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Abstract

This paper studies the question whether skill-biased technical change diffuses internationally and that way contributes to the increasing relative skill demand in other countries. So far, the role of skill-biased technology diffusion has hardly been studied empirically. Using new sectoral data for a panel of 40 emerging and developed countries, 30 industries (covering manufacturing and service industries) and 13 years (1995-2007), the analysis shows that skill-biased technology diffusion is statistically and economically important in explaining skill-biased technical change. Countries further away from the skill-specific technological frontier subsequently show higher skill-specific productivity growth. For that, the bilateral distance between two countries proves to be an important mediating factor, whereas intersectoral trade linkages, so far, explain only a small part of it. The main results hold for both, developed and emerging countries.

JEL Classification: F16, J24, O14, O33, C67.

Keywords: Skill-biased technical change; technology diffusion; distance; input-output linkages; industry-level data; emerging and developed countries;

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1 Introduction

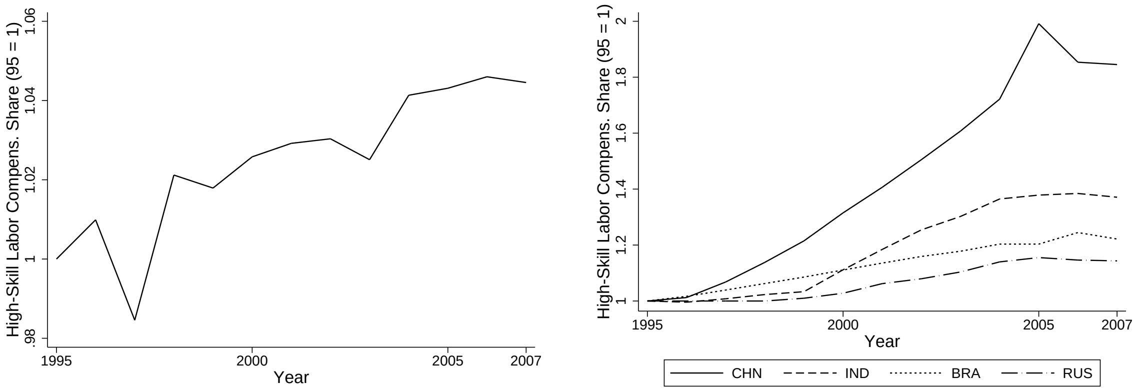
This paper studies the question whether skill-biased technical change (SBTC) diffuses internationally and in this way contributes to the increasing relative skill demand in other countries. Skill-biased technical change, that is a shift in production technologies which favors skilled labor, is usually considered the main cause of the rising skill demand in the United States and other developed countries.[1] Several channels have been proposed to explain SBTC, including technical change embodied in capital goods such as information technology (Autor, Katz, and Krueger 1998, O'Mahony, Robinson, and Vecchi 2008, Michaels, Natraj, and Van Reenen 2014), or disembodied forms of technical change such as organisational change (Caroli and Van Reenen 2001). A wealth of studies provides evidence explaining SBTC within countries, industries and firms, but hardly any empirical evidence exists whether this form of non-neutral technical change, like it has been shown for neutral technical change, diffuses internationally.[2] If skill-biased technical change diffused, it would affect the skill-bias of receiving entities and in this way shape their relative skill demand. This form of technology diffusion, from here on denoted as skill-biased technology diffusion (SBTD), could then be considered as another channel explaining the changing skill demand.

I study this question for both developed and emerging countries. Most of the previous evidence analyzing the increasing relative skill demand concentrates on the United States and other developed, OECD countries. As Figure (1) illustrates, a rising skill demand cannot only be observed in developed countries, but, at least for recent years, also in emerging countries. Thus, providing new evidence on causes and consequences of SBTC

[1] In addition to SBTC, international trade (Wood 1998, Feenstra and Hanson 1999, Krugman 2000, Krugman 2008), capital-skill complementarity (Krusell, Ohanian, Ríos-Rull, and Violante 2000, Duffy, Papageorgiou, and Perez-Sebastian 2004), the role of intersectoral technology-skill complementarities (Voigtländer 2014) and recently imported inputs (for developing countries) (Saravia and Voigtländer 2012, Raveh and Reshef 2015) have been identified as important explanations for the rising skill demand.

[2] For an overview article summarizing the literature studying the diffusion of neutral technical change, see e.g. Keller (2004). Exceptions studying the role of technology diffusion in the context of skill-biased technical change are Berman and Machin (2000), Hollanders and Ter Weel (2002) and Conte and Vivarelli (2007). However, these papers all have a different focus than studying the existence of skill-biased technology diffusion.

Figure 1: Increasing Skill Demand in the US and in Emerging Countries



(a) United States (b) Emerging Countries

Notes: The left panel describes the development of the high-skilled labor compensation share between 1995 and 2007 in the United States. The right panel describes this development for Brasil, Russia, India and China. The high-skilled labor compensation share is computed as a value-added weighted mean of industry's shares within a country. It is denoted as an index which is equal to 1 in 1995.

in emerging countries can be considered a second contribution of this paper. Comparing those two groups is also of particular interest to the study of skill-biased technology diffusion, since it has been shown that for neutral technical change patterns of technology diffusion can strongly differ among country groups. On the one hand, less developed countries might have a higher potential to benefit from technology diffusion because they are further away from the technological frontier. On the other hand, ample evidence is provided that the ability to absorb external knowledge depends very much on characteristics of the recipient entity, so called absorptive capacities. For example, the rate of technology diffusion seems the higher, the more intense an entity's own research efforts are (Griffith, Redding, and Van Reenen 2004, Madsen, Islam, and Ang 2010).[3] Since the ability to absorb external knowledge is usually higher in more developed countries, this effect might offset the higher theoretical diffusion potential. Thus, it is not clear which group of countries benefits more of technology diffusion and comparing them might provide deeper insights into the pattern of skill-biased technology diffusion.

To study skill-biased technology diffusion, I develop a framework which is based on

[3]The eduction level of a country is considered a second important factor increasing the ability to absorb external knowledge (Kneller 2005, Madsen 2014).

central elements of two established lines of research: the empirical SBTC literature and the literature studying international technology diffusion (Coe and Helpman 1995, Keller 2002, Griffith, Redding, and Van Reenen 2004, Madsen 2014). In this framework, skill-specific technical change is modeled as a function of the weighted relative skill-specific distance to the technological frontier. The idea behind: if productivity of skilled (unskilled) labor in external firms, industries or countries is higher than in internal ones, the internal entity might be able to learn from the external one, such that the internal one benefits from technology diffusion, which then increases its own factor-specific productivity level.

Applying it to new sectoral (input-output) data for a panel of 40 emerging and developed countries, 30 industries (covering manufacturing and service industries) and 13 years (1995 - 2007), the obtained results support the presence of skill-biased technology diffusion. For both, skilled and unskilled labor, I find a positive, significant and economically relevant diffusion rate, which explains around 10 to 20 percent of the annual rate of SBTC. That is, the higher the external factor-specific productivity level, given the local skill-specific productivity level, the higher is the subsequent local factor-specific productivity growth rate. The results are obtained controlling for relevant alternative explanatory factors, such as the capital- and R&D-intensity, outsourcing as well as country-industry and time fixed effects. In addition, to get more insights into the mechanisms underlying this form of technology diffusion, I analyze the role of two, frequently studied, mediating factors: the bilateral distance between two countries and the bilateral intersectoral trade volume. The bilateral distance between two countries proves to be an important mediating factor. The closer two countries are located to each other, the higher is the diffusion rate. For intersectoral trade linkages, so far, the results are less clear. Such links seem to explain only a small part of skill-biased technology diffusion. The main results hold for manufacturing and service industries as well as for emerging and developed countries. Comparing the diffusion rates of developed and emerging countries, the results suggest that the contribution of skill-biased technology diffusion to skill-biased technical change is larger for developed than for emerging countries.

The rest of the paper is structured as follows. Section (2) describes the theoretical framework which combines the classical framework used to model skill demand with the modelling approach of the technology diffusion literature. Section (3) lays out the empirical framework later used to test the empirical relevance of the skill-biased technology diffusion, whereas section (4) introduces the data sources and the data set used in the empirical analysis. Section (5) presents the baseline results as well as a set of robustness checks. Section (6) concludes.

2 Theoretical Framework

To study the role of factor-specific technology diffusion in explaining the changing relative skill demand, I extend the canonical modelling framework typically used to examine the drivers of skill-biased technical change (Acemoglu and Autor 2011). It models production as a CES aggregate of skilled labor (H) and unskilled labor (L). In addition, I include capital (K) (Caselli and Coleman 2006):

$$Y = K^{\alpha}\Big[(A_H H)^{\psi} + (A_L L)^{\psi}\Big]^{\frac{1-\alpha}{\psi}}, \tag{1}$$

where the (A_j) are factor-specific productivity terms which convert raw quantities of the two labor types into efficiency units. The elasticity of substitution between skilled and unskilled labor equals $\sigma = 1/(1-\psi)$. Assuming competitive labor markets, relative skill demand equals:

$$\ln\left(\frac{H}{L}\right) = -\sigma \ln\left(\frac{w_H}{w_L}\right) + (\sigma - 1)\ln\left(\frac{A_H}{A_L}\right), \tag{2}$$

where the w_j are wages. Explaining the relative productivity term ($\frac{A_H}{A_L}$) is the aim of the SBTC literature. Various drivers and proxies have been studied. As a very first approach, the changing relative productivity term was modeled by a time trend (Katz and Murphy 1992). In addition, e.g. the role of ICT (Autor, Katz, and Krueger 1998, O'Mahony, Robinson, and Vecchi 2008, Michaels, Natraj, and Van Reenen 2014), R&D (Machin and Van Reenen 1998, Autor, Katz, and Krueger 1998) or organizational change (Caroli and

Van Reenen 2001) have been analyzed and shown to be positively correlated with SBTC.

