The Impact of Trade on Wage Inequality in Developing Countries: Technology vs. Comparative Advantage

Nathalie Scholl

University of Goettingen, Germany, Nathalie.Scholl@wiwi.uni-goettingen.de

Keywords: Wages, Inequality, Trade, Technology Transfer

First draft, 20.09.2014

Summary

During the expansion of world trade since the 1980s, measures of inequality have risen not only in developed countries, but also throughout the developing world. This stylized fact is contrary to the predictions of trade theory that in countries with high endowments of unskilled labor, wages of the same should rise relative to those of skilled labor. This paper empirically tests the effects of trade on wage inequality in a differentiated panel framework wherein countries are classified according to their relative human capital endowments, constituting also the relevant comparative advantage in trade. Employing a newly constructed measure of technological change, an important source of omitted variable bias is removed which has not been addressed in the literature so far. Including the measure, several effects such as an equalizing impact of exports otherwise attributed to trade disappear, underscoring the importance of controlling for technological change. The paper furthermore isolates Heckscher-Ohlin "trade" effects from technology transfer effects, which conflate the former due to opposite impacts. Technology transfer is found to take place in particular through trade flows classified as medium-technology intensive, whereby both equalizing and disequalizing effects arise depending on the trading partner's relative human capital endowment, and the country's own endowment. Evidence is also found for pure "trade"-effects, supporting the Heckscher-Ohlin predictions of the effects of trade on wage inequality once the heterogeneity of the trading partners and the traded goods is taken into account.

1. Introduction

In the 1980s, developing countries have considerably lowered barriers to international trade. Globalization has led to a tremendous increase in both international trade and capital flows ever since. This comprehensive economic change is not without distributional consequences. Heckscher-Ohlin (HO) theory (Heckscher 1991) yields clear predictions of the effects of trade on the distribution of income among production factors. Their relative abundance is also the source of comparative advantage in international trade and countries abundant in one production factor will specialize in the production of goods relatively intensive in that factor. The relatively abundant factor will then gain, while the scarce factor, experiencing the opposite effects, will lose from trade (Stolper and Samuelson 1941).

Developing countries, arguably relatively abundant in low-skilled labor, would hence specialize in low-skilled labor-intensive production. Because low-skilled labor is generally located at the lower end of the wage distribution while high-skilled labor forms the upper end, wage inequality should decrease in developing countries as a result of increased exposure to international trade. Furthermore, because capital is complementary to high-skilled labor in many cases and relatively scarce in developing countries, the same should be true for income inequality (Krusell et al. 2000, Goldin and Katz (1998)).

Available data on both wage and income inequality describe a reality very different from what one would expect based on theory after the large increases in world trade volumes. Inequality has been rising not only in the industrialized countries but also across the developing world. The correlation between the expansion of world trade and rising inequality does, of course, not imply causality. There are many factors related to globalization and trade, some of which may be conflating or counteracting any equalizing effects of trade on the income distribution.

Several papers have shown that trade has a differential impact in high-and low-income developing countries and that this effect differs by the income group of the trading partner country as well (e.g. Gourdon 2011, Meschi and Vivarelli 2007). The differential impact has been attributed to technology transfer from rich to poor countries, although this transmission channel is rarely tested directly (the study by Conte and Vivarelli 2009 being one notable exception). Rising skill premia have indeed been shown to increase wage inequality not only in developed, but also in developing countries (Berman, Bound and Machin 1998). The lack to account for the source of this development leaves open the question of whether technological change does in fact arise through trade, or, on a similar account, whether it could be domestic technological change stemming from technological innovation within the respective country itself which raises skilled wages. Taking technological change into account is important because it is potentially driving both exports and wages in certain sectors and may thereby introduce a spurious correlation between trade and wage inequality. Most studies "assume away" domestically induced technological change in developing countries, referring to the low level of research and development activities as first stated by Coe, Helpman and Hoffmaister (1997). While this may be true for early time periods in certain countries, it does not seem plausible for upper-middle income countries such as South Korea, Spain, or Slovenia even in earlier years, or for countries like India in the early 2000s.

This paper addresses these problems in several ways. Firstly, it directly measures the technology content embedded in trade by categorizing trade flows into different technology levels. Secondly, the potential omitted variable bias introduced by the failure to account for technological change is removed with the inclusion of a new measure of technological change. The measure captures movements in the technological frontier, which is estimated using data envelopment analysis (DEA) and based on the same raw data as the inequality index used. It is hence able to perfectly control for advancements in technology in exactly those sectors included in the inequality measure as well. Thirdly, the measure can also be used to test the transmission channel of trade and see whether technology transfer is taking place, in a similar fashion as in Gourdon (2011). Differentiating between imports and exports helps to further disentangle the two transmission channels, as different types of hypotheses can be tested on the two variables.

In order to maximize the time coverage, a Theil index of between-sectoral wage inequality covering the years 1970-2008 has been constructed. It is based on the UNIDO industrial statistics, covering manufacturing industries in a large number of developing countries. A major advantage of the prolonged time coverage with a maximum of 38 years is that fixed effects estimation delivers reliable estimates despite the dynamic specification of the econometric panel data model. The sample for the preferred specification contains 25 developing countries over an average time span of 16 years.

Results suggest that while technology transfer through trade does play a role in driving up wage inequality in developing countries, it is important to control for endogenous technological change as some of the effects otherwise attributed to trade disappear once the measure is included. In the same manner, some (Heckscher-Ohlin type) effects only appear when technological change is controlled for, as it seems to conflate the opposing effect of trade on the income distribution. Technology transfer is taking place in particular for high-technology trade flows, whereby both equalizing and disequalizing effects can arise depending on the trading countries' relative human capital endowments. The disequalizing effects exclusively stem from trade with relatively more skill-endowed trading partners, providing further indication of technology transfer effects. However, few results are found for trade with advanced (in terms of education) economies, which casts doubt on the hypothesis that it is technology transfer causing the disequalizing impact of trade with developed countries in developing countries.

In the following, two main strands of literature reconciling the concurrent increase in trade and (wage) inequality in developing countries are reviewed, both of which will be incorporated in the empirical set-up. The empirical analysis is covered in section three, which introduces the data and motivates the chosen empirical specification. Estimation results are discussed in section four. Robustness checks are presented in section five, and section six concludes.

2. Literature review

Taking a closer look at the available inequality data, several studies have identified the changes in the distribution of income causing the rise in the average. Generally, the upper quintile has been shown to be the main driver of inequality. The income share of the upper quintile increased at the expense of the middle part of the distribution while there has been little change at the bottom (e.g. Jaumotte, Lall and Papageorgiou 2013). Goldberg and Pavcnik (2007) find a pervasive increase in skill premia across developing countries over the 1980s and 1990s, which translates in most cases into an increase in wage inequality as well.

The determinants of the increase in income and wage inequality in advanced economies are relatively well explored. Even though the co-movement of trade and inequality is in line with the HO-SS predictions, trade has been found to be only of minor importance. Rather, skill-biased technological change (SBTC) has been identified as the main cause for the changes in the distribution of wages and incomes (e.g. Berman, Bound and Machin (1998); see Card and Di Nardo (2002) for a more critical review of the SBTC hypothesis). The basic reasoning is that technological progress is complementary to high-skilled labor and consequently raises demand for the highly skilled (Acemoglu 2003). There is evidence that SBTC is present in developing countries as well, and that trade introduces or reinforces SBTC in those countries (Berman and Machin 2000, Conte and Vivarelli 2007).

The geographical distribution of trends in income inequality points toward another explanation, which is complementary to the SBTC hypothesis. While the advanced and newly industrializing countries throughout Asia, Latin America and Europe have experienced increasing income inequality, this is not generally true for low-income countries, particularly in Sub-Saharan Africa (Jaumotte, Lall and Papageorgiou 2013). This differentiated pattern of the development of income inequality across countries lends support to an argument first introduced by Wood (1997) which explains the apparent lack of an equalizing effect of trade by making a more detailed distinction between country groups. Trade between developing countries, often labeled "South-South trade", obviously does not fit in with the dichotomy of "North-South" trading partners and their relative endowments assumed in most HO-based models. What constitutes a comparative advantage in trade between "Southern" countries must be established before any predictions about the effect on inequality of trade between developing countries can be derived.

In the following, the theory behind the technology and the South-South trade hypotheses will be explained in more detail. Empirical evidence on the roles of trade, technology and South-South trade as well as the effects of their interrelations on income inequality will be reviewed thereafter.

2.1. (Skill-biased) technological change

SBTC has repeatedly been shown to increase income inequality in developed countries. Most studies focus on the US and find that the large increase in wage inequality during the 1980s was due to the effect of SBTC, in particular the upsurge of computer and information technology. Examples include the empirical analyses by Bound and Johnson (1992), and Berman, Bound and Griliches (1994). A few studies focus on other OECD countries, e.g. Katz, Loveman and Blanchflower (1995), Machin and van Reenen (1998) and Berman, Bound and Machin (1998). Machin and van Reenen (1998) conclude that demand shifts alone are not sufficient to explain the rise in relative wages because the shifts have not only occurred between, but also to a large extent within industries. While the SBTC hypothesis is virtually uncontested for the 1980s, evidence for the 1990s is more ambiguous, and as Card and DiNardo (2002) point out, SBTC also fails to explain several other features of the structure of wages in the US.

Katz and Autor (1998) and Conte and Vivarelli (2011) summarize the various patterns on the production side of the economy indicating the occurrence of SBTC. Among them is the constant or increasing ratio of high-skilled to low-skilled workers despite rising skill premia, and thus relative wages, for the highly skilled. This phenomenon has recently been observed in several developing countries as well (as found by e.g. Berman, Bound and Machin 1998), particularly in emerging economies such as India, Hong Kong, and several Latin American countries (for a review of country case studies see Goldberg and Pavcnik 2007). Berman and Machin (2000) find evidence of SBTC, measured by the share of non-production relative to production workers, in middle-income, but not in low-income developing countries. They also notice that the same industries are affected by SBTC in OECD and in developing countries and infer that SBTC in developing countries is driven by a transfer of technology from industrialized countries. Trade is an obvious candidate as one of the vehicles of technology transfer. It can act as a catalyst of (skill-biased) technological change [1] in developing countries, thereby reinforcing the disequalizing effect of rising skill premia. As Berman, Bound and Machin (1998: 2) put it:

> "[…] at the current level of international [….] trade it is hard to imagine major productive technological changes occurring in one country without rapid adoption by the same industries in countries at the same technological level. Thus pervasive SBTC is an immediate implication of SBTC […]"

Imports are an obvious source of technological advancement. They may provide formerly unavailable goods that embody new technology complementary to skilled labor. They can also be investment goods that enable the introduction or modernization of production processes (Pissarides 1997), or final goods that allow for reverse engineering (Meschi and Vivarelli 2008). Capital goods imports can also be substitutes for low-skilled labor and introduce labor-saving technology, which leads to a widening wage gap through the depression of low-skill wages (Behrman, Birdsall and Skékely 2000).

Summarizing the above arguments as the "import channel", Meschi and Vivarelli (2008) also identify an "export channel" through which SBTC is introduced in developing countries. Export partners in developed countries have certain demands on the quality and up-to-dateness of the products they import. They might therefore either directly assist their developing country partners in upgrading their technology and the skills of their workforce, or make an investment in such upgrading profitable.

Intermediate goods imported in order to finalize production in a low-wage developing country and then re-export it to the country of origin can have effects through both the import- and the export channel. Feenstra and Hanson (1996, 2001) argue that the effect on wage inequality is

[1] The term "skill-biased technological change" is in the original sense different from mere technological upgrading in developing countries, which is not necessarily skill-biased from a developed country point of view. However, since such upgrading frequently is skill-biased from the developing country's perspective, the term will be used here to include both meanings.

particularly strong because demand for skilled labor does not only affect the exporting or export-competing industry, but also all the industries that use the intermediate goods as inputs, regardless of whether they trade the final product or not. They also point out that some industries are more suitable for outsourcing than others. Outsourcing is more present in industries in which the production process can be separated into more or less independent stages and in which the different steps of production entail large differences in the skill composition. Feenstra and Hanson (1996) find that these are mainly industries producing semi-durable consumer goods. Their findings also indicate an asymmetric distribution of trade-induced SBTC across industries, which will be explored in more detail in section 4.1.

Given the potential for technological catch-up, the effect of trade on technological upgrading may be particularly strong in developing countries, especially in emerging economies. Schiff and Wang (2004) show that developing countries benefit more from increased import volumes than developed countries in terms of productivity improvements.

The adoption of new or upgraded technologies not only depends on their availability, but also on a country's capability to employ it and take advantage of it. If there is an insufficient supply of knowledge and qualified labor, or low domestic demand, new technologies will not be established. Acemoglu (2003) makes this point in his model of endogenous technological change: Technology used in developing countries prior to trade liberalization is adapted to local circumstances, thus complementing low-skilled labor. New technologies introduced via imports on the other hand are designed to match the mix of production factors in developed countries and are therefore skill-intensive from a developing country point of view. The decision as well as the possibility to adopt skill-intensive technology depends on the ability of a country to use it and to benefit from it, which in turn depends on the composition of its labor force and the supply of skilled labor. Zhu's (2004) model relies on a similar assumption and introduces a link to the product cycle. According to her argument, new, more skill-intensive goods developed in industrialized countries replace older ones. The production of the older goods is then transferred to developing countries and constitutes a new, relatively skill-intensive production technology there. As a consequence, skill premia rise in both country groups. Pissarides (1997) argues that even if a new technology is not skill-biased, its mere introduction requires skilled labor because new technologies have to be learned about and put into use. The effect on the demand for skilled labor is then transitory. This is also true if one considers that skill-biased technologies can sometimes be modified in a way such that they complement unskilled labor. This modification also requires a certain amount of knowledge and skilled labor. A similar point is made by Bernard and Jensen (1997), who show that the activity of exporting is skill-intensive in itself.

