Offshoring, Biased Technical Change and the Increasing Capital Share: an Analysis of Global Manufacturing Production

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Abstract

Current analyses of factor income shares suffer from the observational equivalence of offshoring and factor-biased technical change. In this paper we propose a novel empirical approach that allows for much sharper identification based on an analysis of global production with trade-in-tasks. We model the production process of a final product as an array of tasks that can be performed by domestic as well as foreign factors of production. As in Grossman and Rossi-Hansberg (2008) offshoring is modelled through its effect on factor prices and FBTC is defined as a decline in the relative use of a factor, controlling for relative factor price movements. Based on new information about the factor content of imported intermediates we find declining global prices for low-skilled workers and capital relative to medium- and high-skilled workers. We document also increasing income shares for capital and high-skilled workers in the final output value of 12 manufacturing product groups from 21 advanced countries during 1995-2007. Based on this information we estimate substitution elasticities and factor-biased technical change in a flexible (translog) cost function framework. We find strong evidence of technical change being biased against low- and medium-skilled workers, and in favour of high-skilled workers and capital. The advance of information technology appears to be an important channel and is particularly biased against medium-skilled workers. These findings are found to be robust in various alternative empirical settings.

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1. Introduction

The income shares of production factors are not constant. Recent evidence is showing that the labour share has significantly declined since the early 1980s, with the decline occurring within the large majority of countries and industries (Karabarbounis and Neiman, 2014). At the same time, there was a wide-spread polarization within the labor market as jobs and incomes of medium-skilled workers in many advanced nations declined relative to high-skilled workers, as well as to low-skilled workers (Goos, Manning and Salomons, 2014). Several channels have been proposed to explain these patterns, amongst which most prominently the increase in international trade and advances in information technology. 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 and services tasks. International trade might impact both between-industry and within-industry shifts in factor demand. Due to increased opportunities for international fragmentation, production activities are being relocated to countries where they can be carried out at lowest costs. Off-shored tasks are typically less intensive in skills than tasks that remain domestically, such that part of the decline of incomes of less-skilled workers in the domestic economy can be accounted for by offshoring.

Currently, there is no consensus on the relative importance of these potential drivers. In early work for the US Feenstra and Hanson (1997) found a sizeable role for both international trade and technical change. A number of recent cross-country studies emphasize technology trends and find evidence in favour of the routine-bias in technical change (Goos, Manning and Salomons, 2014; Michaels, Natraj and van Reenen. 2013). Karabarbounis and Neiman (2014) suggest that it is the rapid declining price of investment goods that induces a shift away from labour and toward capital as they find an elasticity of substitution bigger than one. On the other hand, Elsby, Hobijn and Sahin (2013) suggest that offshoring of the labour-intensive component of the U.S. supply chain might be a leading potential explanation for the declining labour share in the US over the past 25 years. And in a study of local labour markets in the U.S., Autor, Dorn and Hanson (2013) indeed find an increasing role for trade in the 2000s as imports accelerate and a shift in the effect of technology from manufacturing to services activities. Similarly, Firpo, Fortin and Lemieux (2012) find that technological change and de-unionization played a central role in the US in the 1980s and 1990s, while offshorability became an important factor from the 1990s onwards.

A major obstacle in empirical work so far that considers trade and technology simultaneously is the observational equivalence of the effects of offshoring and technical change in case both have the same factor bias, as noted early on by Feenstra and Hanson (2003). Studies typically employ a cross-industry regression set up in which employment or labour cost shares are related to relative wages and to an indicator for technological change, such as expenditures on research and development or on information and communication equipment. To account for the effects of international trade, an indicator for off-shoring is added, such as the share of imported intermediates (as e.g. in Michaels et al 2014 and Hijzen et al. 2005, following

Feenstra and Hanson, 1997) or a measure of offshorability of an occupation (based on O*NET data as e.g. Goos et al. 2014 and Firpo et all 2013). However, the existing proxy indicators for offshoring and factor-biased technological change appear to be strongly positively correlated (see e.g. Goos et al. 2014, Table 3) and results are sensitive to the exact measurement of the indicators, as noted early on by Feenstra and Hanson (1997).

In this paper we develop an empirical approach that allows one to clearly distinguish between the effects of offshoring and of biased technical change. The approach is motivated by a simple task-based model of offshoring along the lines of Grossman and Rossi-Hansberg (2008) in which production is modelled as an array of tasks. Each task requires the input of some single factor of production, domestically or abroad. Some tasks can be performed by workers with little skills (referred to as 'L-tasks') while others must be performed by workers with greater skills ('H-tasks').[1] The production technology allows a firm to substitute between L-tasks and H-tasks. For example, a given quality of a product (say number of defects on a wafer) can be achieved by conducting assembly (L) tasks and quality checking (H) tasks repeatedly, or by stepping up assembly (L) tasks such that less checking is needed. Factor prices are exogenous to the firm and depend critically on the opportunities of firms to undertake tasks abroad. Some tasks are more difficult to offshore than others reflecting for example how difficult it is to describe them using rules-based logic. We model offshoring parsimoniously and assume that the number of tasks that can be offshored is exogenously determined.[2] The effective factor price confronting a firm is then determined by this amount and factor prices domestically as well as abroad.

So for example, improvements in communication and transportation technologies increase opportunities for offshoring of L-tasks to low-skilled labour abundant countries. This leads to a decline in the global price of low-skilled labour relative to other factor inputs. Depending on its own price elasticity and the substitution elasticities with other factors the number of low-skilled workers used in production might change. This is captured by the translog specification of our empirical model which represents a flexible production function that allows for various degrees of factor substitution. In the model, the bias in technical change towards say low-skilled labour is straightforwardly defined as any change in the use of low-skilled workers that cannot be explained by the movement in relative factor prices.

A novel characteristic of our approach is that we do not analyse factor costs shares at the level of industries or countries, but at the level of final products as suggested by the task-based model of offshoring. To derive the factor costs shares in production of a particular good we need not only information on the factor content of the industry producing the good, but also the factor content of the offshored tasks. The latter are embodied in imported intermediates and will be identified using information from the World Input-Output Database following the recent insights on measuring the factor content of trade by Trefler and Zhu (2010), Johnson and Noguera (2012) and Koopman, Wang and Wei (2014).

