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The Energy-Bias of North-South Technology Spillovers – A Global, Bilateral, Bisectoral Trade Analysis

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Non-technical Summary

We examine variations in the South-North ratios (emerging vs. industrialized countries) of energy and labor intensities driven by imports. We use the novel World Input-Output Database (WIOD) that provides bilateral and bisectoral data for 40 countries and 35 sectors for 1995-2009. We find South-North convergence of energy and labor intensities, an energy bias of import-driven convergence and no robust difference between imports of intermediate and investment goods. Accordingly, trade helps emerging economies follow a 'green growth' path, and trade-related policies can enhance this path. However, the effects are economically small and require a long time horizon to become effective. Trade-related policies can become much more effective in selected countries and sectors: China attenuates labor intensity via imports of intermediate goods above average. Brazil reduces energy intensity via imports of intermediate and investment goods above average. Production of machinery as an importing sector in emerging countries can immoderately benefit from trade-related reductions in factor intensities. Electrical equipment as a traded good particularly decreases energy intensity. Machinery particularly dilutes labor intensity. Our main results are statistically highly significant and robust across specifications.

Das Wichtigste in Kürze

Wir untersuchen Veränderungen der Süd-Nord-Raten (Schwellen- versus Industrieländer) von Energie- und Arbeitsintensitäten bedingt durch Importe. Wir verwenden den neuen WIOD-Datensatz (World Input-Output Database), der bilaterale und bisektorale Daten für 40 Länder und 35 Sektoren für die Jahre 1995-2009 bietet. Wir finden Süd-Nord-Konvergenz der Energie- und Arbeitsproduktivitäten, eine Ausrichtung der importgetriebenen Konvergenz in Richtung Energieproduktivität und keinen robusten Unterschied zwischen Importen in Form von Zwischenprodukten oder in Form von Investitionsgütern. Demzufolge kann Handel dazu beitragen, dass Schwellenländer einem „grünen" Wachstumspfad folgen. Die Effekte sind allerdings klein und benötigen einen langen Zeithorizont um effektiv zu werden. Handelsspezifische Politiken können in bestimmten Ländern und Sektoren jedoch stärkere Wachstumseffekte generieren: China verringert die Arbeitsintensität der Produktion durch Importe von Zwischenprodukten überdurchschnittlich stark. Brasilien verringert die Energieintensität durch Importe von Investitionsgütern überdurchschnittlich stark. Die Herstellung von Maschinen kann in Schwellenländern besonders von handelsbedingten Produktivitätssteigerungen profitieren. Elektrische Geräte können als Importware insbesondere die Energieintensität verringern, Maschinen dagegen hauptsächlich die Arbeitsproduktivität. Unsere Hauptergebnisse sind statistisch hoch signifikant und robust gegenüber verschiedenen Spezifikationen.

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A Global, Bilateral, Bisectoral Trade Analysis

Michael Hübler[*] and Alexander Glas[†]

May 6, 2013

Abstract

We examine variations in the South-North ratios (emerging vs. industrialized countries) of energy and labor intensities driven by imports. We use the novel World Input-Output Database (WIOD) that provides bilateral and bisectoral data for 40 countries and 35 sectors for 1995-2009. We find South-North convergence of energy and labor intensities, an energy bias of import-driven convergence and no robust difference between imports of intermediate and investment goods. Accordingly, trade helps emerging economies follow a 'green growth' path, and trade-related policies can enhance this path. However, the effects are economically small and require a long time horizon to become effective. Trade-related policies can become much more effective in selected countries and sectors: China attenuates labor intensity via imports of intermediate goods above average. Brazil reduces energy intensity via imports of intermediate and investment goods above average. Production of machinery as an importing sector in emerging countries can immoderately benefit from trade-related reductions in factor intensities. Electrical equipment as a traded good particularly decreases energy intensity. Machinery particularly dilutes labor intensity. Our main results are statistically highly significant and robust across specifications.

JEL Classifications: C23, F18, F21, O13, O33, O47, Q43
Keywords: Energy intensity, labor intensity, trade, technology diffusion, convergence, developing countries

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1 Introduction

Whether the climate change challenge can be resolved via 'green growth' crucially depends on the development of the emerging economies. The reduction of poverty and inequality depends on (per-capita) income growth and distribution. The reduction of energy use depends on energy productivity (efficiency) gains. Both are driven by technical progress. Labor intensity (the inverse of labor productivity) can be treated as a measure for general productivity and thus the state of technology and for per capita income and thus the state of economic development. Energy intensity (the inverse of energy productivity), can be treated as a measure for resource efficiency or the 'greenness' of the economy. A better understanding of the development of these two indicators can thus help us predict whether emerging economies are likely to follow a growth path that reconciles improvements in productivity and income on the one hand, and resource efficiency and decarbonization on the other hand.

In this context, international technology diffusion from industrialized countries, say 'the North', to emerging countries, say 'the South', is expected to reduce factor (energy and labor) intensities. North-South technology spillovers can basically occur in a general disembodied way or in an embodied way such that international trade and international investment are the channel of technology transfer. For the choice of policy measures, it is particularly relevant to examine embodied technology spillovers, more precisely via international trade. If we find strong technology spillovers associated with trade, trade related policy measures like tariffs and quotas may also be effective.

Our analysis addresses a crucial question that has been neglected by the literature so far: are international technology spillovers factor-biased, i.e. directed towards a production factor such as energy or labor in the sense of Acemoglu (2002, 2010) and Acemoglu et al. (2012)? – In these models, endogenous technical change does not affect total factor productivity of all sectors in the same neutral way. It affects different production factors (such as labor and another factor) or sectors (such as clean and dirty production) to differentiated extents and can thus steer the economy onto diverse growth paths such as less labor intensive or cleaner production. – Our paper is one of the first econometric studies using the novel WIOD (World Input Output Data) database. The WIOD database offers bilateral and bisectoral trade flows for 40 countries and 35 sectors over 15 years. This allows us to to set up a sectoral econometric model of South-North convergence and to run regressions with a very large number of observations (up to almost 1.5 million). In particular, we define 31 industrialized countries (belonging to the Organisation for Economic Co-operation and Development, OECD, or the European Union, EU) as source countries and 9 emerging economies (Brazil, Russia, India, China and so forth) as recipient countries.

The novel idea of our econometric model is to define source country-sector, recipient country-sector quadruples. The dependent variable is the growth rate of the sectoral South-North factor intensity ratio for each quadruple. The factors under scrutiny are energy in comparison to labor. Each source-recipient country-sector quadruple is associated with a corresponding bilateral trade flow. The traded goods under scrutiny are investment goods in comparison to intermediate goods. The import intensity derived from these trade flows is the explanatory variable of main interest. This research procedure goes beyond existing analyses of this kind and generates new statistically significant results.

In this analysis, we contrast the effects of investment goods imports to those of intermediate goods imports. This is possible since WIOD provides the necessary information whether imports from a specific country and sector go into the capital stock as an investment good or into a production sector as an intermediate good in each recipient country. The expected mechanisms of technology spillovers differ: investment goods enter the capital stock together with embodied technologies and hence raise the productivity of the (effective) capital at work. This can be viewed as process innovation which directly enhances factor productivity. Intermediate goods are included in or transformed into other goods in further production processes. The technologies embodied in the intermediate goods improve the quality of the further fabricated goods. This can be viewed as product innovation without a direct impact on production. Nonetheless, the value of the fabricated goods relative to the factor input will increase due to the quality improvement. Additionally, the embodied knowledge can create spillovers through learning and the adaptation of production processes to match the characteristics of the imported intermediate goods. In both cases, investment and intermediate goods imports, trade is expected to be accompanied by enhanced cooperation and knowledge flows between supplier and customer firms. Finally, in both cases, the trade linkage is expected to be associated with activities of multi-national enterprises and foreign direct investment which creates an enhanced knowledge flow between the affiliate and parent firms. These mechanisms are, however, expected to vary across source and recipient sectors and countries. Notably, high-tech goods like electrical equipment are supposed to embody more advanced knowledge than standard low-tech goods. Our analysis is to our knowledge the first that systematically examines these aspects.

We find as our main result that trade-related North-South productivity (technology) spillovers are directed towards energy (savings). We find this effect for imported investment and intermediate goods, but not for domestic investment goods. This shows that trade creates productivity gains via technology spillovers and possibly Melitz (2003) type productivity gains. – In the Melitz (2003) model of heterogeneous firms, trade liberalization induces exit of low-productivity firms and an expansion of the market share and the profits of high-productivity firms engaged in exporting. This raises overall productivity and welfare. – This corroborates the view that trade supports a 'green growth' path of developing countries. However, the magnitude of this effect appears small so that trade-related policy measures need a long time horizon to become effective. We identify source and recipient sectors and recipient countries that are especially relevant for technology gains. Policy may pick these sectors in order to raise the magnitude of productivity gains.

We structure our paper as follows. Section 2 reviews the literature. Section 3.1 explains the underlying model and the theoretical background. Section 3.2. describes the data. Section 3.3 explains the test and estimation procedures encompassing the main panel estimations, the specific panel estimations (for selected source sectors, recipient sectors and recipient countries) and the robustness checks (that include factor prices or research and development expenditures and apply a dynamic model). Section 3.4 describes the results of the various estimations set up in section 3.3. Section 3.5 summarizes the results and carries out future extrapolations based on the results to illustrate the magnitude of the estimated effects. Section 3.6 discusses robustness checks and caveats. Section 4 derives policy implications and concludes.

2 Literature

During the last two decades an amazing number of papers on international technology spillovers has been published (e.g. Coe et al., 1997, as one of the seminal papers on North-South spillovers; for overviews see: Saggi, 2002; Keller, 2004; Havranek and Irsova, 2011). The results are overall diverse and ambiguous regarding the significance and strength of international technology spillovers. Nonetheless, one can conclude that spillovers through imports and foreign direct investment (FDI) inflows exist.

In the work specifically dealing with trade and the environment (Grossman and Krueger, 1993; Antweiler et al., 2001; Copeland and Taylor, 2003, as seminal contributions) the focus is on pollutants like sulfur dioxide. The impact of trade on emissions is decomposed into a scale effect (increased output augments emissions), a composition effect (sectoral changes can augment or attenuate emissions per unit produced) and a technique effect (better technologies and a higher environmental awareness with rising per capita income attenuate emissions per unit produced). One can conclude from this literature that free trade improves environmental quality to a limited extent.

Due to the climate and energy challenge, the focus of the literature has then shifted to energy and carbon dioxide intensity. Some papers address international spillovers affecting energy or carbon intensity induced by imports or inward FDI (foreign direct investment) by using country-level data (e.g. Cole, 2006; Perkins and Neumayer, 2009, 2012; Hübler and Keller, 2010). The results are, however, ambiguous regarding the significance and direction of the effects on energy and carbon intensity.

Regionally more specific studies often focus on China and apply province- or city-level data (e.g. Lai et al., 2006; Kuo and Yang, 2008). These China-specific studies suggest that technology spillovers through imports and inward FDI contribute significantly to Chinese growth. Whereas these studies focus on productivity or economic growth, recent studies on China examine various kinds of environmental aspects. Cole et al. (2011) find that China's economic growth in general amplifies most air and water emissions, whereas firms from Hong Kong, Macao and Taiwan exhibit a 'clean' exemption.

Studies that do not use detailed sectoral data have one shortcoming though: one can hardly disentangle the technique effect and the composition effect of trade or FDI (except by drawing on aggregate capital intensity as a proxy, cf. Cole, 2006). The former effect is the one we are interested in when studying international spillovers. The latter effect means the change in the sectoral structure which can affect the average economy-wide productivity.

Other studies do use sector-level data. Egger and Pfaffermayr (2001), for example, find that inward FDI improves general and labor productivity in Australian manufacturing industries. A large number number of studies use firm-level data (e.g. Javorcik, 2004; Girma, 2005; Girma and Görg, 2007; Albornoz et al., 2009, on the dissemination of environmental management systems; Keller and Yeaple, 2009). These studies demonstrate summa summarum that productivity gains through inward FDI or multinational enterprises exist. Madsen (2007) shows that trade-related knowledge spillovers were the main driver of total factor productivity convergence among OECD countries over the period 1870 to 2004. Because of data availability restrictions, these studies often use data for selected OECD countries, not for developing countries. Papers focusing on specific developing countries improve on that (Aitken and Harrison, 1999, on Venezuelan plants; Bwalya, 2006, on Zambian manufacturing firms; Kohpaiboon, 2006, on Thai manufacturing plants; Amiti and Konings, 2007, on Indonesian manufacturing plants; Suyanto and Bloch, 2009, on Indonesian chemical and pharmaceutical plants; Seck, 2011, on a data set of 47 developing countries). These papers approve the existence of technology spillovers via imports and FDI inflows. The results are country-specific though, whereas our results refer to a set of emerging economies that receive technological knowledge and are hence more general.

Mayer-Foulkes and Nunnenkamp (2009), on the contrary, explore the impact of FDI on South-North convergence for the United States as a source country with various recipient countries. They identify FDI-related convergence of per-capita income with the USA for high-income, but not for low-income countries. However, most studies look at FDI (or trade in general), but not at imports used as intermediate goods inputs or as investment goods. Bitzer and Geishecker (2006), for example, improve on that aspect by looking at intermediate goods inputs and affirm resulting technology spillovers. Yet there is lack of studies that use data on imports of investment goods. Notably, these studies address productivity spillovers in general, but not environmental issues, particularly represented by energy or carbon intensities.

On the contrary, studies that affirm international convergence of energy intensities (e.g. Markandya et al., 2006; Barassi et al., 2008; Jakob et al., 2011) leave it open whether convergence is driven by trade, FDI or other factors.

R&D (research and development) as an original driver of technical progress is often not included. Some studies that do apply sector-specific data on R&D expenditures do not take trade and FDI explicitly into account (e.g. Griffith, Redding and van Reenen, 2003, 2004). Lee (2006), for example, expand on that by combining R&D and intermediate goods imports. But these studies do not examine energy or carbon either. Addressing this aspect is difficult or impossible, because so far there is no data on energy-related R&D data available on a global scale including a large set of developing countries.

Carraro and De Cian (2013) are to our knowledge the only scholars who address factor-specificity of technical change in the trade context. They also include R&D expenditures available for thirteen OECD countries (ANBERD[1] data). They find that imports of machinery and equipment reduce the input share of energy, whereas they do not significantly affect the input share of labor and that of capital either or only to a small extent. The hypothesis that the impact of machinery and equipment imports on energy and capital is the same can at least be rejected at the 10% significance level. In contrast to Carraro and De Cian, we utilize relative factor productivities instead of input shares as the dependent variable in a North-South model. Additionally, we treat OECD countries as the sources of technological knowledge and a set of emerging economies as the recipients. This allows us to scrutinize South-North convergence of factor productivity. Furthermore, we utilize various types of imported goods, not only machinery and equipment. Following Carraro and De Cian, we run

[1] `http://stats.oecd.org/Index.aspx?QueryId=18063`.

a robustness check including the ANBERD R&D expenditures for industrialized countries, whereas R&D data are missing for the emerging economies.