To analyze the role of skill-specific technology diffusion, I extend this baseline model and follow the literature which studies factor-neutral technology diffusion theoretically and empirically (Griffith, Redding, and Van Reenen 2004, Kneller 2005, Madsen 2014) by adapting their approach to allow for factor-specific technology diffusion. This literature models productivity growth as a function of a lagged technology pool, which represents a set of technologies an entity can learn from. Instead of assuming that a *factor-neutral* technology pool affects *factor-neutral* productivity growth, I model *factor-specific* productivity growth as a function of a *factor-specific* technology pool. Thus, I assume that productivity growth of skilled (unskilled) labor is a function of a lagged skilled (unskilled) labor-specific technology pool S_k:

$$\Delta \ln A_{kt} = \gamma_{Sk} \ln S_{kt-1}, \qquad k \in \{H, L\}, \tag{3}$$

where γ_{Sk}, the parameter of interest, is the diffusion parameter, which reflects by how much the factor-specific productivity growth rate changes due to changes in the technology pool. The technology diffusion literature suggests that this parameter is positive. Testing this for first time and providing evidence on its size is the aim of this study.

Finally, to illustrate how this then affects SBTC and in this way in a second step the relative skill demand, one can subtract equation (3) for unskilled labor from the one for skilled labor. Assuming $\gamma_{SH} = \gamma_{SL} \equiv \gamma_S$, SBTC then equals:[4]

$$\Delta \ln \Big(\frac{A_H}{A_L}\Big)_t = \gamma_S \ln \Big(\frac{S_{Ht-1}}{S_{Lt-1}}\Big) \equiv \gamma_S \ln S_{t-1}, \tag{4}$$

where S_{t-1} is defined as the relative technology pool. Inserting this expression into a first-differenced version of equation (2) then yields an equation illustrating how skill-specific

[4] I will keep this assumption, which states that the diffusion rates of skilled and unskilled productivity are identical in size, throughout most parts of the paper. As will be shown in the results section, this is, at least in my case, statistically justified. However, of course one can imagine situations where these are not identical. E.g. as described by Gancia and Zilibotti (2009), directed technology adoption could cause them to differ. So studying such differences and their reasons would be highly insightful, but is beyond the scope of this paper, which aims at providing a framework to study such questions and to provide first evidence of its relevance.

technology diffusion affects the change in relative skill demand:

$$\Delta \ln \left(\frac{H}{L}\right)_t = -\sigma \Delta \ln \left(\frac{w_H}{w_L}\right)_t + (\sigma - 1)\gamma_S \ln S_{t-1}. \tag{5}$$

As can be seen, if skilled and unskilled labor are substitutes ($\sigma > 1$), which is what empirical evidence suggests (Ciccone and Peri 2005), an increase in the relative technology pool comes with an increase in demand for skilled over unskilled labor. In case $\sigma < 1$, an increase in the relative technology pool would come with a relative reduction in skilled labor demand.

All three equations (3) - (5) can be used to test whether skill-specific technology diffusion affects skill-specific productivity growth and thus helps explaining the changing relative skill demand. Section (3) lays out how such a test is implemented empirically.

3 Empirical Framework

To study the properties of the diffusion parameter (γ_S), one can estimate one of the equations (3) - (5) econometrically. To do so, it is however necessary first to derive values for the productivity terms (A_k) and secondly to proxy the technology pools (S_k) empirically.

3.1 Backing out Factor-Specific Productivity Terms

Following e.g. Caselli and Coleman (2006) I calibrate the values of the productivity terms A_k using a method which is similar to deriving TFP values based on growth accounting methods. Rearranging the first-order conditions (FOCs) of the production technology outlined by equation (1) yields the following two expressions for the productivity terms:[5]

$$A_H = Y^{\frac{1}{1-\alpha}} K^{\frac{-\alpha}{1-\alpha}} \frac{1}{H} \Big(\frac{w_H H}{w_H H + w_L L} \Big)^{\frac{\sigma}{\sigma-1}} \tag{6}$$

$$A_L = Y^{\frac{1}{1-\alpha}} K^{\frac{-\alpha}{1-\alpha}} \frac{1}{L} \Big(\frac{w_L L}{w_H H + w_L L} \Big)^{\frac{\sigma}{\sigma-1}} \tag{7}$$

For the relative productivity of skilled vs. unskilled labor, i.e. the skill-bias, this implies the following equation:

$$\frac{A_H}{A_L} = \frac{L}{H} \Big(\frac{w_H H}{w_L L} \Big)^{\frac{\sigma}{\sigma-1}}. \tag{8}$$

Making assumptions on σ and α one can use these expressions together with data on wages, capital, labor and output to back out values for A_H and A_L. Following Ciccone and Peri (2005), I set $\sigma = 1.5$ and, in contrast to Caselli and Coleman (2006), who assume $\alpha = 1/3$ for all countries, I allow α to differ by industry and assume that it equals industry-specific average capital shares.[6] Tables 2 and 3 in the Appendix summarize the derived values.

3.2 Constructing Technology Pools

Having derived empirical values for the productivity terms, it is possible to construct various proxies for the technology pools S_k from which a recipient entity can learn. I provide two types of such proxies which represent the modelling approach of two strands of the technology diffusion literature: (1) Proxies based on the concept of the distance-to-the-technological-frontier; (2) Proxies based on the concept of weighted external knowledge stocks. Both approaches have their distinct merits in studying whether technological knowledge diffuses internationally such that I make use of both of them.

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[5]Alternatively, assuming a more simple production technology equal to $Y = \Big[(A_H H)^{\psi} + (A_L L)^{\psi} \Big]^{\frac{1}{\psi}}$, as e.g. Voigtländer (2014), the following two expressions for the productivity terms result:

$$\tilde{A}_H = \frac{Y}{H} \Big(\frac{w_H H}{w_H H + w_L L} \Big)^{\frac{\sigma}{\sigma-1}},$$

$$\tilde{A}_L = \frac{Y}{L} \Big(\frac{w_L L}{w_H H + w_L L} \Big)^{\frac{\sigma}{\sigma-1}}.$$

Using them, overall, I find similar results as with the more complex production technology.

[6]In a robustness check I also set $\alpha = 1/3$ and find qualitatively similar results as with the industry-specific α-values.

The empirical literature represented e.g. by Griffith, Redding, and Van Reenen (2004), Kneller (2005), Madsen, Islam, and Ang (2010) or Madsen (2014) models the technology pool as the ratio of the productivity level of the most productive relevant entity (the technological frontier) to the internal productivity level. This ratio is denoted as the distance-to-frontier (DTF). It represents the idea that the higher this ratio, the further away is an entity from the technological frontier and thus the more it can potentially benefit from technology diffusion. The implicit assumption is that the amount of technology which diffuses towards a recipient entity is proportional to the total potential to learn from external sources. I proxy the industry- and time-specific technological frontier as the geometric mean of the three highest productivity levels of foreign industries of the same type.[7] The technology pool is defined as the ratio of the industry-specific measure of the frontier (A^F_{kit}) to the productivity level (A_{kict}) of the recipient industry i in country c and year t:

$$S^F_{kict} = \frac{A^F_{kit}}{A_{kict}}.$$

Whereas the distance-to-frontier approach, in its basic form, assumes that knowledge diffuses quasi-automatically and proportionally to the total diffusion potential, a second strand of the diffusion literature is more focused on understanding the channels through which knowledge diffuses.[8] Following the pioneering work of Coe and Helpman (1995), it models the technology pool as the weighted average of external knowledge stocks. It is assumed that the actual amount of knowledge which diffuses towards an entity depends not so much on an entity's total distance to the technological frontier but depends more on how much an entity actually learns from each external entity. This depends on (a) an entity's own knowledge stock, (b) the distribution of external knowledge stocks (the potential for diffusion) and (c) on factors affecting how much of the diffusion potential

[7] As an alternative, I also provide a frontier-measure equal to the level of the most productive industry (A^{F1}). However, measuring the productivity level of the technological frontier using only one observation can be expected to come with high measurement error, such that my preferred frontier-proxy uses the information of the three most productive industries.

[8] Of course, also the diffusion literature using the distance-to-frontier approach studies factors which affect the actual diffusion rate. Hereby a focus is on the role of absorptive capacities, where among the many factors that have been proposed two stand out: R&D-efforts (Griffith, Redding, and Van Reenen 2004) and human capital (Kneller 2005, Madsen, Islam, and Ang 2010, Madsen 2014).

is actually realized. E.g. an entity might benefit from technology diffusion more if all external entities are much more productive than it compared to a situation where only one external entity is much more productive than it. In addition, the more intensively an entity is connected (e.g. through input-output linkages) to those external entities from which it can learn something, the more of the diffusion potential might actually be realized. According to the overview article by Keller (2004), the main channels of technological diffusion are trade, FDI and language skills. Thus, measures used in the literature include bilateral trade flows (Lichtenberg and van Pottelsberghe, 1998, Coe et al., 2009 and Dieppe and Mutl, 2013), FDI (van Pottelsberghe and Lichtenberg, 2001) or language skills (Musolesi, 2007). Since the bilateral distance between two countries can be considered a comprehensive measure picking up some of the effects of trade, FDI and language, I follow e.g. Keller (2002) and Ertur and Musolesi (2013) and use it as my main weighting measure. In addition, I provide evidence based on an unweighted and a trade-weighted measure.