[1] Without loss of generality we consider only two types of factor inputs, but in the empirical analysis we will consider three types of workers and capital.

[2] In the empirical exercise we will also provide estimates based on instrumenting this price.

We study production processes of 12 manufacturing product groups in 21 advanced countries which are heavily affected by international fragmentation and for which data is most abundant. We 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 arguably due to a global supply shock after the opening up of China, India and other labour-abundant economies in the 1990s, combined with increasing opportunities to offshore low-skilled tasks. Changes in factor shares are subsequently explained by changes in relative factor prices and biased technical change in a standard translog cost framework. We estimate a system of cost equations and 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 the own price elasticity was found to be moderate. Instead, we find strong evidence of technical change being biased against the use of low- and medium-skilled workers and favouring the use of capital and high-skilled workers. In additional analysis we find that the advance of information technology appears to be an important channel for technical change and is particularly biased against medium-skilled workers, confirming the routinization hypotheses.

The remainder of this paper is organised as follows. Section 2 presents the theoretical model motivating our empirical strategy and outlines the concept of a global production chain. Section 3 describes the data, outlining the method to derive factor content of intermediate inputs, and presents major trends in cost shares and prices of four factors (capital, low-, medium- and high-skilled workers) in global production of manufacturing goods. Section 4 discusses the econometric approach which is based on estimation of a system of cost-share equations 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. A task-based model of factor-biased technical change (FBTC) in the presence of offshoring

In this section we outline a task-based model along the lines of Grosssman and Rossi-Hansberg (2008) that will motivate our empirical approach. It allows us to define factor-biased technical change (FBTC) in the presence of offshoring in a consistent way by modelling not only the tasks in production that are carried out domestically, but also the tasks carried out abroad. We will model the increased opportunity for off-shoring of tasks through its effect on factor prices. For example, improvements in communication and transportation technologies reduce the costs of offshoring to low-skilled labour abundant countries. This effectively leads to a decline in the relative price of low-skilled labour relative to other factor inputs and likely lead to a greater use of low-skilled workers in production, depending on the factor's own price elasticity and the substitution elasticities with other factors. Any change in the use of low-skilled workers (domestically and abroad) that cannot be explained by the movement in relative factor prices must be due to biased technical change. We thus define

factor-biased technical change (FBTC) as a decline in the relative use of that factor, controlling for relative factor price movements

We follow Grossman and Rossi-Hansberg (2008, from here on R&H) and conceptualize the production process in terms of tasks. Each task requires the input of some single factor of production. Some tasks can be performed by workers with little skills (referred to as 'L-tasks') while others must be performed by workers with greater skills ('H-tasks').[3] The production technology allows a firm to substitute between L-tasks and H-tasks. For example, a given quality of a product (say number of defects in a product) can be achieved by conducting assembly (L) tasks and quality checking (H) tasks repeatedly, or by stepping up assembly (L) tasks such that less checking is needed. The intensity of L and H tasks is a choice variable for the firm, given factor prices. This is captured by the translog specification of our empirical model which represents a flexible production function that allows for factor substitution.

The factor prices are exogenous to the firm and depend critically on the opportunities of firms to undertake tasks abroad. Some tasks are more difficult to offshore than others reflecting for example how difficult it is to describe hem using rules-based logic or the importance of face-to-face contact for delivery of the output of the activity. As our main aim is to focus sharply on the measurement of technical change in the production of goods we model offshoring parsimoniously and assume that offshoring opportunity is exogenously determined by general developments in communication and transportation possibilities. The effective global factor price confronting a firm is then determined by the amount of tasks that can be offshored, and factor prices domestically and abroad.

More formally, we index the L-tasks in an industry by $x \in [0,X]$, where X indicates the number of tasks to be carried out by low-skilled workers (which is a choice variable for the firm) and order them so that the opportunity for offshoring is non-increasing (and similarly for H-tasks). In year t, a firm needs $q_L(x, t)$ units (say hours) of low-skilled work to perform task x. This production requirement can change over time as we allow for technical progress in the use of factor L. The total hours needed to perform the L-tasks (η) is then given by:

$$\eta_L(t) = \int_0^X q_L(x,t)dx \qquad (1)$$

Following R&H we assume that a firm needs the same amount of factor input for a given task whether it is carried out by a domestic or foreign factor (and remain silent on whether it is carried out within or outside the firm). This factor requirement is determined by the nature of the task and by the firm's production technology. We further assume that offshoring is costless (as in Feenstra and Hanson 1996), such that when factor prices are lower abroad a cost-minimizing firm will always offshore tasks if feasible. This is an exogenous constraint as argued above. Let $X_L(t)$ represent the last task that can be offshored in year t such that tasks with an index $x < X_L(t)$ are offshored, while tasks with $x > X_L(t)$ will be performed

[3] Without loss of generality we consider only two types of factor inputs, but in the empirical analysis we will consider three types of workers and capital.

domestically. Under these conditions, the cost for the firm to complete all L-tasks in year *t* is given by:

$$c_L(t) = w_L^F(t)\int_0^{X_L(t)} q_L(x,t)dx + w_L^D(t)\int_{X_L(t)}^{X} q_L(x,t)dx$$
$$= w_L^F(t)\eta_L^F(t) + w_L^D(t)\eta_L^D(t) \qquad (2)$$

Where *w* denotes wage and superscripts for foreign (F) and domestic (D) workers, and η_L^F and η_L^D are the two integral terms reflecting the hours that are offshored and remain domestically. Given that $\eta_L^F + \eta_L^D = \eta_L$, we can define the average wage (per hour) for low-skilled labour in the global production process (w_L^*). This is a average of domestic and foreign wages weighted with their share in the total hours worked:

$$w_L^*(t) = [w_L^F(t)\eta_L^F(t) + w_L^D(t)\eta_L^D(t)]/\eta_L(t) \qquad (3)$$

Note that an improvement in offshoring opportunities will lead to a decline in w_L^* as a larger share of the tasks will be offshored and carried out at a lower wage.

