Courant Research Centre
'Poverty, Equity and Growth in Developing and Transition Countries: Statistical Methods and Empirical Analysis'

Georg-August-Universität Göttingen
(founded in 1737)

Discussion Papers

No. 190

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November 2015

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

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Keywords: Wages, Inequality, Trade, Technology Transfer

Draft,04.11.2015

Summary

Since the expansion of world trade in 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 classical trade theory that in countries with high endowments of unskilled labor, their wages should rise relative to those of skilled labor. This paper empirically tests the effects of trade on wage inequality in a differentiated panel framework where 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, not yet addressed in the literature, is removed. With the inclusion of this measure, several effects otherwise attributed to trade disappear, underscoring the importance of controlling for technological change. Technology transfer as well as technological change is found to take place particularly in industries and trade flows classified as medium-technology intensive. 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] **Acknowledgments:** I would like to thank Stephan Klasen, Axel Dreher, Sunil Kanwar, Inma Martínez, Bernhard Brümmer, Atika Pasha, and the participants at of seminars and conferences at the ISI Delhi, the Delhi School of Economics, the Courant Centre Göttingen, the AEL workshop, and the RTG Globalization and Development workshops for helpful comments and suggestions, and Mathis Richtmann for valuable research assistance.

1. Introduction

In the 1980s, developing countries considerably lowered barriers to international trade, thereby substantially boosting trade flows. This comprehensive economic change has not been without distributional consequences. The Heckscher-Ohlin (H-O) 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 gain, while the scarce factor, experiencing the opposite effects, will lose from trade (Stolper and Samuelson 1941).

Developing countries, 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 both globalization and trade which may conflate or counteract any equalizing effects of trade on the income distribution.

Several papers have shown that trade has a differential impact of trade on inequality in high- and low-income developing countries and that this effect differs depending on the trading partner as well (e.g., Gourdon 2011, Meschi and Vivarelli 2007). The differential impact has been attributed to technology transfers from rich to poor countries, although this transmission channel is rarely tested directly (one notable exception being Conte and Vivarelli 2011, who find evidence of such transfers). Rising skill premia have indeed been shown to increase wage inequality not only in developed countries, but in developing countries as well (Berman, Bound and Machin 1998). Failing 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 and argue that all technological advancements stem from external sources. To support their claim, they refer to the low level of research and development activities, as first stated by Coe, Helpman and Hoffmaister (1997). While it may be true that there is very little domestically induced technological advance in earlier time periods (before the 1990s) for certain countries, it does not seem plausible for upper-middle income countries such as South Korea, Spain, or Slovenia even in earlier years of the sample periods used, or for countries like India in the early 2000s.

Another shortcoming of many empirical papers using the H-O model to test the effects of trade on the income distribution is the timing of the trade effect. Certain factors of production cannot be assumed to be mobile between sectors in the short run, and hence the predicted effects may not be visible in a contemporary or one-year lagged specification. The Ricardo-Viner model (Viner 1931, Jones 1971, Mussa 1974), introducing specific factors into the theoretical framework, is often interpreted as a short-run version of the H-O model and is thus likely to better capture the effects within the time horizon of a few years which can be feasibly estimated with the available data. According to the model, immobile factors of production may lose from trade if employed in import-competing industries, even if they are overall relatively abundant. The opposite holds true for relatively scarce factors which are employed in exporting industries and which may gain from trade in the short run. With skilled labor being one of the most frequently cited examples of a specific factor, the model is highly relevant in the context of this paper in which skill premia are a key mechanism in driving up wage inequality.

This paper addresses the identified shortcomings of previous studies in several ways. First, it directly measures the technology content embedded in trade by categorizing trade flows into different technology levels. Second, it includes a new measure of technological change to address potential omitted variable bias. The measure captures movements in the technological frontier, which is estimated using data envelopment analysis (DEA) and based on the same raw data used in the inequality index. It is hence able to control for advancements in technology in exactly those sectors included in the inequality measure as well. Differentiating between imports and exports helps to disentangle the two technology transmission channels. Furthermore, different types of hypotheses can be tested on the two variables. In particular, the H-O model does not provide any insights into the effect of imports, whereas the specific factors model provides clear distributional implications with respect to import-competing industries.

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 lengthy 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 35 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. Technology transfer is taking place through medium-high technology trade flows in particular, and in country groups with medium skill endowments. The disequalizing effects exclusively stem from trade with countries in the third education quartile, that is, with medium-high skill endowments. 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 found in previous studies. Quite to the contrary, the effects that can be found indicate that trading with countries that are better endowed with skilled labor has equalizing effects on the income distribution. Whether this effect stems from technology transfer or is due to import competition effects, as predicated in the specific factors model, cannot however be tested here.

Although there is a large recent literature emphasizing the impact of trade on wage inequality within industries and occupations (broadly categorized into effects due to heterogeneous firms, labor market frictions, and incomplete contracts), the present study focuses exclusively on inequality between sectors and refers to sector-based classical trade theory. Although this choice is partly dictated by the nature of both the wage inequality data as well as the sector-based classification of the trade data, both of which are only available at a sectoral level, this paper addresses several of the previously identified shortcomings of existing sector-based studies. Results suggest that the lack of strong results pertaining to the effects of the neoclassical, sector-based mechanisms is at least partly due to flaws in the empirical approach of estimating the relationship between trade and inequality. Moreover, some of the explanations subsumed as challenges to the neoclassical trade theory, such as Feenstra and Hanson's (1996) offshoring argument (as, e.g., in Harrison, McLaren, and McMillan 2011) can be easily incorporated into the sector-based model.