Given the above considerations, it stands to reason that an educational expansion fostering an increase in the supply of high-skilled workers is a prerequisite as well as an accelerator of SBTC in developing countries. At the same time, it depresses skill premia in the short run because of the time lag of new investments in more skill-intensive technology reacting to the increased abundance of skilled labor. Acemoglu (1998) finds evidence in the US for both the short-run, equalizing effect of education on skill premia and the long-run effect, fostering skill-biased technological change and raising skill premia. In this paper, the short-run (supply) effect will be tested directly, whereas the long-run effect is implicitly incorporated into the classification of countries according to their relative skill levels.

2.2. South-South trade

The basic reasoning behind the South-South trade argument is that countries that are pooled together in a rather undifferentiated manner under the label of "developing countries" are in fact so heterogeneous in terms of economic and human development that the relative abundance of production factors, and hence the impact of trade, differs vastly between them. While the unskilled workforce in the least developed countries generally benefits from trade because it can exploit its comparative advantage in low-skill production sectors, the case is different for middle-income countries, comprising also the newly industrializing countries. These countries have evolved to a stage where they no longer have a comparative advantage in unskilled labor. One can therefore not per se assume that trade with either developed or developing countries leads to a decrease in wage inequality in these countries. The fact that many developing countries felt the need to protect low-skill sectors by tariffs and other trade barriers prior to trade liberalization underpins the hypothesis that this is not where they had their comparative advantage. It rather shifted to medium-skill intense production, in particular when many developing countries with a large unskilled labor force – the most prominent example being China – entered the world market during the period of liberalization in the 1980s (Wood 1997).[2] The impact of trade with low-income countries in the low-skill, labor intensive sectors of middle income developing countries would then again be in line with the predictions of HO-SS: product prices fall and factor rewards are lowered – implying a larger wage gap. Davis (1996) has formalized this point in his theoretical model on the effects of

[2] Dollar and Kraay (2004) provide a list of developing countries they identify as "post-1980 globalizers" based on the increase in trade over GDP between 1980 and 2000 and backed by changes in tariff policies.

trade liberalization on factor rewards within different groups of countries with similar endowments. It is hence crucial to differentiate between different kinds of developing countries in order to get clear results on the effects of trade on wages.

2.3. Empirical evidence

As mentioned initially, the results of "early" studies on the impacts of trade liberalization on the income distribution in developing countries are rather mixed. The term early is used here in the sense that neither technology nor trade between developing countries is taken into account. Several authors have acknowledged the difficulty of drawing conclusions about the relationship between trade and income inequality from these studies because comparability is limited (Milanovic and Squire 2007, Lundberg and Squire 2003). Differences emerge mainly from three sources: the countries and time periods covered; the choice of the inequality- and the openness variables; and the econometric specification and methodology. Consequently, other approaches have been developed and tested that try to explain the apparent lack of a clear-cut relationship between trade and income- or wage inequality in developing countries. SBTC and technology transfer arguments have received a lot of attention. As for the South-South trade hypothesis, only two studies explicitly incorporate trade between different groups of developing countries into their empirical analyses.

2.3.1. Trade and inequality: „Early“ results

Most of the early studies use the Gini coefficients from Deininger and Squire (1996a) as their dependent variable, a few use quintile shares, and only one study analyses wage inequality. An unambiguously negative impact of trade on inequality is found by only few studies. Examples include Bourguignon and Morisson (1990), who find that after controlling for relative factor endowments, trade reduces income inequality in developing countries due to an increase in the income share of the bottom 40 and 60 percent of the population. Calderón and Chong (2001) find that trade decreases inequality in all countries but that the effect is much stronger in developing countries. Positive coefficients on the other hand are found in all countries by Lundberg and Squire (2003), Cornia and Kiiski (2001), and Spilimbergo, Londoño and Székely (1999). Barro (2000), Savvides (1998), and Milanovic and Squire (2007) all find that the disequalizing effects are stronger or only present in developing countries. Studies which find no effect at all include Edwards (1997), and Dollar and Kraay (2002, 2004) who find that average incomes and incomes of the poor are equally affected by trade.

2.3.2. The role of technology

There are numerous country case studies investigating the interrelationships between technology, trade and inequality in developing countries. They predominantly analyze Latin American countries such as Mexico and Brazil, but also a few Asian cases, in particular India and Malaysia. Most of them find evidence for trade-induced technological change driving up skill premia and inequality. For a review, see Robbins (1996) on early evidence and Gourdon (2011) for more recent studies.

The number of cross-country studies is considerably lower. Zhu and Trefler (2005) find that wage inequality in developing countries in terms of relative wages of skilled to unskilled workers has increased due to trade-induced technological catch-up, measured by labor productivity. Zhu (2005) puts her theoretical model of technology transfer through product cycles to an empirical test in a panel of 28 US trading partners. The change in the payroll of skilled workers is regressed on a measure of product cycle goods, which are defined on the basis of trade patterns with the US, the technological leader. Results indicate that product cycle trade leads to skill upgrading in countries which have a GDP per capita of at least 20 percent of the US GDP per capita. No effect is found in the lower income countries. Conte and Vivarelli (2007) estimate the impact of “skill-enhancing technology import” from high income countries on the employment of skilled and unskilled in low and middle income countries. They construct a measure of the technology content of imports and estimate its impact on the absolute number of both production (“blue-collar”) and non-production (“white-collar”) workers. According to their results, trade-induced technological upgrading entails not only a relative, but an absolute skill bias since it not only increases the absolute employment of skilled workers but it actually decreases the number of unskilled workers as well. However, the analysis does not control for the supply of skilled and unskilled labor. Although according to the Rybczinski theorem, domestic relative supply shifts should not matter for relative wages in open economies because they lead to corresponding shifts in production, the fact that education turns out significant in most empirical analyses contradicts this view, at least in the short run. Robbins (1996), including various direct measures of labor supply, also finds that shifts in labor supply have large effects on relative wages, and concludes that labor markets are to some degree insulated from factor price equalization. This means that Conte and Vivarelli’s (2007) results could suffer from omitted variable bias because the supply of skilled labor is not controlled for. In addition, not only imports but also exports can be a source of technology transfer. Finally, Jaumotte, Lall, and Papageorgiou

(2013) in their analysis of both advanced and developing countries conclude that the main driver of inequality is technological change, measured by the share of information and communications technology capital (ICT) in the total capital stock, above and beyond its effect through trade. Trade is found to reduce inequality, and a decomposition of the trade variable reveals that the negative effect mainly stems from exports of agricultural products. They also find that the share of imports from developing countries, but not other developed countries reduces inequality in advanced countries, which runs counter to the HO-SS logic. The authors' explanation for this finding is that low-paying manufacturing jobs located in developing countries are being substituted by higher-paying jobs in the growing service sectors of retail and finance.

2.3.3. Incorporating South-South trade

One of the two studies explicitly testing the South-South trade hypothesis while also taking SBTC into account is Gourdon (2011). To estimate trade-induced technological change, relative total factor productivity between skill-intensive and non-skill intensive sectors is regressed on North-South trade (between high-income and developing countries) and South-South trade (between middle-income and low-income developing countries) in a sample of 68 developing countries over 1976-2000. In a second step, inter-industry wage inequality is regressed on North-South and South-South trade as well as the respective previously identified effects of technology transfer. This procedure allows to separately identifying the direct effect of North- and South-South trade on inequality and their respective indirect effect via technological change. Once technology transfer is controlled for, North-South trade has an equalizing effect on wage inequality while South-South trade increases inequality in both middle-income and low-income developing countries. While the effect in middle-income countries is direct, it operates through technology transfer from middle- to low-income developing countries in the latter. The analysis makes an interesting point in that trade-induced technological change in developing countries can originate not only from developed countries, but also from other developing countries.

Meschi and Vivarelli's (2008) analysis combines both the technology transfer and the South-South trade hypotheses in a sample of 65 developing countries from 1980 to 1999. The analysis relies on the UTIP-EHII measure of income inequality, which combines the Deininger and Squire (1996a) dataset with the UTIP-UNIDO wage inequality data. Trade flows are decomposed by their origin and destination countries and it is found that trade from and to developed countries worsen the income distribution, while trade with other developing countries has an equalizing effect. The sample of developing countries is then further divided into middle- and low-income countries. The results confirm the technology transfer hypothesis: trade with developed countries has a negative impact only in middle-income developing countries, while the effect in low-income countries is insignificant. Trade between low- and middle-income developing countries increases inequality in both groups. Meschi and Vivarelli interpret their finding as evidence for the introduction of SBTC from developed to developing countries. The effect emerges through both imports and exports, which enter the regression separately. However, no measure is inclued of the technologies transferred or the transmission channels through which wages are affected, a concern which has also been raised by Conte and Vivarelli (2007).

3. Empirical Analysis

3.2. Data and descriptive statistics

3.2.1. Country classification

As has been derived from the literature on “South-South” trade, it is important to distinguish between different types of developing countries to arrive at clear predictions about the effects of trade on wages. Typically, developing countries are classified according their income into different levels of development, as in the widely used World Bank classification based on GNI. In the context of this analysis, a classification by relative endowments – i.e. the skill-level of the labor force – is more appropriate. Relative human capital endowments are the source of comparative advantage in trade and hence the relevant characteristic from which to derive hypotheses about the impact of trade on wage inequality. Studies supporting this approach are Gourdon, Maystre and de Melo (2008), who test H-O theory by introducing interactions with country endowments and find supporting evidence for its predictions, and Forbes (2001), who directly tests different country classifications. She concludes that any classification based on comparative advantage (years of education, wages, or a mix of both) performs superior to income-based classifications in that the presumed effects of trade are found with the former classification, whereas the latter one yields only insignificant coefficients.

Human capital is proxied for by average years of schooling of the population aged 25 years and older, extracted from Barro and Lee (2001) and extrapolated for the years missing between the 5-year intervals in which the original data are reported.[3] As it is relative endowments that should matter for trade, countries are grouped into quartiles. In previous analyses, developing countries were divided into two or three groups of low-, lower-middle and/or upper-middle income countries according to their per capita incomes, following the World Bank classification. Translating these groups into education, the resulting classification divides countries into low (LEC), lower-middle (LMEC), upper-middle (UMEC), and high (HEC) education. The lower 3 quartiles are considered "developing" and form the estimation sample. Countries classified as HEC are used for classifying trade flows in order to capture technology transfer from more developed countries, and then removed from the sample. Of the 25 countries and total of 389 observations used in the preferred estimation sample, 16 percent are classified as LEC, 37 percent as LMEC and 47 percent as UMEC. For every developing country, all trade flows to and from countries classified as HEC are summed up. The same is done for the other income categories, so that the South-South hypothesis of trade between developing countries can be tested. The disaggregated trade variables are denoted by affixes numbered 1 to 4 according the trading partner's relative education level from low to high education respectively. They are further decomposed into their technology content as explained in the following.

3.2.2. Trade and technology

The data on trade consists of the total value (in billions of US dollars) of yearly bilateral trade flows between country pairs, provided by the UN Comtrade database.[4] Traded products are coded according to their technology level. The technology classification is taken from

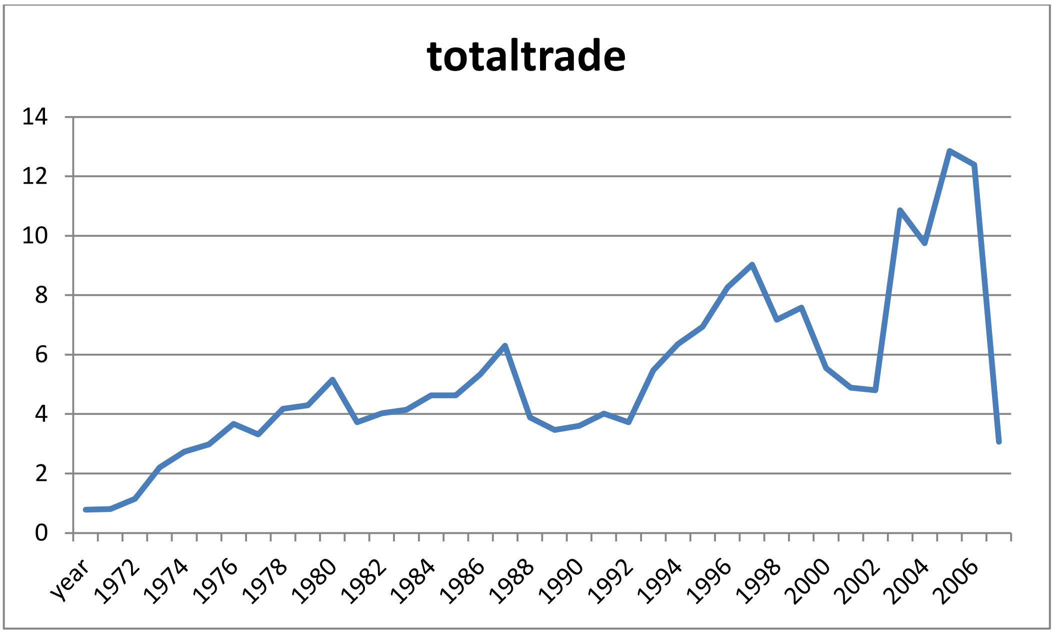
[3] It shall not go unmentioned that there are numerous problems with using years of schooling as a measure for skills without taking quality of schooling into account, which not only varies greatly between countries, but also over time, as noted by e.g. Wößmann (2000). It is even more problematic to equate formal schooling with human capital, which has many other components besides education. However, alternative measures for human capital hardly exist and those for schooling, such as pupil-teacher ratios or educational spending, are equally contested. Even though there have been attempts to measure educational outcomes directly via cognitive tests (for example in the "Schooling Quality in a Cross-Section of Countries" dataset by Lee and Barro (1997)), the resulting data are rather sparse and using them would virtually eliminate the present panel.