Whereas many studies proxy the external knowledge stocks using R&D or patent stocks, I model the knowledge stocks an entity can learn from again by technological distances (A_{kibt}/A_{kict}) which equal productivity ratios of the sending country b to the receiving country c.

The technology pool which is based on the simple average of the technological distances can be considered a most basic variant of the technology proxies which use weighted external knowledge stocks. It is defined as:

$$S^A_{kict} = \sum_{b \neq c} \omega_A \frac{A_{kibt}}{A_{kict}}, \qquad \omega_A = \frac{1}{n-1},$$

where n equals the number of countries considered (in my case, $n = 40$). This proxy allows studying whether an increase in the average technological distance results in technology diffusion.[9]

[9] Using technological distances (A_{kibt}/A_{kict}) as knowledge stocks, it becomes obvious that the two types of proxies S^F and S^A as well as the proxies introduced in the following, are closely related. They only differ in their weighting schemes: S^F weights the most productive external entity with the value 1 and the remaining entities with value 0, whereas the remaining proxies use more equally distributed weights.

The distance-weighted technology pool is defined as follows:

$$S^D_{kict} = \sum_{b \neq c} \omega_D \frac{A_{kibt}}{A_{kict}}, \qquad \omega_D = \frac{d_{bc}^{-1}}{\sum_{b \neq c} d_{bc}^{-1}},$$

where the technological distances are weighted by the inverse relative bilateral distance of two countries (d_{bc}).

One channel through which distance could affect the rate of diffusion is trade. The closer two entities are located to each other, the higher the trade intensity due to lower transportation and coordination costs. Technology has often been shown to diffuse through intersectoral intermediate input-output linkages. Intermediate input-output linkages between firms, industries and countries come with collaboration and contact between them which leads to an intended and unintended exchange of ideas, knowledge and technology. As Voigtländer (2014) shows, intersectoral linkages have an important role in explaining the relative skill demand. He finds evidence for an intersectoral technology-skill complementarity, that is, a high upstream skill intensity comes with a high downstream skill intensity. This could be explained, in parts, by skill-specific technology diffusion. If upstream sectors have a high skill intensity, this can be a sign of a high relative skill productivity, which, if this comes with technology diffusion, could increase the downstream relative skill productivity and with this the downstream skill intensity. To test whether intersectoral linkages are a relevant diffusion channel for skill-specific technology diffusion, I provide a the third variant, which uses the intersectoral trade volumes to weight foreign productivity levels. It equals:

$$S^T_{kict} = \sum_{b \neq c} \omega_T \frac{A_{kidt}}{A_{kict}}, \qquad \omega_T = \frac{T_{bc}}{\sum_{b \neq c} T_{bc}},$$

where T_{bc} is the bilateral time-averaged trade volume between two industries (export + import).[10]

[10] Using as an alternative to trade volumes, intermediate inputs from external industries, as e.g. Voigtländer (2014), does not change my findings substantially. Also, using the current trade volume instead of the average trade volume does not affect the baseline results substantially.

3.3 Econometric Specification

Employing the technology pool proxies in equation (4), adding control variables X_{it} and allowing for a stochastic error term (ϵ_{it}) results in the estimation equation. For brevity of notation, from here on, i represents a country-industry combination. X_{it} includes three controls: the capital intensity ($\frac{K}{Y}$), the R&D-intensity ($\frac{R\&D}{Y}$) and an outsourcing proxy (OS_n). The first one is included to capture the effect of capital-skill complementarity (see e.g. Krusell, Ohanian, Ríos-Rull, and Violante (2000) and Duffy, Papageorgiou, and Perez-Sebastian (2004)). The R&D-intensity shall control for skill-biased technical change caused by local innovation efforts (as in Machin and Van Reenen (1998), Autor, Katz, and Krueger (1998)). OS_n is included to control for the effect of outsourcing (see e.g. Feenstra and Hanson (1999)). There will be unobserved country-industry characteristics, which affect rates of productivity growth and are not captured by the model and which are likely to be correlated with the technology pool proxy. To control for unobserved heterogeneity that is correlated with the explanatory variable I include country-industry fixed effects (α_i). There may also be common macroeconomic shocks that affect productivity growth in all countries, such that in addition I include time dummies (α_t). The model equals then:

$$\Delta \ln \left(\frac{A_H}{A_L}\right)_{it} = \gamma_S \ln S^{\chi}_{it-1} + \beta \ln X_{it-1} + \alpha_i + \alpha_t + \epsilon_{it}, \qquad \chi \in \{F, A, D, T\}. \tag{9}$$

It is worth making two more remarks concerning this specification. First, inserting the technology pool proxies as defined before would carry the risk that a significant estimate of γ_S is only due to serial correlation of the domestic productivity parameter (A_{kit}), which appears in the denominator of both, the dependent variable and the technology pool proxies. In case of a negative serial correlation, a positive productivity shock is followed by a negative one, which would result in a positive estimate for γ_S, independently of a significant influence of the external knowledge stock. To make it transparent whether both parts, the domestic productivity level and the external knowledge stock are significantly related to the domestic productivity growth rate, I split the technology pool proxies (S^{χ})

into two parts: the domestic productivity level (A_{kit}) and the external knowledge stock ($\tilde{S}^{\chi}_{kit}$).[11] Thus, my final estimation equation equals:

$$\Delta \ln \left(\frac{A_H}{A_L}\right)_{it} = \check{\gamma}_S \ln \left(\frac{A_H}{A_L}\right)_{it-1} + \tilde{\gamma}_S \ln \tilde{S}^{\chi}_{it-1} + \beta \ln X_{it-1} + \alpha_i + \alpha_t + \epsilon_{it}. \tag{10}$$

For $\check{\gamma}_S$ I expect a negative estimate. It would indicate, as the idea of the distance-to-frontier suggests, that SBTC is the lower, the higher the lagged own productivity level, given the level of the external knowledge stock ($\tilde{S}^{\chi}_{it-1}$). In contrast, if we expect the size of the foreign knowledge stocks to have a positive effect on domestic productivity growth, $\tilde{\gamma}_S$ should show a positive value.

Next to this issue, in a cross-country cross-industry setting it is necessary to allow for correlation of the error terms across industries within a country. Such a correlation should be expected since industries within a country are typically exposed to common shocks. I therefore allow for clustering of observations at the country level.

4 Data

4.1 Data Sources

The data used in this study are mainly taken from the World Input-Output Database (WIOD), which provides detailed information on value added accounts, including information on labor inputs by three types of educational attainment levels, and world input-output tables. It covers 40 developed and emerging countries, 35 industries (covering all economic sectors) and 15 years (1995 – 2009).[12] Countries covered are the 27 EU countries, Australia, Brazil, Canada, China, India, Indonesia, Japan, Korea, Mexico, Russia, Taiwan, Turkey and the United States.

The value added accounts provide information on the quantities and prices of labor and capital used in production. The labor market data are split on the basis of educational attainment levels as defined in the International Standard Classification of Education

[11] It holds: $\ln S^{\chi} = \ln \tilde{S}^{\chi}_{kit} - \ln A_{kit} = \ln \sum \omega_{\chi} A_{kidt} - \ln A_{kit} = \ln \sum \omega_{\chi} \frac{A_{kidt}}{A_{kit}}$. In my tables $\tilde{S}^{\chi}_{kit}$ is denoted as A^{χ}_{kit}.

[12] For a description of the database, see Timmer (2012) and Timmer, Dietzenbacher, Los, Stehrer, and Vries (2015).

(ISCED) into three groups: low skilled (ISCED categories 1 and 2), medium skilled (ISCED 3 and 4) and high skilled (ISCED 5 and 6). This roughly corresponds to: below secondary schooling; secondary schooling and above, including professional qualifications, but below college degree; and college degree and above (see Timmer, Erumban, Los, Stehrer, and de Vries (2014)).[13] To aggregate these three groups into a high- and a low-skilled labor aggregate, I combine low- and medium-skilled workers into a low-skilled labor aggregate and keep high-skilled workers in a high-skilled labor aggregate.[14]

For the empirical analysis I require data on wages and labor input quantities by skill level as well as capital stock and value added data. Labor quantities are directly available in WIOD, whereas wages, by education-level, have to be calculated by dividing skill-specific labour compensation values by skill-specific hours worked. Measures of value added and the capital stock are directly available in WIOD. In addition to the labor, capital and value added data, I also use the available international input-output data to construct intersectoral trade volumes. These equal the sum of intermediate inputs and outputs from one country-industry combination to another. The input-output data are also used to construct outsourcing proxies, which will be used as control variables. My main outsourcing proxy (OS_n), which is based on the narrow definition of outsourcing (see Feenstra and Hanson (1999)), is defined as the share of an industry's intermediate inputs coming from the same type of industries in total intermediate inputs of this industry.