Taking a detailed look at the available inequality data, several studies have identified changes in the upper quintile of the income distribution 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 during the 1980s and 1990s, which translates in most cases into an increase in wage inequality. The two decades are particularly interesting and are the focus of most empirical studies because not only has inequality gone up, but many countries have opened their economies to trade at the same time.

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 H-O-SS predictions, trade has been found to be only of minor importance for the large increases in inequality in the 1980s and 1990s. 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 DiNardo 2002 for a more critical review of the SBTC hypothesis and Kurokawa 2014 for a survey of trade-based versus other explanations). The basic reasoning behind this 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). More recent studies focusing on European countries ascribe a larger role to trade in increasing inequality through exporter wage premia (Klein, Moser, and Urban 2013; Egger, Egger, and Kreickemeyer 2013; Baumgarten 2013), which is even more pronounced if import penetration is also accounted for (du Caju, Rycx, and Tojerow 2012). The latter study even finds that the negative impact of imports on wage levels is larger for trade with developing countries. However, it remains unclear how large the contribution of trade is to overall wage inequality, and whether corresponding effects are present in developing countries.

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 in Asia, Latin America, and Europe have experienced increasing income inequality over the 1980s and 1990s, this is not generally true for low-income countries, particularly in Sub-Saharan Africa (Jaumotte, Lall and Papageorgiou 2013). Several countries, in particular in Latin America, have also experienced marked decreases in income inequality since the mid-1990s (Cornia 2014). This differentiated pattern of 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 of trade on inequality 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. The empirical analysis is covered in section 3, which introduces the data and motivates the empirical specification. Estimation results are discussed in section 4. Robustness checks are presented in section 5, and section 6 concludes.

2. Literature review

2.1. (Skill-biased) technological change

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 (e.g., Berman, Bound and Machin 1998), particularly in emerging economies such as India, Hong Kong, and several Latin American countries (for a review 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 [2] in developing countries, thereby reinforcing the disequalizing effect of rising skill premia. Imports 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). Imported capital goods 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 Székely 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 can have effects through both the import- and the export channel. Feenstra and Hanson (1996, 2001) argue that their impact on wage inequality is 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. The manufacturing sector therefore seems particularly prone to such effects.

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

[2] 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.

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's 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, wherein 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 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) and Matsuyama (2007), who argue 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 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 through 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).[3] 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 reduced – implying a larger wage gap. Davis (1996) has formalized this point in a theoretical model on the effects of 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 previously mentioned, the results of "early" studies (meaning that neither technology nor trade between developing countries is taken into account) on the impacts of trade liberalization on the income distribution in developing countries are mixed. Most of them use the Gini coefficients from Deininger and Squire (1996) 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, and Calderón and Chong 2001). Positive effects are identified by

[3] 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.

Lundberg and Squire (2003), Cornia and Kiiski (2001), and Spilimbergo, Londoño and Székely (1999). Barro (2000), Savvides (1998), and Milanovic and Squire (2007) all conclude 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 affected equally by trade.

Several authors have acknowledged the difficulty of drawing conclusions about the relationship between trade and income inequality from these studies because comparability is limited due to differences in the countries and time periods covered, the choice of the inequality- and the openness variables, and the econometric specification and methodology used (Milanovic and Squire 2007, Lundberg and Squire 2003).Consequently, other approaches have been developed to explain the apparent lack of a clear-cut relationship between trade and inequality in developing countries, of which the SBTC and technology transfer arguments have received the most 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. The role of technology: SBTC and technology transfer

A large number of country case studies investigate the interrelationships between technology, trade, and inequality in developing countries. Most of them find evidence for trade-induced technological change driving up skill premia and inequality – an exception being Ferreira, Leite, and Wai-Poi (2007), who conclude that trade has led to a decrease in inequality through sector reallocation effects of employment, as suggested by H-O theory. For a review, see Robbins (1996) on early evidence and Gourdon (2011) for more recent studies. The number of cross-country studies on the other hand 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. 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, while 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 the skilled and unskilled in low and middle income countries. According to their results, trade-induced technological upgrading entails not only a relative, but an absolute skill bias also since it not only increases the absolute employment of skilled workers, but decreases the number of unskilled workers as well. However, the analysis does not control for the supply of skilled and unskilled labor. Robbins (1996), including various direct measures of labor supply, 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. López-Calva and Lustig (2010) argue that an educational expansion, lowering the gap between skilled and unskilled labor, is one of the main factors responsible for the decrease in labor income inequality observed in Latin America over the 2000s. 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) measure technological change by the share of information and communications technology capital (ICT) in the total capital stock in their analysis of both advanced and developing countries and conclude that the main driver of inequality is technological change, above and beyond its effect through trade. Trade is found to reduce inequality, though mainly through exports of agricultural products, with no separate effect of manufactured goods.

2.3.2. 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. Inter-industry wage inequality is then regressed on North-South and South-South trade as well as the respective previously identified effects of technology transfer. This procedure allows for 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, 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 (1996) 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. Further 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. However, no measure is included 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). The present paper therefore differentiates trade flows by technology, thereby measuring the inherent skill content of trade. This enables the testing of whether it is indeed more skill-intensive technology which increases wage inequality through technology transfer.