In summary, the literature leaves the following notable aspects open that we address in our analysis: first, to our knowledge, no econometric study has examined the *direction (bias) of trade-related South-North convergence* towards labor or energy (in the sense of directed technical change *à la* Acemoglu, 2002, and Acemoglu et al., 2012). Second, to our knowledge, no econometric study has compared imports used as an investment good with imports used as an intermediate input. Third, the literature has to our knowledge not yet examined how technology spillovers differ across the type of the traded goods and the recipient sectors and countries. Fourth, to our knowledge, there is no study that combines a large country dimension with a large sector dimension – for source and recipient countries – and a time dimension. Fifth, we introduce a novel model specification, in which the *sectoral* South-North ratio of factor productivity is the dependent variable. These aspects allow us to study factor-specific South-North convergence and its country- and sector-specific facets, exploiting a large number of observations. The model specification will be detailed in the following part.

3 Analysis

We set up an innovative econometric model that includes bilateral trade between distinct sectors and countries and corresponding energy and labor intensities. We eliminate the scale effect (increased output augments emissions) by computing all variables in *intensity* form. We define the model at the *sector* level so that the composition effect (sectoral changes can augment or attenuate emissions per unit produced) is taken into account and we are left with measuring the technique effect (better technologies and a higher environmental awareness with rising per capita income attenuate emissions per unit produced). We take into account disembodied and embodied spillovers. Herein, we compare the impact of imports used as an investment good to the impact of imports used as an intermediate input. In the former case, we hypothesize that advanced machinery and equipment imported from abroad enter the productive capital stock via investment and raise productivity. In the latter case, we hypothesize that the embodied technological knowledge not only improves the quality of the produced goods but also the productivity of the underlying production processes. Moreover, we hypothesize that productivity gains from trade through firm selection exist (as demonstrated theoretically by Melitz, 2003, in a model of heterogeneous firms[2]). Overall, the high

[2] In the Melitz (2003) model, trade liberalization induces exit of low-productivity firms and and an expansion of the market share and the profits of high-productivity firms engaged in exporting. This raises overall productivity and welfare.

sectoral resolution provides clearer results than a crude country-level analysis using aggregate trade and more general results than a one-country analysis – as usually done in the literature. Importantly, we also compare the results for energy and for labor intensity to identify the direction of technology diffusion. This distinction is important when considering climate and energy issues and poverty and development issues in a joint way. We also compare the effect of imported investment goods to the effect of domestically produced investment goods. We hypothesize that imported investment goods generate productivity gains that domestically produced ones do to generate. Thus, in our analysis, we carry out three comparisons: energy versus labor, intermediates versus investment, foreign versus domestic, in which we always apply the same model specification. If the estimated coefficients depend on the econometric specification, we will still be able to detect differences in a consistent way. This is another strength of our paper.

The novel WIOD (World Input Output Data) database allows us to carry out a detailed country- and sector-specific analysis, including energy and labor inputs, that goes beyond existing studies. Since 40 countries and 35 source are covered over 15 years, we can run regressions with a very large number of observations (up to 1,483,371 in our regressions). We split the country sample into 31 source and 9 recipient countries and create subsamples of 14 manufacturing sectors and one investment good sector as recipient sectors. Countries and sectors are interconnected via bilateral and bisectoral trade flows. This means, a good (commodity or service) is transferred from a sector j in country s to a sector i in country r. The database does not cover a large number of developing countries, but it does cover the main emerging economies which are the main future carbon emitters: China, India, Russia, Brazil and Indonesia. Besides, it covers Bulgaria, Mexico, Romania and Taiwan. And it covers manufacturing sectors such as machinery and equipment that are expected to create technology spillovers. We also make use of the advantage that WIOD provides all required variables without any need to add external data that may not fit to the sectoral resolution. In this sense, we use one consistent data set.

The following subsections provide the theoretical background in form of a simplified, stylized model in 3.1, our data set in 3.2, our test and estimation procedures in 3.3, the main, specific and robustness check results in 3.4, a summary and a prediction in 3.5 and a critical discussion in 3.6. Tables 1, 2 and 3 introduce the notation that we use.

3.1 Model setup

We scrutinize South-North convergence in energy and in labor intensities and their drivers, particularly education (absorptive capacity) and trade (imports).

t	Time period	15 years, {1995, 1996, ..., 2009}
s	Source country	31 industrialized countries
r	Recipient country	9 emerging economies, {Brazil, Bulgaria, China, India, Indonesia, Mexico, Romania, Russia, Taiwan}
u	Source country	24 industrialized countries, subset of s
j	Source sector	35 sectors (covering agriculture, industry and services)
i	Recipient sector	m or k
m	Manufacturing sector	14 recipient sectors, subset of i
k	Investment (capital) good	1 economy-wide sector as an input to all destination sectors, subset of i
l	Source sector	21 sectors, subset of j

Table 1: Sets.

Y	Output value in mill. 1995-US$
F	Factor input in physical units, $F = \{E, L\}$
E	Energy input in Terajoule
L	Labor (work) input in mill. working hours
H	High-skilled labor input in mill. working hours
X	Trade value in mill. 1995-US$
α_0	Overall constant effect
$\alpha_{1,srji}$	Source and recipient country- and sector-specific effect
$\alpha_{2,t}$	Time-specific effect

Table 2: Variables.

We build on the approach by Nelson and Phelps (1966) who state that the change in technology increases in education (human capital) and in the technology gap (originally the distance to the technology frontier) in a proportional fashion. As a result, technological laggard economies or sectors catch up faster in terms of technology than those close to the leading technology level. This results in a convergence process. We also follow Findlay (1978) who add investment flows between countries as an additional determinant of technical progress. Different from the literature, we look at the change in the South-North technology *gap* over time. For this purpose, we set up the following model:

$$\frac{\frac{F_{rit}}{Y_{rit}}}{\frac{F_{sjt}}{Y_{sjt}}} = e^{\alpha_0+\alpha_{1,srji}+\alpha_{2,t}} \cdot \left(\frac{\frac{F_{ri(t-1)}}{Y_{ri(t-1)}}}{\frac{F_{sj(t-1)}}{Y_{sj(t-1)}}}\right)^{\beta_0} \cdot \left(\frac{H_{r(t-1)}}{L_{r(t-1)}}\right)^{\beta_1} \cdot \left(\frac{X_{srji(t-1)}}{Y_{ri(t-1)}}\right)^{\beta_2}, \quad F = \{E, L\} \qquad (1)$$

On the left hand side, the model explains the relative sector- and country-specific factor intensity in period t that differs from that in $t-1$ on the right hand side. Relative means recipient (destination) country r and recipient sector i relative to source country s and source sector j. The factors F under examination are energy E and labor L. This means, the equation can be alternatively written for energy or for labor. The relative factor intensity represents a technology gap between sectors: the smaller the relative factor intensity, the smaller is the South-North technology gap. We measure the factors relative to output Y, i.e. in intensity form. Technology transfer is expected to narrow the technology gap so that the relative factor intensity is expected to decline over time. In general, we measure the factor intensity in any recipient country sector i relative to any source country sector j. This means, we compare sectors with in general different production technologies. Thus, their factor intensities naturally differ. Nonetheless, we are interested in the change of such cross-sectoral factor intensities over time. We do not look at cross-sectoral factor intensities themselves at any point of time. (When imports are used as an investment good in the following analysis, there will only be one recipient sector, investment, and recipient factor intensities will be measured recipient economy-wide.) We examine whether the South-North technology gap under scrutiny changes over time and why. In other words, we ask the question whether the data show international convergence in factor intensities over time and what the drivers are. We cannot directly infer whether recipient country factor intensities rise or fall in absolute terms though. However, if we know from descriptive statistics that factor intensities have declined in the Northern countries and our model shows that the South-North technology gap has on average declined, we will also know that factor intensities have on average declined in the Southern countries in *absolute terms*.

On the right hand side, the model lists the determinants of the change in the relative factor intensity, particularly high-skilled labor H and trade X from sj to ri. Both are measured in intensity form, relative to total labor L or output Y respectively. Herein, we assume for the moment that all determinants on the right hand side have an effect on the left hand side with a one-period time lag.

First, we assume that there is an autonomous driver of convergence denoted by α_0 that is common for all countries and sectors. α_0 is the constant overall annual growth rate. $\alpha_{1,srji}$ is the annual growth rate of the (source and destination) sector- and country-specific autonomous driver. It represents a trade-specific effect: there is one individual effect for each source country and sector interacting with each destination country and sector, i.e. for each $(srji)$-quadruple. $\alpha_{2,t}$ captures any time varying processes not captured by the model.

Second, the relative factor intensity in period t is supposed to depend upon the relative factor intensity of the previous period $t-1$ as explained above. This implies path dependency of factor intensity.

Third, we assume that education (human) capital is an important country-specific driver of convergence. We measure education (absorptive capacity) as the economy-wide high-skilled labor share in all labor (in terms of working hours) $\frac{H_{r(t-1)}}{L_{r(t-1)}}$. High-skilled labor means first stage and second stage of tertiary education (1997 ISCED levels 5 and 6). Education can (a) directly support convergence since workers with better education and skills are supposed to be more productive in terms of labor productivity. They might also have better managerial skills that help improve overall efficiency and energy efficiency of production. Education can (b) indirectly support convergence when it is treated as a measure for the absorptive capacity. It then represents factors like infrastructure, the legal system, access to media etc. It can in this sense support embodied spillovers, brought about by the following driver.

Fourth, international trade in terms of imports used for investment or imports used as intermediate inputs is the driver of main interest. We measure it relative to the destination country production value in each destination sector as $\frac{X_{srji(t-1)}}{Y_{ri(t-1)}}$. We expect that a higher import intensity lowers the relative factor intensity. We (a) expect that trade intensifies competition and firm selection resulting in increased productivity in the Melitz (2003) sense. While one might first think of final products in this context, we only consider competition and firm selection in intermediate goods and investment goods markets in an implicit way in this analysis. Most importantly, we (b) expect that trade enhances embodied international technology spillovers as summarized by Saggi (2002) and Keller (2004). Regarding investment goods, we suppose that for example new electrical equipment embodies superior new technologies. Regarding intermediate inputs, we suppose that for example the delivery of new electric circuits is accompanied by information on how to to integrate them in final products. Hence, we expect that the way they are technically integrated in final products changes compared to the past. This implies process innovation additionally to product innovation. As a result, not only the quality of products improves but also the efficiency of the underlying production processes. We expect a positive interaction between education (absorptive capacity), the technology gap and imports (cf. Nelson and Phelps, 1966; Findlay, 1978).

3.2 Data description

We use the novel WIOD (World Input Output Data) database throughout the analysis. The WIOD project has been funded by the European Commission, Directorate General Research, as part of the 7^{th} Framework Programme, Theme 8: Socio-Economic Sciences and Humanities. WIOD has been available for the public since April 2012.[3] It is to our knowledge the first database that provides bilateral and bisectoral input-output relations for a number of years as well as environmental indicators within one consistent data set. The full input-output table provides 1,483,371 observations. We divide the full data set into 31 source countries[4] s and 9 recipient countries[5] r, 35 source sectors[6] j, 14 recipient manufacturing sectors[7] m and one recipient investment good sector[8] k as well as 15 years (1995 until 2009). t. Although the industrialized countries covered by WIOD (listed in the footnote) do not perfectly match the OECD member state list in 2013 nor the OECD plus the EU member state list in 2013, we will for simplicity refer to them as OECD countries throughout the paper. Inversely, we will refer to the nine emerging countries covered by WIOD as non-OECD countries for simplicity of the terminology.

Within the WIOD database, we take data on imports of intermediate goods and investment goods and domestically produced investment goods from the World Input-Output Tables (WIOTs). We take data on working hours, output, high-skilled labor shares[9] and price indices used to deflate variables from the Socioeconomic Accounts (SEAs). We take

[3] http://www.wiod.org/database/.

[4] 1. Australia, 2. Austria, 3. Belgium, 4. Canada, 5. Cyprus, 6. Czech Republic, 7. Denmark, 8. Estonia, 9. Finland, 10. France, 11. Germany, 12. Greece, 13. Hungary, 14. Ireland, 15. Italy, 16. Japan, 17. Korea, 18. Latvia, 19. Lithuania, 20. Luxembourg, 21. Malta, 22. Netherlands, 23. Poland, 24. Portugal, 25. Slovak Republic, 26. Slovenia, 27. Spain, 28. Sweden, 29. Turkey, 30. United Kingdom, 31. United States of America.

[5] 1. Brazil, 2. Bulgaria, 3. China, 4. India, 5. Indonesia, 6. Mexico, 7. Romania, 8. Russia, 9. Taiwan.

[6] 1. Agriculture, Hunting, Forestry and Fishing, 2. Mining and Quarrying, 3. Food, Beverages and Tobacco, 4. Textiles and Textile Products, 5. Leather, Leather and Footwear, 6. Wood and Products of Wood and Cork, 7. Pulp, Paper, Printing and Publishing, 8. Coke, Refined Petroleum and Nuclear Fuel, 9. Chemicals and Chemical Products, 10. Rubber and Plastics, 11. Other Non-Metallic Minerals, 12. Basic Metals and Fabricated Metal, 13. Machinery, NEC, 14. Electrical and Optical Equipment, 15. Transport Equipment, 16. Manufacturing, NEC, Recycling, 17. Electricity, Gas and Water Supply, 18. Construction, 19. Sale, Maintenance and Repair of Motor Vehicles and Motorcycles, Retail Sale of Fuel, 20. Wholesale Trade and Commission Trade, Except of Motor Vehicles and Motorcycles, 21. Retail Trade, Except of Motor Vehicles and Motorcycles, Repair of Household Goods, 22. Hotels and Restaurants, 23. Inland Transport, 24. Water Transport, 25. Air Transport, 26. Other Supporting and Auxiliary Transport Activities, Activities of Travel Agencies, 27. Post and Telecommunications, 28. Financial Intermediation, 29. Real Estate Activities, 30. Renting of M&E and Other Business Activities, 31. Public Admin and Defense, Compulsory Social Security, 32. Education, 33. Health and Social Work, 34. Other Community, Social and Personal Services, 35. Private Households with Employed Persons.