Next, we define technical progress as an efficiency improvement in the use of a particular factor, which affects all tasks carried out by the factor (domestic or abroad) but might differ across factors such that technical change can be factor biased. Let $\zeta_L(t+1)$ denote the efficiency with which L-tasks are carried out in t+1 (normalised to period *t*) then the required hours of task *x* in year t+1 is given by:

$$q_L(x,t+1) = q_L(x,t)/\zeta_L(t+1) \qquad (4)$$

It is important to note that this factor-specific technical change has no impact on the global factor price as it is assumed to symmetrically affect all workers of the same type irrespective of their location. This can be easily deducted from equation (3), realising that total hours needed will go down $\eta_L(t+1) = \eta_L(t)/\zeta_L(t+1)$ and similarly for η_L^F and η_L^D. In this model, factor prices will only be determined by changes in offshoring opportunities and wages movements within countries as in (3). This characteristic of our set-up will allow us to separately identify the effects of offshoring and FBTC on factor income shares. This will be done through estimating a system of cost share equations based on a flexible translog production function as will be outlined in section 4. We first turn to a discussion of the data needed to measure factor income shares in global production chains, as well as global factor prices.

3. Factor cost shares and prices in global production chains

In this section we first outline our empirical strategy in identifying factor cost shares and prices as suggested by our model of global production in the previous section. Section 3.2 discusses data sources and section 3.3 documents new evidence on the trends in factor costs shares and prices in the global production of 12 manufacturing product groups.

3.1 Measuring the factor content of global production

To measure the factor content of global production we need to decompose the value of a final product into the contributions of all factors that were used in the production process of the good. We will trace these factors through an input-output approach pioneered by Leontief (1936) and comparable in spirit to the attempts by Koopman et al. (2013) and Johnson and Noguera (2013) to measure the value added content of trade in a multilateral setting, as well as Reimer (2006) and Trefler and Zhu (2010) who calculated the factor content of trade in a bilateral setting. More formally, we will study value chains of final products that are identified by the last stage of production: a particular industry *i* located in a specific country *j*, denoted by *(i,j)*. To produce good *(i,j)* activities in industries $s = 1,\ldots,S$ in each of the countries $n = 1,\ldots,N$ are needed. To decompose its value, we need to start with finding the levels of gross output in all industries associated with the production of (*i*,*j*). These can be estimated by applying standard input-output methods to global input-output tables. Global input-output tables contain information on the values of intermediate input flows among all country-industries in the world, as well as on the values of flows from each of these country-industries to final use in each of the countries. Combining information on values of sales and factor cost per dollar of sales leads to estimates of total factor costs in each of the *SN* industries as a consequence of final demand product (i,j). For this we use an equation that has been a standard tool in input-output analysis for over decades (see Miller and Blair, 2009):

$$\mathbf{g} = \hat{\mathbf{v}}(\mathbf{I} - \mathbf{A})^{-1}(\mathbf{Fe}) \qquad (5)$$

In this equation, **g** is the vector of factor costs in each of the *SN* country-industries involved in a value chain. The choice for a specific final output matrix **F** determines which value chain is considered. Final output is output delivered for household consumption and investment demand.[4] **e** is a summation vector. $(\mathbf{I}-\mathbf{A})^{-1}$ is the well-known Leontief inverse, the use of which ensures that factor contributions in all tiers of suppliers are taken into account. I is an identity matrix and **A** a matrix of global intermediate input coefficients. **v** is a vector with factor requirements per unit of gross output for each of the country-industries.[5]

This calculation is made for four factor inputs that together exhaust value added in an industry (3 labour types and capital). The sum across all four factor inputs will be equal to the output value of the product.[6]

3.2 Data sources

Throughout the paper we will focus on global production of final manufacturing goods. Production systems of manufactures are highly prone to international fragmentation as

[4] Note that all final demand for the output of (*i*,*j*) is considered, so it includes both domestic and foreign demand.

[5] Matrices are indicated by bold capital symbols and (column) vectors by bold lowercases. Hats denote diagonal matrices with the corresponding vector on the main diagonal.

[6] This decomposition methodology 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 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* be a column vector of final goods consumption. The production of *z* requires intermediate inputs given by **A**z. In turn, the production of these intermediates requires the use of other intermediates given by $\mathbf{A}^2$z, and so on. As a result the increase in output in each sector is given by the sum of all direct and indirect effects, that is $1+A+A^2+A^3+\ldots$. This geometric series converges to $(\mathbf{I}-\mathbf{A})^{-1}$.

activities have a high degree of international contestability: they can be undertaken in any country with little variation in quality. Note that these also include activities 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 in the world (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 equation (5) is complete.

In line with our motivating theoretical model we measure the global price of a production factor in a particular chain by dividing the costs by the quantities used. Both numerator and denominator are summed across all industries that contributed to the final product. Factor quantities are derived in a similar way as factor costs using equation (5), but now with **g** the vector of factor quantities in each of the *SN* country-industries. Factor requirements are derived from the WIOD where labour quantities are given in number of workers and capital quantities as the stock of fixed reproducible capital in constant prices.

One might argue that despite our use of an internationally standardized educational classification, these prices might reflect cross-country quality differences within a given skill-category. In a robustness analysis we will also provide an alternative based on correction for possible productivity differences of workers 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 12 groups of final manufacturing goods from twenty-one 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.) Countries include fifteen advanced EU countries (Austria, Belgium, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, Spain, Sweden and United Kingdom) and five non-European countries (Australia, Japan, South Korea, Taiwan and the United States). The twelve product groups are Food products (produced by firms coded in industries 15 and 16 in the ISIC rev.3 industrial classification); Textile products (17,18); Leather products (19); Paper and printing products (21,22); Chemical products (24); Rubber and plastics (25); Other non-metallic minerals (26); Basic and fabricated metals (27,28); Other machinery (29); Electronic products (30-33); Transport products (34,35) and Other manufacturing products (36).

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 252 value chains: 12 manufacturing product groups with 21 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 decreasing (see also Timmer et al., 2014).

[Figure 1 about 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 (unweighted) averaged across all products and thirteen years. The total number of observations is less than 13*252=3276 as some industry-countries do not have any final output. Table 1 shows that capital captures around 37% of cost share in the value chain. 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 and Figure 2 further report on the changes in cost shares, prices and quantities of each factor (unweighted across products). 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. This is shown in Figure 3. 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. In contrast, use of high-skilled workers grew the fastest. Whether these price and quantity trends are mainly driven by biased technical change or through factor substitution will be formally tested in the next section.

