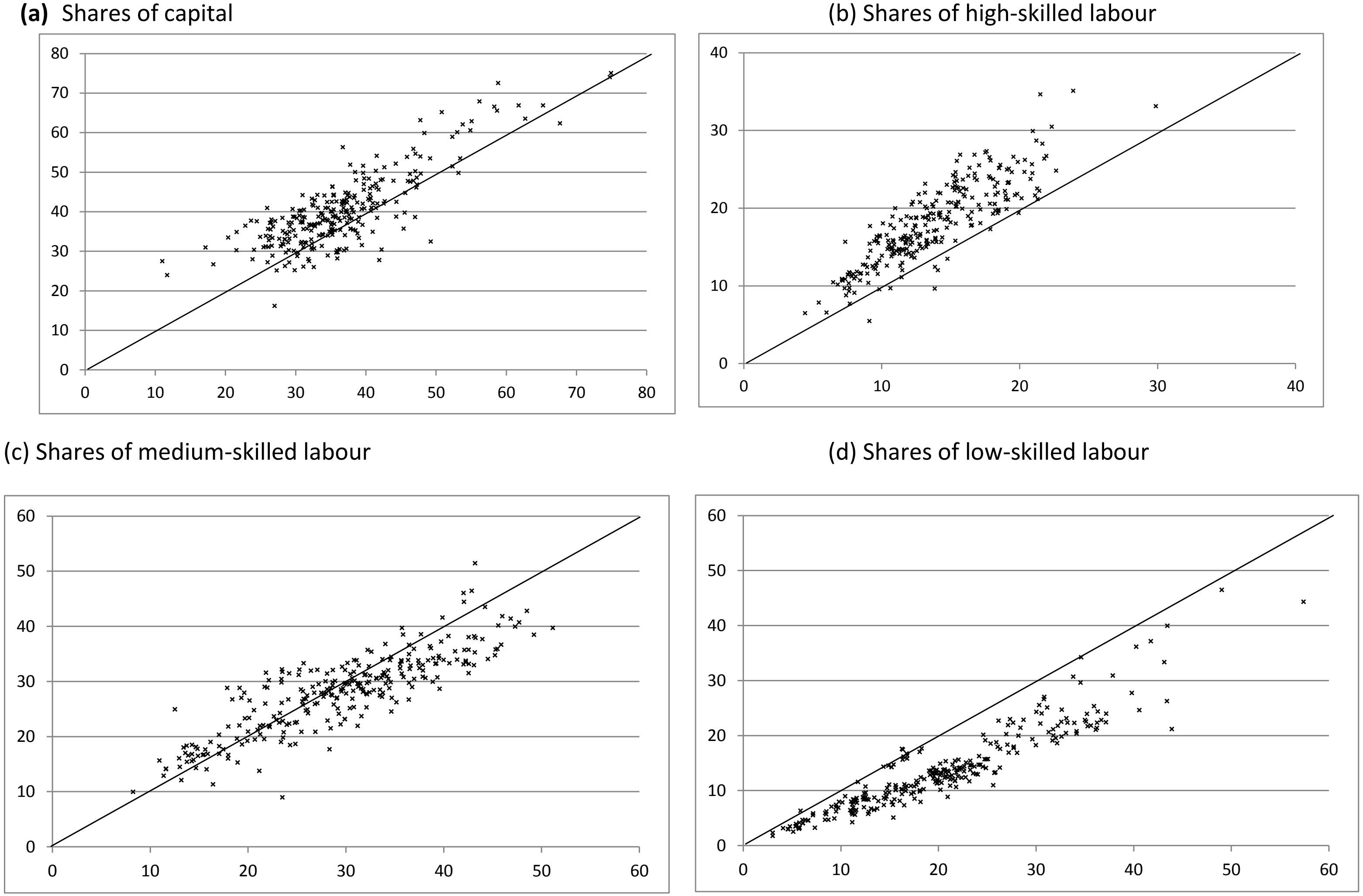
Note: Hessian matrices and implied elasticities from fixed-effects regressions with time-trends for various groups of manufacturing products, corresponding to Table 4. Eigenvalues of Hessian matrices are given below.

Figure 2 Cumulative factor bias in technological change, 1995-2007



Note: in percentage points. Based on regression results in Table 3. Trend results are based on fixed effects regression with time trends (dotted line) and with year dummies (sold line). Variables refer to high-skilled labor (H), medium-skilled labor (M), low-skilled labor (L) and capital (K)

Figure 1 Factor shares in 280 global value chains of manufactures.



Note: Factor shares in 560 global value chains, identified by 14 manufacturing industries of completion in 20 countries, in 1995 (x-axis) and in 2008 (y-axis). The dashed line is the 45 degree line. *Source:* Authors' calculations based on World Input-Output Database, November 2013 release.