[7] 1. Food, Beverages and Tobacco, 2. Textiles and Textile Products, 3. Leather, Leather and Footwear, 4. Wood and Products of Wood and Cork, 5. Pulp, Paper, Paper, Printing and Publishing, 6. Coke, Refined Petroleum and Nuclear Fuel, 7. Chemicals and Chemical Products, 8. Rubber and Plastics, 9. Other Non-Metallic Minerals, 10. Basic Metals and Fabricated Metal, 11. Machinery, NEC, 12. Electrical and Optical Equipment, 13. Transport Equipment, 14. Manufacturing, NEC, Recycling.

[8] The investment good adds to the recipient economy-wide capital stock used for production in any sector of the recipient country.

[9] High-skilled labor means first and second stage of tertiary education (1997 ISCED levels 5 and 6).

data on total energy use from the Environmental Accounts (EAs).

The variables of main interest are factor (energy and labor) intensity $\frac{F_t}{Y_t}$, $F = \{E, L\}$, high-skilled labor intensity $\frac{H_t}{L_t}$, and import (investment and intermediate input) intensity $\frac{X_t}{Y_t}$. The country and sector indexes are left out here because Figure 1 (a–c) plots these variables as cross-sectional averages over the 31 industrialized source countries and sectors, denoted by 'OECD', and averages over the 9 emerging recipient countries and sectors, denoted by 'non-OECD', for the time horizon 1995 to 2009 which WIOD covers.[10] Figure 1 (d) plots trade flows from aggregate OECD to aggregate non-OECD. For this purpose, the bilateral, bisectoral trade flows are summed up over source as well as recipient countries and sectors and expressed in relation to total recipient GDP (gross domestic product). Apparently, energy intensity is much higher in the non-OECD region than in the OECD region. Energy intensity fell in both regions, but to a much stronger extent in the non-OECD region as shown in Figure 1 (a). This illustrates that a tendency of South-North convergence exists. However, the data also show that the South-North ratio of energy intensity, i.e. relative energy intensity $\frac{E_{rt}}{Y_{rt}}/\frac{E_{st}}{Y_{st}}$, fell to a minor extent from about 3.2 in 1995 to 3.1 in 2009.

Similarly, Figure 1 (b) reveals a much higher labor intensity in the non-OECD than in the OECD region and South-North convergence. Different from energy intensity, labor intensity stayed almost constant in OECD and fell to a larger extent than energy intensity in non-OECD. The data show that the South-North ratio of labor intensity, i.e. relative labor intensity $\frac{L_{rt}}{Y_{rt}}/\frac{L_{st}}{Y_{st}}$, clearly fell from about 22.3 in 1995 to 15.1 in 2009. This means, the South-North productivity gap is much larger for labor than for energy, and the speed of closing the gap has been much larger for labor than for energy too. This is in accordance with classical theory like Nelson and Phelps (1966) suggesting that catching up is faster the larger the initial technology gap is.

Figure 1 (c) depicts the rise in high-skilled labor intensity as an indicator for eduction and absorptive capacity (in terms of absorbing technological knowledge) in both regions. The OECD high-skilled intensity rose from 18.9% in 1995 to 27.5% in 2009. The non-OECD high-skilled intensity rose from 8.9% in 1995 to 13.4% in 2005. Nevertheless, the South-North ratio of the high-skilled intensity improved only slightly from 0.47 to 0.49 within this time frame.

Nonetheless, only a rigorous statistical analysis can take into account sectoral differences, country-specific effects and specific drivers of convergence. Only a sectoral analysis can disentangle the technique effect from the (sectoral) composition effect. One of the drivers

[10] The sum of OECD energy use divided by the sum of OECD GDP (gross domestic product)). The same for non-OECD.

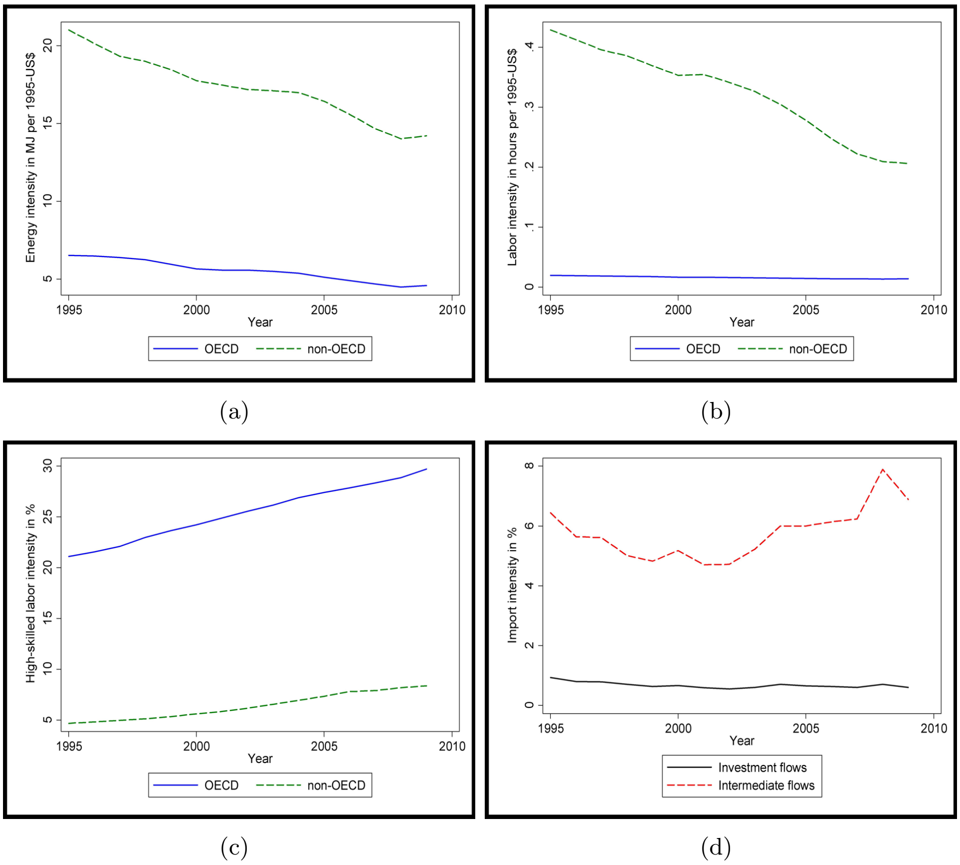


Figure 1: Historical time paths computed from WIOD for the aggregate regions of 31 industrialized countries (mostly OECD countries) and 9 emerging countries (mostly non-OECD countries) as averages over countries and sectors. (a) Energy intensity (energy input to GDP) $\frac{E_t}{Y_t}$; (b) Labor intensity (labor input to GDP) $\frac{L_t}{Y_t}$; (c) High-skilled labor intensity (share of high-skilled working hours in all working hours) $\frac{H_t}{L_t}$; (d) Import intensity (imports used for investment and imports used as intermediate inputs) $\frac{X_t}{Y_t}$.

is presumably international trade as visualized by Figure 1 (d). The figure depicts trade flows from OECD to non-OECD in both graphs.[11] The upper graph looks at trade in products used as intermediate inputs in non-OECD manufacturing sectors in intensity form. Accordingly, the intensity of intermediate goods imports fell from 6.4% of GDP to 4.7% in the first half of the time frame and rose to 7.9% in the second half. The intensity of imports used as investment goods depicted in the lower graph, on the contrary, slightly fell from 0.9% to about 0.6 % of GDP in the first half and then stabilized around that percentage number. This means that the import intensity did not clearly rise within the time frame as one might expect. This, however, does not contradict our hypothesis of international productivity spillovers via imports. The model that we set up in the previous section states that a positive import share in a certain period influences the South-North technology gap in the following period (and thereafter via the lagged dependent variable). Thus, a contribution

[11] The value of trade from OECD to non-OECD divided by non-OECD GDP.

of trade to convergence does not require that the import share is intensified over time, it just requires that the trade intensity is positive (and not zero).

Notwithstanding, the figures might depict a kind of spurious correlation. Thus, we carry out unit root tests for panel data. Herein, we focus on the Fisher-type Augmented Dickey Fuller test for unit roots in panel data (based on Dickey and Fuller, 1979). Additionally, we apply the Im-Pesaran-Shin (2003) test. In accordance with other studies (e.g. Hübler and Keller, 2010), the tests indicate a unit root in energy intensity. The same is true for labor intensity. We resolve this problem by using *relative* factor intensity (the South-North ratio of energy or labor intensity) as the dependent variable which is not subject to a unit root. The other variables, import intensity and high-skilled labor intensity, do *not* have unit roots according to the test results.

Table 8 in the Appendix summarizes the descriptive statistics for our main variables. Energy intensity $\frac{E}{Y}$, labor intensity $\frac{L}{Y}$ and high-skilled intensity $\frac{H}{L}$ are reported for OECD source countries s and non-OECD recipient countries r, both with the time (year) index t. Trade intensities $\frac{X}{Y}$ represent flows from OECD to non-OECD at the sector level so that each trade flow has the index $srjkt$ or $srjmt$ whereas the output value referring to the destination country and sector has the index rit. Looking at manufacturing sectors m as recipient sectors results in a larger number of observations than looking at the investment good k only. In the former case, the data are computed sector-wise, in the latter case, economy-wise. For source countries, the intensities are reported including all sectors, i.e. at the country level. For recipient countries, they are reported for all sectors as well as for manufacturing sectors only.

It is visible in Table 8 in the Appendix that non-OECD countries have on average a higher energy and labor intensity and a higher variance in these variable than OECD countries.[12] On the opposite, they have on average a lower high-skilled labor intensity and therein a lower variance than OECD countries. The average high-skilled labor intensity of OECD countries over time is 2.1 times that of non-OECD countries. This reflects a higher average education and technology and thus productivity level in OECD countries. Within non-OECD countries, manufacturing sectors have on average a higher energy intensity, a lower labor intensity and a lower high-skilled intensity than all sectors have on average. This points to a more intensive use of machinery in manufacturing which replaces labor but uses energy. At the same time, there are more labor-intensive activities in manufacturing that demand low-skilled labor.

[12]The high maximum of manufacturing energy intensities on a sectoral level comes from 'Inland Transport' in Russia. While Russia's energy intensity is in general about 2.5 to 3 times higher than that of China or India, the energy intensity in this particular sector is even higher.

We compute three-year moving averages of all data used in the regressions in order to mitigate outliers and possible endogeneity problems due to measurement errors and factors outside the model that simultaneously influence an explanatory and the dependent variable. Endogeneity due to omitted variables (factor productivity has various possible determinants for which no data covering the countries, sectors and years in our model are available) will in general be addressed by fixed effects and more specifically by the inclusion of R&D expenditures and factor prices in the robustness check. Notably, we define the dependent variable as a South-North ratio. This has an important advantage with respect to endogeneity: if the labor (or energy) productivity of the South is inversely proportional to per capita income and hence the state of economic development, the high-skilled labor, import and investment intensity are – following straightforward economic reasoning – supposed to be dependent on the state of economic development and hence endogenous. This effect is tackled or at least mitigated through the definition of the dependent variable as the sectoral growth rate of the South-North *ratio* of factor intensity. It is for example not straightforward that the high-skilled labor intensity depends on this sectoral, relative measure.

Tables 9 and 10 in the Appendix show the correlation matrix for the investment good sample and the manufacturing sectors sample respectively. The latter sample is larger than the former because it distinguishes more recipient sectors. The matrices show that all correlations are low so that there is no collinearity problem.

In a robustness check, we will also use data from ANBERD (Analytical Business Enterprise Research and Development).[13] The sectoral coverage is reduced to 21 sectors[14] denoted by l because some sectors are summed up in ANBERD. The country coverage is additionally reduced to 24 source countries[15] denoted by u.

In another robustness check, we will use factor prices. Since factor prices are not directly provided by WIOD, we construct them by dividing factor input quantities in currency value form (1995-US$) by input quantities in physical units (number of working hours or Joule). Labor input in working hours is available in WIOD, whereas the energy input in value form is not directly available. Hence, we make the assumption that intermediate inputs from the

[13] `http://stats.oecd.org/Index.aspx?DataSetCode=ANBERD2011_REV3`.

[14] 1. Agriculture, Hunting, Forestry and Fishing, 2. Mining and Quarrying, 3. Food, Beverages and Tobacco, 4. Textiles and Textile Products, 5. Leather, Leather and Footwear, 6. Wood and Products of Wood and Cork, 7. Pulp, Paper, Printing and Publishing, 8. Coke, Refined Petroleum and Nuclear Fuel, 9. Chemicals and Chemical Products, 10. Rubber and Plastics, 11. Other Non-Metallic Minerals, 12. Basic Metals and Fabricated Metal, 13. Machinery, NEC, 14. Electrical and Optical Equipment, 15. Transport Equipment, 16. Manufacturing, NEC, Recycling, 17. Electricity, Gas and Water Supply, 18. Construction, 19. Hotels and Restaurants, 20. Financial Intermediation, 21. Other Community, Social and Personal Services.

[15] 1. Australia, 2. Austria, 3. Belgium, 4. Canada, 5. Czech Republic, 6. Germany, 7. Spain, 8. Estonia, 9. Finland, 10. France, 11. Great Britain, 12. Greece, 13. Hungary, 14. Ireland, 15. Italy, 16. Japan, 17. Korea, 18. Netherlands, 19. Poland, 20. Portugal, 21. Slovak Republic, 22. Slovenia, 23. Turkey, 24. United States.

sectors coal, lignite and peat; crude petroleum and natural gas; services incidental to oil and gas extraction excluding surveying; coke, refined petroleum products and nuclear fuels; electrical energy, gas, steam and hot water taken from the National Supply and Use Tables (SUTs) represent energy use. Computing the share of these energy inputs in all inputs and multiplying by total expenditure on inputs yields the required energy input value. These constructed price measures are, however, only an approximation of real prices.[16]

3.3 Estimation strategy

This subsection explains our estimation strategy. Table 3 depicts the notation used in the econometric model.

In order to simplify the notation, we write: $RFY_{srjit} := \ln\left(\frac{F_{rit}}{Y_{rit}} / \frac{F_{sjt}}{Y_{sjt}}\right)$, $HL_{rt} := \ln\left(\frac{H_{rt}}{L_{rt}}\right)$, and $XY_{srjit} := \ln\left(\frac{X_{srjit}}{Y_{rit}}\right)$, and add an error term ε_{srjit} that includes all disturbances not captured by the model. Taking logs of Equation (1) and using this notation results in the following $log - log$ specification:

$$RFY_{srjit} = \alpha_0 + \beta_0 \cdot RFY_{srji(t-1)} + \beta_1 \cdot HL_{r(t-1)} + \beta_2 \cdot XY_{srji(t-1)} + \varepsilon_{srjit} \tag{2}$$

We recall that s denotes source countries, r recipient countries, j source sectors, i recipient sectors, and t time (years). We estimate this dynamic model for $F = \{E, L\}$, i.e. for relative energy and labor intensity excluding the fixed effects $\alpha_{1,srji}$ and $\alpha_{2,t}$.