[4] Because the trade data is not available in the ISIC scheme, it has to be converted from the Standard International Trade Classification (SITC) using correspondence tables. While a direct conversion is possible for post-1987 data which is provided in the SITC Rev.3, data from 1970 is only available in ISIC Rev.1, for which there is no direct correspondence table to ISIC Rev.3. The data therefore has to first be converted into the SITC Rev.3, and then further into the ISIC classification. Correspondence tables are taken from the EU RAMON database. Conversion is always based on the most detailed (5 digit) product level, whereas the trade data is provided at all levels of aggregation. However, "The values of the reported detailed commodity data do not necessarily sum up to the total trade value for a given country dataset. Due to confidentiality, countries may not report some of its detailed trade. This trade will - however - be included at the higher commodity level and in the total trade value." (Comtrade 2014). After conversion, whenever a higher commodity level trade value deviates from the sum of its sublevel trade value and the higher level contains different sub-level technology groups as per the official classification scheme, a precise recording and grouping of all data is not possible. Hence, only data provided at the 5-digit level is retained so that all the data can be coded into technology levels.

Loschky (2010), who calculates R&D intensities of product groups at the ISIC Rev. 3 level.[5] Three categories of technology intensity are employed: Low technology (LT), medium-low technology (MLT), and medium-high to high technology (MHT). Aggregation is again carried out by adding up the total value of yearly trade in each technology category, separately for imports and exports.

The following graphs depict some basic trends in the trade data along the dimensions technology and trading partners. Figure 1 depicts the rise in developing country trade (in-sample average) in billions of US $ over the sample period. Trade has grown an impressive 1000 percent between 1970 and its peak in the early 2000s. The share of trade with other relatively low-educations countries relative to the advanced economies has risen over time, as is apparent from Figure 2. Suffixes 1 to 4 represent the quartiles of years of educations with one being the lowest quartile. Lastly, trade shares of technologically more advanced products have been relatively volatile over time, as depicted in Figure 3. However, some of the spikes are attributable to sample composition effects.

Figure 1: Total developing country trade, in US $ bn.



[5] Although Loschky (2010) differentiates between low-, medium low-, medium high-, and high-technology, the upper two categories are pooled together. This is done for two reasons: (1) Retaining consistency with the classification of industries used in the dependent variable, which is based on the 2-digit level of ISIC Rev. 3. The distinction between medium-high technology and high technology is made on a deeper level of product classification which often involves four digits, and pooling the top categories together avoids the resulting overlaps of medium-high and high technology sectors in the wage inequality measure. (2) The trade share of the combined category is already relatively small (around 20% on average), so separating between the categories would lead to more missings, thereby aggravating country composition effects and further complicating the analysis with the introduction of a fourth category.

Figure 2: South-South trade

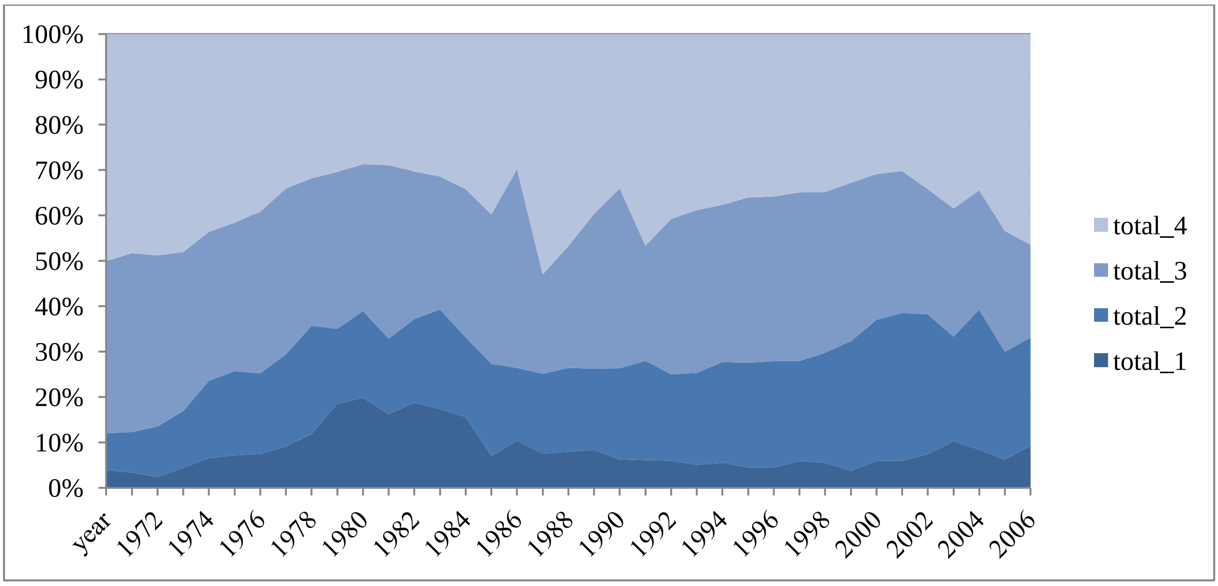
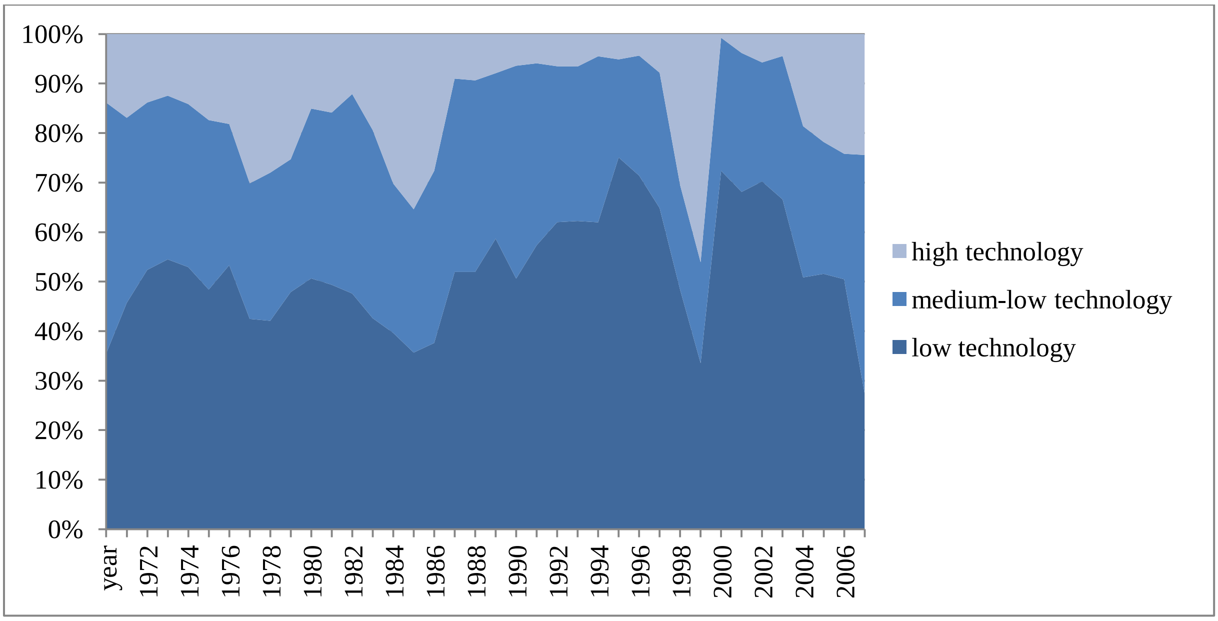


Figure 3: Technology shares of developing country trade



3.2.3. Inequality: a sectoral approach

This paper considers the effects of trade on wage inequality rather than income inequality, which is more frequently analyzed in the literature. This more narrow focus has several advantages. It is closer to the theoretical argument that the influence of trade and technology on inequality works via their impact on skill premia. Skill premia directly affect the wage structure, but presumably have a weaker impact on overall income, which has many more components besides wage income. Related to the first point, the fact that income consists of several components also means that they have to be considered in order to determine the overall effect of trade on the income distribution. One would have to identify the impact of trade on the return to other production factors such as capital and land which are both a source of comparative advantage in international trade and a component of income. Finally, wage data are more comparable across countries than the available income data, which differ considerably in both quality and content both between countries and over time.

A Theil index of between-sectoral wage inequality has been constructed to serve as the dependent variable in the empirical analysis. The index is based on the UNIDO industrial statistics on manufacturing, using data from 1970 to 2008. Although a similar index has been built by the University of Texas Inequality Project (UTIP), it is not clear which data is entering their index, as the raw data requires several choices as to which sectors to include in order to retain consistency and ensure comparability over time. Hence, the index has been re-calculated for the entire time period. Different versions of the index are employed to test the robustness of the results to the choices made in obtaining a consistent inequality measure. A discussion of the advantages and weaknesses of the sectoral approach using the UNIDO data vis-à-vis Deininger and Squire's (1996a) more frequently used individual-based dataset of Gini coefficients can be found in Conceição and Galbraith (2000).

Like the technology classification, the UNIDO statistics are also based on the ISIC sectoral classification and thus match the trade data perfectly. The entire analytical set-up is based on a sectoral approach. It hence captures sector-biased ("asymmetric") rather than "simple" factor-biased technological change which affects all sectors of the economy to more or less the same extent (symmetric). There are two reasons for choosing the sector-based approach. Firstly, the technology content of trade flows is measured by the technology content of the traded goods, which is based on the classification of the respective industry from low- to high technology. This measure does not capture differences in the within-industry composition of skills – it can therefore only explain changes in the distribution of wages *between* industries, which is what the inequality index measures. Secondly, a sector bias of skills is a much more reasonable assumption than simple factor bias, especially if one drops the unrealistic assumption of the homogeneity of labor. A highly qualified worker in the metal working industry is most likely to have different kind of skills than a highly qualified worker in, say, the apparel industry. Even though they may have the same level of qualification, the wage premia of the two are likely to be driven up to a different extent by factor-biased SBTC. Similar to the terminology used by Haskel and Slaughter (2002), the term sector-biased SBTC is used here obviously to include not only the obvious *sector*-specific SBTC, but also pervasive but asymmetric *factor*-biased SBTC because it affects some sectors more than others.

While there are several theoretical analyses on the effects of factor- vs. sector-biased SBTC on wages (see e.g. the studies referred to by Slaughter 2002), Stehrer (2010) points out that the results depend on the specific assumptions of the theoretical models and there is no conclusive overall result. Unfortunately, there are only few studies that empirically examine the importance of sector- vs. factor-biased technical change and they are limited to developed countries. The results do, however, all indicate an important role of sector-biased SBTC in explaining relative wages. Haskel and Slaughter (2002) conclude that the sector bias of SBTC is the decisive factor in explaining changes in skill premia, but they also find a smaller role for a factor bias. De Santis (2002) also finds in his analysis of a general equilibrium model with HO-trade applied to US and UK data that sector-biased technical change performs relatively better than factor-biased technical change in explaining the data.

One drawback of the sector-focused approach is that factor-biased SBTC which affects sectors asymmetrically can be conflated in the computation of industry wage averages, which the employed between-sector inequality measure relies on. The problem arises because the skill-composition of the workforce varies between sectors. The following numerical example illustrates the problem.

Table 1. Factor-biased SBTC, sector composition and average wage

		Sector A		Sector B			Sector C		
Wage growth of skilled workforce			20%		20%	40%		20%	80%
Composition of wages	Skilled	100	120	50	60	70	25	30	45
	Unskilled	100	100	150	150	150	175	175	175
Average wage		1	**1.1**	1	1.05	**1.1**	1	1.025	**1.1**

For reasons of simplicity, it is assumed that all sectors employ the same number of workers, which is stable over time. Furthermore, in the initial state before SBTC, skilled and unskilled workers earn the same wage, which is normalized to one and equal across sectors. The first column in each sector therefore describes both the composition of the workforce and each group's total wage. SBTC then leads to an increase in the skill premium, leading to higher wages for the skilled. The second and third columns in each sector describe the resulting total wage for each skill group for different wage growth rates. With factor-biased SBTC only, the effect on the average wage depends on the composition of the workforce in each sector. The higher the share of skilled workers, the larger increase in the average wage. However, if factor-biased SBTC is asymmetrical (and thus also sector-biased), a larger increase in wages in one sector (e.g. 40 percent in sector B) can be partly or completely offset by the smaller share of skilled workers in that sector – which cannot be observed in the data at hand. One can see that in order to assess the overall effect of SBTC of wages, it is necessary to also take the distribution of wages within each sector into account. In the illustrated case, a between-sector measure would understate the effect of SBTC on the distribution of wages in the economy.

It can be argued that the above reasoning also holds true for the opposite effect, namely trade-induced increase in the demand for unskilled labor. However, it is reasonable to assume that unskilled labor is more homogenous and exchangeable between sectors than skilled labor. Factor-biased SBTC favoring the unskilled therefore is therefore likely to affect unskilled wages rather symmetrically throughout the sectors of the economy.

In sum, while there are a few caveats associated with employing a sector-based rather than a factor-based analysis, there is little reason to suspect that results will be distorted systematically. On the question of the importance of the within-group component of wage inequality, Conceição and Galbraith (2000: 71) argue that

> "when the underlying data set is drawn from industrial classification schemes, the answer will generally be "not very important." Industrial classification schemes, after all, are designed to group together entities that are comprised of firms engaged in similar lines of work, and firms, like all bureaucracies, tend to maintain their internal relative pay structures comparatively stable from one period to the next."