2.3.3. Summary and Hypotheses

The main innovation of this paper vis-à-vis the existing studies is the introduction of an index of technological change, representing the most important control variable in the empirical analysis. The paper furthermore expands on existing studies in three ways: i.) it employs a comparative advantage-based rather than an income-based country classification; ii.) it classifies trade flows according to their technology content – measured by the degree of human capital necessary to produce the goods, which allows for the testing of which types of technology matter most for wage inequality in developing countries, and whether it is indeed more skill-intensive technology which raises inequality the most; and iii.) it uses a consistent version of the Theil index of inter-industry wage inequality, based exclusively on the UNIDO industrial statistics, with comparable values over time containing the same sectors every year. The sectoral classification used for the computation of the inequality index is the same as for the trade data as well as the classification of industries into different skill levels, and is therefore able to capture the effects of trade on between-sectoral inequality in manufacturing quite well.

A number of hypotheses regarding the effects of different types of traded goods, different groups of trading partners, and different receiving countries can be derived from the literature. For aggregate trade flows, 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.

As for different levels of technology, a disequalizing (i.e., positive) impact is expected for trade in higher levels of technology, both due to technology transfer as well as H-O effects. Low-technology trade is expected to decrease inequality through exports, while no effect should be present for imports if one believes the predictions of the specific factors model.

The next set of hypotheses pertains to the differential impacts in countries of different relative skill endowments. Country group interactions are used to test whether the effects of trade on wage inequality differ between particular groups of countries. South-South trade theory suggests that medium-low technology exports have a particularly strong disequalizing impact in the medium-education countries, since this is where their comparative advantage is located. The “absorptive capacity” argument would furthermore suggest that technology transfer effects of medium- and high-technology imports are stronger (in absolute terms) in the more educated trading partners, i.e. UMECs and LMECs. Overall, we therefore expect to find strong disequalizing effects of medium-low technology in the LMEC and UMEC groups. A structured summary of the hypotheses derived for the different country groups is presented in Table 1.

Table 1: Hypotheses by technology level and country group

	H-O theory (SS trade version)	Specific factors model	Technology transfer	Overall
High technology exports	+	+	+ (in UMEC)	+
Medium-low technology exports	+ (in UMEC/LMEC)	++	+ (in UMEC/LMEC)	++
Low technology exports	-	?	?	-
High technology imports	?	--	+ (in UMEC)	-
Medium-low imports	?	-	+ (in UMEC/LMEC)	?
Low technology imports	?	?	?	?

Note: HEC=High-education country (highest quartile), UMEC=Upper-middle education country (third quartile), LMEC= Medium-low education country (second quartile)

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. Countries are typically classified into different levels of development according to their income, 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 the two) 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 (2013) and extrapolated for the years missing between the 5-year intervals in which the original data are reported.[4] 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

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

the 60 countries and total of 1151 observations used in the estimation sample, 20 percent are classified as LEC, 41 percent as LMEC and 39 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 section.

3.2.2. Trade and technology

The data on trade consist of the total value (in billions of US dollars) of yearly bilateral trade flows between country pairs, provided by the UN Comtrade database.[5] Traded products are coded according to their technology level. The technology classification is taken from Loschky (2010), who calculates R&D intensities of product groups at the ISIC Rev. 3 level.[6] Three categories of technology intensity are employed: Low technology (LT), medium-low technology (MT), and medium-high to high technology (HT). Aggregation is again carried out by adding up the total value of yearly trade in each technology category, separately for imports and exports.

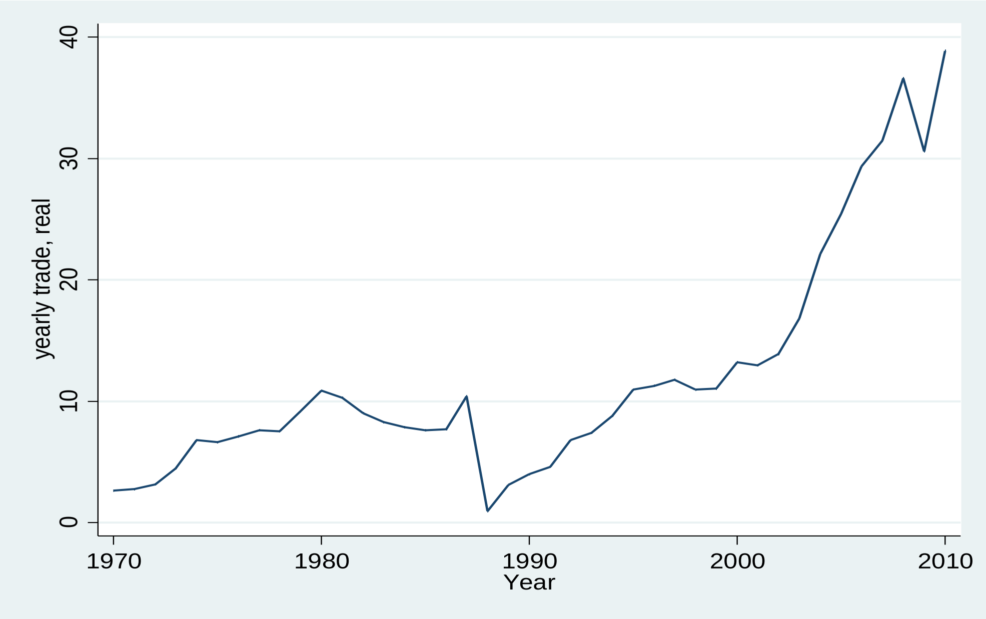
The following graphs depict some basic trends in the trade data. Figure 1 shows the rise in developing country trade (estimation sample average) in billions of USD over the sample period. Trade has grown tremendously between 1970 and its peak value in 2010. The share of

[5] Because the trade data are not available in the ISIC scheme, they have 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 are only available in ISIC Rev.1, for which there is no direct correspondence table to ISIC Rev.3. The data therefore have 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.