[Table 1 about here]
[Table 2 about here]
[Figures 2-3 about here]

4. Econometric methodology and results

4.1 Econometric set-up

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). This flexible production function set-up allows for a wide range of varying elasticities of substitution and has been used in some recent studies on the effects of outsourcing on skill-demand such as Hijzen et al. (2005), Foster-McGregor et al. (2013) and Michels et al. (2014), as well as in older literature on the nature 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 as discussed above. Hence the cost function of a particular product is defined in the prices and quantities of all capital and labour used in its production process.

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):

$$\begin{aligned}\ln C(\boldsymbol{p}_t, y_t, t) = \alpha &+ \sum_{i\in F}\beta_i \ln p_{it} + \frac{1}{2}\sum_{j\in F}\sum_{i\in F}\gamma_{ij}\ln p_{it}\ln p_{jt} \\ &+\beta_Y \ln y_t + \frac{1}{2}\sum_{i\in F}\gamma_{iY}\ln p_{it}\ln y_t + \frac{1}{2}\gamma_{YY}(\ln y_t)^2 \\ &+\beta_T t + \frac{1}{2}\sum_{i\in F}\gamma_{iT} t\ln p_{it} + \frac{1}{2}\gamma_{TT}t^2\end{aligned} \tag{6}$$

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 $\gamma_{iT}<0$). 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

$$S_{it} = \beta_i + \sum_{j \in F} \gamma_{ij} \ln p_{jt} + \gamma_{iY} \ln y_t + \gamma_{iT} t \tag{7}$$

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.[7] 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).[8] We use the cost share equation restrictions to implicitly derive the parameters for capital later on. The transformed unrestricted equation system to be estimated is as follows:

$$\begin{aligned}
S_{Lt} &= \beta_L + \gamma_{LL} \ln(p_{Lt}/p_{Kt}) + \gamma_{LM} \ln(p_{Mt}/p_{Kt}) + \gamma_{LH} \ln(p_{Ht}/p_{Kt}) + \gamma_{LY} \ln y_t \\
&\quad + \gamma_{Lt}\, \mathrm{t} \\
S_{Mt} &= \beta_M + \gamma_{ML} \ln(p_{Lt}/p_{Kt}) + \gamma_{MM} \ln(p_{Mt}/p_{Kt}) + \gamma_{MH} \ln(p_{Ht}/p_{Kt}) + \gamma_{MY} \ln y_t \\
&\quad + \gamma_{Mt}\, \mathrm{t} \\
S_{Ht} &= \beta_H + \gamma_{HL} \ln(p_{Lt}/p_{Kt}) + \gamma_{HM} \ln(p_{Mt}/p_{Kt}) + \gamma_{HH} \ln(p_{Ht}/p_{Kt}) + \gamma_{HY} \ln y_t \\
&\quad + \gamma_{Ht}\, \mathrm{t}
\end{aligned} \tag{8}$$

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

[7] 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.

[8] 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.

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 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[9]:

$$\sigma_{ij} = \frac{\gamma_{ij}}{s_i s_j} + 1, \qquad \text{(for } i \neq j\text{)} \tag{9}$$

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

$$\varepsilon_{ij} = \sigma_{ij} S_j \qquad \text{(for } i \neq j\text{)} \tag{10}$$
$$\varepsilon_{ii} = \frac{\gamma_{ii}}{s_i} + s_i - 1$$

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.

4.2 Main 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-fixed as well as product-fixed effects (fixed-effect ISUR). It is estimated with time trends in column 2 and year dummies in column 2 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. 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.[10]

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)

[9] See Berndt (1991) for details.

[10] Sometimes weighted regression is used to take account of difference in economic significance of or measurement error in the observations. Weighting with final output value has little effect on the results however.

provide a simpler alternative namely whether the Hessian 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.[11]

Our main variables of interest are the estimated parameters on FBTC which are 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 that $\sum_i \gamma_{ij} = 0$ for all factors j, it follows that $\gamma_{iK} = -(\gamma_{iL} + \gamma_{iM} + \gamma_{iH})$ and these implicit estimates are reported as well. The trend for capital is found to be strongly positive.

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 4 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 4 about here]

The role of price changes on changing factor shares 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 (9) and (10). 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

[11] 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.

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 the majority of the falling cost-share is attributable to biased technical change (*back-of-the-envelope calculation will be added*).

Also interesting are the elasticities of substitution between the various factor inputs given in the right part of the table. Low- and medium-skilled labour have an elasticity well above one, suggesting that they are substitutes in global production of manufacturing products. High-skilled labour appears to be somewhat complementary to the other types of labour however. Most notable is the low substitution elasticities of capital with all labour type. Capital appears to be particularly complementary to high-skilled workers, less to medium-skilled and the least to low-skilled.

[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 12 manufacturing products into three broad groups based on similarities in factor cost shares: light manufacturing, heavy manufacturing and machinery. Regression results for each group together with the pooled results (model 2 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 have non-positive eigenvalues throughout (see Appendix Table 2)

We find for all industry subgroups that the substitution elasticities between all labour types and capital is relatively low. But the substitution elasticities between different labour types differ substantially across groups. In light manufacturing, all labour types are substitutes for each other. But in heavy industries and machinery and electronics high-skilled workers are strongly complementary to medium- and low-skilled workers, 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 of Table 5. 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]

4.3 Robustness analysis

A set of alternative regressions are given in Table 6. A major worry in our set-up might be the assumed exogenous nature of factor prices. One might argue that the number of tasks to be

outsourced is not exogenously given but the result of firms' decision making based on domestic and foreign factor prices and the costs of offshoring, thus making the global price endogenous. We therefore follow an instrumenting strategy using predicted factor prices based on offshoring trends in other countries and industries in the vein of Autor, Dorn and Hanson (2013). In the first stage we predict the share of the tasks that are off-shored. This prediction is based on the offshoring propensity of all other industries in the country, as well as on the offshoring propensity of the same industry in other countries. Thus we take account of possible country-specific as well as industry-specific circumstances that determine offshoring. Off shoring propensity is defined as the share of offshored hours to non-advanced countries and are unweighted averages across industries or countries. Both propensities are highly significant in predicting offshoring for all three labour types with the country-environment having the largest predictive power. In the second stage we use predicted factor prices and results are given in column 2 of Table 6. Compared to the baseline results in column 1, little has changes and in particular the estimates of technical change bias remain almost the same.