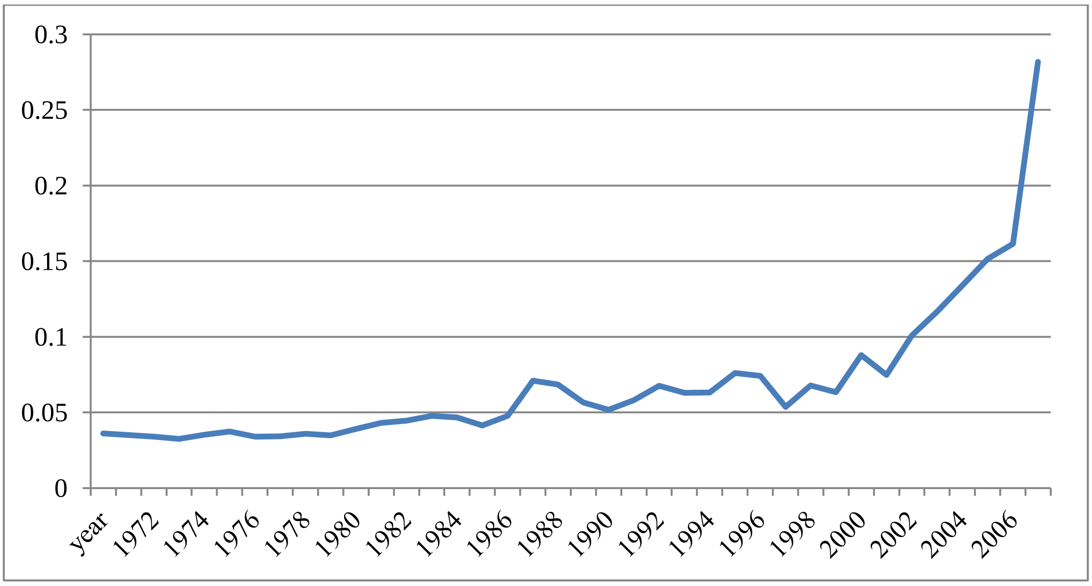
When unskilled labor also (at least partly) profits from an increase in the wages of skilled labor within a sector, this mitigates the abovementioned problem of asymmetrical factor bias conflating the true extent of SBTC. If anything, a between-unit measure can be interpreted as the lower bound to overall inequality (Conceição and Ferreira 2000).

The dataset resulting from the construction of the Theil index contains 1375 observations over the years 1970-2008, but observations and countries covered are reduced substantially in the course of the sample construction. The between-sector component of the Theil is defined as

$$T' = \sum_{g=1}^{G} Y_g \log\left(\frac{Y_g}{n_g}\right)$$

with G denoting the different sectors, g=1, …, G. Y_g represents the wage share of sector g, defined as the sector average over the total average wage of all industries. n_g represents each sector's wage share, defined as the sector's population Ng over total population N (cf. Theil 1967: 95). The original representation of the index is not commonly used, yet it is insightful because it makes it easy to illustrate several properties of the index. Firstly, the sector's wage share can be interpreted as the weight with which each sector enters the measure. Secondly, if the ratio of the wage share and the population share are equal, taking their logarithm yields zero, which implies that the sector does not enter the measure. Consequently, if all income shares and population shares are equal, the between-group Theil takes its lower bound value of zero, indicating a perfectly equal distribution of income. The measure has no upper bound, which makes an intuitive interpretation difficult. It therefore enters the regression in log-specification to make interpretation easier. The development of the (in-sample) Theil index over the sample period (1970-2008) is displayed in Figure 4. As in the previously presented development of trade volumes, there is a clearly discernible upward trend, which his even more pronounced in the inequality data.

Figure 4: Development of the Theil index of inter-industry wage inequality



3.2.3. Control variables

Technological change

The difficulty with including technological change in empirical analyses is measurement. Even though efforts have been made to find appropriate proxies, technological change is often simply defined as the unexplained residual of wage determination models. As argued by Topel (1997: 60), this "makes it nearly impossible for [the theory that technological change, altering the demand for the two kinds of labor by changing their relative productivities, is responsible for an increase in wage inequality] to fail" An attempt to find a measure of technological change has been made by Jaumotte, Lall and Papageorgiou (2013), who use the share of domestically produced information and communications technology capital in the total capital stock. The variable turns out to significantly increase inequality in both developed and developing countries while trade itself has an equalizing effect on the income distribution. However, technological change in developing countries is likely to start at much less sophisticated levels of technology, which this measure does not capture. Technological change would then be underestimated. Zhu and Trefler (2005) use labor productivity to measure technological change and also find a positive relationship with trade. Gourdon (20011) argues that total factor productivity (TFP) would be more appropriate but also uses labor productivity in his analysis because of better data availability. Lipsey and Carlaw (2004) challenge the interpretation of TFP as measuring technological change. They argue that positive changes in TFP simply reflect the surplus returns that emerge from investing in new technologies which are necessary to recoup the investment. Consequently, if there are no surplus returns, technological change goes unmeasured. Nevertheless, although it may underestimate the true extent of technological change, TFP-based measures are the best feasible option given the data available. As long as the unmeasured components of TFP are not occurring systematically, this merely adds more noise to the data.

To arrive at a measure of technological change, a productivity index is calculated which decomposes observed changes in the input-output ratio of production into different components. Besides different aspects of technical and scale efficiency, this also entails a component of technical change, capturing movements in the production frontier. Data Envelopment Analysis (DEA) is employed to estimate the technological frontier, defined as the maximum level of TFP observed in all the production units of the data. The DPIN program (V.3), developed and provided by O'Donnell (2011), uses linear programs for estimation. Different productivity indices are available, but a Färe-Primont index is chosen since it fulfills the transitivity criterion by which obtained values can be meaningfully compared across time as well as production units. The UNIDO data, which have partly already been used in the inequality index, are exploited again for the calculation of the index. Besides wages, the dataset also contains information on capital, output, and value added. In order to not get biased results due to unaccounted intermediate inputs, value added rather than output is used as the output measure, and both wages and capital are included as inputs. Unfortunately, the data on capital is scarce, and using the TFP technological frontier reduces the sample by 40%, despite the imputation of missings as described shortly. The index is therefore estimated again measuring only labor productivity. The same procedure as for the TFP index is applied, but using only labor as an input. Correlation analysis between the total- and the labor-productivity indices for those cases where both are available suggest that they capture the same movements of the production frontier in all but a few countries. Hence, the labor productivity index is used in the preferred specifications as it results in wider country coverage, and the TFP index is employed as a robustness check, yielding qualitatively similar results. As the data is reported at the sectoral level, sectors are "production units" in the estimation of productivity.[6] The technically most efficient sector determines the production frontier, which is then used as the control variable for technological change in the regressions. Three different version of the index are constructed, which use different sectors and imputation methods for missing values: One wherein missing sectors are substituted for by other sectors (imputation across sectors, tech_cross), one wherein the same procedure is applied but only the those sectors are used which have less than 50% missings (imputation for part of the sectors, tech_part), and one wherein all sectors are used and missings are substituted for with values from the same sector in earlier years.[7] The index relying on cross-imputed values is used in the preferred estimations as it adds no new information to the data in a given year, which is used for the estimation of the technological frontier. As a robustness check, the other two indices are tested as well and the results show that they yield virtually the same estimates (Table 10 of section 5).

Labor supply

Value added in agriculture is included as a supply-side control variable in the spirit of Lewis' (1954) dual-sector model. The variable is supposed to measure the amount of unskilled surplus labor in an economy, which might prevent wages at the very bottom of the distribution from rising despite increased demand through trade and/or technology. The data comes from the World Bank's World Development Indicators (WDI). Value added in agriculture is chosen over the share of employment in agriculture, which seems closer to the labor supply it is supposed to capture, and has been used by e.g. Jaumotte, Lall and

[6] Productivity is estimated separately across country, as the structure of the DPIN program does not allow a multi-level equation system (country- and sectors-level). This implies that values can only be meaningfully compared within a country over time. Since a within-estimator is used in the empirical analysis, this does not represent a problem in the present context.

[7] Values from earlier years are used in order to not overestimate technological progress, which is assumed to evolve positively over time. Values from subsequent years are only used in the exceptional cases where no values are available for previous years.

Papgeorgiou (2013), due to a greater country coverage. In preliminary tests on the data, the two measures produce the same results.

Human capital

Although countries have already been grouped according to their relative human capital endowments, education levels still matter as they constitute a (short-term) measure of the supply of skilled labor, which can mitigate pressures high-skilled wages and lower skill premia. The same linearly interpolated Barro and Lee (2001) data are used as for the country classification.

FDI

Inward FDI flows (taken from UNCTAD) are included in order to control for an alternative source of technology transfer likely to be correlated with trade. The direction and form of the effect has not been established unambiguously in the literature (on a review of recent results from empirical studies, see Figini and Görg 2011). However, since the assumption that FDI influences inequality via skill premia follows the same line of argument as the hypotheses on the effects of trade, the variable has been frequently included in analyses on the effects of trade on income inequality (e.g. Jaumotte, Lall and Papageorgiou 2013, Gourdon 2011, and a number of country case studies) and has been often found to significantly increase inequality.

GDP

GDP is included in order to control for "size-effects": All other things equal, richer economies trade more and hence without taking economic size into account, one might hypothesize that larger countries are always more (un-)equal, depending on the assumed effect of trade on inequality. Real expenditure-based GDP in current-price in US dollars is taken from the Penn World Tables, Version 8.0 (Feenstra, Inklaar and Timmer 2013), and the variable enters in logarithms.

The in-sample means of the most important variables, as well as the countries in the sample can be found in appendix table A1.

3.3 Model specification

The basic model has the following functional form:

$$\mathrm{Log\ THEIL}_{\mathrm{i,t}} = \alpha + \rho \log \mathrm{THEIL}_{\mathrm{i,t-1}} + \beta \mathrm{TRADE}_{\mathrm{i,t}} + \sum_{\mathrm{k}} \delta_{\mathrm{k}} \mathrm{X}_{\mathrm{i,k,t}} + y_{\mathrm{t}} + \mu_{\mathrm{i}} + \varepsilon_{\mathrm{i,t}}$$

the indices t and i denoting year and country, respectively. Trade covers the different specifications of the trade variable (e.g. interactions with country dummies, separate consideration of imports and exports), which enters the model with a one-period lag to allow for a time lag in the adoption of imported technology.[8] X is the set of k control variables, all of which enter the regression in levels. Both country fixed effects (μ_i) and time dummies (y_t) are included. $\varepsilon_{i,t}$ denotes the usual error term.

Even though the inter-industry Theil index exhibits considerably less inertia than other measures of income inequality such as the Gini index, misspecification tests in a static model indicate the presence of autocorrelation. A dynamic specification is therefore appropriate. The dynamic fixed effects OLS model delivers biased estimates in a finite sample due to the correlation between the lagged dependent variable and the error term as described by Nickell (1981) and therefore referred to as “Nickell bias”, or LSDV bias. Although alternative (IV-based) estimation techniques are available for dynamic panel models, the most widely used being the Generalized Method of Moments (GMM) (Arellano and Bond 1991), the preferred specification here is the simple FE model. Tentative faith is put in these estimates for two reasons: Firstly, the LSDV bias is a problem of small T, and although an average of 15 years is not considered “large T”, it is definitely not small, either. Secondly, while the bias is quite severe in the AR-term, it is much smaller for the "$\boldsymbol{\beta}$"-variables, i.e. all other (“control-”) variables in the model. Results from several simulation studies suggest that the bias amounts to less than one percent of the coefficient estimate given the values of $\boldsymbol{\rho}$ and T in the panel at hand (e.g. Judson and Owen 1999; Köhler, Sperlich and Vortmeyer 2011). A robustness check using GMM is nevertheless conducted, which indicates that the LSDV bias is not a problem in the present sample.

4. Hypotheses and results

For testing hypotheses about the impact of trade in different country groups, at different technology levels, and from different trading partners, many possible specifications can be employed. At the most disaggregated level of the trade data and with the introduction of the country dummies, the number of variables would rise to 72, which is not operational given that with the inclusion of the technological change control variable, the number of cross-sections is around 25 on average. The approach taken is to start from the most aggregated

[8] The inclusion of the trade variable with a lag of 1 period is chosen for several reasons. Descriptive correlations between trade in different technology levels and the inequality measure suggest that the first lag is the most relevant one. Furthermore, most of the literature has used one-period lagged trade variables. Lastly, the inclusion of further lags would significantly reduce the estimation sample.

level and to stepwise move to more disaggregated specifications. Total trade volumes are investigated first, before moving to exports and imports separately. Each group is further disaggregated by technology and trading partners, for which differential impacts in countries of different relative education levels are also tested.

The technological change variable is included into the model in two versions: A contemporary one, which is supposed to capture the transmission channel of trade on wages via **technology transfer**; and a lagged one, which represents the previously discussed control for **domestic technological change**.

If coefficients of the trade variables vanish, or change substantially with the inclusion of the contemporary technological change variable, this is interpreted as evidence for technology transfer through trade, as the technological frontier in a country is affected by trade in the previous period.

If on the other hand the coefficients are affected by *lagged* technological change, this means that the observed effects on wage inequality are possibly not due to trade, but rather that both variables are driven by domestic technological change. The effect can of course also go the other way, i.e. technological change can be disequalizing and drive trade flows which have per se an equalizing impact, in which case the two opposing effects become apparent only after technological change is controlled for.

For exports, it makes sense to include both variables at the same time in order to retrieve the pure H-O trade effects. H-O theory does not yield any predictions about the effect of imports on the distribution of factor rewards – they are merely the mirror image of a country's specialization as according to its comparative advantage, which is reflected in the export structure. Hence, testable hypotheses differ between exports and imports, and the "trade" effects of imports are not immediately interpretable.