RFY_{srjit}	Logarithm of factor intensity, recipient relative to source, $F = \{E, L\}$
HL_{rt}	Logarithm of high-skilled labor intensity, recipient
XY_{srjit}	Logarithm of international trade flow relative to recipient output value
DY_{rt}	Logarithm of domestic investment goods intensity, recipient
IY_{slnt}	Logarithm of R&D intensity, source
PF_{rmt}	Logarithm of factor price measure
α_0	Overall constant
$\alpha_{1,srji}$	Source and recipient country- and sector-specific fixed effect
$\alpha_{2,t}$	Time-specific effect
β_n	n^{th} coefficient to be estimated
ε_{srjit}	Error term

Table 3: Symbols of the econometric model.

[16]Due to missing data, Romania is left out in the energy price sample and in the robustness check regression based on that.

3.3.1 Main estimation

In order to derive the static model used in our main estimations, we assume $\beta_0 = 1$ and subtract $\beta_0 RFY_{srji(t-1)}$ on both sides.[17] Then on the left hand side, $\Delta RFY_{srji(t-1)} = RFY_{srjit} - RFY_{srji(t-1)}$ describes the growth rate of the relative factor intensity within period $t-1$. We then write the model for $\Delta RFY_{srjit} = RFY_{srji(t+1)} - RFY_{srjit}$ instead of $\Delta RFY_{srji(t-1)}$ to simplify the notation. We expect a time lag between the inflow of goods and their impact on the relative productivity because the technology diffusion requires time. In particular, we assume a three-year time lag (for a discussion see section 3.5). We arrive at the following static $dlog - log$ specification for $F = \{E, L\}$ with individual and time-specific effects:

$$\Delta RFY_{srjit} = \alpha_0 + \alpha_{1,srji} + \alpha_{2,t} + \beta_1 \cdot HL_{r(t-3)} + \beta_2 \cdot XY_{srji(t-3)} + \varepsilon_{srjit} \tag{3}$$

We structure our estimation procedure as follows:

We always look at the industrialized (OECD and EU) countries s as source countries and the emerging (non-OECD) countries r as recipient countries.

Our first set of regressions, denoted by K looks at the investment (capital) good k as the single destination sector i. We focus on the investment good because we expect that especially products that enter the capital stock, such as new machinery, bring about new technologies and thus productivity gains. In this case, the recipient factor intensity is the economy-wide one because we only know the total economy-wide investment volume, not the sectoral investment volume from the data. In the same manner, the high-skilled labor share is the economy-wide share. Source sectors encompass all sectors j.

The second set denoted by M looks at all manufacturing sectors m as recipient sectors i. We focus on manufacturing sectors because we expect that manufacturing firms can most likely deploy the technological knowledge embodied in intermediate goods. Source sectors encompass again all sectors j. In this case, the high-skilled labor share refers to manufacturing sectors only. Factor intensities are now measured at the sector level.

The first subset of regressions denoted by E uses energy productivity, the second subset, denoted by L, uses labor productivity. We estimate each set and subset with the static model lain out by Equation (3):

Estimation 1: We estimate the basic static model in Equation (3) as it stands. We carry out an F-test for fixed effects versus pooled regression. The null hypothesis of all fixed effects

[17] As we will see in the dynamic estimations in the robustness check, the estimated value of β_0 is only slightly below one.

being zero is rejected so that we choose a specification with individual effects as given by Equation (3). Moreover, we carry out a Hausman test for fixed versus random effects. The null hypothesis of consistent random effects is rejected for our different specifications so that we choose fixed effects. In all the regressions we run, we carry out standard F-tests for the null hypothesis of all coefficients jointly being zero, which is always clearly rejected with p-values very close to zero. We always report adjusted R^2 values too. We report robust standard errors.

Estimation 2: We add the total value of domestically produced (within-country) investment goods relative to GDP, i.e. $\beta_3 \cdot DY_{r(t-3)}$, for each recipient country in the static regression. Herein, domestic investment goods are measured economy-wide. By doing this, we intend to check whether the influence of investment goods from abroad is significantly different from the influence of domestic investment goods. If so, this points to embodied technology spillovers or increased competition and firm selection via trade.

Estimation 3: We leave out domestic investment goods but include the relative factor intensity $\beta_5 \cdot RFY_{ri(t-3)}$ as a regressor. Now we want to know whether the past relative factor intensity of a country leads to a change in the relative factor intensity today in the sense of a convergence process. Following convergence theory (cf. Nelson and Phelps, 1966) we expect that a higher past factor intensity results in a stronger reduction in the relative factor intensity today. This static specification comes close to our dynamic model in Equation (2). The first difference is that in Equation (2) the relative factor intensity RFY_{srjit} appears as the dependent variable instead of the change in the relative factor intensity denoted by ΔRFY_{srjit}. The second difference is that $RFY_{ri(t-3)}$ now appears with a one-period lag instead of a three-period lag as a regressor.

Estimation 4: We are interested in the interaction of imports with the absorptive capacity and with the existing relative factor intensity. This leads to the interaction term $\beta_6 \cdot HL_{r(t-3)} \cdot XY_{srji(t-3)} \cdot RFY_{ri(t-3)}$ in the static model and with a one-period lag $(t-1)$ in the dynamic model.

This yields 2 x 2 x 4 static regressions S. In the robustness check explained below we will additionally specify 1 x 2 x 2 dynamic regressions D. Regression (SME1) for example denotes the basic static model looking at intermediate goods and energy intensity. Regression (DKL3) for example denotes the dynamic model without the interaction term looking at the investment good and labor intensity.

3.3.2 Specific estimation

To identify cross-section heterogeneity, we select machinery and equipment sectors as single source sectors, and different energy- or labor-intensive recipient sectors thereafter, both based on regression (2). Additionally, we will look at the BRIC-countries (Brazil, Russia, India and China) as single recipient countries based on regression (1). The aim of these specific estimations is not to check the robustness of the results, but to scrutinize the heterogeneity of spillover effects across countries and sectors and to identify prevailing patterns.

First, we examine source country heterogeneity with respect to the creation of technology spilllovers. We estimate the static model (SK.2 and SM.2) including domestic investment goods as a separate regressor for E and L for selected source sectors j. In particular, we choose the manufacturing sectors 'Basic Metals and Fabricated Metal', 'Machinery, Nec', 'Electrical and Optical Equipment' and 'Transport Equipment' as single source sectors. These sectors produce machinery and equipment used as investment goods, and we expect that these investment goods are in particular associated with international technology diffusion. Herein, it is our aim to identify which source sectors are in particular relevant for catching up through technology transfer. For comparison, we also estimate the effects of these goods if they are used as intermediate inputs. This appears straightforward since fabricated material, machinery and equipment can also create productivity gains when they are further fabricated, for example due to information provided together with the equipment.

Second, we want to detect which recipient sectors are in particular able to catch up through technology transfer. These sectors could be supported by policy measures with priority. For this purpose, we estimate the static model (SM.2) with intermediate goods imports including domestic investment goods as a separate regressor for E and L for selected recipient sectors m. In particular, we choose the manufacturing sectors 'Textiles and Textile Products', 'Pulp, Paper, Printing and Publishing', 'Chemicals and Chemical Products' and 'Machinery, Nec' as single recipient sectors. 'Textiles and Textile Products' is a sector where manual work and imports of raw material play an important role in countries like China. 'Pulp and Paper', although not 'Printing and Publishing', and 'Chemicals and Chemical Products' are typical energy-intensive sectors. 'Machinery' is not a typical energy-intensive, nor a typical labor-intensive sector, whereas intermediate inputs like metal products might generate productivity gains in this sector.

Third, we run our static regressions for selected destination countries, i.e. for the BRIC-countries, Brazil, Russia, India and China, in order to detect recipient country heterogeneity. In these regressions, we apply the basic static model (1) represented by Equation (3). We need to leave out the high-skilled share and the intensity of domestic investment goods because the data exhibit small variation over time when looking at a single recipient country. Nonetheless, we include individual and time-specific effects as before. Once again, we run the regressions looking at energy versus labor intensity and at investment good use versus intermediate good use.

3.3.3 Robustness check

As a first robustness check, we will estimate Equation (2) excluding fixed effects α_{srji} by applying *dynamic* panel estimators (Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; xtabond2 by Roodman, 2009a, in Stata). We keep the original model specification with one-period time lags which is the common specification of a dynamic model. Our GMM (Generalized Method of Moments) type estimation addresses 'Nickel bias' (Nickel, 1982) and others kinds of endogeneity (omitted variable bias, measurements errors and simultaneity as discussed in section 3.2). We apply the two-step method and reduce the instrument count (cf. Roodman, 2009b), i.e. time lags, and restrict the instrumentation to instruments in levels with the aim to fulfill the Sargan/Hansen J-test for overidentifying restrictions (the null hypothesis of joint validity of all instruments). We also apply the Arellano-Bond test for autocorrelation (AR(1) and AR(2)). It turns out that due to the very large cross-section but relatively small time series of the data, it is difficult to find a valid dynamic specification that fulfills the J- and AR-test. This is especially true for the larger sample with manufacturing sectors as recipient sectors. Hence, we report only the results for the smaller investment good sample. We rely in general more on the static estimations. The dynamic estimation is nevertheless important for better understanding the dynamic behavior with respect to convergence and to address endogeneity in a robustness check.

We will run two more robustness checks that insert further control variables into the static model. *Factor prices*, i.e. wages and energy prices, are closely related to factor productivity following basic economic reasoning. This involves two problems though: data availability and endogeneity. Regarding data availability, the required prices are not directly provided by WIOD, but constructed as detailed in section 3.2. Regarding endogeneity, our price measures are similar to the inverse of the dependent variable. Different from the dependent variable, the price measures are not applied in form of South-North ratios, but in form of sectoral recipient country prices. This mitigates the endogeneity risk. The endogeneity risk would even be present if the real wages and energy prices were directly available, because the wage is determined by labor productivity and the energy price is determined by energy productivity according to producer theory. This leads us to treat the estimation including factor prices not as our preferable main estimation, but as a robustness check. We perform this robustness check for the basic intermediate goods model (SME1 and SML1).[18] We label the constructed energy price $PE_{rm(t-3)}$ and the constructed labor price (wage) $PL_{rm(t-3)}$.

The next robustness check addresses that our model leaves open what the origin of technical progress is. A common variable capturing this origin is *R&D expenditures*. Data on R&D expenditures are unfortunately only fully available for OECD countries, in particular from ANBERD. The focus of our work, however, is on productivity gains in emerging economies, not in OECD countries. Besides this restriction, we need to reduce the sectoral coverage (cf. section 3.2). Nonetheless, it can provide further insights to differentiate the R&D capability of the OECD source countries of technology spillovers. Hence, we treat the estimations with R&D expenditures as a robustness check. We define source-sector and source-country-specific R&D expenditures per output value (R&D intensity) and label them $IY_{ul(t-3)}$ (I for innovation). We also let R&D intensity interact with the import and the high-skilled labor intensity in order to check whether they generate a positive joint effect.

3.4 Estimation results

This section details the results of the (static) main regressions (energy and labor intensity, investment and intermediate goods imports, hence four sets of regressions), the (static) sector- and country-specific regressions (source-sector-specific, recipient-sector-specific and recipient-country-specific) and the robustness checks (dynamic, with factor prices and with R&D expenditures).

3.4.1 Main estimation results

This section reports and interprets the regression results for the static, general (not sector- or region-specific) panel model. We always report heteroscedasticity robust standard errors in the tables. Due to the large number of observations, the regressions are expected to generate highly significant results. We thus report the significance levels 10%, 5%, 1%, 0.5%, and 0.1% ranging from one to five stars. We also report adjusted R^2 values. The coefficients of this $dlog - log$ specification can be interpreted as follows:

A negative coefficient implies that the relative factor intensity and thus the South-North technology gap decline resulting in South-North convergence. A coefficient of -0.05 for HL means that doubling the high-skilled intensity (a 100% increase in HL) decreases the annual

[18] We do not apply the dynamic model because of the caveats sketched above.

Regressions SKE1...4

	1	2	3	4
	ΔREY_{srjkt}	ΔREY_{srjkt}	ΔREY_{srjkt}	ΔREY_{srjkt}
$HL_{r(t-3)}$	-0.042**	-0.048***	-0.031*	-0.025*
	(0.017)	(0.018)	(0.016)	(0.015)
$XY_{srjk(t-3)}$	-0.0041*****	-0.0045*****	-0.0017*	-0.00094
	(0.0011)	(0.0011)	(0.0010)	(0.0014)
$DY_{r(t-3)}$		0.0058**		
		(0.0028)		
$REY_{rjk(t-3)}$			-0.16*****	-0.17*****
			(0.011)	(0.013)
$HL_{r(t-3)} \cdot XY_{srjk(t-3)}$				0.00017
$\cdot REY_{rk(t-3)}$				(0.00030)
$Constant$	-0.17*****	-0.17*****	0.20*****	0.23*****
	(0.047)	(0.049)	(0.045)	(0.035)
#Obs.	97,942	97,942	97,942	97,942
R^2	0.004	0.004	0.037	0.037

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 4: Panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source sectors include all sectors, recipient sectors only the investment (capital) good.

growth rate of the relative factor intensity (the South-North ratio of factor intensities) by 5 percentage points. The resulting half-time of the relative factor intensity solely driven by HL is then about 14 years. A coefficient of -0.005 for XY means that doubling the import intensity (a 100% increase in XY) decreases the annual growth rate of the the relative factor intensity (the South-North ratio of factor intensities) by 0.5 percentage points. The resulting half-time of the relative factor intensity solely driven by XY is now about 138 years.

Table 4 shows the results of estimating the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source sectors include all sectors, recipient sectors only the economy-wide used investment (capital) good. The coefficient of the import intensity has in all cases the expected negative sign, this means imports reduce the energy intensity of production in developing countries. The coefficient is in three of four cases significant too.