A second robustness check relates to our assumption that workers in different countries but with the same level of educational attainment have similar productivities. We group workers by three levels of educational attainment according to an international standard classification, 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).

Lastly, we tried to identify what type of technologies could explain the bias in technical change. 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 4. 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 routinization hypothesis put forward by Autor, Levy and Murnane (2003).

[Table 6 about here]

5. Concluding remarks

Current analyses of factor income shares suffer from the observational equivalence of offshoring and factor-biased technical change. In this paper we proposed a novel empirical approach that allows for much sharper identification based on an analysis of global production with trade-in-tasks. We modelled the production process of a final product as an array of tasks that can be performed by domestic as well as foreign factors of production. As in Grossman and Rossi-Hansberg (2008) offshoring is modelled through its effect on factor prices and FBTC is defined as a decline in the relative use of a factor, controlling for relative factor price movements. Based on new information about the factor content of imported intermediates we found declining global prices for low-skilled workers and capital relative to medium- and high-skilled workers. We documented also increasing income shares for capital and high-skilled workers in the final output value of 12 manufacturing product groups from 21 advanced countries during 1995-2007. Based on this information we estimated substitution elasticities and factor-biased technical change in a flexible (translog) cost function framework. We found strong evidence of technical change being biased against low- and medium-skilled workers, and in favour of high-skilled workers and capital. The advance of information technology appears to be an important channel and is particularly biased against medium-skilled workers. These findings are found to be robust in various alternative empirical settings. 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 costs in output value of final manufacturing goods. Observations are averaged across all 21 countries, 12 manufacturing product groups and 13 years.

Table 2. Changes in factor cost shares, prices and quantities (% points change between 1995 and 2007)

	Factor	Mean	Std. Dev	5% pct	25% pct	Median	75% pct	95% pct
Cost shares	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
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

Note: mean, standard deviation and percentile distribution of changes in factor cost shares, prices and quantities. Unweighted average across 252 observations (21 countries time 12 manufacturing product groups).

Table 3 Determinants of factor cost shares, all products.

	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	***	0.065	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	***	-		
Implied γ associated with Capital									
γ_{LK}	-0.0183	0.0022	***	-0.0378	0.0015	***	-0.0375	0.0015	***
γ_{MK}	-0.0696	0.0025	***	-0.0757	0.0018	***	-0.0767	0.0018	***
γ_{HK}	-0.0113	0.0020	***	-0.0512	0.0014	***	-0.0513	0.0014	***
γ_{KK}	0.0993	0.0028	***	0.1647	0.0024	***	0.1654	0.0024	***
γ_{KY}	-0.0015	0.0006	**	0.0008	0.0008		0.0007	0.0008	
γ_{KT}	0.0032	0.0003	***	0.0036	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*	0.432			0.9193			0.9215		
R^2 - *HS*	0.165			0.8733			0.8748		

Notes. Estimation of parameters determining factor costs shares in system of equations as given in formula (10). 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), Capital (K) and Y to output. Parameters involving K are implicitly derived using the parameter restrictions discussed in the main text. R^2 are reported for each regression equation. Both country and product group dummies show jointly significance at high level and are not reported. 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 Determinants of factor cost shares, product groups.

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	-0.159	-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	-0.04	-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	-0.003	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	-0.002	0.002
	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***
Implied γ associated with Capital				
γ_{LK}	-0.0414	-0.0385	-0.0312	-0.0378
	0.0024***	0.0030***	0.0027***	0.0015***
γ_{MK}	-0.0871	-0.075	-0.0631	-0.0757
	0.0027***	0.0040***	0.0030***	0.0018***
γ_{HK}	-0.0472	-0.0438	-0.0481	-0.0512
	0.0023***	0.0027***	0.0022***	0.0014***
γ_{KK}	0.1757	0.1573	0.1424	0.1647
	0.0036***	0.0053***	0.0036***	0.0024***
γ_{KY}	0.0038	0.0057	0.004	0.0008
	0.0014**	0.0018***	0.0014**	0.0008
γ_{KT}	0.0037	0.003	0.0037	0.0036
	0.0002***	0.0002***	0.0002***	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	4.5	4.29

Notes to Table 5: 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 model results.

Variable	Base Model (1)	Instru-menting (2)	MFP Adjusted (3)	Include ICT (4)
β_L	0.1566	0.1767	0.1429	0.1376
	0.0103***	0.0111***	0.0108***	0.0121***
β_M	-0.0623	0.0275	-0.0784	-0.053
	0.0121***	0.0128*	0.0124***	0.0164***
β_H	-0.2065	-0.1866	-0.1941	-0.1874
	0.0099***	0.0103***	0.0100***	0.0125***
γ_{LL}	0.0316	0.0272	0.0274	0.0309
	0.0024***	0.0036***	0.0029***	0.0027***
γ_{LM}	0.0109	0.0045	0.0138	0.0094
	0.0024***	0.0035	0.0030***	0.0029***
γ_{LH}	-0.0047	0.0005	-0.0028	-0.0009
	0.0018**	0.0028	0.0023	0.0021
γ_{MM}	0.0743	0.0945	0.07	0.0832
	0.0047***	0.0065***	0.0060***	0.0057***
γ_{MH}	-0.0096	-0.0268	-0.0063	-0.0171
	0.0038**	0.0050***	0.0047	0.0043**
γ_{HH}	0.0655	0.0742	0.0595	0.065
	0.0038***	0.0050***	0.0046***	0.0043***
γ_{LY}	-0.0005	-0.0012	-0.0008	-0.0005
	0.0006	0.0005*	0.0006***	0.0007
γ_{MY}	-0.0022	-0.0034	-0.0028	-0.0026
	0.0006***	0.0007***	0.0006***	0.0009**
γ_{HY}	0.002	0.0014	0.0014	0.0017
	0.0005***	0.0004***	0.0005***	0.0006**
γ_{LT}	-0.0052	-0.0053	-0.0056	-0.0045
	0.0001***	0.0001***	0.0001***	0.0001***
γ_{MT}	-0.0016	-0.0016	-0.0017	-0.0001
	0.0001***	0.0001***	0.0001***	0.0002
γ_{HT}	0.0032	0.0034	0.0033	0.0037
	0.0001***	0.0001***	0.0001***	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	3258	3258	2003
R^2 - LS	0.9437	0.9398	0.9421	0.9512
R^2 - MS	0.9193	0.909	0.9169	0.9172
R^2 - HS	0.8733	0.8654	0.8711	0.9019

Notes to Table 6. Results based on ISUR regressions with time-trends. All regressions include country and industry fixed-effects. ***,** 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. In the *Instrumenting* variant (2) we predict in first stage the share of the tasks that are off-shored based on offshoring in other industries and countries, and use that to predict the factor prices used in the second stage. The *ICT* model (3) 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 (4) 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).