Finally, since I am interested in analyzing a cross-country panel setting, it is necessary to transform all monetary units into common units (real 2005 US dollars). This is achieved by using deflators and exchange rates available in WIOD.

Next to the information taken from WIOD I make use of sectoral R&D data and infor-

[13] For most advanced countries the data are constructed by extending and updating the EU KLEMS database using the methodologies, data sources and concepts described in O'Mahony and Timmer (2009). For other countries additional data has been collected according to the same principles, mainly from national labor force surveys, supplemented by household surveys for relative wages. For a more extensive description of the data, see Appendix (8.1).

[14] As an alternative, I use only low- and high-skilled (but not medium-skilled) labor input and compensation shares to decompose total labor input and compensation quantities into low- and high-skill aggregates. This requires the assumption, that medium-skilled workers can be allocated to low- and high-skilled labor groups according to the ratio of high- to low-skilled labor. Doing so, I find similar results as with the base variables.

mation on bilateral distances between countries. The R&D data are taken from the OECD ANBERD (Analytical Business Enterprise Research and Development) database.[15] I use expenditures by main activity denoted in PPP-adjusted 2005 US dollars and compute a R&D-intensity variable ($\frac{R\&D}{Y}$) which equals R&D divided by real value added. Information on the distance between two countries is taken from CEPII's GeoDIST database.[16] I use the population-weighted distance measure (in km).[17]

A detailed description of the variables finally available is provided in Table 1 of the Appendix.

In my analysis I use data on all 40 WIOD countries, but only on 30 out of 35 industries and can only cover the period between 1995 and 2007. For the years 2008 and 2009 several countries provide no data on capital stocks. The industries that are dropped are the Agricultural sector (NACE AtB), the Mining sector (NACE C), the Coke, Refined Petroleum and Nuclear Fuel industry (NACE 23), the Real Estate Activities industry (NACE 70) and the Private Households sector (NACE P). These show exceptional production structures (e.g. has the real estate activities industry an exceptionally high capital input share) or are only very partially covered and therefore are often neglected in empirical studies. In addition to those 5 industries, observations are dropped which feature exceptionally high or low values in my dependent variable, the measure of skill-biased technical change.[18] Thus, the final sample covers 40 countries, 30 industries, 13 years (1995 - 2007) and forms an unbalanced panel of 6381 observations.

4.2 Summary Statistics

Summary statistics for the full sample as well as for two country-subgroups (low- and high-developed countries) are presented in Table 2. This split into two country groups

[15] Unfortunately, for several countries and some industries no information on R&D expenditures are available, such that including this variable as a control variable strongly reduces the number of observations.

[16] For a description see Mayer and Zignago (2011).

[17] The basic idea behind a population-weighted distance measure is to calculate the distance between two countries based on bilateral distances between the biggest cities of those two countries, where intercity distances being weighted by the share of the city in the overall country's population.

[18] I keep observations within one standard deviation around the mean growth rate. That is, I keep observations with an annual growth rate larger than -10 percent and smaller than 20 percent.

is done to allow studying whether the pattern of skill-biased technology diffusion differs by development status. Countries are classified as low- or high-developed according to a simple criterion: the twenty countries having the highest average labor productivity are defined as high-developed, whereas the remaining countries are classified as lower-developed.[19]

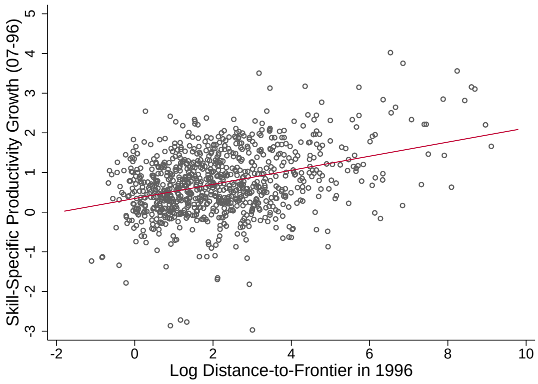
The average annual growth rate of the high-skilled labor share (S_H) is equal to 2.05 percentage points, indicating that the countries covered by this sample show a steady shift in demand towards skilled labor. This development takes place both in developed and lower-developed countries. For high-developed countries this growth rate is equal to 2.38 percentage points, whereas for low-developed ones it equals 1.69. Skill-biased technical change, as measured by the growth rate of equation (8), also shows, again for both country groups, a positive average annual growth rate of 4.75 percent for the full sample. For lower-developed countries this value is slightly smaller, equal to 3.99 percent, whereas for high-developed countries it is equal to 5.43 percent.

The distance-to-frontier variables show that for skilled labor, on average, the distance-to-frontier is larger than for unskilled labor, such that, according to our model, we can expect technology diffusion to drive technical change towards a higher skill-bias. In line with what one would expect, the average distance-to-frontier is for both types of labor lower for high-developed countries than for lower-developed countries.[20] The growth rates of the relative knowledge stocks (A_H^F/A_L^F, A_H^D/A_L^D, A_H^T/A_L^T) are on average all positive, i.e. they show that at the technological frontier technical change is directed towards relative skill-enhancing technologies. Their average growth rates range from 5.43 to 7.09 percent, such that all of them grow faster than the average skill-bias. This indicates again that there is potential for technology diffusion to cause local skill-biased technical change. Finally, the summary statistics illustrate that some variables vary quite strongly. E.g.

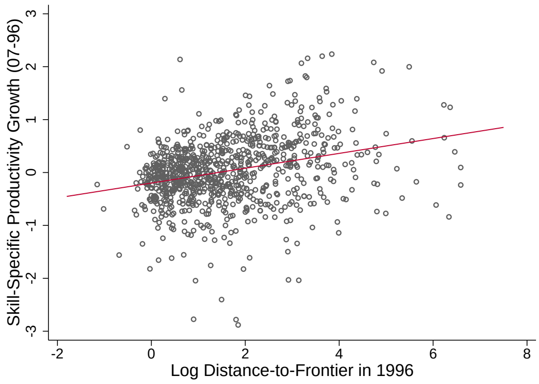
[19] High-income countries are: AUS, AUT, BEL, CAN, CYP, DEU, DNK, ESP, FIN, FRA, GBR, GRC, IRL, ITA, JPN, LUX, MLT, NLD, SWE, USA, whereas low-income countries are: BGR, BRA, CHN, CZE, EST, HUN, IDN, IND, KOR, LTU, LVA, MEX, POL, PRT, ROU, RUS, SVK, SVN, TUR, TWN.

[20] The negative values for the distance-to-frontier measures are a consequence of computing the technological frontier as the geometric mean of the three most productive entities within an industry, such that the most productive industries might have a slightly negative measure of the distance-to-frontier.

Figure 2: Distance-to-Frontier and Long-Run Productivity Growth



(a) High-Skilled Labor



(b) Low-Skilled Labor

Notes: Both figures display on the x-axis the skill-specific log distance-to-frontier in 1996 of country-industry observations ($\ln(A^F_{k96}/A_{ki96})$). The y-axis shows the skill-specific productivity growth rate between 1996 and 2007 ($\ln(A_{ki07}) - \ln(A_{ki96})$). The sample consists of all country-industry observations available in 2007 and 1996.

the growth rates show very large outliers, which is in parts caused by structural breaks in the underlying data. However, assuming that these breaks are uncorrelated with the variables of interest, they should not systematically influence the results.

4.3 Graphical Evidence

The scatter plots in Figure 2 provide first evidence on the relationship of skill-specific technology pool proxies and subsequent skill-specific productivity growth. They show the relationship between the skill-specific log distance-to-frontier in 1996 and the long-run skill-specific productivity growth rate (for the period from 1996 to 2007).[21] The sample used for plotting them consists of all observations available in 1996 and 2007. Panel (a) shows the relationship for high-skilled labor. It reveals a positive relationship between the distance to the technological frontier and subsequent high-skill-specific productivity growth. For low-skilled labor, panel (b) provides a similar picture. There is positive relationship between both variables. These findings can be considered as first suggestive evidence for the idea of skill-specific technology diffusion.

[21]The skill-specific log distance-to-frontier equals ($\ln(A^F_{k96}/A_{ki96})$). The long-run skill-specific productivity growth is computed as: $\ln(A_{ki07}) - \ln(A_{ki96})$. The data for 1995 were excluded since for several country-industry combinations no observations are available for that year.

5 Empirical Results

In this section I provide estimation results obtained by estimating equation (10), which models SBTC as a function of the lagged own skill-bias ($\frac{A_H}{A_L}$) and of the various proxies of the lagged relative knowledge stocks ($\frac{A_H^\chi}{A_L^\chi}$). The results support the idea that skill-biased technical change diffuses internationally. First, I show results based on using the classical distance-to-frontier measure (S^F), which enables insights into how the potential to benefit from external knowledge sources affects internal productivity growth. In a second step, I apply the three technology pool proxies (S^A, S^D, S^T), where the latter two proxies allow identifying channels through which such knowledge diffuses: namely, the bilateral distance between two countries and the degree of intersectoral linkedness. The overall findings are robust to a variety of controls, specifications and samples.