Similarly, the coefficient of the high-skilled intensity is always significantly negative. However, the coefficient is about an order of magnitude higher than the import coefficient. The

Regressions SKL1...4

	1	2	3	4
	ΔRLY_{srjkt}	ΔRLY_{srjkt}	ΔRLY_{srjkt}	ΔRLY_{srjkt}
$HL_{r(t-3)}$	-0.021*****	-0.015****	-0.11*****	-0.098*****
	(0.0042)	(0.0043)	(0.0032)	(0.0051)
$XY_{srjk(t-3)}$	-0.0013*****	-0.00085**	2.2e-06	0.0015****
	(0.00036)	(0.00037)	(0.00026)	(0.00051)
$DY_{r(t-3)}$		-0.0061*****		
		(0.0011)		
$RLY_{ri(t-3)}$			-0.17*****	-0.19*****
			(0.0030)	(0.0059)
$HL_{r(t-3)} \cdot XY_{srjk(t-3)}$ $\cdot RLY_{ri(t-3)}$				0.00027***
				(0.000077)
$Constant$	-0.064*****	-0.055*****	0.10*****	0.17*****
	(0.012)	(0.012)	(0.011)	(0.024)
#Obs.	98,173	98,173	98,155	98,155
R^2	0.051	0.051	0.250	0.251

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Panel estimation of the drivers of the growth rate of the relative South-North labor intensity including individual and time-specific effects (not reported in the table). Source sectors include all sectors, recipient sectors only the investment (capital) good.

coefficient of domestically produced investment goods in column 2 of Table 4 has a similar magnitude as imported investment goods – but it is significantly positive. These results indicate that education, or more generally speaking absorptive capacity, has a stronger positive impact on factor productivity growth than imports of investment goods. Domestically produced investment goods, on the opposite, likely raise energy intensity, or in other words, lower energy productivity. This indicates that in the non-OECD countries in our sample, *domestic* investment goods shift production towards energy-intensive production and do not bring about technical progress sufficiently to reduce energy intensity – in contrast to imported investment goods.

Furthermore, the relative energy intensity with a three-year lag enters in a significantly negative way in column 3 as suggested by theory: the lower the initial productivity level and thus the larger the technology gap, the higher becomes the growth rate and thus technological catching up. We do not identify a significant interaction bonus of absorptive capacity, imports and the previous technology level in column 4 though. – More details will be discussed in

Regressions SME1...4

	1	2	3	4
	ΔREY_{srjmt}	ΔREY_{srjmt}	ΔREY_{srjmt}	ΔREY_{srjmt}
$HL_{r(t-3)}$	-0.031*****	-0.068*****	-0.048*****	-0.049*****
	(0.0042)	(0.0048)	(0.0040)	(0.0036)
$XY_{srjm(t-3)}$	-0.0028*****	-0.0050*****	-0.0019*****	-0.0020*****
	(0.00025)	(0.00027)	(0.00023)	(0.00026)
$DY_{r(t-3)}$		0.027*****		
		(0.00085)		
$REY_{ri(t-3)}$			-0.15*****	-0.15*****
			(0.0015)	(0.0022)
$HL_{r(t-3)} \cdot XY_{srjm(t-3)}$ $\cdot REY_{ri(t-3)}$				-0.000036
				(0.000058)
$Constant$	-0.11*****	-0.22*****	0.021*	0.017*
	(0.012)	(0.014)	(0.011)	(0.0093)
#Obs.	1,478,944	1,478,944	1,478,944	1,478,944
R^2	0.004	0.005	0.054	0.054

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source sectors include all sectors, recipient sectors only manufacturing sectors.

section 3.4.

Table 5 shows the regressions of Table 4 for labor intensity instead of energy intensity. Now the import intensity of investment goods has only in the first two regressions a significantly negative impact on the growth rate of relative labor intensity. Notably, in the first two columns the magnitude of the negative coefficients is smaller than in the first two columns of Table 4. This indicates an energy bias of trade-related productivity gains. In the fourth column, the trade impact has the opposite sign, i.e. imports of investment goods raise relative labor intensity. This means, in comparison with Table 4, the energy bias is even more obvious.

The coefficient of high-skilled labor intensity is again always negative, but its magnitude is more diverse (in the first two regressions lower, in the last two higher than in Table 4). Domestic investment now enters with a significantly negative sign.

The past relative labor intensity enters with a negative sign and a slightly higher magnitude than in the previous energy intensity regressions. The coefficient of the interaction term is significantly positive and small. Thus, the expected joint benefit of absorptive capacity, Regressions SML1...4

	1	2	3	4
	ΔRLY_{srjmt}	ΔRLY_{srjmt}	ΔRLY_{srjmt}	ΔRLY_{srjmt}
$HL_{r(t-3)}$	-0.095*****	-0.13*****	-0.15*****	-0.15*****
	(0.0016)	(0.0018)	(0.0012)	(0.0013)
$XY_{srjm(t-3)}$	0.00066*****	-0.0013*****	0.00071*****	0.00082*****
	(0.00017)	(0.00018)	(0.00014)	(0.00018)
$DY_{r(t-3)}$		0.024*****		
		(0.00049)		
$RLY_{ri(t-3)}$			-0.17*****	-0.17*****
			(0.00048)	(0.0012)
$HL_{r(t-3)} \cdot XY_{srjm(t-3)}$ $\cdot RLY_{ri(t-3)}$				0.000029
				(0.000025)
$Constant$	-0.22*****	-0.32*****	-0.12*****	-0.12*****
	(0.0048)	(0.0052)	(0.0034)	(0.0050)
#Obs.	1,483,623	1,483,623	1,483,371	1,483,371
R^2	(0.0048)	(0.0052)	(0.0034)	(0.0050)

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Panel estimation of the drivers of the growth rate of the relative South-North labor intensity including individual and time-specific effects (not reported in the table). Source sectors include all sectors, recipient sectors only manufacturing sectors.

imports and the previous technology level is not confirmed.

Table 6 looks again at relative energy intensity – now with imports of intermediate goods instead of investment goods. The results are similar to those in Table 4. Some coefficients of the import intensity are larger than in Table 4, some are lower. Thus, we do not detect a clear difference between imports used as intermediate goods or investment goods. The coefficients of the high-skilled intensity are in most cases larger and still significantly negative. The coefficient of domestic investment is again positive and even much larger than in Table 4.

Table 7 looks again at relative labor intensity – now with imports of intermediate goods instead of investment goods. The most striking difference to the previous results is the significantly positive impact of import intensity in most regressions. This counteracts expectations of strong labor productivity gains from imports resulting in South-North convergence of labor intensities and per-capita income. This is a clear difference to energy intensity where we always find negative coefficients of imports. This clearly indicates that trade-related productivity spillovers are biased towards energy productivity. We also find much larger negative coefficients of the high-skilled intensity than in the previous regressions.

3.4.2 Specific estimation results

This section discusses the static sector- and country-specific regression results.

The results for different source sectors, or in other words different traded goods, are reported in Tables 12 to 14 in the Appendix. Tables 12 and 13 refer to investment goods imports, Tables 14 and 15 to intermediate goods imports. The results follow intuition: machinery, electrical equipment and transport equipment reduce the relative energy intensity when they are used as investment goods, but not metal products. The former likely include new, energy-efficient devices while metal products do not, and the latter are not a typical investment good. Herein, electrical equipment deploys the strongest effect. This shows that high-tech products have an especially high potential for creating productivity gains. Electrical equipment also has the strongest effect on relative energy intensity when it is used as an intermediate input. When used as intermediate goods, metal products reduce energy intensity as well. Similarly, machinery, electrical equipment and transport equipment reduce the relative labor intensity, but not metal products. Now machinery has the strongest impact. This appears intuitive because machinery can be directly used by workers.

The results for different recipient sectors are reported in Tables 16 and 17 in the Appendix. With respect to individual recipient sectors, we find heterogeneity too. The high-skilled labor share reduces relative factor intensities as in our other regressions except in the regression for energy intensity and intermediate goods imports in the chemical sector. Similarly, high-skilled labor has the weakest impact in the chemical sector when looking at relative labor intensity. This indicates that skills do not play a crucial role for factor productivity in the chemical sector. The coefficients of import intensity are all negative with the exception of intermediate imports in the chemical sector though. The strongest reduction of relative energy as well as labor intensity via imports shows up in the machinery sector. This appears intuitive since fabricated intermediate inputs like metal products play an important role in this sector. As one could expect, the coefficient of imports with respect to labor intensity is higher in the labor-intensive textile sector than in the energy-intensive pulp and paper sector. Regarding the impact on relative energy intensity, the coefficient of import intensity is higher in the energy-intensive chemical sector than in the textile sector, but the coefficient is lower in the energy-intensive pulp and paper sector. Thus, the results do not clearly reveal a higher potential for energy savings via intermediate imports in energy-intensive sectors.

The results for different recipient countries are reported in Tables 18 to 21 in the Appendix. Tables 18 and 19 report the results for investment goods imports, Tables 20 and 21 for intermediate goods imports. Regarding the BRIC countries (Brazil, Russia, India and

China), we find that imports used as investment goods or as intermediate inputs reduce the relative energy intensity, and in most cases with a higher magnitude than in the general static regressions. Imports used as intermediate inputs also reduce Russia's labor intensity. We do not find a significant impact of imports on Chinese energy intensity though. The picture changes when looking at relative labor intensity: now China can clearly benefit, but only through imported intermediate goods, not through investment goods. This appears intuitive since China's comparative advantage is cheap, abundant labor employed in fabricating goods from imported intermediate goods. We also find this effect for Brazil and India, but with a smaller magnitude. We do not find this effect for Russia which does not have its comparative advantage in fabricating goods from imported intermediate goods but in exporting fossil energy. Regarding the impact of imported investment goods on relative labor intensity we only find a weakly significant and small effect for India.

3.4.3 Robustness check results

This section discusses the results of the robustness checks: the inclusion of constructed factor prices and of R&D expenditures and the dynamic model estimations.

First, we discuss the dynamic model estimation with a lagged dependent variable. The results for both, energy and labor intensity (DKE3/4 and DKL3/4), are reported in Table 11 in the Appendix. In the dynamic regressions given by Equation (2) without fixed effects, the standard errors are robust against heteroscedasticity and autocorrelation. We also apply Windmeijers (2005) finite-sample correction for the two-step covariance matrix. We limit the instrument count by using only two time lags of regressors as instruments, and we collapse the instrument set to avoid proliferation of instruments. Note that the coefficients are not directly comparable to those of the $dlog - log$ specification in the static model regarding their magnitude. We now look at very short-term effects using one-period lags whereas we use three-period lags in the static regressions. The coefficients of the dynamic $log - log$ specification can be interpreted as in the following example:

In 2009 the South-North ratio of energy intensities was 3.1, and the ratio of labor intensities was 15.1 according to WIOD. Table 11, column 3 reports a coefficient of -0.018 for HL with respect to the relative labor intensity. This means that doubling the high-skilled intensity (a 100% increase in HL) decreases the relative labor intensity itself by 1.8 percentage points per year. The resulting time to reduce the relative factor intensity to 7.55 is then about 11 years. A coefficient of 0.03 for XY with respect to the labor intensity means that doubling the import intensity (a 100% increase in XY) *increases* the relative labor intensity by 3 percentage points per year. The resulting time to reduce the relative factor intensity to 7.55 would then be about 66 years.

The first striking aspect of the results reported in Table 11 is the positive sign of the coefficients of import intensity in the labor intensity regressions, while the coefficients of imports are insignificant in the energy intensity regressions. This means, imports reduce labor productivity and enhance South-North divergence. This supports our previous finding that trade-related North-South productivity spillovers are biased towards energy productivity. Regarding the magnitude of the coefficients, the dynamic estimations are in line with the static ones. Additionally, the interaction term in regression (4) is positive. This means that the interplay of skills (absorptive capacity), imports and backwardness reduces relative labor productivity.

The second striking aspect is the insignificance of the high-skilled intensity in the energy intensity regressions. This depicts that skills directly affect labor, not necessarily energy.

The main advantage of the dynamic specification is to have a direct measure of convergence. A coefficient of 0.94 to 0.99 as found in the four dynamic regressions implies a 1% to 6% reduction in the relative factor intensity per year. This is in line with the WIOD data that show an average growth rate of non-OECD of -5% for labor intensity and -3% for energy intensity. Notably, these results corroborate the assumption of $\beta_0 = 1$ that we made when deriving the static model in section 3.3.1. More details regarding the magnitude of the effects will be discussed in section 3.5.

The dynamic estimations allow us to distinguish short- and long-run effects. β_0 is the coefficient of the lagged relative factor intensity, and β_2 is the coefficient of the import intensity in Equation (2). Then β_2 describes the short-run impact of the import intensity on the relative factor intensity, and $\frac{\beta_2}{1-\beta_0}$ describes the long-run impact. The long-run impact takes into account that a higher import intensity not only influences the relative factor intensity in the next period, but also in all proceeding periods via the lagged factor intensity term. Since the dynamic regression results reported in Table 11 yield significant coefficients in the labor intensity regressions, but not in the energy intensity regressions, we compute the long-run effect only for labor intensity. The long-run effects of investment good import intensity on relative labor intensity are accordingly 0.6 (in DKL3) and 0.5 (in DKL4 including the threefold interaction term), whereas the respective short-run effects reported in the table are 0.012 and 0.030. This result highlights that although the reported short-run effects appear small, long-run effects are much higher and exhibit a considerable magnitude.

Nevertheless, we rely more on the static regressions since the dynamic regressions are subject to overidentification and autocorrelation problems as discussed in section 3.6.

The results of the robustness checks including factor prices and R&D expenditures are depicted in Tables 22 and 23 in the Appendix.

Second, Table 22 in the Appendix depicts the results of the regressions including constructed factor prices for recipient countries. Accordingly, the energy price has a negative sign and thus contributes to South-North convergence, whereas the labor price has a positive sign and contributes to divergence. The negative sign directly follows economic intuition: a higher energy price reduces (relative) energy intensity. The positive sign indicates that sectors with higher or increasing wages nonetheless operate with higher labor intensities. The remaining coefficients partly differ from the main regression results. The coefficient of the import intensity in the energy-specific regression is similar to that in column three of Table 6. Surprisingly, the sign of the high-skilled intensity has switched to a positive value. In the labor-specific regression, the sign of the high-skilled intensity is still negative, but the magnitude is smaller than in the main regressions listed in Table 7. In the labor-specific regression, the coefficient of the import intensity is positive and larger than in Table 7. This implies an even more pronounced trade-related energy bias than in the main regressions.

Third, Table 23 in the Appendix reports the robustness check results including lagged R&D expenditures per output value of source countries $IY_{ul(t-3)}$ (R&D intensity). The index u indicates the reduced source country sample, the index l the reduced source sector sample compared with the previous regressions. The positive coefficients of $IY_{ul(t-3)}$, not significant for energy intensity though, are counterintuitive at first glance: a higher R&D intensity accordingly leads to higher positive growth of the relative factor intensity and thus *divergence*. At second glance, our results fit to theory: in the classical Nelson and Phelps (1966) theory, a higher rate of technical progress of the leading technology augments the gap between the technology in practice and the leading technology. Under the assumption that a higher R&D intensity of the North fosters its rate of technical progress, the South-North technology gap will become larger so that we will observe divergence as depicted by our results.