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

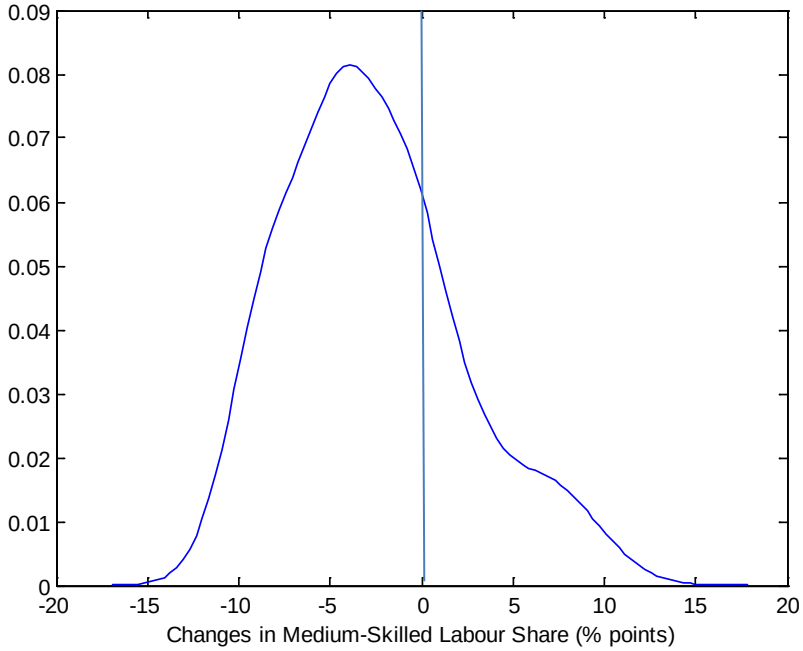
Note: Standard errors are given below. Those values that are not significant at 1% level are in italics.

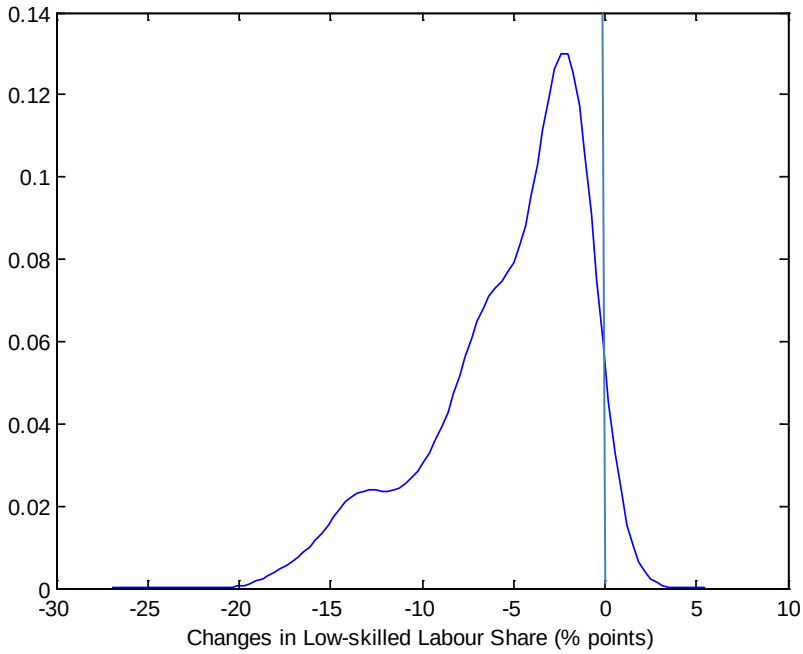
Appendix Table 2 Hessian Matrices and Implied Elasticities

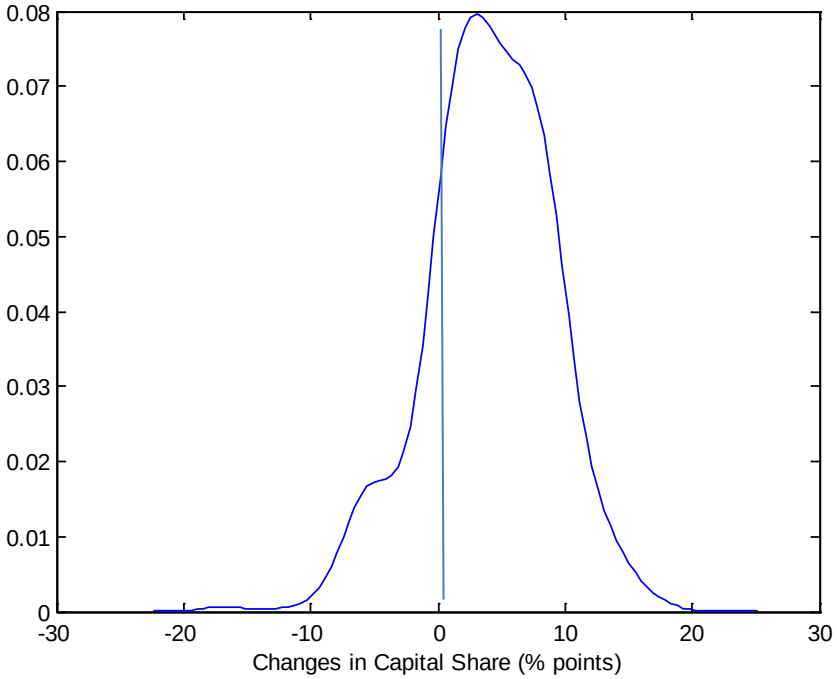
		Implied Price Elasticity				Implied Elasticity of Substitution				*H*-Diag(*s*)+*ss*' Matrix and Eigenvalues			
		w_L	w_M	w_H	R	L	M	H	K	L	M	H	K
Light Manufacturing	L	-0.636	0.315	0.197	0.124	-	1.05	1.185	0.351	-0.116	0.057	0.036	0.022
	M	0.191	-0.468	0.216	0.062	1.05	-	1.296	0.175	0.057	-0.141	0.065	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			