5.1 SBTC and the Skill-Specific Distance-to-Frontier

Table 4 contains the results I obtain using the classical distance-to-frontier measure (S^F). Column 1 and 2 show results based on estimating equation (3) for high-skilled and low-skilled labor separately. As theory predicts, both columns show a significant negative effect for the lagged own productivity level. This implies that factor-specific productivity growth rates decrease the higher the lagged own productivity level, given the productivity level of the factor-specific technology frontier. In contrast, the variables of interest, the external factor-specific knowledge stocks, measured by the productivity level of the technological frontier, show a positive significant coefficient. That is, for a given own productivity level, an increase in the external technological frontier comes with a subsequent increase in the domestic factor-specific productivity growth rate. This suggests the presence of factor-specific technology diffusion. These and the following specifications can also be used to analyze whether splitting the technology pool proxies S^χ into own productivity levels and weighted external knowledge stocks is justified, by testing whether $\tilde{\gamma} = -\check{\gamma}$ holds. Based on F-tests, in all specifications I can reject the null hypothesis that the regression coefficients of the two parts of the original technology pool proxies are of the same size, i.e. empirically, it is justified not to restrict them to have the same coefficient size and not to combine the two parts into one variable.

Column 3 combines the models underlying the first two columns by subtracting the specification concerned with low-skilled labor (column 2) from the one concerned with high-skilled labor (column 1). The dependent variable now equals the difference of the two skill-specific productivity growth rates and thus is a measure of skill-biased technical change. Using this model, I find similar results as before: the coefficients remain significant but are slightly reduced in size. The low-skilled-specific coefficients change signs, which is to be expected, since low-skilled productivity growth was subtracted from the high-skilled one in computing the dependent variable. This model allows comparing the size of the two coefficients of interest. The high-skilled diffusion parameter equals 0.014, whereas the low-skilled one equals 0.02. A simple F-test with $H_0 : \tilde{\gamma}_{SH} = -\tilde{\gamma}_{SL}$ provides a p-value of 0.5338 such that we cannot reject the equality of the two coefficients. Thus, from column 4 on I restrict the two diffusion parameters to be equal in absolute value which allows me to combine the two factor-specific knowledge stock proxies into a relative one (as in equation 4).[22]

I consider column 4 as my baseline specification. It shows how the skill-bias of the technological frontier, given the domestic skill-bias, affects subsequent domestic skill-biased technical change. Using this specification, I find a positive significant effect for the frontier skill-bias. It indicates that a change in the frontier skill-bias affects the internal direction of technical change: an increase in the frontier skill-bias comes with higher skill-biased technical change, a decrease in the frontier skill-bias results in a shift towards unskilled-biased technical change.

Columns 5 to 8 provide robustness checks for this finding. Column 5 includes the three control variables outlined before: the capital and the R&D-intensity as well as an outsourcing proxy. Doing so, reduces the number of observations since the R&D-variable

[22]Although the coefficients of the two lagged productivity levels A_H and A_L differ statistically, for simplification, from here on I assume they are identical in size. Doing so, does not change the main conclusions.

is highly unbalanced. Still, I again find a positive significant effect of the frontier-bias. Among the three control variables only the lagged capital and R&D-intensity variables are significant. But in contrast to what previous evidence suggests, both coefficients are negative. This would indicate that a higher lagged capital intensity and a higher lagged R&D-intensity come with a lower subsequent skill-biased technical change. Again the coefficient of the variable of interest, the frontier-bias is significant and positive. Column (6) then uses the baseline frontier proxy but without splitting the distance-to-frontier measure into two parts. Doing so, I find a strongly significant positive effect. This specification is most closely in line with the way the technology proxy is modeled by e.g. Griffith, Redding, and Van Reenen (2004) or Madsen (2014). Column (7) uses the alternative frontier proxy which is based on the information from the single most productive industry only. It confirms the results found with the baseline specification. Finally, column (8) makes use of an alternative frontier proxy which is based on calibrated productivity terms from the more simple production structure as outlined in footnote (8). Using it instead of the baseline version, hardly affects the estimates. Again the lagged own productivity level has a negative effect whereas the frontier-bias has a significantly positive effect.

Taken together, these results suggest that technical change which affects the skill-bias of the technical frontier indeed diffuses internationally and thus affects the local rate of skill-biased technical change. These findings can be seen as first evidence in support of the existence of factor-biased technology diffusion. These results were obtained using various measures of the distance-to-frontier. The next section provides first insights on potential diffusion channels.

5.2 Geographic Distance and Intersectoral Linkages

In this section I describe the results I obtain by applying the alternative technology pool proxies. Table 5 contains the results, where columns 1 and 2 focus on the average external skill-bias (S^A), columns 3 to 5 use the distance-weighted knowledge stocks (S^D), columns

6 to 8 use the trade-weighted knowledge stocks (S^T) and columns 9 to 11 combine the distance- and trade-weighted ones. In all specifications the dependent variable is the rate of SBTC.

Column 1 uses only the lagged own skill-bias and the average external skill-bias. It shows, as before, a negative significant effect for the own lagged skill-bias and a significant positive effect for the external knowledge stock. However, adding in column 2 the skill-bias of the technological frontier, now both technology proxies become insignificant. This indicates that both, the frontier-bias and the mean-bias proxy contain similar information. Thus, from here on, I consider only the classical measure of the frontier skill-bias.

In column 3, I introduce the distance-weighted proxy. It is, controlling for the own lagged skill-bias, positively significant, whereas as before the own lagged skill-bias is negative and significant. Thus, using the distance-weighted technology pool proxy also brings supportive evidence for the idea of skill-biased technology diffusion. Before interpreting the role of bilateral distances for technology diffusion in more detail, a noteworthy feature of the distance- and trade-weighted proxies has to be discussed. Both, the distance- and the trade-weighted technology pools (S^D and S^T) as defined so far might not capture the entire role of distance and trade for technology diffusion. The weights used in their construction are shares of bilateral distances or trade volumes, not levels, such that they do not reflect the full effect of those levels. It might however be expected that among two countries which have the same composition of bilateral distances and foreign knowledge stocks, the one which is on average more closely located to its neighbors will benefit more from technology diffusion. The same holds true for bilateral trade volumes. To account for that, inspired by Coe and Helpman (1995), I extend these two specifications by including an interaction term of (a) the respective technology pool proxy ($\tilde{S}^D$ or $\tilde{S}^T$) and (b) either the log of the inverted sum of all bilateral distances of a country to all other countries or the log of the total trade volume of an industry relative to its real value added. Applying it in column 4, the specification equals:

$$\Delta \ln\left(\frac{A_H}{A_L}\right)_{it} = \check{\gamma}_S \ln\left(\frac{A_H}{A_L}\right)_{it-1} + \tilde{\gamma}_S \ln \tilde{S}^D_{it-1} + \breve{\gamma}_S \ln(D_i^{-1}) \ln \tilde{S}^D_{it-1} + \alpha_i + \alpha_t + \epsilon_{it}, \quad (11)$$

where $D_i = \sum_{b \neq i} d_{bi}$.[23] A positive significant estimate of $\breve{\gamma}_S$ would indicate that the effect of the distance-weighted knowledge stock is the higher the more closely a country is located to the remaining countries in the sample.

Indeed, in column 4 both the distance-weighted proxy and the interaction term show a positive and highly significant coefficient. That is, an increase in the distance-weighted knowledge stock comes with a higher skill-biased technical change the closer a country is located to its neighbors. This strengthens the interpretation that the bilateral distance between two countries is an important mitigating factor for the rate of technology diffusion. The closer two entities are located to each other, ceteris paribus, the more knowledge will diffuse between them. To facilitate the interpretation of the effect size, it is useful to compute the marginal effect of a change in the distance-weighted knowledge stock at e.g. the average log inverted total distance. It is defined as: $\frac{\partial \Delta \ln(A_H/A_L)}{\partial \ln \tilde{S}^D} = \tilde{\gamma}_S + \breve{\gamma}_S \ln(D_i^{-1})$ and is in specification (4) equal to 0.024. That is, a one percent increase of the relative distance-weighted knowledge stock comes with a 0.024 percentage points increase in the annual growth rate of the skill-bias. The important role of the bilateral distance for technology diffusion is corroborated by column 5 which adds the three control variables (capital intensity, R&D-intensity and outsourcing proxy) as well as the frontier-bias ($\tilde{S}^F$). Doing so comes with a slight reduction in the marginal effect and an insignificant coefficient for the frontier-bias. This indicates, that the measure of the frontier skill-bias, controlling for the distance-weighted terms, provides little additional information.

In columns 6 to 8 the same specifications as in the previous three columns are used but the distance-weighted measures are replaced by the trade-weighted measure. Doing so, I find similar results which however are less significant with respect to the trade-weighted measures. In column 6, the trade-weighted measure is insignificant. Adding the interaction term renders both terms positively significant. However, including in addition in column 8 the frontier-bias and the control variables comes with an insignificant trade-weighted proxy again. So, it is not really clear whether trade is a relevant diffusion

[23] For readability the control variables X_{it} have been dropped.

channel. Also, here the coefficient of the frontier-bias remains positive significant and is not reduced in size (compared to the baseline specification in column 4 of Table 4). Thus, so far, measuring intersectoral linkages by bilateral trade volumes, they seem to have a minor role in explaining skill-biased technology diffusion.