Table 23 also reports the threefold interaction of the R&D intensity of source countries with the high-skilled labor intensity of recipient countries and the investment good trade flow between them.[19] In both cases, with relative energy and labor intensity as the dependent variable, the threefold interaction term has the expected negative sign. This means that the joint incidence of conducive source and recipient country characteristics enhances South-

[19]We also check the twofold interaction of the R&D intensity with the investment good trade flow, yet without finding a significant impact.

North *convergence* of factor intensities (additionally to the divergence effect discussed above). Notably, the coefficient of the threefold interaction term is the same for relative energy and labor intensity as the dependent variable and has a relatively small magnitude of -0.00015.

The remaining coefficients are not much affected by the inclusion of R&D expenditures. Notably, the changes in the coefficients compared with the previous main estimations are mainly caused by the reduction of the sample size.[20] This means, there is almost no omitted variable bias when leaving out R&D expenditures. The coefficient of investment goods import intensity $XY_{urlk(t-3)}$ with respect to relative energy intensity growth ΔREY_{urlkt} reported in the first column of Table 23 has the same value as in the third column of the main regression in Table 4, i.e. -0.0017. This value is, however, clearly lower than in the first and second column of Table 4. The coefficients of the high-skilled labor intensity $HL_{r(t-3)}$ are in Table 23 only slightly higher than the corresponding values in Tables 4 and 5. The coefficient of investment goods import intensity $XY_{urlk(t-3)}$ with respect to relative labor intensity growth ΔRLY_{urlkt} is in the third column of Table 23 slightly larger than in the main regression in Table 5 and negative, i.e. -0.0018. Hence, the trade-related energy bias is not visible here.

3.5 Summary and prediction

In summary, we can formulate the following results:

First, we find that Southern (non-OECD) energy and labor intensities converge to Northern (OECD) ones. This is shown by the static regressions S..4 including the lagged relative factor intensity: the coefficients of the lagged relative factor intensity are all highly significant and negative. It is confirmed by the dynamic regressions: the coefficients of the lagged dependent variable are always positive and in most cases significant – and they are smaller than one so that the relative factor intensity (the South-North ratio of factor intensities) shrinks over time.

Second, international trade in form of imports of investment and intermediate goods in general supports convergence: the coefficient of imports is in most cases significant and often negative. However, the effect of imports is an order of magnitude smaller than the effect of education or absorptive capacity in form of the high-skilled labor intensity in Southern countries. Theory (going back to Nelson and Phelps, 1966, and Findlay, 1978) suggests that trade and foreign investment positively interact with education and with technological back-

[20]We show this by running the reduced sample R&D regression without R&D expenditures as a regressor for comparison.

wardness. Thus, we include the interaction of import intensity, high-skilled labor intensity and lagged relative factor intensity in the regressions. Its estimated coefficient is often not significant though. If it is significant, its sign is often opposite of what we expect, i.e. it is positive and enhances divergence, and it has a small magnitude.

Besides looking at the threefold interaction of the import intensity with the high-skilled labor intensity and with the lagged relative factor intensity as suggested by theory, we also look at the twofold interaction of the import intensity with the high-skilled labor intensity (not reported in the tables). In the static regressions for energy or labor intensity and for investment or intermediate goods imports (SKE4, SKL4, SME4 and SML4) the estimated coefficient of the twofold interaction in log-form is in most cases -0.0017 and -0.0060 and is always highly significant. This suggests a notable additional effect of imports in the presence of high skills. The twofold interaction specification is, however, subject to a caveat: it is highly correlated with both, the high-skilled labor intensity and the import intensity, which appears to bias the results. For this reason and for consistency with theory, we rely more on the threefold interaction specification as reported in the tables.

Third, and importantly, we find a clear difference between Southern investment goods stemming from the North and stemming from the same Southern country: domestic investment goods always have a stronger effect on the relative factor intensity than foreign investment goods. In three of four cases (Tables 4 to 7), the sign is positive. This means, in contrast to foreign investment goods, domestic investment goods tend to enlarge the relative factor intensity and thus contribute to divergence of factor productivity. This confirms the presumption that international trade (and international investment) are associated with productivity gains via technology spillovers and competition and firm selection. This appears especially intuitive when considering that only foreign products embody advanced technologies that are not yet available in the South.

Fourth, having a closer look at the difference between energy and labor intensities in the general static regressions, it turns out that imports always reduce relative energy intensity. On the contrary, imports reduce relative labor intensity in most cases to a much smaller extent. In some cases they even raise relative labor intensity, indicated by positive coefficients (in Tables 5 and 7). This implies South-North divergence. This result is backed up by our source-sector-specific regressions, in which investment goods imports reduce energy intensity to a larger extent than labor intensity. This indicates that international technology diffusion is not equal for all factors (total factor productivity) but directed or biased – in this case towards energy productivity rather than labor productivity (in the sense of Acemoglu, 2002).

This result is surprising when recalling that our descriptive statistics reveal stronger South-North convergence of labor- than of energy-intensity. Nevertheless, the impact of trade on convergence appears to be stronger regarding energy intensity as explained above. Hence, trade policy can be a measure to enhance 'green growth'.

The difference between imports used as intermediate inputs or investment goods is not that clear-cut though: in some cases, the coefficient of the import intensity is higher for investment goods, in other cases it is higher for intermediate goods (in Table 4 to 7).

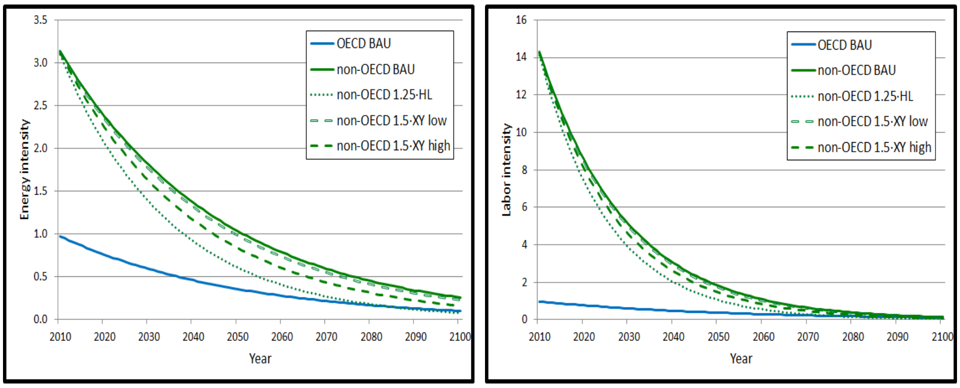
Fifth, the results become more diverse when looking at specific source and recipient sectors or recipient countries (Tables 12 to 21 in the Appendix). – For a summary, the reader may refer to the concluding section 4. – It is relevant for the policy implementation to take this heterogeneity into account so that policy measures can be targeted at sectors and countries where they have a high potential.

Sixth, a higher R&D intensity and a consequently stronger technological momentum of an industrialized country appear to impede technological catching up by emerging countries and thus enhance divergence. This finding is in accordance with the classical Nelson and Phelps (1966) theory. Nonetheless, the joint incidence of conducive characteristics of source (R&D intensity) and recipient countries (high-skilled labor intensity) enhances South-North *convergence* of factor intensities.

Seventh, with regard to the magnitude and relevance of the estimated effects, we can formulate the following approximate results:

In the static regressions, the magnitude of the coefficients of the lagged relative factor intensity is pronounced and robust in the range of -0.15 to -0.19, averaging around -0.17. Thus, there is convergence in both, energy and labor intensities. Being 100% further backward, i.e. having twice a relative factor intensity, reduces the growth rate of the relative factor intensity by around 17% per year. This implies that this driver declines during the catching up process so that growth rates decline. This is a typical convergence mechanism. We find in the static model that this effect is somewhat higher for labor than for energy intensities. In the dynamic model, we find coefficients of 0.97 and 0.99 for lagged relative energy intensity, and 0.98 and 0.94 for lagged labor intensity. This implies relative changes of the relative factor intensity of -1 to -6% per year and a resulting half-time of factor intensity of 101 to 33 years.

How important are the results economically regarding their magnitude? Turning back to the drivers of convergence, our general (not specifically for machinery or BRIC-countries) regressions yield coefficients of the high-skilled labor intensity of around -0.05. This means



(a) (b)

Figure 2: Extrapolated future time paths based on the regression results for the aggregate regions OECD and non-OECD. (a) Energy intensity (energy input to GDP) $\frac{E_t}{Y_t}$; (b) Labor intensity (labor input to GDP) $\frac{L_t}{Y_t}$. BAU assumes that the historical averages of factor intensity growth prevail in every year in the future. 1.25·HL assumes a 25% increase in the high-skilled intensity in non-OECD; 1.5·XY low assumes a 50% increase in the import intensity in non-OECD and a low coefficient governing the impact of the import intensity; 1.5·XY high assumes the same increase with a high coefficient.

that doubling the high-skilled intensity (a 100% increase) decreases the annual growth rate of the the relative factor intensity (the South-North ratio of factor intensities) by 5 percentage points. The resulting half-time of the relative factor intensity solely driven by high-skilled labor will then be about 14 years. This is a strong effect. However, such a change in the high-skilled intensity is challenging and would need much time. The graphs plotted in Figure 2 for (a) energy and (b) labor intensities thus assume only a 25% increase in the high-skilled ratio in scenario 'non-OECD 1.25·HL'. The business as usual (BAU) scenario assumes that energy and labor intensity fall at a constant annual rate which equals the average growth rate within the time frame 1995 to 2009 as given by the descriptive statistics.[21] Accordingly, full South-North convergence would already be achieved in the 2080s for energy intensity and in the 2070s for labor intensity. Thereby, we keep the exogenous business as usual growth rate constant. However, on would expect that the growth rate declines during the catching up process, which we leave aside for simplicity and clarity of the graphical presentation.

Our general regressions yield coefficients of around -0.005 for import intensity (investment as well as intermediate good). This means that doubling the import intensity (a 100% increase) decreases the annual growth rate of the the relative factor intensity by 0.5 percentage points. The resulting half-time of the relative factor intensity solely driven by imports is now about 138 years. Since the coefficients vary across the regressions between about half and double the average coefficient of -0.005, we assume two scenarios: 'non-OECD 1.5·XY low'

[21] The average annual growth rate of energy intensity in OECD between 1995 and 2009 is -2%, in non-OECD it is -3%. The average annual growth rate of labor intensity in OECD is also -2%, in non-OECD it is -5%.

with a 50% increase in the import intensity and half the average coefficient, and 'non-OECD $1.5{\cdot}XY$ high' with a 50% increase in the import intensity and twice the average coefficient. Herein, a 50% change in the import intensity appears realistic according to the descriptive statistics (Figure 1d). It turns out that the impact is rather small in the 'low' scenario and moderate in the 'high' scenario. In 'high', the productivity gap can be halved by 2100. This result applies to energy intensities (Figure 2a) as well as labor intensities (Figure 2b).

3.6 Discussion and caveats

Our analysis is due to some caveats. Taking these aspects into account, our main results are rather robust across different model specifications. Particularly, the energy bias of international technology diffusion holds for multi-country as well as single-country and single-sector specifications. Due to the large number of observations, many coefficients are significant at the 0.1% or 0.5% level.

First, the high-skilled labor intensity HL represents education and more generally speaking the absorptive capacity (infrastructure, legal system, security, media access etc.) of a non-OECD country. However, we cannot clearly identify what it captures and what the country-specific fixed effects capture. Particularly, the WIOD data do not include R&D expenditures so that R&D is only implicitly captured in the fixed effects of our main and specific regressions. There is to our knowledge no global data set on R&D expenditures including most developing countries. This applies especially to R&D expenditures on energy productivity. Notwithstanding, we include R&D expenditures available for OECD countries from ANBERD in a robustness check with a small impact on the main results.

Second, technology diffusion processes require time. It is therefore difficult to decide upon the appropriate time lag between the impact, such as importing, and the result, measurable technical progress. We assume a three-year lag, taking into account that on the one hand technology diffusion requires time, on the other hand our sample encompasses only 15 years so that long-term effects can hardly be measured. We also try other time lags. We find that the coefficients will become lower when the time lag is smaller. This supports our expectation that technology diffusion processes require time so that the measurable impact increases over time. We also find in some cases with smaller time lags a positive impact of imported intermediate goods on the growth rate of relative energy intensity. This indicates that in the short-run scale or rebound effects dominate, while the technology effect has not yet been exploited. This means that intermediate imports can enhance divergence in the short-run. Notwithstanding, this effect is stronger for relative labor intensity than for relative energy intensity. In this sense, imports of intermediates result in stronger divergence of labor intensities than of energy intensities in the short-run. This in turn means that the energy bias of trade-induced technology spillovers is confirmed. Thus, in general, our key conclusions are qualitatively robust. In the dynamic specification, we nevertheless stay with the standard one-period lag specification. Despite the one-period lag specification, each impact propagates to future periods through the lagged dependent variable. Besides using three-year time lags, we also smooth the data with three-period moving averages. The smoothing has, however, a small impact on the results.

Third, we apply general method of moments (GMM) estimations (Arellano-Bond) to address Nickel bias and other reasons for endogeneity as discussed in sections 3.2 and 3.3.3. While the static regressions yield rather robust results, the dynamic regressions often run into overidentification and autocorrelation problems (indicated by the Arellano-Bond test for autocorrelation and the Sargan/Hansen J-test for overidentifying restrictions) and do not produce robust results. The reason could be that we have a very large cross-section but a short time series. Hence, for each variable and time lag, the instrument count becomes very high. This applies particularly to the larger sample with intermediate inputs. Hence, we focus on the static regressions. Nonetheless, the dynamic regressions back up the results of the static regressions, provide further insights into the dynamics, long-term and short-term effects and take endogeneity issues into account.

Fourth, a number of potential explanatory variables cannot be included since no data are available, for example energy and labor taxes and energy subsidies. Foreign direct investment (FDI) is another channel for technology spillovers. FDI data are not available for the countries and sectors in the sample though. Nonetheless, we construct approximate wage and energy price variables for recipient countries from WIOD that we include in a robustness check. As a result, the trade-related energy bias is very pronounced. We also include R&D expenditures for source countries in a reduced sample. The trade-related energy-bias is not visible here. Overall, the results are relatively robust to these modifications.