[6] 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.

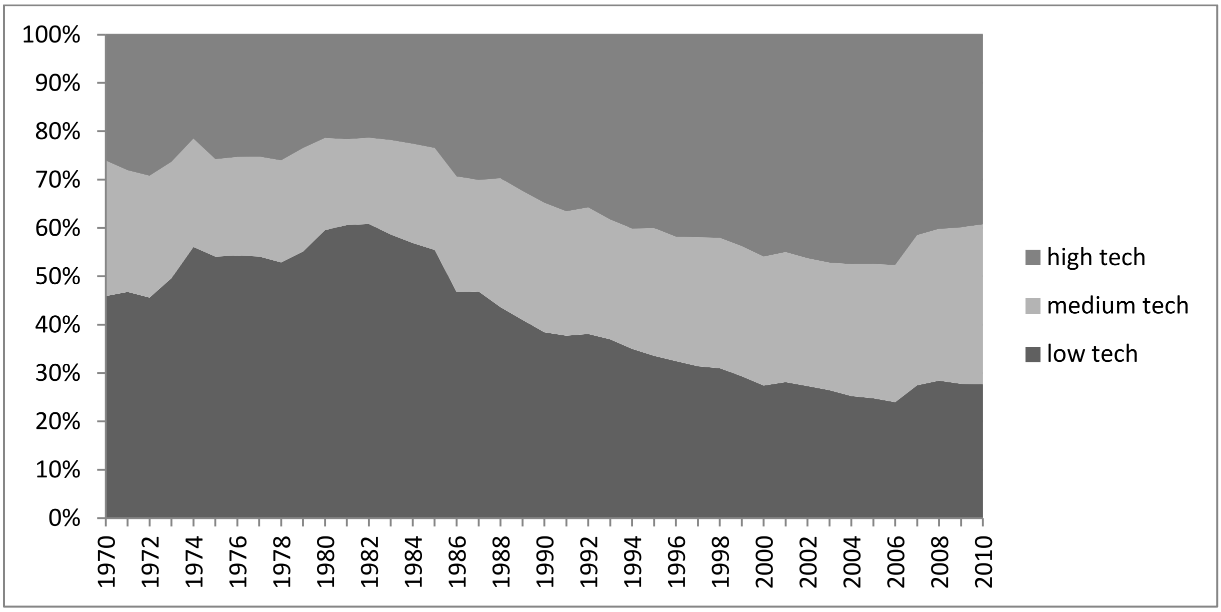
trade with relatively more high-technology intensive goods has also risen over time, as is apparent from Figure 2.

Figure 1: Total developing country trade, in constant (2005) US $ bn.



Note:nominal USD values from comtrade have been deflated using the US GDP deflator from the WDI.

Figure 2: Trade by technology levels (imports and exports)



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 for the purpose of this paper. 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 and where household formation and composition plays an important role. 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. Also, 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 2010. Although a similar index has been built by the University of Texas Inequality Project (UTIP), it is not clear which data enter their index, as the raw data require 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 (1996) more frequently used individual-based dataset of Gini coefficients can be found in Conceição and Galbraith (2000). The main results are robust to using the UTIP index rather than the newly calculated index, as discussed in the robustness checks.

Similar to 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. First, 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. Second, 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 kinds 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 to include not only the obvious *sector*-specific SBTC, but also the pervasive,asymmetric *factor*-biased SBTC because it affects some sectors more than others.[7]

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. A numerical example for the problem can be found in part B of the appendix. However, there is little reason to suspect that results will be distorted systematically, and the 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 more than 3000 observations over the years 1970-2010, but the observations and countries covered are reduced substantially in the course of the sample construction. The between-sector component of the Theil is defined as