4.1 Aggregate trade

A simplistic view of developing countries would hypothesize an equalizing impact of trade on wages. Technology transfer might have opposing effects, conflating the negative impact and rendering a prediction on the overall impact difficult. Finally, trade could really be driven by domestic technological change, and hence the effect might diminish with the inclusion of the control variable.

Adding up all trade flows, trade has a significant and negative impact on wage inequality, as shown in table 1. The effect is robust to the inclusion of the control variable for technological change (column 4), and does not change with the inclusion of technology transfer (column 3). Columns 1 and 2 show the results obtained without controlling for technology. Column 1 contains the full sample, which is reduced by almost 1/3 with the inclusion of the technological change measures. To show that the changes in coefficients are not driven by the sample composition, columns 2 also reports the results for the smaller sample, containing only observations used in column 3. FDI has the expected positive sign and the coefficient increases with the inclusion of the technology transfer transmission channel, indicating a conflating negative effect of the latter, as also confirmed by the negative and significant impact of the variable itself.

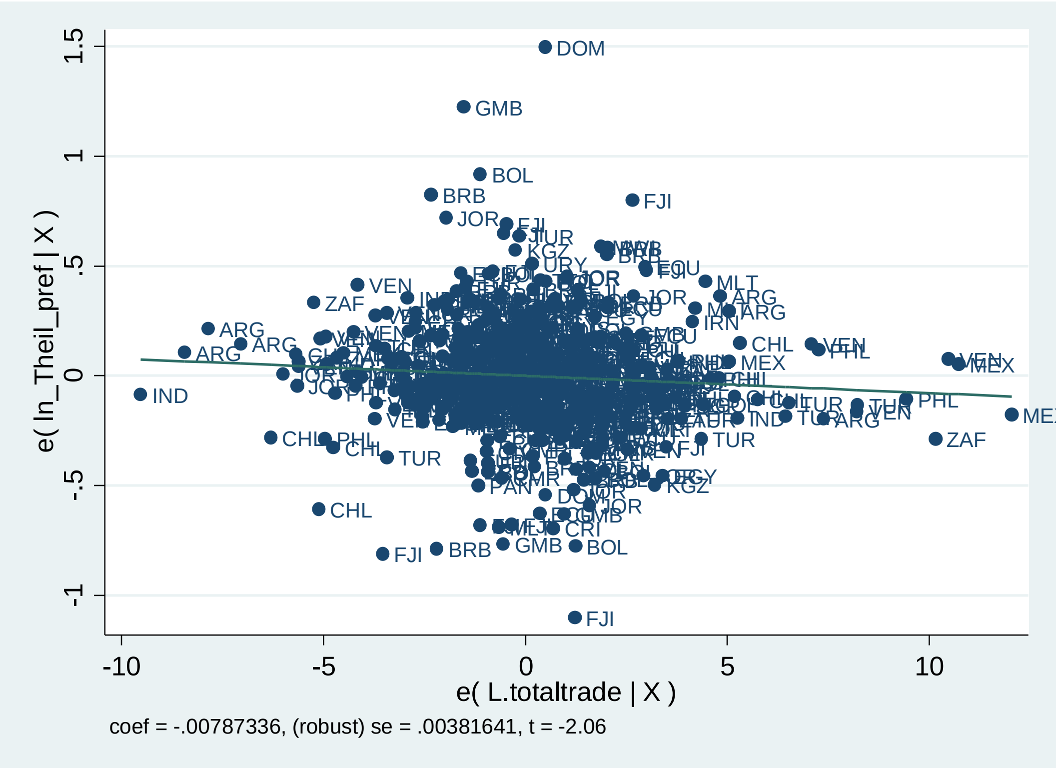
To give an impression of the dispersion of the data, figure 5 shows the partial correlation between the trade variable and the Theil index, corresponding to specification (1) of table 2.

Table 2: Results total trade

	(1)	(2)	(3)	(4)	(5)
VARIABLES	ln_Theil	ln_Theil	ln_Theil	ln_Theil	ln_Theil
tech			-0.439*		-0.186
			(0.236)		(0.365)
L.tech				-0.247***	-0.195
				(0.0806)	(0.152)
L.totaltrade	-9.481e+06***	-9.743e+06**	-9.841e+06**	-7.873e+06**	-9.823e+06**
	(3.220e+06)	(3.916e+06)	(3.626e+06)	(3.747e+06)	(3.626e+06)
ln_rgdpe	0.140	0.181	0.160	0.127	0.131
	(0.113)	(0.157)	(0.142)	(0.125)	(0.131)
BL	-0.0260	-0.0518	-0.0367	-0.0120	-0.0349
	(0.0349)	(0.0562)	(0.0451)	(0.0376)	(0.0455)
ValAddAgri	-0.00673	-0.00534	-0.00226	-0.00356	-0.00301
	(0.00545)	(0.00758)	(0.00615)	(0.00552)	(0.00624)
L.fdi	0.0201***	0.0139**	0.0220**	0.0133**	0.0125**
	(0.00478)	(0.00529)	(0.0100)	(0.00549)	(0.00609)
2.quartile	-0.0601	-0.0142	-0.0362	-0.00993	-0.0324
	(0.0676)	(0.102)	(0.0884)	(0.0757)	(0.0794)
3.quartile	-0.00901	0.0598	0.0201	0.0464	0.0422
	(0.101)	(0.149)	(0.120)	(0.0929)	(0.107)
Observations	584	462	529	535	518
R-squared	0.680	0.633	0.658	0.665	0.661
Number of id	38	32	34	36	34
Year FE	YES	YES	YES	YES	YES

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

Figure 5: Partial correlation plot of total trade and wage inequality



To check whether the effect is driven by exports and imports, trade flows are decomposed in table 2. Both imports and exports have negative signs, but only exports are significant, and the coefficient is substantially larger than for imports in most specifications. The effect diminishes and loses significance in column 4 however, where the control variable for technological change is included. This provides some indication that the previously discussed problem of omitted variable bias is present, and that controlling for technological change is important in order not to falsely attribute technology effects to trade. The technological change variables[9] are negative and significant, another indication that they influence both exports and wage inequality, and the equalizing effects stemming from technological change are falsely attributed to trade. The overall impact of exports is still negative, as also confirmed by columns (5), where both technology variables are controlled for, and which measures the "pure" trade effect. Interestingly, the coefficient on imports shrinks when the technology transfer transmission channel is included – a result that speaks in favor of the import channel of technology transmission. However, since none of the coefficients are significant, more detailed specification shall provide further evidence of the presumed effects in the following.

[9] For simplicity reasons, the coefficients will not be shown in the remaining tables. Instead, the top row will indicate the form in which the technological change variable is included in the model.

Table 3: Results total exports and imports

VARIABLES	(1) Large sample	(2) Small sample	(3) Tech(0)	(4) Tech(-1)	(5) Tech(0, -1)
tech			-0.439*		-0.180
			(0.236)		(0.364)
L.tech				-0.246***	-0.198
				(0.0809)	(0.152)
L.totalexp	-0.0103**	-0.0135**	-0.00999*	-0.00874	-0.0119**
	(0.00484)	(0.00615)	(0.00516)	(0.00570)	(0.00583)
L.totalimp	-0.00838	-0.00534	-0.00964	-0.00676	-0.00744
	(0.00600)	(0.00896)	(0.00820)	(0.00694)	(0.00780)
ln_rgdpe	0.137	0.167	0.159	0.123	0.123
	(0.117)	(0.157)	(0.145)	(0.126)	(0.133)
BL	-0.0264	-0.0538	-0.0368	-0.0125	-0.0358
	(0.0351)	(0.0555)	(0.0450)	(0.0379)	(0.0454)
L.fdi	0.0202***	0.0138**	0.0220**	0.0133**	0.0125*
	(0.00492)	(0.00561)	(0.0101)	(0.00568)	(0.00631)
ValAddAgri	-0.00704	-0.00664	-0.00232	-0.00390	-0.00373
	(0.00566)	(0.00747)	(0.00589)	(0.00562)	(0.00604)
2.quartile	-0.0594	-0.00564	-0.0359	-0.00826	-0.0284
	(0.0677)	(0.0978)	(0.0877)	(0.0746)	(0.0779)
3.quartile	-0.00658	0.0749	0.0207	0.0498	0.0495
	(0.102)	(0.140)	(0.118)	(0.0922)	(0.104)
Observations	584	462	529	535	518
R-squared	0.680	0.634	0.658	0.665	0.661
Number of id	38	32	34	36	34
Year FE	YES	YES	YES	YES	YES

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

4.2 Exports

In the following, the effect of exports is considered separately in more detail. This enables the testing of different hypotheses pertaining to the effect of H-O versus technology transfer effects. Because H-O theory only yields predictions about the effects of exports, not imports, on the distribution of wages, only the export regressions can be used to directly estimate these effects. Controlling for technological change is crucial in the export regressions, as the results from table 2 have already indicated that it is likely to play a role in the determination of both exports and wage inequality, thereby possibly introducing a spurious correlation between the two.

Since for H-O effects it should not matter which type of trading partner a country is exporting to, differing impact between trading partners can be attributed to technology transfer. According to the technology transfer argument as well as previous findings in the literature, we expect to find a disequalizing impact of trade from high-education countries, and possibly from upper-middle education countries, in the relatively less educated trading partner countries. The “absorptive capacity” argument would furthermore suggest that these effects are stronger in the more educated trading partners, respectively. Differentiating between levels of technology furthermore allows the testing of whether it is indeed high-tech exports which lead the largest increases in inequality, or whether there is a role for technology transfer in other technology groups as well. Furthermore, the South-South trade argument would suggest that medium-low technology exports are potentially driving up inequality in less developed countries, where they constitute the main comparative advantage in trade as well as the upper end of the skill distribution.

Again, the regressions move from the most aggregate level to more detailed distinctions between technology levels, trading partners, and country groups in a stepwise manner.

The results for when exports are decomposed into the different trading partners are displayed in table 4. The suffixes indicate the education quartile of the trading partner. In all three technology groups, only exports to UMECs are significant. This is particularly surprising given that the lion’s share of exports from developing countries still goes to industrialized trading partners. The results indicate that both exports in low- and in high-skill intensive good have equalizing effects on the distribution of wages, while medium-low technology exports are disequalizing. That high-technology exports to UMECs are equalizing runs counter to the assumption that high-technology exports are high-skill intensive and should therefore increase wage inequality. The change in the coefficient, which becomes larger with the inclusion of the technology transfer variable (columns 3 and 5) indicates a disequalizing effect through technology transfer of high-tech exports which conflates the otherwise equalizing impact of the same. The change in the low- and medium-low tech trade effects in columns 3 and 5 are not substantial enough to be certain about the technology transfer transmission channel. Nevertheless, the mere fact that exports to UMECs have a separately identifiable effect on wage inequality already speaks in favor of some sort of technology transfer, although the results clearly indicate that this effect would be equalizing and does not work via the technological frontier. The remaining trade effects have the expected signs: low-technology exports, being located at the lower end of the skill distribution, are equalizing, and medium-skill exports, corresponding to skill levels in the middle of the distribution, are disequalizing.

Table 4: Results exports by technology and trading partner

VARIABLES	(1) Large sample	(2) Small sample	(3) Tech(0)	(4) Tech(-1)	(5) Tech(0, -1)
L.higtexp_1	0.955	-0.899	-0.436	1.342	0.274
	(1.592)	(1.342)	(1.271)	(1.698)	(1.659)
L.higtexp_2	0.0187	0.171	0.159	-0.0706	0.0904
	(0.222)	(0.216)	(0.205)	(0.315)	(0.263)
L.higtexp_3	-0.426**	-0.344*	-0.416**	-0.368*	-0.494**
	(0.186)	(0.177)	(0.203)	(0.202)	(0.216)
L.higtexp_4	0.233	0.145	0.210	0.233	0.273
	(0.170)	(0.161)	(0.171)	(0.208)	(0.190)
L.mltexp_1	-0.323	0.413	-0.453	-0.824	-0.402
	(0.710)	(1.088)	(0.780)	(0.752)	(0.804)
L.mltexp_2	-0.366	-0.608	-0.412	-0.185	-0.406
	(0.387)	(0.409)	(0.368)	(0.369)	(0.371)
L.mltexp_3	0.119	0.382***	0.302***	0.227**	0.276***
	(0.0842)	(0.121)	(0.0989)	(0.0924)	(0.0872)
L.mltexp_4	0.0126	0.0262	0.0200	-0.0328	0.00974
	(0.117)	(0.0985)	(0.109)	(0.111)	(0.113)
L.lowtexp_1	-0.0730	-0.163	-0.0705	-0.0975	-0.0915
	(0.104)	(0.105)	(0.0995)	(0.0976)	(0.109)
L.lowtexp_2	0.0718	0.0485	0.0644	0.0337	0.0461
	(0.114)	(0.0853)	(0.0814)	(0.0908)	(0.0880)
L.lowtexp_3	-0.203**	-0.272***	-0.226***	-0.225***	-0.218***
	(0.0853)	(0.0675)	(0.0737)	(0.0698)	(0.0724)
L.lowtexp_4	-0.0256	-0.0459	-0.0228	-0.0259	-0.0286
	(0.0762)	(0.0715)	(0.0708)	(0.0789)	(0.0754)
ln_rgdpe	0.0920	-0.123	-0.00908	0.0141	-0.0319
	(0.376)	(0.363)	(0.393)	(0.402)	(0.367)
BL	-0.142	-0.180	-0.139	-0.127	-0.142
	(0.112)	(0.155)	(0.121)	(0.122)	(0.124)
L.fdi	0.0158	0.0120	0.0175	0.0156	0.0189
	(0.0159)	(0.0132)	(0.0158)	(0.0145)	(0.0165)
ValAddAgri	-0.0370**	-0.0494**	-0.0413**	-0.0375*	-0.0398**
	(0.0173)	(0.0188)	(0.0190)	(0.0189)	(0.0178)
L.totalimp	0.323	0.459**	0.394	0.419	0.307
	(0.265)	(0.225)	(0.279)	(0.290)	(0.278)
2.quartile	0.548	0.781**	0.639	0.624	0.506
	(0.387)	(0.383)	(0.402)	(0.399)	(0.399)
3.quartile	0.0920	-0.123	-0.00908	0.0141	-0.0319
	(0.376)	(0.363)	(0.393)	(0.402)	(0.367)
Observations	340	462	416	419	406
R-squared	0.420	0.404	0.399	0.392	0.398
Number of id	27	36	32	34	32
Year FE	YES	YES	YES	YES	YES