4 Conclusion

We scrutinize South-North convergence of energy and labor intensity driven by international trade. We are to our knowledge the first who apply the novel global WIOD (World Input-Output Data) to a *regression* analysis. WIOD combines two (source and recipient) large country dimensions with two large sector dimensions and a time dimension, and it consistently includes all required variables. The sectoral resolution disentangles the technique effect from the sectoral decomposition effect, and different from other studies WIOD provides a global multi-economy view at the same time. The use of all variables in intensity form eliminates the scale effect.

We show that embodied North-South technology spillovers are biased (directed) towards energy intensity rather than labor intensity. Additionally, we show that there is no robust difference between imports used as an investment good and imports used as an intermediate input in this respect visible in the results. We also show that in contrast to imported investment or intermediate goods, domestically produced investment goods do in most cases not reduce but raise non-OECD factor intensities. This indicates that foreign goods embody knowledge that domestic investment goods do not embody, or that trade is associated with productivity gains from increased competition and firm selection.

Our results suggest that trade policy measures (reductions of tariffs and of trade barriers or import and export subsidies) will achieve stronger improvements in energy than in labor intensity. One may call this 'green growth'. This result holds for the multi-country, multi-sector analysis as well as for the single-country and the single-sector analysis. However, our regressions and future extrapolations indicate that the trade channel contributes only to a small extent to South-North convergence of both, energy and labor intensity. Referring to our dynamic model estimations, trade-induced short-run effects appear small, whereas a longer time horizon can result in a considerable impact. The time horizon of halving the South-North ratio in factor intensities solely through the import channel can exceed 100 years by far. The climate change challenge as well as the poverty challenge require immediate action though. As a consequence, the decarbonization of energy supply (not studied in this paper) appears as the more important policy field for reducing CO_2 emissions in the mid-term. Similarly, more direct measures targeting at poverty reduction and equality appear more promising in the mid-term. In this respect, our results confirm the important role of skills for enhancing productivity – in this case without a clear factor bias.

Nonetheless, trade policy measures can become more effective when policy targets certain recipient countries or source and recipient sectors. We show that imported electrical equipment – presumably due to its high-tech content – has an especially strong potential to reduce relative energy intensity. Thus, 'green funding' policies that aim at the reduction of energy use may focus on electrical or more generally speaking high-tech equipment. If a policy aims at improving labor productivity, our analysis suggests focusing on machinery. Regarding recipient sectors, our estimations show a high potential for reducing energy intensity as well as labor intensity in the production of machinery via increased imports of intermediate goods.

Our analysis of recipient countries shows that the BRIC (Brazil, Russia, India, China) countries can realize above-average gains from spillovers. China gains less in terms of energy productivity, but more in terms of labor productivity via imports of intermediate goods. Thus, relying on embodied international technology spillovers as a means to reduce Chinese energy consumption and hence carbon emissions appears not sufficient. On the opposite, Brazil gains more than the other BRIC countries and the non-OECD average from imports in terms of energy productivity. Thus, policies that support international trade and international investment could particularly create energy productivity gains in Brazil.

Our results are not only relevant for policy makers but also for modelers. The latter need to make assumptions on the strength of technical progress. In climate and energy models, the distinction between general or labor-related and energy-related technical progress is essential. Our analysis provides applicable results for this. Future research could look at CO_2 emissions and specific pollutants instead of energy and test for spillovers in energy generation technologies.

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6 References

Acemoglu, D. (2002). Directed Technical Change. The Review of Economic Studies, 69(4), 781-809.

Acemoglu, D. (2010). When Does Labor Scarcity Encourage Innovation? Journal of Political Economy, 118(6), 1037-1078.

Acemoglu, D., Aghion, P., Bursztyn, L. and Hemous, D. (2012). The Environment and Directed Technical Change. The American Economic Review, 102(1), 131-166.

Aitken, B.J. and Harrison, A.E. (1999). Do domestic firms benefit from direct foreign investment? Evidence from Venezuela. The American Economic Review, 89(3), 605-618.

Albornoz, F., Cole, M.A., Elliott, R.J.R. and Ercolani, M.G. (2009). In Search of Environmental Spillovers. The World Economy, 32, 136-163. doi: 10.1111/j.1467-9701.2009.01160.x

Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. The Review of Economic Studies, 58(2), 277-297.

Arellano, M. and Bover, O. (1995). Another look at the instrumental variable estimation of error-components models. Journal of Econometrics, 68, 29-51.

Amiti, M. and Konings, J. (2007). Trade Liberalization, Intermediate Inputs, and Productivity: Evidence from Indonesia. American Economic Review, 97(5), 1611-1638.

Antweiler, W., Copeland, B.R. and Taylor, M.S. (2001). Is free trade good for the environment? The American Economic Review, 91(4), 877-908.

Barassi, M.R., Cole, M.A. and Elliott, R.J.R. (2008). Stochastic Divergence or Convergence of Per Capita Carbon Dioxide Emissions: Re-examining the Evidence. Environmental and Resource Economics, 40, 121-137. doi: 10.1007/s10640-007-9144-1

Bitzer, J. and Geishecker, I. (2006). What Drives Trade-Related R&D Spillovers? Decomposing Knowledge-Diffusing Trade Flows? Economics Letters, 93(1), 52-57.

Blundell, R. and Bond, S. (1998). Initial conditions and moment restrictions in dynamic panel data models. Journal of Econometrics, 87(1), 115-143.

Bwalya, S.M. (2006). Foreign Direct Investment and Technology Spillovers: Evidence from Panel Data Analysis of Manufacturing Firms in Zambia. Journal of Development Economics, 81(2), 514-526.

Carraro, C. and De Cian, E. (2013). Factor-augmenting technical change: an empirical assessment. Environmental Modeling and Assessment, 18(1), 13-26.

Cole, M.A. (2006). Does trade liberalization increase national energy use? Economics Letters, 92, 108-112.

Cole, M.A., Elliott, R.J.R. and Zhang, J. (2011). Growth, Foreign Direct Investment and the Environment: Evidence from Chinese Cities. Journal of Regional Science, 51(1), 121138.

Coe, D., Helpman, E. and Hoffmaister, A. (1997). North-South R&D Spillover, The Economic Journal, 107, 134-149.

Copeland, B.R. and Taylor, M.S. (2003). Trade and the Environment: Theory and Evidence, Princeton, NJ, Princeton University Press.

Dickey, D.A. and Fuller, W.A. (1979). Distribution of the Estimators for Autoregressive Time Series with a Unit Root. Journal of the American Statistical Association, 74, 427-431.

Egger, P. and Pfaffermayr, M. (2001). A Note on Labor Productivity and Foreign Inward Direct Investment. Applied Economics Letters, 8(4), 229-232.

Findlay, R. (1978). Relative backwardness, direct foreign investment, and the transfer of technology: a simple dynamic model. The Quarterly Journal of Economics, 92(1), 1-16.

Girma, S. (2005). Absorptive capacity and productivity spillovers from FDI: A threshold regression analysis. Oxford Bulletin of Economics and Statistics, 67, 3, 281-306.

Girma, S. and Görg, H. (2007). The role of the efficiency gap for spillovers from FDI:

Evidence from quantile regressions. Open Economies Review, 18(2), 215-32.

Griffith, R., Redding, S. and van Reenen, J. (2003). R&D and Absorptive Capacity: Theory and Empirical Evidence. Scandinavian Journal of Economics, 105(1), 99-118.

Griffith, R., Redding, S. and van Reenen, J. (2004). Mapping the Two Faces of R&D: Productivity Growth in a Panel of OECD Industries. The Review of Economics and Statistics, 86(4), 883-895.

Grossman, G. and Krueger, A. (1993). Environmental impacts of a North American Free Trade Agreement. In P. Garber (ed.), The U.S.Mexico Free Trade Agreement, Cambridge, MA, MIT Press, 13-56.

Havranek, T. and Irsova, Z. (2011). Estimating vertical spillovers from FDI: Why results vary and what the true effect is. Journal of International Economics, 85, 234-244.

Hübler, M. and Keller, A. (2010). Energy Savings via FDI? Empirical Evidence from Developing Countries. Environment and Development Economics, 15(1), 59-80.

Im, K.S., Pesaran, M.H. and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. Journal of Econometrics, 115, 53-74.

Jakob, M., Haller, M. and Marschinski R. (2012). Will History Repeat Itself? Economic Convergence and Convergence in Energy Use Patterns. Energy Economics, 34, 95-104.

Javorcik, B.S. (2004). Does foreign direct investment increase the productivity of domestic firms? In search of spillovers through backward linkages. The American Economic Review, 94(3), 605-627.

Keller, W. (2004). International technology diffusion. Journal of Economic Literature, 42(3), 752-782.

Keller, W. and Yeaple, S.R. (2009). Multinational Enterprises, International Trade and Productivity Growth: Firm-Level Evidence from the United States. The Review of Economics and Statistics, 91(4), 821-831.

Kohpaiboon, A. (2006). Foreign Direct Investment and Technology Spillover: A Cross-Industry Analysis of Thai Manufacturing. World Development, 34(3), 541-556.

Kuo, C.-C. and Yang, C.-H. (2008). Knowledge capital and spillover on regional economic growth: Evidence from China. China Economic Review, 19, 594-604.

Lai, M., Peng, S. and Bao, Q. (2006). Technology spillovers, absorptive capacity and economic growth. China Economic Review, 17, 300-320.

Lee, G. (2006). The Effectiveness of International Knowledge Spillover Channels. European Economic Review, 50(8), 2075-2088.
Madsen, J.B. (2007). Technology Spillover through Trade and TFP Convergence: 135 Years of Evidence for the OECD Countries. Journal of International Economics, 72(2), 464-480.

Markandya, A., Pedroso-Galinato, S. and Streimikiene, D. (2006). Energy intensity in transition economies: Is there convergence towards the EU average? Energy Economics, 28, 121-145.

Mayer-Foulkes, D. and Nunnenkamp, P. (2009). Do Multinational Enterprises Contribute to

Convergence or Divergence? A Disaggregated Analysis of US FDI. Review of Development Economics, 13(2), 304-318.

Melitz, M.J. (2003). The Impact of Trade on Intra-Industry Reallocations and Aggregate Industry Productivity. Econometrica, 71(6), 1695-1725.

Nelson, R. and Phelps, E. (1966). Investment in Humans, Technological Diffusion, and Economic Growth. The American Economic Review, Papers and Proceedings, 61, 69-75.

Nickell, S.J. (1981). Biases in dynamic models with fixed effects. Econometrica, 49(6), 1417-1426.

Perkins, R. and Neumayer, E. (2009). Transnational linkages and the spillover of environment-efficiency into developing countries. Global Environmental Change, 19(3), 375-383.

Perkins, R. and Neumayer, E. (2012). Do recipient country characteristics affect international spillovers of CO2-efficiency via trade and foreign direct investment? Climatic Change 112(2), 469-491.

Roodman, D. (2009a). How to Do xtabond2: An Introduction to "Difference" and "System" GMM in Stata. Stata Journal, 9(1), 86-136.

Roodman, D. (2009b). A note on the theme of too many instruments. Oxford Bulletin of Economics and Statistics, 71(1), 135-158.

Saggi, K. (2002). Trade, foreign direct investment, and international technology transfer: a survey. The World Bank Research Observer, 17(2), 191-235.

Suyanto, R.A.S. and Bloch, H. (2009). Does Foreign Direct Investment Lead to Productivity Spillovers? Firm Level Evidence from Indonesia. World Development, 37(12), 1861-1876.

Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step GMM estimators. Journal of Econometrics, 126, 25-51.

7 Supplementary Appendix

Variable	Unit	#Obs.	Mean	Med.	Min.	Max.	Var.
$\frac{X_{srjkt}}{Y_{rit}}$	-	128325	6.10e-06	8.77e-09	0.000	0.005	5.36e-09
$\frac{X_{srjmt}}{Y_{rit}}$	-	1913052	4.21e-05	1.94e-07	0.000	0.252	5.38e-07
$\frac{E_{st}}{Y_{st}}$	$\frac{MJ}{US\$}$	465	8.968	6.382	1.631	50.430	67.057
$\frac{E_{rt}}{Y_{rt}}$	$\frac{MJ}{US\$}$	135	21.051	15.956	4.873	67.457	231.987
$\frac{E_{rmt}}{Y_{rmt}}$	$\frac{MJ}{US\$}$	1890	31.275	6.092	0.188	748.910	6529.555
$\frac{L_{st}}{Y_{st}}$	$\frac{h}{US\$}$	465	0.038	0.020	0.005	0.197	0.001
$\frac{L_{rt}}{Y_{rt}}$	$\frac{h}{US\$}$	135	0.267	0.188	0.022	1.214	0.068
$\frac{L_{rmt}}{Y_{rmt}}$	$\frac{h}{US\$}$	1890	0.154	0.095	0.000	2.692	0.047
$\frac{H_{st}}{L_{st}}$	-	465	0.224	0.224	0.064	0.483	0.007
$\frac{H_{rt}}{L_{rt}}$	-	135	0.107	0.098	0.0230	0.350	0.004
$\frac{H_{rmt}}{L_{rmt}}$	-	1890	0.079	0.050	0.004	0.394	0.005

#Obs. = number of observations, Mean = arithmetic mean, Med. = median, Min. = minimum value, Max. = maximum value, Var. = variance.

Table 8: Descriptive statistics of the WIOD data used in the regressions (X = trade, E = energy, L = labor, H = high-skilled, all in intensity form; s = OECD source countries, r = non-OECD recipient countries, m = manufacturing sectors, k = investment good).

	ΔREY	REY	ΔRLY	RLY	HL	XY	DY
ΔREY	1.0000						
REY	0.0753	1.0000					
ΔRLY	0.1755	-0.0401	1.0000				
RLY	0.0122	0.0906	-0.0057	1.0000			
HL	0.0130	-0.0938	0.0155	-0.4718	1.0000		
XY	0.0050	0.1625	0.0260	0.2428	0.0198	1.0000	
DY	0.0687	-0.2196	-0.0170	0.0805	-0.0996	0.0215	1.0000

Table 9: Correlation matrix for the sample with the investment good k as the only recipient sector (smaller sample).

	ΔREY	REY	ΔRLY	RLY	HL	XY	DY
ΔREY	1.0000						
REY	0.0436	1.0000					
ΔRLY	0.3060	-0.0409	1.0000				
RLY	-0.0094	-0.0504	0.0879	1.0000			
HL	0.0405	-0.0773	0.0499	-0.2748	1.0000		
XY	-0.0054	-0.0369	0.0160	0.2691	0.0553	1.0000	
DY	0.0780	-0.1572	0.0489	-0.0674	-0.0186	0.0434	1.0000

Table 10: Correlation matrix for the sample with manufacturing sectors m as recipient sectors (larger sample).