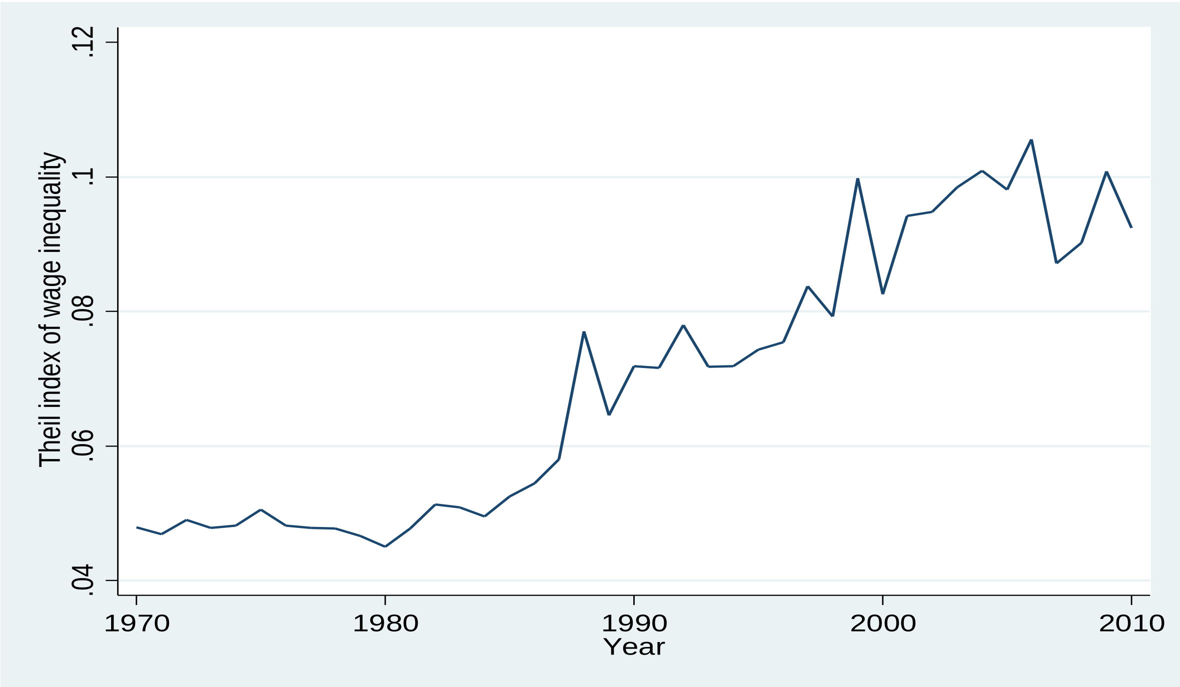
$$\mathrm{T}' = \sum_{g=1}^{G} \mathrm{Y_g} \log \left(\frac{\mathrm{Y_g}}{\mathrm{n_g}}\right)$$

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 population 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. First, the sector's wage share can be interpreted as the weight with which each sector enters the measure. Second, 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

[7] 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.

bound value of zero, indicating a perfectly equal distribution of income. The measure has no fixed 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 (1970-2010) is displayed in Figure 4. As with trade, there is a clearly discernible upward trend over time.

Figure 3: 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 consequently be underestimated. Zhu and Trefler (2005) use labor productivity to measure technological change and also find a positive relationship with trade. Gourdon (2011) 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 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 the 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. Of the several available productivity indices, a Färe-Primont index[8] 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 are scarce, and using the TFP technological frontier reduces the sample by 40%, despite the imputation of missings as described below. 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. The correlation analysis between the total- and the labor-productivity indices for those cases where both are available suggests 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

[8] The Färe-Primont index has been developed by O’Donnell (2011) and is based on the ratio of two versions of the (more commonly known) Malmquist index developed by Färe and Primont (1995).

country coverage, and the TFP index is employed as a robustness check, yielding similar results. As the data are reported at the sectoral level, sectors are "production units" in the estimation of productivity.[9] 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 versions 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), one wherein the same procedure is applied but only those sectors which have less than 50% missings are used, and one wherein all sectors are used and missings are substituted for with values from the same sector in earlier years.[10] The index relying on cross-imputed values is used in the preferred estimations as it adds no "new" information from other years to the data in a given year. As a robustness check, the other two indices are tested as well and the results show that they yield virtually the same estimates (Table 6).

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 come 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 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 pressure on high-skilled wages, and reduce skill

[9] Productivity is estimated separately across country, as the DPIN program does not allow a multi-level equation system (country and sectoral level). Values can therefore only be meaningfully compared within a country over time. Though the within-estimator is used in the empirical analysis, this does not represent a problem here.

[10] Values from earlier years are used in order to not overestimate technological progress, which can reasonably be 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.

premia. The same linearly interpolated Barro and Lee (2013) data are used as for the country classification.[11]

FDI

Inward FDI flows (taken from UNCTAD) are included (in Mio. USD) 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 in absolute terms 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. On the other hand, larger economies tend to trade less in relative terms due to a larger domestic market, so the overall effect remains unclear. Real expenditure-based GDP in (2005) PPP adjusted US dollars is taken from the Penn World Tables, Version 8.0 (Feenstra, Inklaar and Timmer 2013), and the variable enters in logarithms.

A list of the countries in the sample, as well as the in-sample means of the most important variables can be found in appendix Table A1.

3.3 Model specification

The basic model has the following functional form:

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

Indices t and i denote 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

[11] The fact that the same measure is used does not affect the estimates, neither for the aggregated, nor the disaggregated (education-based) country group data. In fact, the impact of the education variable on the coefficients of interest is negligible. Results are available upon request.

the adoption of imported technology.[12] 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 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 (primarily of the lagged dependent variable) 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: First, the LSDV bias is a problem of small T, and although an average of 16-19 years is not yet "large T" (starting from around 20 years), it is not considered small either. Second, while the bias is quite severe in the autoregressive (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, indicating that the LSDV bias is not a problem in the present sample given that the more precisely estimated coefficients change very little between fixed effects and the GMM specification and even increase in several instances.

3. Results and discussion

For testing hypotheses about the impact of trade on wage inequality 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 trade variables would rise to 72, which is not operational given that the number of cross-sections is around 60. The approach taken is to start from the most aggregated level and to move stepwise to more disaggregated specifications. Total trade values are investigated first, before moving to exports and imports

[12] 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.

separately. Each group is further disaggregated by technology, and differential impacts in countries of different relative education levels are tested in the next step.