To get more insights on the role of intersectoral linkages and bilateral distances, specifications (9) to (11) combine both types of measures. In column 9, where no additional control variables are included, I again find a highly significant impact of distance on technology diffusion, whereas the trade-related variables and the frontier measure are insignificant. Again, this suggests that trade, controlling for bilateral distance, has at least not a very important role in explaining skill-biased technology diffusion. This finding, however should be interpreted with care. There are several ways in modeling bilateral trade, e.g. yet I am only using input-output linkages with industries of the own type. Perhaps, including input-output linkages with other sectors and thus allowing for technology diffusion from other types of industries would change these findings. Also, as columns 10 and 11 suggest, there might be heterogeneity with respect to the relevance of certain diffusion channels. As discussed before, the development status could matter for the rate of skill-biased technology diffusion due to differences in absorptive capacities. For low-developed countries (column 10) I find no significant effect of the trade-weighted knowledge stocks, but for high-developed countries (column 11) there is a positive significant effect. The measures capturing the role of distance as before are positive and significant in both specifications, that is for both high- and low-developed countries. The frontier measure is insignificant in both specifications. This suggests that the bilateral distance between countries is a very important mediating factor affecting the rate of skill-biased technology diffusion, whose role in parts, at least for developed countries, might be explained by intersectoral linkages. Given these findings, from here on I concentrate on the distance-weighted measure and test the robustness of the results obtained with it by using alternative samples and specifications.

5.3 Quantification

To understand the economic significance of the results obtained one can compute the average contribution of skill-biased technology diffusion to annual skill-biased technical change. Using the coefficient of $\ln(A_H^F/A_L^F)$ from the baseline specification (column 4 of Table 4), which describes the effect of the frontier-bias on skill-biased technical change and which equals 0.018, for the average country the contribution of skill-biased technology diffusion to skill-biased technical change equals 0.94 percentage points. This represents around 20% of annual skill-biased technical change.[24] Using instead the obtained estimates from the main distance-weighted specification (column 4, Table 5), the contribution is equal to around 11% of the average annual rate of skill-biased technical change. Thus, both results show that skill-biased technology diffusion is an economically important force behind skill-biased technical change over the period 1995 to 2007.

As to be seen in Table 6, in both higher- and lower-developed countries the external distance-weighted knowledge stocks show a significant coefficient, which however is larger for high-developed countries. For the average lower-developed country the coefficient suggests an average annual contribution to skill-biased technical change of around 6% (16% according to the specification using the frontier-bias). For high-developed countries this share is around 17% (27%), which indicates that in higher-developed countries skill-biased technology diffusion contributes more to skill-biased technical change than in lower-developed countries. This result is driven by the higher coefficient estimate for high-developed countries, which suggests a higher diffusion rate. It overcompensates the effect of a higher diffusion potential, i.e. a higher distance-to-frontier and a lower rate of skill-biased technical change in lower-developed countries.

In total these results show the economic significance of skill-biased technology diffusion in explaining skill-biased technical change.

[24]This value is computed as: 0.018 times the difference of the mean values of $\ln(A_H^F/A_L^F)$ and $\ln(A_H/A_L)$ divided by the mean value of $\Delta\ln(A_H^F/A_L^F)$.

5.4 Robustness Checks

In this subsection I consider the robustness of the results to the following concerns: (1) parameter heterogeneity as well as (2) validity of the statistical assumptions and the functional forms.

5.4.1 Parameter Heterogeneity

Among the assumptions used the most restrictive one is probably that of homogeneous estimation coefficients across development levels, regions and sectors. In the following, I relax these assumptions.

Table 6 reports the results from specifications where I allow for more parameter heterogeneity. Columns 1 and 2 split the sample into low- and high-developed countries (using again the simple productivity criterion as in section 5.2). For both samples both the distance-weighted external knowledge stock and the interaction term with the log inverted sum of bilateral distances are positively significant. Thus, for both an increase in the distance-weighted knowledge stock comes with an increase in the domestic rate of skill-biased technical change, which is the stronger the more closely these external countries are located to each other. Although the coefficients for the low-developed country group are larger than those for the high-developed countries, the marginal effect of change in the distance-weighted knowledge stock for the high-developed countries is, at least at the mean bilateral distance, bigger than that for the lower developed countries. For the low-developed countries an increase of the distance-weighted external skill-bias by one percent comes with an increase of the local skill-biased technical change growth rate of 0.018 percentage points. For high-developed countries this value is equal to 0.036 percentage points. Finding a larger effect for more developed countries is in line with the literature studying the role of absorptive capacities. This literature shows that the ability to absorb external knowledge increases with the ability to understand external knowledge.

Columns 3 and 4 provide results where countries are spilt into EU and non-EU countries. One concern could be that the results are driven by common unobserved institutional developments, which could affect both the external skill-bias and the rate of skill-biased technical change in these countries in a nonlinear way.[25] Since the EU features common institutional developments, it is interesting to see whether the results are robust in less homogeneous country groups such as the non-EU countries. And indeed, for both country groups I find highly significant results, which shows that the findings hold for both, homogeneous and heterogeneous country groups in terms of institutional settings.

Finally, columns 5 and 6 compare the properties of skill-biased technology diffusion for manufacturing and service industries. For both the manufacturing and the service sector I find a positive significant effect of external knowledge stocks on local skill-biased technical change.

5.4.2 Alternative Specifications

Table 7 provides several checks in order to test the robustness of the main findings with respect to alternative statistical assumptions and functional forms.

The baseline specification allows for clustering of observations at the country level. In column 1, however, I allow for clustering of observations at the industry level, since it is not certain at beforehand which form of cross-sectional correlation, within countries or within industries, is stronger. Doing so, does not change the previous findings. Both, the distance-weighted knowledge stock and the interaction term become even more statistically significant. Clustering at the industry level decreases the obtained standard errors.

Another concern is related to heteroscedasticity. Smaller industries might be measured less accurately, which could induce heteroscedasticity. To avoid this, I weight in a second specification observations using the average country-industry specific real value added. It has no large effect. The size of the coefficients changes slightly, but the overall findings remain unchanged.

[25] Keep in mind that linear unobserved country-industry specific trends in skill-biased technical change pose no identification problem to my estimation since my dependent variable is the growth rate of skill-bias technical change and I control for country-industry fixed-effects.

Furthermore, the effect of the foreign knowledge stocks on domestic skill-biased technical change might be overestimated due to common factors, such as common institutional changes, driving both the external skill-bias and the subsequent domestic SBTC. To tackle this issue, I employ two approaches: (1) I make use of a alternative lag-structure and (2) I control for more potential source of common factors. In the first case, I study whether using explanatory variables lagged two periods instead of only one period affects the results. This is not the case, the results are both from their size as well as of their significance level comparable to the previous findings. For the second approach, to control for more potential source of common factors, in column 4 I include in addition to the country-industry fixed-effects country-year and industry-year fixed-effects. Doing so, however again does not change the results very much and does not reduce the coefficient size of the distance related variables. Moreover, with this specification, the marginal effect at the mean of the log inverted total distance is equal to 0.053, which is largest value of all specifications.[26]

I also examine the sensitivity of the results to alternative functional forms. E.g. Kneller (2005) assumes that the current productivity level is a function of the current frontier-productivity level. Inspired by this, in column 5 the dependent variable is the current skill-bias and as explanatory variables are included the current distance-weighted knowledge stock as well as the interaction of the current distance-weighted knowledge stock and the log inverted sum of bilateral distances. Controlling again for country- and industry-year fixed-effects, both distance-related variables are positive significant. Interestingly, however, here the marginal effect is strongly negative, equal to -0.266.

Finally, a last robustness check (column 7) uses equation (5) as functional form, where the dependent variable is the growth rate of the relative skill-demand. This illustrates the effect of skill-biased technology diffusion on the changing skill demand. Again, with this specification, I find a positive significant effect for both distance-related variables.

[26]In this specification as well as in column 5 the frontier-bias is dropped since it varies quasi only by year within an industry, such that its effect is picked up by the industry-year dummies.

6 Conclusion

While for neutral technical change the existence of technology diffusion has been shown extensively, hardly any empirical evidence for diffusion of non-neutral technical change, such as skill-biased technical change, exists. At the same time, existing empirical work explaining within-industry skill-biased technical change cannot fully explain the relative rise in skill demand. This paper studies the question whether skill-biased technical change diffuses internationally and in this way explains parts of the rising skill demand in other, less productive, countries and industries. Based on a framework that combines the canonical SBTC model with central elements of the standard models used to study factor-neutral technology diffusion, it provides empirical evidence that supports the presence of skill-biased technology diffusion. It shows that skill-biased technology diffusion is statistically and economically important in explaining skill-biased technical change. Skill-biased technology diffusion explains around 10 to 20 percent of the annual rate of SBTC. Countries further away from the skill-specific technological frontier subsequently see higher skill-specific productivity growth. For that, the bilateral distance between two countries proves to be an important mediating factor. The closer two countries are located to each other, the higher is the diffusion rate. In parts, this might be explained by intersectoral linkages. The more strongly two industries are linked via bilateral trade, the more knowledge seems to diffuse between them. The main results hold for both, developed and emerging countries. The findings are obtained using new sectoral (input-output) data for a panel of 40 emerging and developed countries, 30 industries and up to 13 years (1995-2007). The results are robust towards (1) controlling for the capital- and R&D-intensity, outsourcing as well as country-industry and time fixed effects, (2) the use of various technology pool proxies, (3) parameter heterogeneity with respect to economic sectors, regions and development status as well as (4) functional specifications.