Regressions DKE3/4 & DKL3/4

	3 REY_{srjkt}	4 REY_{srjkt}	3 RLY_{srjkt}	4 RLY_{srjkt}
$REY_{rjk(t-1)}$	0.97*****	0.99*****		
	(0.073)	(0.16)		
$RLY_{rjk(t-1)}$			0.98*****	0.94*****
			(0.0058)	(0.014)
$HL_{r(t-1)}$	-0.0062	-0.0037	-0.018**	0.040*****
	(0.028)	(0.082)	(0.0072)	(0.0096)
$XY_{srjk(t-1)}$	0.0060	-0.0022	0.012**	0.030*****
	(0.061)	(0.058)	(0.0063)	(0.0068)
$HL_{r(t-1)} \cdot XY_{srjk(t-1)}$		0.0043		
$\cdot REY_{rk(t-1)}$		(0.0031)		
$HL_{r(t-1)} \cdot XY_{srjk(t-1)}$				0.0013*****
$\cdot RLY_{rk(t-1)}$				(0.00029)
$Constant$	0.15	-0.028	0.22*	0.65*****
	(1.12)	(1.20)	(0.11)	(0.14)
#Obs.	114,353	114,353	114,620	114,620
AR(1) test (z)	-2.77	-2.91	1.43	2.74
p-value	0.006	0.004	0.153	0.006
AR(2) test (z)	2.01	2.10	-1.60	-0.77
p-value	0.045	0.035	0.11	0.44
Hansen J test (χ^2)	10.9	11.0	36.4	19.1
p-value	0.0043	0.0040	2.4e-07	0.00076

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 11: Robustness check: dynamic panel estimation of the drivers of the change in the relative South-North energy and labor intensity excluding individual and time-specific effects. Source sectors include all sectors, recipient sectors only the investment (capital) good.

Regression SKE2				
	Metals $\Delta REY_{sr(j1)kt}$	Machinery $\Delta REY_{sr(j2)kt}$	Elec. equip. $\Delta REY_{sr(j3)kt}$	Trans. equip. $\Delta REY_{sr(j4)kt}$
$HL_{r(t-3)}$	-0.054***	-0.058****	-0.055*	-0.059**
	(0.020)	(0.020)	(0.031)	(0.027)
$XY_{srjk(t-3)}$	-0.0022	-0.0053***	-0.0086**	-0.0058**
	(0.0018)	(0.0020)	(0.0039)	(0.0024)
$DY_{r(t-3)}$	0.0047	0.0078	0.011	0.0076
	(0.0061)	(0.0061)	(0.0094)	(0.0078)
$Constant$	-0.14***	-0.15****	-0.17**	-0.15**
	(0.052)	(0.052)	(0.085)	(0.074)
#Obs.	3,337	3,342	3,270	3,277
R^2	0.078	0.119	0.230	0.106

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 12: Source-sector-specific estimation: panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source sectors include only one of the following sectors ($j1...4$): Basic Metals and Fabricated Metal; Machinery, Nec; Electrical and Optical Equipment; Transport Equipment. Recipient sectors include only the investment (capital) good.

Regression SKL2				
	Metals $\Delta RLY_{sr(j1)kt}$	Machinery $\Delta RLY_{sr(j2)kt}$	Elec. equip. $\Delta RLY_{sr(j3)kt}$	Trans. equip. $\Delta RLY_{sr(j4)kt}$
$HL_{r(t-3)}$	-0.026	-0.033	-0.023	-0.037*
	(0.017)	(0.023)	(0.022)	(0.021)
$XY_{srjk(t-3)}$	0.00059	-0.010*****	-0.0063**	-0.0047***
	(0.0018)	(0.0027)	(0.0027)	(0.0017)
$DY_{r(t-3)}$	-0.0051	0.0051	0.00063	-0.0024
	(0.0038)	(0.0056)	(0.0059)	(0.0047)
$Constant$	-0.11**	-0.21****	-0.14**	-0.18****
	(0.045)	(0.060)	(0.059)	(0.054)
#Obs.	3,337	3,342	3,270	3,277
R^2	(0.045)	(0.060)	(0.059)	(0.054)

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 13: Source-sector-specific estimation: same as previous table, but growth rate of the relative South-North labor intensity as dependent variable.

Regression SME2

	Metals $\Delta REY_{sr(j1)mt}$	Machinery $\Delta REY_{sr(j2)mt}$	Elec. equip. $\Delta REY_{sr(j3)mt}$	Trans. equip. $\Delta REY_{sr(j4)mt}$
$HL_{r(t-3)}$	-0.069*****	-0.065*****	-0.067*****	-0.065*****
	(0.0098)	(0.0097)	(0.012)	(0.011)
$XY_{srjm(t-3)}$	-0.0026****	-0.0079*****	-0.012*****	-0.0026**
	(0.00093)	(0.0010)	(0.0014)	(0.00100)
$DY_{r(t-3)}$	0.024*****	0.028*****	0.031*****	0.024*****
	(0.0028)	(0.0029)	(0.0035)	(0.0032)
$Constant$	-0.16*****	-0.17*****	-0.23*****	-0.098****
	(0.025)	(0.024)	(0.030)	(0.029)
#Obs.	46,714	46,772	45,754	45,316
R^2	0.026	0.057	0.126	0.051

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 14: Source-sector-specific estimation: panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source sectors include only one of the following sectors ($j1...4$): Basic Metals and Fabricated Metal; Machinery, Nec; Electrical and Optical Equipment; Transport Equipment. Recipient sectors include manufacturing sectors, i.e. we look at imports used as intermediate inputs.

Regression SML2

	Metals $\Delta RLY_{sr(j1)mt}$	Machinery $\Delta RLY_{sr(j2)mt}$	Elec. equip. $\Delta RLY_{sr(j3)mt}$	Trans. equip. $\Delta RLY_{sr(j4)mt}$
$HL_{r(t-3)}$	-0.13*****	-0.13*****	-0.13*****	-0.13*****
	(0.0089)	(0.0099)	(0.0098)	(0.0097)
$XY_{srjm(t-3)}$	-0.0011	-0.012*****	-0.0066*****	-0.0027****
	(0.00082)	(0.0010)	(0.00091)	(0.00088)
$DY_{r(t-3)}$	0.025*****	0.033*****	0.029*****	0.024*****
	(0.0024)	(0.0027)	(0.0028)	(0.0026)
$Constant$	-0.31*****	-0.44*****	-0.35*****	-0.33*****
	(0.023)	(0.024)	(0.025)	(0.026)
#Obs.	46,714	46,772	45,754	45,316
R^2	0.047	0.097	0.135	0.058

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 15: Source-sector-specific estimation: same as previous table, but growth rate of the relative South-North labor intensity as dependent variable.

Regression SME2

	Textiles $\Delta REY_{srj(m1)t}$	Pulp & Paper $\Delta REY_{srj(m2)t}$	Chemicals $\Delta REY_{srj(m3)t}$	Machinery $\Delta REY_{srj(m4)t}$
$HL_{r(t-3)}$	-0.073*****	-0.12*****	-0.010	-0.38*****
	(0.018)	(0.017)	(0.017)	(0.019)
$XY_{srjk(t-3)}$	-0.0042*****	-0.0030****	-0.0049*****	-0.0092*****
	(0.00096)	(0.00094)	(0.00089)	(0.0011)
$DY_{r(t-3)}$	0.036*****	0.036*****	-0.0089****	0.078*****
	(0.0028)	(0.0030)	(0.0029)	(0.0031)
$Constant$	-0.15****	-0.30*****	-0.14****	-0.99*****
	(0.045)	(0.049)	(0.044)	(0.052)
#Obs.	105,885	105,784	106,170	105,318
R^2	0.010	0.021	0.010	0.086

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 16: Recipient-sector-specific estimation: panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source sectors encompass all sectors. Recipient sectors include only one of the following manufacturing sectors ($m1...4$): Textiles and Textile Products; Pulp, Paper, Paper, Printing and Publishing; Chemicals and Chemical Products; Machinery, Nec; i.e. we look at imports used as intermediate inputs.

Regression SML2

	Textiles $\Delta RLY_{srj(m1)t}$	Pulp & paper $\Delta RLY_{srj(m2)t}$	Chemicals $\Delta RLY_{srj(m3)t}$	Machinery $\Delta RLY_{srj(m4)t}$
$HL_{r(t-3)}$	-0.19*****	-0.20*****	-0.076*****	-0.15*****
	(0.0049)	(0.0052)	(0.0060)	(0.0064)
$XY_{srjk(t-3)}$	-0.0025*****	-0.0018****	0.00055	-0.0042*****
	(0.00058)	(0.00063)	(0.00065)	(0.00069)
$DY_{r(t-3)}$	0.048*****	0.048*****	0.035*****	0.042*****
	(0.0014)	(0.0015)	(0.0013)	(0.0015)
$Constant$	-0.43*****	-0.50*****	-0.16*****	-0.41*****
	(0.014)	(0.016)	(0.016)	(0.019)
#Obs.	106,231	106,124	106,508	105,633
R^2	0.087	0.093	0.049	0.223

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 17: Recipient-sector-specific: same as previous table, but growth rate of the relative South-North labor intensity as dependent variable.

Regression SKE1

	Brazil $\Delta REY_{s(r1)jkt}$	Russia $\Delta REY_{s(r2)jkt}$	India $\Delta REY_{s(r3)jkt}$	China $\Delta REY_{s(r4)jkt}$
$XY_{srjk(t-3)}$	-0.0068****	0.0016	-0.0055****	-0.0023
	(0.0021)	(0.0021)	(0.0019)	(0.0016)
$Constant$	-0.097**	0.0079	-0.100****	-0.049*
	(0.044)	(0.034)	(0.035)	(0.027)
#Obs.	10,594	11,568	10,913	11,252
R^2	0.006	0.009	0.051	0.003

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 18: Recipient-country-specific: panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source countries include all OECD countries, but we use only one of the BRIC countries ($r1...4$) as a recipient country of trade in investment goods at a time. Source sectors include all sectors, recipient sectors include only the investment (capital) good.

Regression SKL1

	Brazil $\Delta RLY_{s(r1)jkt}$	Russia $\Delta RLY_{s(r2)jkt}$	India $\Delta RLY_{s(r3)jkt}$	China $\Delta RLY_{s(r4)jkt}$
$XY_{srjk(t-3)}$	-0.0016	0.00058	-0.0021*	-0.0016
	(0.0012)	(0.0017)	(0.0012)	(0.0010)
$Constant$	0.014	-0.039	-0.095*****	-0.066*****
	(0.024)	(0.029)	(0.021)	(0.018)
#Obs.	10,620	11,599	10,946	11,281
R^2	0.107	0.037	0.195	0.230

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 19: Recipient-country-specific: same as previous table, but growth rate of the relative South-North labor intensity as dependent variable.

Regression SME1

	Brazil $\Delta REY_{s(r1)jmt}$	Russia $\Delta REY_{s(r2)jmt}$	India $\Delta REY_{s(r3)jmt}$	China $\Delta REY_{s(r4)jmt}$
$XY_{srjm(t-3)}$	-0.0087*****	-0.0027****	-0.0028*****	-0.00025
	(0.00059)	(0.00094)	(0.00055)	(0.00051)
$Constant$	-0.097*****	0.046***	-0.0074	-0.026***
	(0.011)	(0.017)	(0.0090)	(0.0091)
#Obs.	159,087	172,232	160,069	168,405
R^2	0.008	0.026	0.054	0.016

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 20: Recipient-country-specific: panel estimation of the drivers of the growth rate of the relative South-North energy intensity including individual and time-specific effects (not reported in the table). Source countries include all OECD countries, but we use only one of the BRIC countries ($r1...4$) as a recipient country of trade in intermediate goods at a time. Source sectors include all sectors, recipient sectors include manufacturing sectors, i.e. we look at imports used as intermediate inputs.

Regression SML1

	Brazil $\Delta RLY_{s(r1)jmt}$	Russia $\Delta RLY_{s(r2)jmt}$	India $\Delta RLY_{s(r3)jmt}$	China $\Delta RLY_{s(r4)jmt}$
$XY_{srjm(t-3)}$	-0.0014**	-0.00099	-0.0023*****	-0.0041*****
	(0.00067)	(0.00078)	(0.00033)	(0.00047)
$Constant$	0.018*	0.035****	-0.014**	-0.10*****
	(0.011)	(0.012)	(0.0054)	(0.0071)
#Obs.	159,410	172,822	160,581	168,839
R^2	0.047	0.116	0.292	0.056

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 21: Recipient-country-specific: same as previous table, but growth rate of the relative South-North labor intensity as dependent variable.

Regressions SME1 & SML1

	ΔREY_{srjmt}	ΔRLY_{srjmt}
$HL_{r(t-3)}$	0.033*****	-0.059*****
	(0.0056)	(0.0016)
$XY_{srjm(t-3)}$	-0.0018*****	0.0025*****
	(0.00029)	(0.00018)
$PE_{rm(t-3)}$	-0.034*****	
	(0.0010)	
$PL_{rm(t-3)}$		0.026*****
		(0.0004)
$Constant$	0.22*****	-0.13*****
	(0.016)	(0.0043)
#Obs.	1,310,162	1,483,623
R^2	0.008	0.045

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 22: Robustness check including recipient-sector-specific factor price measures (PE for energy and PL for labor) as regressors. Source sectors include all sectors, recipient sectors only manufacturing sectors.

Regressions SKE1 & SKL1

	ΔREY_{urlkt}	ΔREY_{urlkt}	ΔRLY_{urlkt}	ΔRLY_{urlkt}
$HL_{u(t-3)}$	-0.050*****	-0.069*****	-0.026*****	-0.045*****
	(0.0065)	(0.0096)	(0.0049)	(0.0076)
$XY_{urlk(t-3)}$	-0.0017***	-0.0044*****	-0.0018*****	-0.0045*****
	(0.0006)	(0.0012)	(0.0005)	(0.000096)
$IY_{ul(t-3)}$	0.00042	0.0074*	0.0024***	0.0095*****
	(0.0013)	(0.0030)	(0.0009)	(0.0024)
$HL_{u(t-3)} \cdot XY_{urlk(t-3)}$		-0.00015***		-0.00015****
$\cdot IY_{ul(t-3)}$		(0.000059)		(0.000048)
$Constant$	-0.15*****	-0.25*****	-0.089*****	-0.21*****
	(0.0215)	(0.043)	(0.0163)	(0.034)
#Obs.	41,644	41,644	41,617	41,617
R^2	0.0140	0.0140	0.1078	0.1090

Robust standard errors in parentheses
***** $p < 0.001$, **** $p < 0.005$, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 23: Robustness checks including source-sector-specific R&D expenditures per output value (IY). Source sectors encompass a reduced sample of countries and sectors, recipient sectors encompass only the investment (capital) good.