The technological change variable is included with a two-year time lag in the preferred specification. This is done because in its contemporary version, technological change is likely to be influenced by trade itself, which also enters the model with a one period lag. The impact of the variable is interpreted as follows: If the coefficients are affected by the inclusion of the variable, this means that the observed effects on wage inequality are possibly not due to trade, but rather that both variables are at least partly driven by domestic technological change. The effect can of course also go the other way, i.e., technological change can be disequalizing and generate trade flows which have per se an equalizing impact, in which case the two opposing effects may become apparent only after technological change is controlled for.

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 according to its comparative advantage, which is reflected in the export structure. The specific factors model on the other hand would suggest that imports may have distributional effects. In particular, skill-intensive imports may lower the gains from trade for those at the upper end of the wage distribution and thereby mitigate disequalizing technology transfer effects which exert pressure on skill premia.[13]

4.1 Aggregate Trade

Table 3 shows the results for the most basic specification, where all trade flows (imports and exports) have been added up.[14] Trade has a significant and negative impact on wage inequality, but in terms of economic size, the effect is rather small. According to the coefficient estimate, a 1 billion dollar increase in trade reduces wage inequality by little over 0.04 percent. The effect persists with the inclusion of the control variable for technological change (column 2), but is reduced substantially and becomes insignificant. This indicates that a major part of the effect on wage inequality attributed to trade might indeed stem from technological change, which, in line with expectations, leads to higher wage inequality and is significant at the five percent level. As for the remaining insignificant control variables, FDI has the expected positive coefficient, but the sign on the education variable is not in line with

[13] Low-skill intensive imports on the other hand could theoretically increase wage inequality since they compete with local industries employing labor from the lower end of the wage distribution. However, low-skilled labor is arguably much less specific than skilled labor and hence less susceptible to such effects.

[14] Including imports and exports separately does not yield any new insights, with neither variable being individually significant. Results are available upon request.

expectations: a higher (short-run) supply of skilled labor, as captured by the "years of education" control variable, does not seem to lower the pressure on skill premia. Rather, even within the already more homogeneous country groups, a better educated workforce is associated with more inequality. Although insignificant, the fact that the variable is reduced substantially by the inclusion of the technological change control variable suggests that this effect could have something to do with its absorptive capacity, wherein a more educated workforce is more apt to adopt (inequality-increasing) technology. A higher share of unskilled workers, proxied by the share of value added from agriculture in GDP, does not seem to have any appreciable impact on wage inequality given the small and volatile coefficient. Finally, a higher GDP seems to be associated with lower inequality, which might have to do with the fact that large economies trade relatively less, but the effect is not significant either.

Table 2: Results total trade

	(1)	(2)	(3)	(4)
VARIABLES	ln_Theil	ln_Theil	ln_Theil	ln_Theil
L.ln_Theil	0.789***	0.781***	0.788***	0.781***
	(0.0335)	(0.0365)	(0.0342)	(0.0368)
L2.tech		**0.244****		**0.243****
		(0.0915)		(0.0917)
L.totaltrade	**-0.000415***	**-0.000105**		
	(0.000237)	(0.000509)		
L.lowtech			-0.00152	0.000747
			(0.00229)	(0.00328)
L.medtech			0.00107	-0.000814
			(0.00193)	(0.00320)
L.hightech			-0.000722	-0.0000161
			(0.000563)	(0.000889)
GDP	-0.0662	-0.0280	-0.0692	-0.0258
	(0.0716)	(0.0865)	(0.0759)	(0.0910)
edcuation	0.0189	0.00790	0.0199	0.00763
	(0.0352)	(0.0347)	(0.0351)	(0.0353)
ValAddAgri	0.00224	-0.000368	0.00213	-0.000188
	(0.00414)	(0.00429)	(0.00427)	(0.00463)
L.fdi	0.00290	0.00290	0.00252	0.00299
	(0.00414)	(0.00322)	(0.00415)	(0.00338)
2.quartile (LMEC)	0.0919	0.0915	0.0926	0.0903
	(0.0678)	(0.0852)	(0.0681)	(0.0858)
3.quartile (UMEC)	0.119	0.115	0.120	0.114
	(0.0819)	(0.1000)	(0.0825)	(0.0999)
Observations	1,151	903	1,151	903
R-squared	0.689	0.679	0.689	0.679
No. of countries	60	58	60	58
Year FE	YES	YES	YES	YES

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

To check whether the effect is driven by trade of a particular technology intensity, trade flows are decomposed into low-, medium-, and high technology in columns 3 and 4 of table 2. Although none of the coefficients are significant, it is interesting to again note the substantial decrease in the coefficients on all three variables once the technological change control is included in column 4. The sign on the low- and medium-technology coefficients even reverses. This again provides indication that the previously discussed problem of omitted variable bias is present, and that controlling for technological change is important[15] in order not to falsely attribute technology effects to trade.

4.2 Disaggregated Results: Technology

Next, imports and exports are considered separately, while at the same time retaining the three different technology levels. Columns 1 and 2 of table 3 show the export regressions and columns 3 and 4 the import ones. Total imports (exports) are included as a control variable, and the first and second column of each panel contain the estimates with and without the technological change control, respectively, as also indicated in the top row. The full set of the previously discussed control variables is included, but omitted from the table for simplicity[16].