Although this study might be an important step in analyzing the existence of skill-biased technology diffusion, there are several limitations. To identify a truly causal effect of skill-biased technology diffusion, additional evidence making use of instrumental variables would be necessary. So far, the findings have to interpreted as conditional correlations. Future research could extend the approach by allowing for factor-specific diffusion rates, i.e. by not restricting the diffusion rates of skilled and unskilled labor to be identical in size. They could differ due to absorptive capacities or because of directed technology adoption (Gancia and Zilibotti 2009). In addition, future research could strive for evidence on factor-biased technology diffusion with respect to alternative production factors (such as e.g. capital vs. labor or energy- vs. non-energy inputs).

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8 Appendix

8.1 Data Appendix

Description of the WIOD (taken from Timmer et al., 2014)

In WIOD 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 1 and 2), medium skilled (ISCED 3 and 4) and high skilled (ISCED 5 and 6). This roughly corresponds to: below secondary schooling; secondary schooling and above, including professional qualifications, but below college degree; and college degree and above. For most advanced countries this data is constructed by extending and updating the EU KLEMS database using the methodologies, data sources and concepts described in O'Mahony and Timmer (2009). For other countries additional data has been collected according to the same principles, mainly from national labor force surveys, supplemented by household survey for relative wages. Numbers of workers include employees, self-employed and family workers. Prices for labor refer to wages and additional non-wage benefits, with an imputation for self-employed income. Capital income is derived as gross value added minus labor income as defined above. It is the gross compensation for capital, including profits and depreciation allowances. Being a residual measure it is the remuneration for capital in the broadest sense, including tangible capital, intangible capital (such as R&D, software, database development, branding and organization capital), mineral resources, land and financial capital.

Table 1: Variable Description and Units of Measurement

Variable Description and Unit of Measurement	
Factor Quantities and Output	
H	High-skilled labor services in hours worked by persons engaged
L	Low-skilled labor services in hours worked by persons engaged
K	Capital services in real 2005 US dollar
Y	Value added in real 2005 US dollar
Factor Prices	
w_H	High-skilled labor service wage in real 2005 US dollar per hour worked
w_L	Low-skilled labor service wage in real 2005 US dollar per hour worked
Factor Shares	
S_H	Share of high-skilled labor compensation
Skill-Specific Productivity Terms ($k \in H, L$)	
A_k	Skill-specific productivity level
$\tilde{A}_k$	Alternative skill-specific productivity level
A_k^F	Skill-specific technological frontier by industry (mean of 3 most productive countries)
A_k^{F1}	Alternative skill-specific technological frontier by industry (highest productivity level)
A_k^A	Average skill-specific productivity
A_k^D	Distance-weighted mean skill-specific productivity
A_k^T	Trade-weighted mean skill-specific productivity
D	Population-weighted bilateral distance (in km)
T	Intersectoral trade volume (import + export) in real 2005 US dollar
Additional Control Variables	
$R\&D$	$R\&D$ expenditures by main activity in PPP adjusted 2005 US dollar
OS_n	Outsourcing share (narrow definition)

8.2 Tables

Table 2: Summary Statistics - All Countries and Industries (1995 - 2007)

	All Countries					Low	High
	mean	sd	p1	p50	p99	mean	mean
$\Delta \ln(S_H)$	2.05	3.36	-6.24	1.39	11.41	1.69	2.38
$\Delta \ln(A_H/A_L)$	4.75	7.37	-9.45	3.95	19.61	3.99	5.43
$\ln(A_H/A_L)$	-1.67	1.82	-6.24	-1.92	3.40	-1.70	-1.64
$\ln(A_H^F/A_H)$	2.13	1.67	-0.37	1.88	7.90	3.06	1.29
$\ln(A_L^F/A_L)$	1.61	1.24	-0.21	1.45	4.98	2.55	0.76
$\Delta \ln(A_H^F/A_L^F)$	7.09	16.24	-42.72	6.36	51.33	7.02	7.15
$\ln(A_H^F/A_L^F)$	-1.15	1.05	-2.97	-1.43	1.46	-1.19	-1.10
$\Delta \ln(A_H^D/A_L^D)$	5.92	13.48	-38.61	6.08	42.76	5.72	6.11
$\ln(A_H^D/A_L^D)$	-1.45	1.20	-3.46	-1.85	2.21	-1.50	-1.41
$\ln(D^{-1})$	-12.21	0.46	-13.22	-11.93	-11.79	-12.30	-12.13
$\Delta \ln(A_H^T/A_L^T)$	5.43	18.04	-50.27	5.80	58.54	5.08	5.75
$\ln(A_H^T/A_L^T)$	0.11	0.51	-1.11	0.11	1.51	0.11	0.11
$\ln(T/Y)$	-17.69	2.88	-24.75	-17.06	-13.27	-17.72	-17.66
$\ln \frac{K}{Y}$	-13.33	0.75	-15.09	-13.30	-11.73	-13.24	-13.42
$\ln OS_n$	-4.89	2.68	-11.25	-4.24	-0.91	-5.05	-4.75
Observations			6368			3024	3344

Notes: Growth rates are measured as annual growth times one hundred, i.e. they are denoted in percentage points. The sample differs from the estimation sample by 13 observations since these get lost in computing growth rates of variables, which are not used in estimation but are used for the table. *Low* indicates that the sample of less productive countries is used, whereas *High* indicates the use of the high-developed country sample.

Table 3: Top- and Worst-Peformer by Industry (1995 - 2007)

	A_H				A_L			
	1st	2nd	39th	40th	1st	2nd	39th	40th
15t16	GBR	USA	IND	CHN	CAN	IRL	BGR	IND
17t18	GBR	DEU	IND	CHN	DNK	GBR	RUS	IND
19	GBR	DEU	BGR	CHN	GBR	ITA	IDN	IND
20	GBR	NLD	IND	CHN	CAN	GBR	IDN	IND
21t22	IRL	GBR	IND	CHN	IRL	AUS	BRA	IND
24	IRL	USA	ROU	CHN	IRL	SWE	RUS	IND
25	GBR	FIN	IDN	CHN	DNK	CAN	IDN	IND
26	GBR	FIN	IND	CHN	CAN	AUT	IDN	IND
27t28	GBR	DEU	ROU	CHN	CAN	LUX	IDN	IND
29	GBR	DEU	ROU	CHN	NLD	BEL	RUS	IND
30t33	FIN	GBR	ROU	CHN	IDN	FIN	RUS	IND
34t35	DEU	USA	ROU	CHN	IDN	CAN	RUS	IND
36t37	GBR	DEU	IND	CHN	GBR	CAN	CHN	IND
50	USA	FRA	IND	CAN	BEL	SWE	KOR	IND
51	IRL	JPN	CHN	IDN	IRL	NLD	KOR	IDN
52	USA	FIN	IDN	CHN	SWE	DNK	IND	CHN
60	IRL	FRA	IDN	CHN	ITA	DNK	IND	IDN
61	FRA	CYP	RUS	IDN	GRC	FRA	MEX	IDN
62	CYP	ESP	BGR	POL	JPN	GRC	POL	HUN
63	CYP	LTU	CHN	IDN	ROU	BEL	KOR	IDN
64	IRL	ESP	CHN	ITA	BRA	BEL	HUN	CHN
71t74	GBR	TUR	IND	CHN	SWE	GBR	KOR	IND
E	GBR	BRA	RUS	CHN	AUS	GBR	SVN	IND
F	KOR	DEU	IND	CHN	IRL	GBR	IND	CHN
H	CYP	USA	IND	CHN	ESP	DNK	BRA	IND
J	IRL	BRA	ROU	CHN	DNK	LUX	ROU	IND
L	TWN	AUS	IDN	CHN	BEL	ITA	IND	IDN
M	NLD	ESP	CHN	IDN	BEL	CAN	LTU	TWN
N	ESP	ITA	IDN	CHN	BEL	SWE	IND	IDN
O	USA	NLD	IND	CHN	SWE	BEL	IND	CHN

Notes: 1st indicates that a country has on average in this industry the highest skill-specific productivity level.

Table 4: Skill-Specific Distance-to-Frontier and Skill-Biased Technical Change

	$\Delta \ln A_H$	$\Delta \ln A_L$	$\Delta \ln(A_H/A_L)$					$\Delta \ln(\tilde{A}_H/\tilde{A}_L)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln A_{Ht-1}$	-0.111***		-0.041***					
	(0.020)		(0.009)					
$\ln A^F_{Ht-1}$	0.027*		0.014*					
	(0.014)		(0.008)					
$\ln A_{Lt-1}$		-0.177***	0.057***					
		(0.019)	(0.010)					
$\ln A^F_{Lt-1}$		0.030**	-0.020***					
		(0.015)	(0.007)					
$\ln(A_H/A_L)_{t-1}$				-0.045***	-0.053***		-0.053***	
				(0.009)	(0.014)		(0.014)	
$\ln(A^F_H/A^F_L)_{t-1}$				0.018***	0.017**			
				(0.006)	(0.006)			
$\ln(\frac{A^F_H/A_H}{A^F_L/A_L})_{t-1}$						0.040***		
						(0.009)		
$\ln(A^{F1}_H/A^{F1}_L)_{t-1}$							0.007**	
							(0.003)	
$\ln(\tilde{A}_H/\tilde{A}_L)_{t-1}$								-0.053***
								(0.014)
$\ln(\tilde{A}^F_H/\tilde{A}^F_L)_{t-1}$								0.016*
								(0.009)
$\ln \frac{K}{Y}_{t-1}$					-0.034**	-0.032*	-0.035**	-0.035**
					(0.015)	(0.016)	(0.015)	(0.015)
$\ln \frac{R\&D}{Y}_{t-1}$					-0.004*	-0.003	-0.004*	-0.004*
					(0.002)	(0.002)	(0.002)	(0.002)
$\ln OS_{nt-1}$					0.006	0.006	0.006	0.006
					(0.004)	(0.004)	(0.004)	(0.004)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$H_0 : \tilde{\gamma} = -\check{\gamma}$	0.000	0.000	0.021 / 0.004	0.020	0.017		0.004	0.015
Adjusted R^2	0.067	0.110	0.056	0.054	0.069	0.063	0.068	0.068
Observations	6381	6381	6381	6381	3785	3785	3785	3785

Notes: Clustered standard errors (by country) in parentheses; ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels, respectively; Annual data, 1995-2007, for 30 industries and 40 countries; All regressions include a full set of year dummies and a full set of country-industry interactions (within-group estimators); $H_0 : \tilde{\gamma} = -\check{\gamma}$ provides the p-value of a F-test which tests whether $\tilde{\gamma} = -\check{\gamma}$.