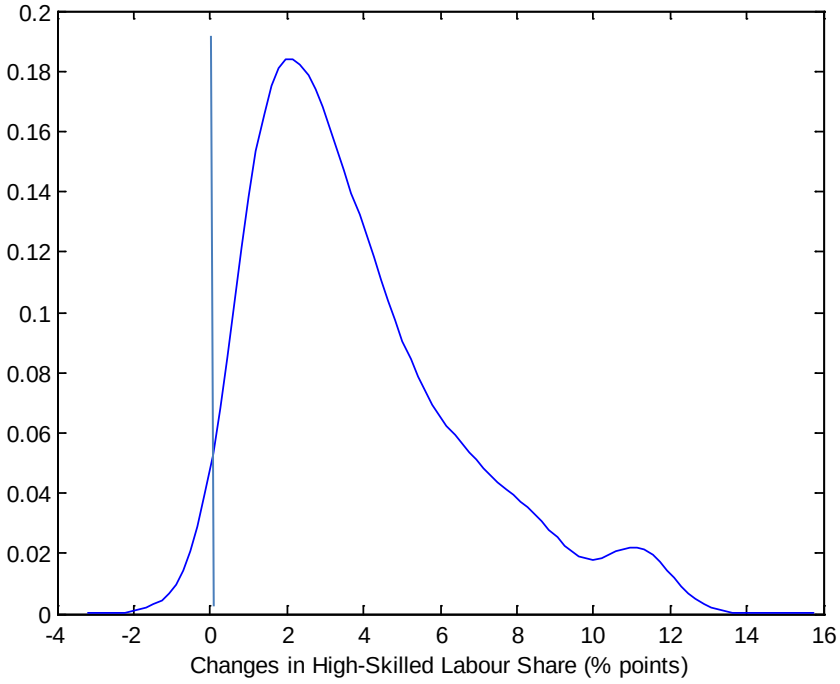
Note: Hessian matrices and implied elasticities from fixed-effects regressions with time-trends for various groups of manufacturing products, corresponding to Table 4. Eigenvalues of Hessian matrices are given below.

Figure 2 Kernel distributions of changes in factor income shares in final output of manufacturing between 1995 and 2007.









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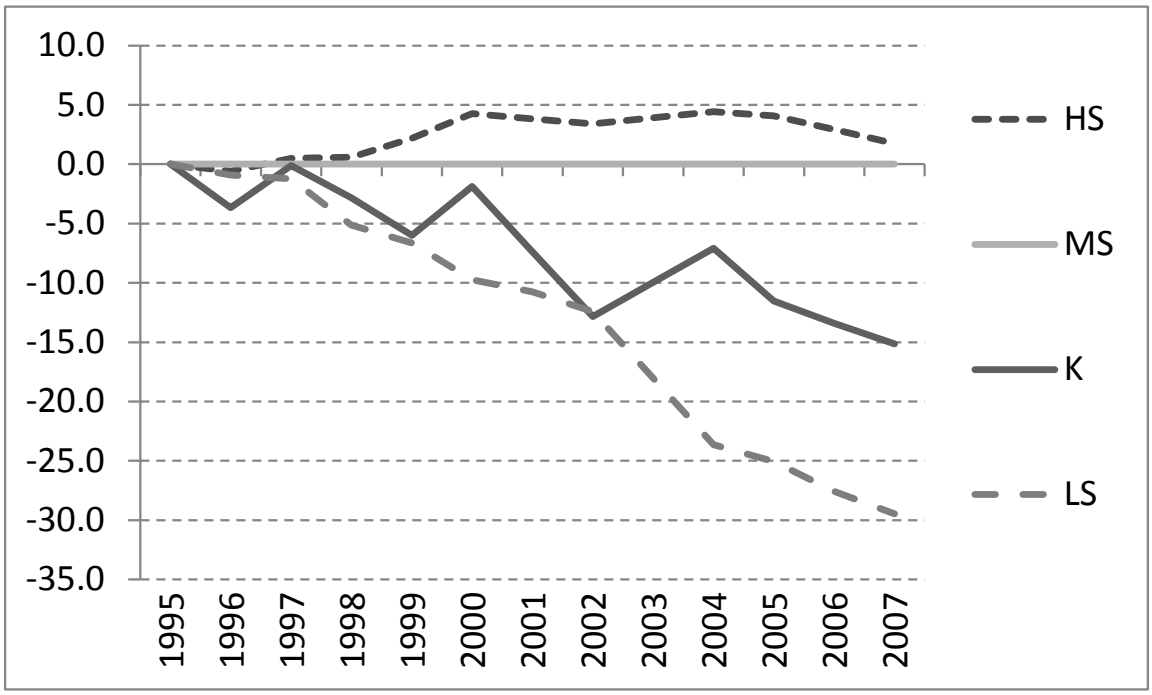
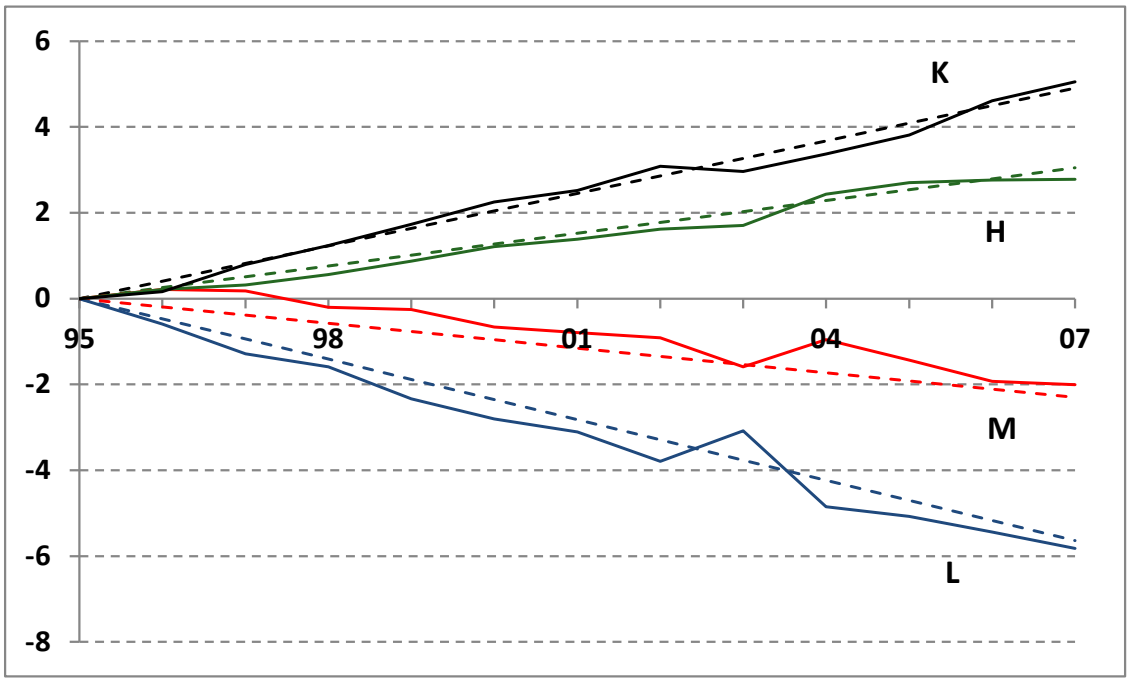
Note: change in factor income share between 1995 and 2007 (in percentage points of final output value). Based on 12 product groups from 21 countries. Mass of each observation is by final output value.