Table 3: Results imports and exports by technology levels

	(1)	(2)	(3)	(4)
	Exports		Imports	
VARIABLES	No tech	Tech(-2)	No tech	Tech(-2)
L.lowtech	-0.00462	-0.00119	0.00827	0.00206
	(0.00306)	(0.00352)	(0.00801)	(0.00864)
L.medtech	**0.00692****	0.00337	-0.00968	-0.00512
	(0.00313)	(0.00448)	(0.00600)	(0.00583)
L.hightech	-0.000422	-1.11e-05	-0.00122	-0.000582
	(0.00143)	(0.00147)	(0.00148)	(0.00199)
L.totalimp/exp	-0.00187	-0.00158	0.000544	0.000712
	(0.00132)	(0.00147)	(0.000853)	(0.000498)
Observations	1,151	903	1,151	903
R-squared	0.690	0.679	0.690	0.679
No. of countries	60	58	60	58
Control variables	YES	YES	YES	YES
Year FE	YES	YES	YES	YES

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index of wage inequality.

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

[16] The estimates for the control variables for columns 2 and 4 can also be found in appendix table A4, columns 1 and 3.

A few interesting results emerge. Firstly, high-technology trade remains negative and insignificant for both exports and imports. Secondly, the signs on both medium- and low-technology trade flows are opposite for imports and exports. The equalizing impact of low-technology exports as well as the disequalizing effect of medium technology exports are in line with expectations and the hypotheses derived from South-South trade theory. Thirdly, while it seems that medium-low technology exports are significantly increasing wage inequality, this effect disappears with the inclusion of technological change in column 2. It would appear that technological change is driving at least part of the positive impact of medium-low technology trade – in fact, the coefficient estimates suggest that around half of the effect is due to technological change rather than trade. Finally, it is also worth noting that once the trade flows are disaggregated a bit more, some of the coefficients are substantially larger than those on the aggregate trade variable from table 2. For example, the coefficient estimate of column 1 would imply that a billion dollar increase in medium-technology intensive export reduces wage inequality by approximately 0.7 percent (although, as just discussed, the effect actually attributable to trade is only around half of that).

4.3 Disaggregated Results: Country Groups

As summarized by the hypotheses in Table 1, the next set of regressions uses country interactions to test whether differential effects materialize in particular groups of countries. The lack of results for high-technology trade, for example, could be due to opposing effects in different country groups which offset each other, which can be disentangled in this more differentiated set-up. Whether these can be attributed to imports and exports separately is then also tested. Estimation results are presented in Table 4 and are ordered according to technology, starting with high technology trade. Again, the control variables are included, but not shown. Results for total trade, comprising both imports and exports, is shown in the first panel (columns 1 and 2), and exports and imports are separately accounted for in panels 2 and 3, respectively.

In line with the results from the previous set of regressions, the effects of high-technology exports are nowhere near significance, neither for total trade, nor the export and import regressions. In particular, there is no evidence for a disequalizing technology transfer through imports in the more educated country groups, where the coefficients are in fact negative.

The results from columns 1 and 2 indicate that the previously found positive coefficient on medium-technology trade mainly occurs in the more educated country groups, which is in line with the with the South-South trade logic and the adaptive capacity argument. Both exports

Table 4: Results by technology level and country group

	(1)	(2)	(3)	(4)	(5)	(6)
	Total trade		Exports		Imports	
VARIABLES	No tech	Tech(-2)	No tech	Tech(-2)	No tech	Tech(-2)
L.ht_trade	0.0107	0.0121	-0.0232	-0.0132	0.0137	0.0166
	(0.0175)	(0.0154)	(0.0287)	(0.0296)	(0.0195)	(0.0203)
LMEC*L.ht_trade	-0.0121	-0.0140	0.0205	0.00279	-0.0147	-0.0165
	(0.0176)	(0.0154)	(0.0299)	(0.0318)	(0.0195)	(0.0200)
UMEC *L.ht_trade	-0.0104	-0.0120	0.0244	0.0127	-0.0137	-0.0166
	(0.0177)	(0.0158)	(0.0292)	(0.0300)	(0.0196)	(0.0205)
L.mt_trade	-0.0181	-0.0196	0.00300	-0.0124	-0.0371	-0.0338
	(0.0129)	(0.0128)	(0.0139)	(0.0178)	(0.0232)	(0.0252)
LMEC*L.mt_trade	**0.0198**	**0.0263***	0.0105	0.0401	0.0227	0.0299
	(0.0130)	(0.0137)	(0.0183)	(0.0259)	(0.0244)	(0.0269)
UMEC*L.mt_trade	0.0174	0.0170	-0.00361	0.0101	0.0301	0.0253
	(0.0132)	(0.0130)	(0.0150)	(0.0178)	(0.0247)	(0.0269)
L.lt_trade	**0.0185***	**0.0178***	0.0113	0.0181	**0.0468***	**0.0359**
	(0.00961)	(0.00973)	(0.00957)	(0.0125)	(0.0273)	(0.0304)
LMEC*L.lt_trade	**-0.0193****	**-0.0229****	**-0.0195***	**-0.0310****	-0.0363	-0.0387
	(0.00944)	(0.0109)	(0.0109)	(0.0153)	(0.0278)	(0.0328)
UMEC*L.lt_trade	-0.0194*	-0.0163	-0.00949	-0.0146	-0.0501	-0.0383
	(0.0100)	(0.0111)	(0.0107)	(0.0147)	(0.0305)	(0.0353)
Observations	1,151	903	1,151	928	1,151	903
R-squared	0.689	0.680	0.690	0.302	0.691	0.680
No. of countries	60	58	60	58	60	58
Control variables	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index of wage inequality.