Table 5: Distance and Intersectoral Linkages

	Average Skill-Bias		Distance			Intersectoral Linkages			Distance & Linkages		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
$\ln(A_H/A_L)_{t-1}$	-0.044***	-0.045***	-0.045***	-0.046***	-0.054***	-0.044***	-0.045***	-0.054***	-0.047***	-0.028**	-0.070***
	(0.009)	(0.009)	(0.009)	(0.008)	(0.012)	(0.009)	(0.009)	(0.014)	(0.009)	(0.011)	(0.011)
$\ln(A_H^F/A_L^F)_{t-1}$		0.011			0.007			0.017**	0.008	0.009	0.006
		(0.009)			(0.009)			(0.006)	(0.008)	(0.010)	(0.009)
$\ln(A_H^D/A_L^D)_{t-1}$			0.027**	0.818***	0.947***				0.792***	1.087***	0.576***
			(0.010)	(0.169)	(0.246)				(0.175)	(0.295)	(0.159)
$\ln(D^{-1}) \times \ln(A_H^D/A_L^D)_{t-1}$				0.065***	0.076***				0.063***	0.088***	0.045***
				(0.014)	(0.020)				(0.015)	(0.024)	(0.014)
$\ln(A_H^T/A_L^T)_{t-1}$						0.009	0.089**	0.065	0.035	0.006	0.070**
						(0.007)	(0.038)	(0.046)	(0.037)	(0.059)	(0.030)
$\ln(\frac{T}{Y}) \times \ln(A_H^T/A_L^T)_{t-1}$							0.005**	0.004*	0.002	0.001	0.004*
							(0.002)	(0.003)	(0.002)	(0.003)	(0.002)
$\ln(A_H^A/A_L^A)_{t-1}$	0.025**	0.013									
	(0.010)	(0.014)									
$\ln \frac{K}{Y}_{t-1}$					-0.021*			-0.034**			
					(0.012)			(0.015)			
$\ln \frac{R\&D}{Y}_{t-1}$					-0.003			-0.004*			
					(0.002)			(0.002)			
$\ln OS_{nt-1}$					0.004			0.006			
					(0.003)			(0.004)			
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sample	All	All	All	All	All	All	All	All	All	Low	High
ME				0.024	0.021		0.002	-0.011	0.017	0.008	0.027
$H_0: \tilde{\gamma} = -\breve{\gamma}$	0.140	0.056	0.165			0.003					
Adjusted R^2	0.05	0.05	0.05	0.07	0.09	0.05	0.05	0.07	0.07	0.09	0.10
Observations	6381	6381	6381	6381	3785	6370	6370	3785	6370	3026	3344

Notes: Clustered standard errors (by country) in parentheses; ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels, respectively; Annual data, 1995-2007, for 30 industries and 40 countries; All regressions include a full set of year dummies and a full set of country-industry interactions (within-group estimators); The dependent variable is $\Delta \ln(A_H/A_L)$; *Sample* indicates use of: full sample (All), low-developed country sample (Low) or high-developed country sample (High); ME provides the marginal effect of either a change in $\ln(A_H^d/A_L^d)_{t-1}$ or in $\ln(A_H^T/A_L^T)_{t-1}$ at the mean of either $\ln(D^{-1})$ or $\ln(\frac{T}{Y})$; $H_0: \tilde{\gamma} = -\breve{\gamma}$ provides the p-value of a F-test which tests whether $\tilde{\gamma} = -\breve{\gamma}$.

Table 6: Heterogeneity in Distance-Weighted Results

	Development Status		Region		Sector	
	Low	High	Non-EU	EU	Manu.	Serv.
$\ln(A_H/A_L)_{t-1}$	-0.028**	-0.069***	-0.050***	-0.046***	-0.056***	-0.039***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.014)	(0.010)
$\ln(A_H^D/A_L^D)_{t-1}$	1.101***	0.630***	0.557***	4.787***	0.851***	0.791***
	(0.282)	(0.164)	(0.182)	(1.587)	(0.231)	(0.263)
$\ln(D^{-1}) \times \ln(A_H^D/A_L^D)_{t-1}$	0.088***	0.049***	0.044**	0.400***	0.067***	0.065***
	(0.023)	(0.014)	(0.015)	(0.134)	(0.019)	(0.022)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
ME	0.013	0.041	-0.000	0.038	0.038	0.002
Adjusted R^2	0.09	0.10	0.11	0.07	0.10	0.06
Observations	3037	3344	2769	3612	2770	3425

Notes: Clustered standard errors (by country) in parentheses; ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels, respectively; Annual data, 1995-2007, for 30 industries and 40 countries; All regressions include a full set of year dummies and a full set of country-industry interactions (within-group estimators); The dependent variable is $\Delta \ln(A_H/A_L)$; ME provides the marginal effect of a change in $\ln(A_H^d/A_L^d)_{t-1}$ at the mean of $\ln(D^{-1})$; *Low* indicates that the sample of less productive countries is used, whereas *High* indicates the use of the high-developed country sample; *EU* indicates that only EU-countries are used, whereas $Non - EU$ indicates that only non-EU countries are used; $MANU$ indicates manufacturing industries, whereas $SERV$ indicates service industries.

Table 7: Alternative Distance-Weighted Results

	$\Delta\ln(A_H/A_L)$				$\ln(A_H/A_L)$	$\Delta\ln(\tilde{A}_H/\tilde{A}_L)$	$\Delta\ln(H/L)$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(A_H/A_L)_{t-1}$	-0.046***	-0.063***		-0.047***			-0.025***
	(0.005)	(0.010)		(0.011)			(0.007)
$\ln(A_H^D/A_L^D)_{t-1}$	0.815***	0.665***		0.698***			0.750***
	(0.076)	(0.199)		(0.241)			(0.211)
$\ln(D^{-1}) \times \ln(A_H^D/A_L^D)_{t-1}$	0.066***	0.053***		0.053***			0.063***
	(0.006)	(0.018)		(0.019)			(0.017)
$\ln(A_H/A_L)_{t-2}$			-0.042***				
			(0.010)				
$\ln(A_H^D/A_L^D)_{t-2}$			0.870***				
			(0.201)				
$\ln(D^{-1}) \times \ln(A_H^D/A_L^D)_{t-2}$			0.069***				
			(0.017)				
$\ln(A_H^D/A_L^D)_t$					3.968**		
					(1.768)		
$\ln(D^{-1}) \times \ln(A_H^D/A_L^D)_t$					0.347**		
					(0.144)		
$\ln(\tilde{A}_H/\tilde{A}_L)_{t-1}$						-0.047***	
						(0.008)	
$\ln(\tilde{A}_H^D/\tilde{A}_L^D)_{t-1}$						0.896***	
						(0.179)	
$\ln(D^{-1}) \times \ln(\tilde{A}_H^D/\tilde{A}_L^D)_{t-1}$						0.072***	
						(0.015)	
Year FE	Yes	Yes	Yes	No	No	Yes	Yes
Country-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	No	No	No	Yes	Yes	No	No
Industry-Year FE	No	No	No	Yes	Yes	No	No
Frontier-Bias	Yes	Yes	Yes	No	No	Yes	Yes
ME	0.014	0.024	0.022	0.053	-0.266	0.017	-0.014
Adjusted R^2	0.07	0.10	0.07	0.36	0.71	0.07	0.07
Observations	6381	6381	5552	6381	6381	6381	6381

Notes: Clustered standard errors (by country) in parentheses; ***, **, * significantly different from 0 at the 1%, 5%, and 10% levels, respectively; $Frontier - Bias$ indicates whether the frontier-bias proxy was included; (1) provides clustered standard errors (by industry); In (2) observations are weighted using average real value added; in (3) the right-hand side variables are lagged two periods; (4) includes country- and industry-year fixed effects; In (5) the right-hand side variables are not lagged; In (6) alternative productivity term values $\tilde{A}_j$ are employed; In (7) the dependent variable is the growth rate of relative skill demand $\Delta\ln(X_H/X_L)$; Annual data, 1995-2007, for 30 industries and 40 countries; All regressions include a full set of year dummies (except of specifications 4 and 5) and a full set of country-industry interactions (within-group estimators); ME provides the marginal effect of a change in $\ln(A_H^d/A_L^d)_{t-1}$ at the mean of $\ln(D^{-1})$.