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

Table 5 shows the results for exports, distinguished by technology levels and interacted with the exporting country's education level. Surprisingly, no significant effects arise for high-technology exports (first panel). However, the results on medium-low tech exports (second panel) reveal some interesting patterns. Disequalizing effects are discernible in the relatively more educated quartiles, whereas the effect is negative in the least educated countries. In line with the South-South trade argument, the effect is stronger in the UMEC (third quartile), whereas the effect in the second quartile almost cancels out with the unconditional effect. The robustness of the coefficient to the technology transfer transmission channel indicates a pure H-O "trade" effect. Low technology exports are negative, as expected, in LMECs and UMECs, while the unconditional effect in LECs is positive, but insignificant in the preferred specification (column 4), and the magnitude of the coefficient is very stable across specifications. Both the small size of the coefficient and the fact that this result is counterintuitive given that low-skill intensive jobs are generally located at the lower end of the wage distribution speak in favor of the point made by Bernard and Jensen (1997) that the activities of exporting and technology adoption are inherently skill-intensive, regardless of the technology embedded in the goods involved. Such activities would naturally also not be captured by the sector-based technological frontier, and hence estimates are virtually unaffected by the technology variables. Both the low-tech coefficient for the other country groups and the medium-tech coefficients are greatly affected by the inclusion of the technological change control, however. All increase in absolute size, implying opposite effects of technological change and exports on inequality. In this case, controlling for technological change brings out the disequalizing effects of trade. The technology transfer variable yields no additional insights – the coefficients remain almost unchanged. In sum, this provides clear evidence of technological change driving both exports and inequality, and underscores the need to control for the former. Otherwise, the results are in line with expectations: low-tech exports decrease wage inequality in UMECs and LMECs (although the coefficient is insignificant in the latter), and medium-low tech exports are positive in both country groups, with a stronger effect in UMECs as opposed to LMECs, where the effects again almost cancel out to zero.

Table 5: Results exports by technology level and country group

VARIABLES	(1) Large sample	(2) Small sample	(3) Tech(0)	(4) Tech(-1)	(5) Tech(0, -1)
L.ht_exp	0.0315	0.0800	0.134	0.107	0.0971
	(0.0557)	(0.0680)	(0.177)	(0.181)	(0.178)
2.quartile*L.ht_exp	0.0138	-0.0895	-0.00855	-0.0162	0.000749
	(0.0580)	(0.0703)	(0.197)	(0.196)	(0.194)
3.quartile*L.ht_exp	-0.0438	-0.103	-0.182	-0.154	-0.151
	(0.0552)	(0.0691)	(0.177)	(0.181)	(0.179)
L.mlt_exp	-0.117**	-0.167**	-0.282***	-0.261***	-0.276***
	(0.0446)	(0.0676)	(0.0881)	(0.0903)	(0.0850)
2.quartile*L.mlt_exp	0.0863	0.153	0.245***	0.255***	0.256***
	(0.0640)	(0.0904)	(0.0837)	(0.0830)	(0.0816)
3.quartile*L.mlt_exp	0.118**	0.151*	0.320***	0.319***	0.320***
	(0.0567)	(0.0755)	(0.106)	(0.108)	(0.105)
L.lt_exp	0.0470	0.0707*	0.0785	0.0724	0.0821*
	(0.0281)	(0.0403)	(0.0471)	(0.0463)	(0.0432)
2.quartile*L.lt_exp	-0.0574	-0.0728	-0.122	-0.121	-0.125
	(0.0359)	(0.0513)	(0.0772)	(0.0729)	(0.0738)
3.quartile*L.lt_exp	-0.0596*	-0.0824	-0.186**	-0.191**	-0.188**
	(0.0319)	(0.0504)	(0.0717)	(0.0708)	(0.0707)
L.totalimp	-0.00980	-0.0101	-0.00125	0.00310	0.000220
	(0.0105)	(0.0136)	(0.0359)	(0.0370)	(0.0361)
ln_rgdpe	0.140	0.206	0.154	0.137	0.122
	(0.126)	(0.181)	(0.404)	(0.402)	(0.390)
BL	-0.0374	-0.0678	-0.160	-0.144	-0.142
	(0.0389)	(0.0616)	(0.123)	(0.113)	(0.119)
L.fdi	0.0158***	0.0144*	0.0123	0.00740	0.0118
	(0.00521)	(0.00709)	(0.0125)	(0.0126)	(0.0128)
ValAddAgri	-0.00707	-0.00431	-0.0121	-0.0145	-0.0134
	(0.00687)	(0.00853)	(0.0197)	(0.0202)	(0.0200)
2.quartile	-0.0187	0.0191	0.260	0.266	0.144
	(0.0691)	(0.0954)	(0.354)	(0.351)	(0.356)
3.quartile	0.0485	0.119	0.591	0.598	0.447
	(0.113)	(0.158)	(0.416)	(0.417)	(0.434)
Observations	584	462	532	538	521
R-squared	0.681	0.638	0.354	0.356	0.355
Number of id	38	32	34	36	34
Year FE	YES	YES	YES	YES	YES

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

Summing up the insights obtained from the export regressions, one can extract four main findings from the many results.

Firstly, low-technology exports seem to be equalizing, as predicted by H-O theory. The positive (and sometimes marginally significant) coefficient in LECs can be explained with the argument brought forward by Bernard and Jensen (1997) that exporting is an inherently skill-intensive activity.

Secondly, medium-low technology exports are disequalizing in all but the countries in lowest education quartile. The positive impact can be attributed to H-O trade effects, as no indication for technology transfer is found in any of the specifications, and seems to stem predominantly from trade with UMECs as per the result in table 4.

Thirdly, while no evidence is found for a technology transfer through neither low- nor medium-low technology exports, there seem to be small effects for high-technology goods, at least for exports to UMECs.

Lastly, the results from table 4 suggest that all effects stem mainly from trade with UMECs. One explanation for this finding is that the mix of production factors in this group of countries is particularly favorable for technology adoption, although it is still not clear why the H-O effects identified are not discernible for exports to other country groups, and why the technology transfer effects do not show up more clearly in the regressions.

That there are only few findings pertaining to technology transfer through high-technology trade, and no significant effects from trade with HECs in the export regressions may be due to the fact that the export channel of technology transfer is just not very strong. Import may be the more relevant trade flow to capture technology transfer effects from relatively more- to relatively less educated countries, and are tested in the following.

4.3 Imports

The following set of regressions test the effect of imports on the distribution of wages. In checking for technology transfer, the impact of the transmission channel on the coefficients of the trade variables is of particular interest. Testing for pure H-O effects is redundant, hence the specification previously contained in column 5 is dropped. Nevertheless, because imports can be considered complementary to a country's export structure, they might indirectly be also a result of technological advancements in certain sectors, and controlling for technological change is still necessary. Interpreting the coefficients on imports is consequently also not straightforward, and the discussion of results will therefore mostly focus on the technology transfer effects. If anything, the effects of imports not stemming from technology can be interpreted as "trade" effects, i.e. the general impact of trade in certain goods, with certain groups of countries. Again, the specifications move stepwise from an aggregate to a more detailed differentiation of imports.

Differentiating only by the technology level of imports, one can see in table 5 that medium-low technology imports are disequalizing. This time, medium-low technology imports are affected by the inclusion of the technology transfer transmission channel (column 3) – the coefficient diminishes slightly in size (compared to the smaller, constant sample of column 2). The result does not seem to be driven by technological change, as the coefficient remains significant in column 4. Both low-technology and high-technology imports have negative signs throughout, but only high-technology imports are significant. This results corresponds to the one obtained for exports, and is equally surprising.

Table 6: Results imports by technology level

VARIABLES	(1) Large sample	(2) Small sample	(3) Tech(0)	(4) Tech(-1)
L.totalexp	-0.00829	-0.00999	-0.00747	-0.00567
	(0.00501)	(0.00666)	(0.00569)	(0.00613)
L.total_lt_imp	-0.0183	-0.0241	-0.0156	-0.0222
	(0.0196)	(0.0256)	(0.0218)	(0.0213)
L.total_mlt_imp	0.0506	0.0970*	0.0717	0.0880*
	(0.0511)	(0.0547)	(0.0584)	(0.0493)
L.total_ht_imp	-0.0368	-0.0494*	-0.0566*	-0.0504*
	(0.0293)	(0.0290)	(0.0299)	(0.0264)
ln_rgdpe	0.135	0.167	0.156	0.121
	(0.113)	(0.150)	(0.141)	(0.119)
BL	-0.0139	-0.0178	-0.0205	0.0126
	(0.0321)	(0.0493)	(0.0421)	(0.0360)
L.fdi	0.0189***	0.0108	0.0216*	0.0105
	(0.00563)	(0.00734)	(0.0110)	(0.00690)
ValAddAgri	-0.00599	-0.00422	-0.000878	-0.00174
	(0.00620)	(0.00814)	(0.00664)	(0.00637)
Observations	584	462	529	535
R-squared	0.680	0.635	0.658	0.666
Number of id	38	32	34	36
Year FE	YES	YES	YES	YES

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

Repeating the disaggregation exercise for imports, the variable is in the following further decomposed by trading partners in table 7 and interacted with the country group dummies in table 8.

The disaggregation into different trading partners is presented in table 7. The results for high-technology imports are surprising in that only imports from LMECs are significant, and moreover that the impact is negative. Medium-low technology results are more in line with expectations and, as has been the case with exports, indicate a disequalizing impact for all but the HEC trading partners. The coefficients for the two middle education group trading partners are positive and significant, and only small technology transfer effects are discernible, with a slight absolute increase of all significant coefficients in column (3). Technology transfer does not seem to play a large role for medium-low technology imports, at least when one does not differentiate between importing country groups, although the fact that the effects are present for the two middle education country groups again speaks in favor of the proposition that the mix of production factors is more favorable to technology adaption from these countries in other developing countries. As for the low-tech results, most coefficients have positive signs, although they are all insignificant and will not be further discussed.

Table 7: Results imports by technology and trading partner

VARIABLES	(1) Large sample	(2) Small sample	(3) Tech(0)	(4) Tech(-1)
L.higtimp_1	-0.145	0.746	0.0340	0.952
	(1.667)	(2.183)	(1.966)	(2.263)
L.higtimp_2	-0.483***	-0.385***	-0.494***	-0.475***
	(0.144)	(0.111)	(0.130)	(0.160)
L.higtimp_3	-0.104	-0.181	-0.147	-0.110
	(0.160)	(0.193)	(0.157)	(0.137)
L.higtimp_4	0.242	0.190	0.235	0.201
	(0.152)	(0.179)	(0.173)	(0.175)
L.mltimp_1	0.500	0.930	0.842	0.867
	(0.682)	(0.886)	(0.905)	(0.826)
L.mltimp_2	0.763***	0.771***	0.782***	0.765**
	(0.174)	(0.218)	(0.213)	(0.281)
L.mltimp_3	0.659***	0.555**	0.654***	0.617***
	(0.178)	(0.202)	(0.185)	(0.169)
L.mltimp_4	-0.732***	-0.676***	-0.775***	-0.679***
	(0.178)	(0.186)	(0.204)	(0.213)
L.lowtimp_1	0.0496	-0.0112	0.0176	0.0122
	(0.0654)	(0.0762)	(0.0765)	(0.0770)
L.lowtimp_2	0.0464	-0.0422	0.0194	0.0180
	(0.0898)	(0.0954)	(0.0953)	(0.0942)
L.lowtimp_3	0.0346	0.0283	-0.0234	-0.0284
	(0.0967)	(0.105)	(0.105)	(0.115)
L.lowtimp_4	0.0156	0.0687	0.0706	0.0747
	(0.101)	(0.101)	(0.110)	(0.109)
L.totalexp	-0.0755**	-0.0577	-0.0622*	-0.0653*
	(0.0295)	(0.0363)	(0.0330)	(0.0380)
ln_rgdpe	0.242	0.208	0.198	0.108
	(0.183)	(0.219)	(0.198)	(0.185)
BL	0.0692	0.0372	0.0419	0.114

	(0.0664)	(0.109)	(0.0933)	(0.0724)
L.fdi	-0.00686	-0.00206	-0.00464	-0.00370
	(0.0113)	(0.0126)	(0.0137)	(0.0131)
ValAddAgri	0.00717	0.00513	0.00763	0.00977
	(0.00932)	(0.0114)	(0.0103)	(0.0112)
Observations	401	321	372	375
R-squared	0.650	0.653	0.639	0.649
Number of id	31	27	28	29
Year FE	YES	YES	YES	YES

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

More results emerge when differing impacts in countries of different education groups are allowed for.

The results that high-tech imports are equalizing in UMECs sheds some light on the surprising result from table 7, where an equalizing impact was found for imports from LMECs. This effect seems to be present predominantly in UMECs, a country group with relatively higher education levels, and correspondingly there is again no indication of a technology transfer.