Figure 3 Global prices of factors used in production of manufacturing goods.



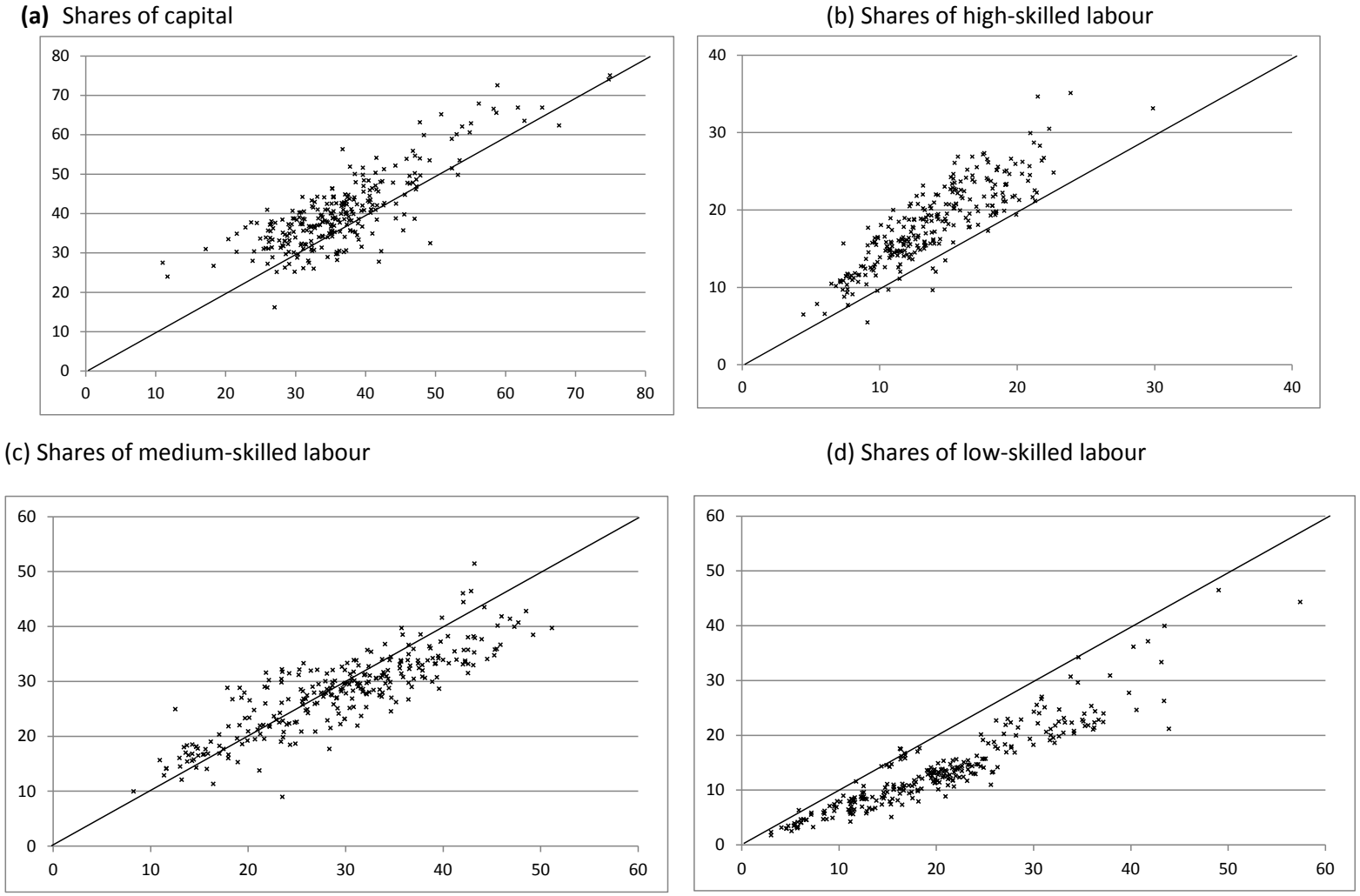
Note: development of prices of factors used in global production of manufacturing goods. Trends for high-skilled labor (HS), medium-skilled labor (MS), low-skilled labor (LS) and capital (K). Prices are calculated as total factor costs in production divided by quantity. All series are 1 in 1995 and normalized to change in MS price. Based on unweighted average of changes in 12 product groups from 21 countries. 2003 is interpolated.

Figure 4 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 240 global value chains of manufactures.



Note: Factor shares in 240 global value chains, identified by 12 manufacturing industries of completion in 20 countries, in 1995 (x-axis) and in 2007 (y-axis). The dashed line is the 45 degree line. *Source:* Authors' calculations based on World Input-Output Database, November 2013 release.