The results for medium-low tech imports correspond to the earlier finding on exports: there is a disequalizing impact in the higher two education groups which is stronger in UMECs, and an equalizing impact in LECs (the reference group). The effect in LMECs is not robust to the technological change control variable, indicating that (disequalizing) technology transfer through medium-low technology trade seems to be present in LMECs, where the coefficient diminishes and loses significance. No such effects are found in UMECs, where the coefficient remains stable across specifications.

For low technology imports, the coefficients are small in absolute size, and only the negative coefficient in LMECs is significant, but vanishes once domestic technological change is controlled for (column 4). Again, no indication is found for technology transfer through low-tech trade.

Table 8: Results imports by technology level and country group

VARIABLES	(1) Large sample	(2) Small sample	(3) Tech(0)	(4) Tech(-1)
L.ht_imp	0.101	0.145	0.145	0.150
	(0.0881)	(0.123)	(0.103)	(0.0960)
2.quartile*L.ht_imp	-0.0975	-0.274	-0.200	-0.228
	(0.153)	(0.166)	(0.172)	(0.147)
3.quartile*L.ht_imp	-0.165*	-0.224	-0.228*	-0.227**
	(0.0961)	(0.138)	(0.113)	(0.102)
L.mlt_imp	-0.131	-0.137	-0.153*	-0.145*
	(0.0780)	(0.104)	(0.0899)	(0.0766)
2.quartile*L.mlt_imp	0.175	0.355**	0.284	0.306**
	(0.147)	(0.171)	(0.174)	(0.144)
3.quartile*L.mlt_imp	0.203**	0.263*	0.228**	0.252***
	(0.0969)	(0.134)	(0.109)	(0.0907)
L.lt_imp	0.0226	0.0280	0.0276	0.0179
	(0.0295)	(0.0345)	(0.0338)	(0.0319)
2.quartile*L.lt_imp	-0.0660*	-0.0817*	-0.0749*	-0.0648
	(0.0381)	(0.0452)	(0.0420)	(0.0388)
3.quartile*L.lt_imp	-0.0351	-0.0484	-0.0418	-0.0390
	(0.0315)	(0.0413)	(0.0355)	(0.0330)
L.totalexp	-0.00611	-0.00671	-0.00328	-0.00245
	(0.00634)	(0.00776)	(0.00666)	(0.00742)
ln_rgdpe	0.164	0.198	0.196	0.149
	(0.124)	(0.169)	(0.154)	(0.133)
BL	-0.0247	-0.0460	-0.0345	-0.00550
	(0.0365)	(0.0578)	(0.0458)	(0.0435)
L.fdi	0.0184***	0.00970	0.0220**	0.0101
	(0.00539)	(0.00638)	(0.0105)	(0.00613)
ValAddAgri	-0.00401	-0.00139	0.00325	0.00132
	(0.00715)	(0.00924)	(0.00792)	(0.00752)
2.quartile	-0.0223	0.0913	0.0316	0.0585
	(0.0798)	(0.123)	(0.102)	(0.0944)
3.quartile	0.0334	0.174	0.103	0.130
	(0.116)	(0.176)	(0.140)	(0.115)
Observations	584	462	529	535
R-squared	0.683	0.642	0.664	0.671
Number of id	38	32	34	36
Year FE	YES	YES	YES	YES

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

Summing up the insights obtained from the import regressions, most results again pertain to medium- low technology trade. There is again little indication of substantial technology transfer effects, and those that can be identified are again mostly taking place through medium- technology trade. That the effects stem mostly from trade with trading partners of medium education levels fits the South-South trade story. Similarly, that the mlt imports are disequalizing in the relatively more educated country groups is in line with the absorptive capacity as well as the South-South trade arguments.

As expected, the technological change control plays a lesser role for imports and changes results in only one case (low-tech imports in LMECs in table 8). The export control variable is negative throughout, and significant in some cases. In general, the results are less clear for imports. This also shows in the control variables, which were stable throughout all of the export regressions, but sometimes even switch signs in the import ones.

5 Robustness tests

Although the structure of the present dataset is not ideal for GMM estimation given the comparatively long T of 16 years relative to the number of groups (23), the method is employed in order to demonstrate that the effect of the LSDV bias on the estimates of the "$\boldsymbol{\beta}$"-variables, i.e. the variables of interest, does not change the results substantially. In order to avoid the problem of a too-large number of instruments weakening the Hansen test of overidentification (Roodman 2009), the year dummies are omitted. Since the purpose of this exercise is not to address omitted variable bias, but rather to demonstrate the magnitude of the LSDV bias, this seems justifiable, especially since results do not change substantially in the FE specification when compared to the results from table 1.

The results from difference GMM two-step estimation are shown in column 2 of Table 9, and compared with those obtained using FE in column 1. Orthogonal deviations are used to transform the instruments in order to mitigate the unbalancedness of the panel. Instruments are restricted to the first few valid lags (3 to 5), and are additionally collapsed in order to keep the number of instruments down. All variables are treated as endogenous in line with the endogeneity concerns raised in the literature about other variables. Results show that the negative impact of trade does not vanish when GMM is employed – on the contrary, the coefficient becomes even larger and remains significant, whereas the LSDV bias would entail an upward bias in the FE estimation. Apart from GDP and technology, most of the control variables remain almost unchanged or even increase in magnitude, although FDI loses its significance. The coefficient on the lagged dependent variable changes and gets larger, which is in line with the prediction that the LSDV bias entails a relatively larger downward bias on the AR-term. Overall, the results provide indication that the LSDV bias does not seem to be a problem for the validity of the FE estimates, at least for the variables of interest.

Table 9: GMM results, total trade

VARIABLES	(1) FE	(2) GMM
L.ln_Theil	0.720***	0.826***
	(0.0521)	(0.146)
L.totaltrade	-0.00762*	-0.0444*
	(0.00383)	(0.0251)
ln_rgdpe	0.138	0.0271
	(0.0889)	(0.211)
BL	0.0143	0.0333
	(0.0333)	(0.0759)
ValAddAgri	-0.00423	-0.0182
	(0.00606)	(0.0186)
L. tech	-0.237***	-2.075
	(0.0596)	(1.759)
L.fdi	0.00939**	0.0373
	(0.00459)	(0.0418)
2.quartile	-0.0388	0.165
	(0.0782)	(0.309)
3.quartile	0.00460	0.381
	(0.0989)	(0.448)
Observations	535	499
R-squared	0.646	
Number of id	36	32
Year FE	NO	NO
Number of instruments		24
Hansen Test		0.598
Sargan Test		0.932
AR(1)		0.00314
AR(2)		0.256

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

Table 10 contains the estimates obtained when using different version of the technology index, as described in section 3.2.3. Only the results for the preferred specification of the relatively aggregated trade variables are shown here (Column 4 of Table 2 and 3), and the original results using the cross-imputed index are displayed in columns (1) and (4) for comparison. The lagged dependent variable is omitted. Both the coefficients and the standard errors change very little when the alternative versions of the technology index are used, and the technology indices themselves also yield similar results, although the “part-tech” one is insignificant, which is in line with the fact that is contains fewer sectors and consequently yield less clear results.

Table 10: Robustness of FE results on aggregate trade to different technology indices

VARIABLES	(1) ln_Theil	(2) ln_Theil	(3) ln_Theil	(4) ln_Theil	(5) ln_Theil	(6) ln_Theil
L.totaltrade	-0.00787**	-0.00771*	-0.00806**			
	(0.00375)	(0.00384)	(0.00388)			
L.totalexp				-0.00186	-0.00196	-0.00201
				(0.00541)	(0.00531)	(0.00522)
L.totalimp				-0.00812	-0.00813	-0.00823
				(0.00802)	(0.00797)	(0.00794)
2.quartile	-0.00993	-0.00914	-0.0132	-0.00826	-0.00750	-0.0116
	(0.0757)	(0.0759)	(0.0754)	(0.0746)	(0.0749)	(0.0744)
3.quartile	0.0464	0.0461	0.0450	0.0498	0.0494	0.0483
	(0.0929)	(0.0935)	(0.0932)	(0.0922)	(0.0928)	(0.0926)
ln_rgdpe	0.127	0.121	0.129	0.123	0.118	0.125
	(0.125)	(0.129)	(0.128)	(0.126)	(0.130)	(0.130)
BL	-0.0120	-0.0106	-0.0130	-0.0125	-0.0111	-0.0135
	(0.0376)	(0.0377)	(0.0383)	(0.0379)	(0.0381)	(0.0387)
ValAddAgri	-0.00356	-0.00377	-0.00387	-0.00390	-0.00410	-0.00420
	(0.00552)	(0.00550)	(0.00559)	(0.00562)	(0.00563)	(0.00570)
L.fdi	0.0133**	0.0136**	0.0135**	0.0133**	0.0136**	0.0135**
	(0.00549)	(0.00554)	(0.00630)	(0.00568)	(0.00573)	(0.00646)
L.cross_tech	-0.247***			-0.246***		
	(0.0806)			(0.0809)		
L.all_tech		-0.246***			-0.246***	
		(0.0805)			(0.0807)	
L.part_tech			-0.234			-0.233
			(0.285)			(0.287)
Observations	416	416	416	416	416	416
R-squared	0.711	0.711	0.711	0.712	0.712	0.712
Number of id	25	25	25	25	25	25
Year FE	YES	YES	YES	YES	YES	YES

6 Conclusion

This paper has attempted to shed some light on the impact of trade on wage inequality in developing countries. It finds that impacts are very heterogeneous once relative endowments are taken into account and technology transfer effects are separated from trade effects. Introducing a new control variable of technological change, empirical findings demonstrate the need to control for this source of potential omitted variable bias, as some results change substantially, appear only when the variable is included, or even disappear with its inclusion. Most notably, evidence is found for an equalizing technology transfer through exports, which disappears once technological change is controlled for. This indicates a spurious correlation between the trade and the inequality variable which is really driven by technological change, and corrobates the need to include a measure of technological change in analyses of the impact of trade on inequality. Technological change itself has been shown to significantly decrease between-sectoral wage inequality, meaning that technological change in developing countries does not seem to be skill-biased, but rather benefits low-wage sectors disproportionately.

As for the "pure" trade effects, they are found to be generally in line with Heckscher-Ohlin theory. Equalizing impacts are mostly found for low-technology trade, and disequalizing for medium-low technology trade, confirming the predictions of the South-South trade hypothesis. However, the negative impact of high-technology trade remains puzzling.

The proposition made in the previous literature that trade to- and from developed countries is disequalizing due to technology transfer can only partly be confirmed. While some results indicate technology transfer, the effects are small and mostly do not stem from trade with developed countries, but rather from countries grouped in the third education quartile. Also, not only "middle-education" countries experience technology transfer, but also countries in the second-lowest quartile. Moreover, technology adoption is found to take place almost exclusively through trade with goods classified as medium-low technology, and effects go in both directions: some of the transferred technology is equalizing, while other parts are disequalizing.

References

Acemoglu, Daron (1998): Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality. Quarterly Journal of Economics, Vol. 113(4), pp. 1055–1089.

Acemoglu, Daron (2003): Patterns of Skill Premia. Review of Economic Studies, Vol. 70, pp. 199–230.

Arellano, Manuel/ Bond, Stephen (1991): Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment. Review of Economic Studies, Vol. 58(2), pp. 277–297.

Barro, Robert J. (2000): Inequality and Growth in a Panel of Countries. Journal of Economic Growth, Vol. 5, pp. 5–32.

Barro, Robert J./ Lee, Jong-Wha (2000): International Data on Educational Attainment: Updates and Implications. CID Working Paper No. 42.

Behrman, Jere R./ Birdsall, Nancy/ Székely, Miguel (2000): Economic Reform and Wage Differential in Latin America. Inter-American Development Bank Working Paper No. 435.

Berman, Eli/ Machin, Stephen (2000): Skill-Biased Technology Transfer. Evidence of Factor Biased Technological Change in Developing Countries. University of Boston Mimeo.

Berman, Eli/ Bound, John/ Griliches, Zvi (1994): Changes in the Demand for Skilled Labor within U.S. Manufacturing: Evidence from the Annual Survey of Manufacturers. Quarterly Journal of Economics, Vol. 109(2), pp. 367–397.

Berman, Eli/ Bound, John/ Machin, Stephen (1998): Implications of Skill Biased Technological Change: International Evidence. Quarterly Journal of Economics, Vol. 113(4), pp. 1245–1279.

Bernard, Andrew B./ Jensen, Bradford J. (1997): Exporters, Skill Upgrading, and the Wage Gap. Journal of International Economics, Vol. 42(1–2), pp. 3–31.

Bound, John/ Johnson, George (1992): Changes in the Structure of Wages in the 1980's: An Evaluation of Alternative Explanations. American Economic Review, Vol. 82(3), pp. 371–392.

Bourguignon, François J./ Morrisson, C. (1990): Income distribution, development and foreign trade: A cross-sectional analysis. European Economic Review, Vol. 34, pp. 1113–1132.

Calderón, César/ Chong, Alberto (2001): External sector and income inequality in interdependent economies using a dynamic panel data approach. Economics Letters, Vol. 71, pp. 225–231.

Card, David/ DiNardo, John E. (2002): Skill-Biased Technological Change and Rising Wage Inequality: Some Problems and Puzzles. Journal of Labor Economics, Vol. 20(4), pp. 733–782.

Coe, David T./ Helpman, Elhanan/ Hoffmaister, Alexander W. (1997): North.South R&D Spillovers. Economic Journal, Vol. 107(440), pp. 134–149.

Conceição, Pedro/ Ferreira, Pedro (2000): The Young Person’s Guide to the Theil Index: Suggesting Intuitive Interpretations and Exploring Analytical Applications. UTIP Working Paper No. 14.

Conceição, Pedro/ Galbraith, James K. (2000): Constructing Long and Dense Time-Series of Inequality Using the Theil Index. Eastern Economic Journal, Vol. 26 (1), pp. 61–74.

Conceição, Pedro/ Galbraith, James K./ Bradford, Peter (2000): The Theil Index in Sequences of Nested and Hierarchic Grouping Structures: Implications for the Measurement of Inequality through Time with Data Aggregated at Different Levels of Industrial Classification. UTIP Working Paper No. 15.

Conte, Andrea/ Vivarelli, Marco (2011): Globalization and Employment: Imported Skill Biased Technological Change in Developing Countries. The Developing Economics, Vol. 49(1), pp.36–65.

Cornia, Giovanni Andrea/ Kiiski, Sampsa (2001): Trends in Income Distribution in the Post-World War II Period. Evidence and Interpretation. UNU-WIDER Discussion Paper No. 2001/89.

De Santis, Roberto A. (2002): Wage inequality between and within groups: trade-induced or skill-bias technical change? Alternative age models for the UK. Economic Modelling, Vol.19, pp. 725–746.

Deininger, Klaus/ Squire, Lyn (1996a): A New Data Set Measuring Income Inequality. World Bank Economic Review, Vol. 10(3), pp. 565–591.

Deininger, Klaus/ Squire, Lyn (1996b): New ways of looking at old issues: inequality and growth. Journal of Development Economics, Vol. 57, pp. 259–287.

Dollar, David/ Kraay, Aart (2002): Growth is Good for the Poor. Journal of Economic Growth, Vol. 7, pp. 195–225.

Dollar, David/ Kraay, Aart (2004): Trade, Growth, and Poverty. The Economic Journal, Vol. 114, pp. 22–49.

Edwards, Sebastian (1997): Trade Policy, Growth, and Income Distribution. American Economic Review, Vol. 87(2), pp. 205–210.

Feenstra, Robert C. /Inklaar, Robert /Timmer, Marcel P. (2013): The Next Generation of the Penn World Table. Available for download at www.ggdc.net/pwt.

Feenstra, Robert C./ Hanson, Gordon H. (1996): Foreign Investment, Outsourcing and Relative Wages. In: Feenstra, Robert C./ Grossman, Gene M./ Irwin, Douglas A. (eds.): Political economy of trade policy: Essays in honor of Jagdish Bhagwati. MIT Press: Cambridge, pp. 89–127.

Feenstra, Robert C./ Hanson, Gordon H. (2001): Global Production Sharing and Rising Inequality: A Survey of Trade and Wages. NBER Working Paper 8372.

Figini, Paolo/ Görg, Holger (2011): Does Foreign Direct Investment Affect Wage Inequality? An Empirical Investigation. The World Economy, Vol. 34(9), pp. 1455-1475.

Goldberg, Pinelopi Koujinou/ Pavcnik, Nina (2007): Distributional Effects of Globalization in Developing Countries. Journal of Economic Literature, Vol. 45(1), pp. 39–82.

Goldin, Claudia/Katz, Lawrence F. (1998): The origins of technology-skill complementarity. Quarterly Journal of Economics, Vol. 113, pp. 693–732.

Gourdon, Julien (2011): Trade and Wage Inequality in Developing Countries: South-South Trade Matters. International Review of Economics, Vol. 58(4), pp 359–383.

Gourdon, Julien/Maystre, Nicolas, and Jamie de Melo (2008): Openness, Inequality, and Poverty: Endowments Matter. The Journal of International Trade & Economic Development, Vol. 17(3), pp. 343–378.

Haskel, Jonathan E./ Slaughter, Matthew J. (2002): Does the sector bias of skill-biased technical change explain changing skill premia? European Economic Review, Vol. 46(10), pp. 1757–1783.

Heckscher, Eli F. (1991): The Effect of Foreign Trade on the Distribution of Income. In: Heckscher, Eli F./ Ohlin, Bertil: Heckscher-Ohlin Trade Theory. MIT Press: London, pp. 39–69.

Jaumotte, Florence/ Lall, Subir/ Papageorgiou, Chris (2013): Rising Income Inequality: Technology, or Trade and Financial Globalization? IMF Economic Review, Vol. 61(2), pp. 271–309.

Judson, Ruth A./ Owen, Ann L. (1999): Estimating dynamic panel data models: a guide for macroeconomists. Economics Letters, Vol. 65, pp. 9–15.

Katz, Lawrence F./ Autor, David H. (1998): Changes in the Wage Structure and Earnings Inequality. In: Ashenfelter, Orley/ Card, David E: Handbook of Labor Economics, Vol. 3, Part A. North Holland: Amsterdam, pp. 1463–1555.

Katz, Lawrence F./ Loveman, Gary W./ Blanchflower, David O. (1995): A Comparison of Changes in the Structure of Wages in Four OECD Countries. In: Freeman, Richard B./ Katz, Lawrence F.: Differences and Changes in Wage Structures. University of Chicago Press: Chicago, pp. 25–66.

Köhler, Max/Sperlich, Stefan/Vortmeyer, Julian (2011): The Africa-Dummy in growth regressions. Courant Research Centre: Poverty, Equity and Growth Discussion Paper.

Krusell, Per/Ohanian, Lee E./Ríos-Rull, José-Víctor/Violante, Giovalli L. (2000): Capital-skill complementarity and inequality: a macroeconomic analysis. Econometrica, Vol. 68, pp. 1029–53.

Lee, Jong Wha/ Barro, Robert J. (1997): Schooling Quality in a Cross-Section of Countries. NBER Working Paper 6198.

Lewis, W. Arthur (1954): Economic Development with Unlimited Supplies of Labor. The Manchester School, Vol. 28(2), pp. 139–191.

Lipsey, Richard G./ Carlaw, Kenneth I. (2004):Total factor productivity and the measurement of technological change. Canadian Journal of Economics, Vol. 37(4), pp. 1118–1150.

Lundberg, Mattias/ Squire, Lyn (2003): The Simultaneous Evolution of Growth and Inequality. The Economic Journal, Vol. 113(487), pp. 326–344.

Machin, Stephen/ Van Reenen, John (1998): Differences and Changes in Wage Structure. Quarterly Journal of Economics, Vol. 113(4), pp. 1215–1244.

Meschi, Elena/ Vivarelli, Marco (2008): Trade and Income Inequality in Developing Countries. World Development, Vol. 37(2), pp. 287–302.

Milanovic, Branko/ Squire, Lyn (2007): Does Tariff Liberalization Increase Wage Inequality? Some Empirical Evidence. In: Harrison, Ann (ed.): Globalization and Poverty. University of Chicago Press: Chicago, pp. 143–181.

Nickell, Stephen (1981): Biases in Dynamic Models with Fixed Effects. Econometrica, Vol. 49(6), pp. 1417–1426.

Pissarides, Christopher A. (1997): Learning by Trading and the Returns to Human Capital in Developing Countries. World Bank Economic Review, Vol. 11(1), pp. 17–32.

Robbins, Donald (1996): Evidence on Trade and Wages in the Developing World. OECD Development Centre Working Paper No. 119.

Roodman, David (2009): PRACTITIONERS' CORNER: A Note on the Theme of Too Many Instruments. Oxford Bulletin of Economics and Statistics, Vol. 71(1), pp. 135–158.

Savvides, Andreas (1998): Trade policy and income inequality: new evidence. Economics Letters, Vol. 61, pp. 365–372.

Schiff, Maurice/ Wang, Yanling (2004): On the Quantity and Quality of Knowledge: The Impact of Openness and Foreign Research and Development on North-North and North-South Technology Spillovers. World Bank Policy Research Working Paper No. 3190.

Spilimbergo, Antonio/ Londoño, Juan Luis/ Székely, Miguel (1999): Income distribution, factor endowments, and trade openness. Journal of Development Economics, Vol. 59, pp.77–101.

Stehrer, Robert (2010): The effects of factor and sector biased technical change revisited. Economic Change and Restructuring, Vol. 43(1), pp. 65–94.

Stolper, Wolfgang F./ Samuelson, Paul A. (1941): Protection and Real Wages. Review of Economic Studies, Vol. 9(1), pp. 58–73.

Theil, Henri (1967): Economics and Information Theory. North-Holland: Amsterdam.

Thoenig, Mathias/ Verdier, Thierry (2003): A Theory of Defensive Skill-Biased Innovation and Globalization. American Economic Review, Vol. 93(3), pp. 709–728.

Topel, Robert H. (1997): Factor Proportions and Relative Wages: The Supply-Side Determinants of Wage Inequality. Journal of Economic Perspectives, Vol. 11(2), pp. 55–74.

UNCTAD (2011): Inward and outward foreign direct investment flows, annual, 1970-2010. URL: http://unctadstat.unctad.org/TableViewer/tableView.aspx?ReportId=88 (accessed on August 20, 2011).

Wood, Adrian (1997): Openness and Wage Inequality in Developing Countries: The Latin American Challenge to East Asian Conventional Wisdom. World Bank Economic Review, Vol. 11(1), pp. 33-57.

World Bank (2011): World Bank's World Development Indicators.

World Bank (2011): World Bank GNI per capita Operational Guidelines & Analytical Classifications. URL:

http://siteresources.worldbank.org/DATASTATISTICS/Resources/OGHIST.xls (accessed on November 18, 2013).

Wößmann, Ludger (2000): Specifying Human Capital: A Review, Some Extensions, and Development Effects. Kiel Working Paper No. 1007.

Zhu, Susan Chun (2004): Trade, product cycles, and inequality within and between countries. Canadian Journal of Economics, Vol. 37(4), pp. 1042–1060.

Zhu, Susan Chun (2005): Can product cycles explain skill upgrading? Journal of International Economics, Vol. 66, pp. 131–155.

Zhu, Susan Chun/ Trefler, Daniel (2005): Trade and inequality in developing countries: a general equilibrium analysis. Journal of International Economics, Vol. 65(1), pp. 21–48.

Appendix

Table A1: Sample means of key variables

Country	no. of years	Theil index	Total imports	Total Exports	Educ. quartile	Years of educ.	Value added in agri.	fdi	GDP
Argentina	15	0.0536	10.6412	6.7877	3.0	8.2	6.4	6.1	304353.3
Bolivia	28	0.0536	0.5097	0.3374	2.5	5.4	18.7	0.2	13899.3
Barbados	24	0.0332	0.1353	0.0821	3.0	7.4	8.3	0.0	3362.2
Chile	29	0.0540	4.1226	4.3859	3.0	7.2	7.6	1.5	89193.8
Cote d'Ivoire	13	0.0583	0.9025	0.8278	1.0	1.1	26.6	0.0	17788.2
Cameroon	19	0.1402	0.2542	0.3789	1.2	2.6	28.5	0.1	17648.0
Colombia	33	0.0353	3.3541	2.8829	2.0	5.2	17.4	1.4	193546.2
Costa Rica	14	0.0358	1.3998	1.5022	3.0	7.4	11.4	0.4	27947.3
Cyprus	18	0.0216	0.6370	0.6262	3.0	7.4	8.8	0.1	5965.0
Dominican Republic	15	0.0514	0.3381	0.2091	2.0	3.8	19.1	0.1	21662.8
Ecuador	36	0.0404	1.6860	0.8446	2.7	6.0	19.1	0.3	42319.6
Egypt	28	0.0413	3.8106	1.8650	1.3	2.8	21.8	1.1	115512.1
Fiji	29	0.0445	0.2342	0.1645	3.0	6.9	20.7	0.0	2971.8
Gambia	6	0.0113	0.0153	0.0072	1.0	0.6	29.1	0.0	708.7
Croatia	16	0.0066	2.8708	2.4570	3.0	8.1	13.9	0.1	37929.8
Indonesia	34	0.0767	0.0000	24.6476	1.0	5.2	14.3	1.9	706999.3
India	22	0.0789	2.3871	10.1750	1.0	2.7	29.7	0.8	1087365.8
Iran	17	0.0426	1.4578	3.2388	1.5	4.1	13.1	1.0	343571.6
Jamaica	29	0.1389	0.0000	0.1831	3.0	7.0	8.0	0.1	11558.4
Jordan	34	0.0812	0.4552	1.3835	2.1	5.8	5.2	0.6	14372.3
Kyrgyzstan	13	0.4664	0.0000	0.5713	3.0	9.2	32.2	0.2	10701.1
Mexico	33	0.0315	1.5306	7.2380	2.0	6.2	6.7	9.4	872260.1
Malta	30	0.0086	0.2748	0.7779	3.0	7.5	4.0	0.1	4039.4
Mauritius	21	0.0523	0.0000	0.6645	2.0	6.0	11.3	0.0	10488.3
Malawi	25	0.0515	0.0817	0.0486	1.0	1.6	41.8	0.0	5070.7
Panama	20	0.0444	0.1645	0.1272	3.0	6.9	8.4	0.0	14629.7
Philippines	34	0.0525	1.6733	7.1544	3.0	6.7	23.0	0.7	174302.7
Paraguay	2	0.0276	0.0000	0.3992	2.0	6.3	14.9	0.0	17912.8
Singapore	18	0.0616	7.0300	7.0914	2.0	3.8	2.0	0.4	20177.2
El Salvador	21	0.0565	1.1652	0.8147	2.0	5.0	13.9	0.3	5447.0
Syria	23	0.1291	0.0000	0.7751	1.0	4.7	26.5	0.1	28377.9
Trinidad and Tobago	28	0.1824	0.0455	0.7285	3.0	8.0	2.0	0.5	12481.7
Turkey	31	0.0485	3.1014	8.0675	2.0	3.8	22.8	0.5	418047.6
Uruguay	27	0.0561	0.1397	1.3917	3.0	7.5	10.1	0.3	28810.3
Venezuela	26	0.0417	3.3972	4.0079	2.3	4.6	5.3	0.5	131012.7
South Africa	8	0.0650	0.0000	24.8963	2.0	7.6	3.3	3.1	318447.6