and imports have a disequalizing impact, but are not separately significant. Despite not being significant, the results on medium-low tech exports confirm the previous patterns: the coefficients are highly affected by the inclusion of the technological change control variable, with the coefficient increasing substantially for LMECs, and turning positive for UMECs. No such effects are found for imports, rendering credibility to the story of a third variable bias through technological change, which works via exports.

For low technology trade, surprisingly, a significant disequalizing effect emerges in the least educated country groups. When consulting columns 3-6, it is clear that this effect arises mainly through low-technology imports, where the coefficients are larger and the positive coefficient in LECs is significant as long as technological change is not included. One explanation for the disequalizing impact could be import competition; another one could be the introduction of labor-saving technology. The lack of results pertaining to low technology imports once technological change is controlled for supports the hypotheses derived from the

H-O and the specific factors models, as they do not predict any effects for low-skill (and hence unspecific) factor intensive imports. The negative coefficients in the other country groups on the other hand are in line with H-O theory, with clearer results for exports, which are significant for LMECs.

Another point worth mentioning is that again, coefficients increase compared to the previous, more aggregate specification. It seems that the more detailed the specification, the more it is able to capture the various heterogeneous effects of trade flows, which, at the aggregate level, cancel each other out and lead to a very small overall effect. To provide an example of the size of the impact, the significant coefficient in lower-middle education countries indicates that a billion dollar increase in of low-technology exports decreases wage inequality around 3 percent in these country groups. Given the yearly mean of 5.7 billion for LMECs a, this is a potentially rather powerful equalizer. It is also worth noting that again, the import coefficients are affected much less than the export by the inclusion of the technological change control variable, supporting that the variable indeed captures what it is supposed to: domestic technological change, rather than technological change through trade.

Summary of results

Summing up the insights obtained from the regressions, one can extract four main findings from the many results. First, although the coefficients are mostly insignificant, low-technology trade seems to be generally equalizing, as predicted by H-O theory.

Second, medium-low technology exports have positive coefficients and seem to be disequalizing in all but the countries in the lowest education quartile. This finding fits with the South-South trade story as well as the technology transfer hypotheses, in particular the absorptive capacity argument.

Third, there is evidence of technological change driving both exports and inequality in the export regressions, in particular in the medium-low technology sectors and in the more skill-abundant countries, underscoring the need to control for the variable. As expected, the technological change control plays a lesser role for imports, with a lot of coefficients remaining virtually unchanged with the inclusion of the variable, which is in stark contrast to the export results and renders credibility to both the measure and the supposition of omitted variable bias.

Lastly, in contrast to the findings of previous studies, no results emerge for high-technology trade. While it may not be surprising that there are not findings pertaining to exports since little domestic technological advancements in high-tech sectors can be expected in the countries which are relatively less endowed with skilled labor, the fact that there are also no results for imports is surprising. In fact, not only are there no significant positive effects, but the coefficient on high-technology imports is negative throughout all specifications, as well as in upper-middle education countries which arguably are the most apt to introducing such technology. Rather, most technological advancements seems to take place in medium-low technology sectors, both through domestic technological change which also boosts exports, and through technology transfer through imports in the relatively more educated country groups. The latter result should be taken with caution, however, since none of the import coefficients are significant.

5 Robustness tests

Although the structure of the present dataset is not ideal for GMM estimation given the comparatively long T of 16-19 years relative to the number of groups (58-60), 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 “too many instruments”, weakening the Hansen test of (Roodman 2009), the instrument set has been restricted in several ways. The results from difference GMM two-step estimation are shown in columns 2 and 4 of 30Table 4, and compared with those obtained using FE in columns 1 and 3. Instruments are restricted to the first few valid lags, and are additionally collapsed in order to keep the number of instruments down. Orthogonal deviations are used in order to mitigate the unbalancedness of the panel. Since the concern here is exclusively with the LSDV bias, only the lagged dependent variable is treated as endogenous. Results show that the negative impact of trade does not vanish when GMM is employed – only some of the coefficients are reduced slightly. Generally, the more precise the coefficient estimate, the more stable it is across different specifications. Some of the more precisely estimated coefficients (most notably, the technological change control variable, but also trade) even slightly increase with the GMM estimator. The coefficient on the lagged dependent variable does increase more substantially, 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 LSDV bias does not threaten the validity of the FE estimates.[17]

[17] The results for the remaining specifications can be found in appendix tables A1.1 and A1.2

Table 5: GMM results, total trade

VARIABLES	(1) FE	(2) GMM	(3) FE	(4) GMM
L.ln_Theil_pref	0.781***	0.856***	0.781***	0.811***
	(0.0365)	(0.192)	(0.0368)	(0.212)
L.totaltrade	-0.000105	-0.000141		
	(0.000509)	(0.000714)		
L.total_lt			0.000747	0.00243
			(0.00328)	(0.00483)
L.total_mt			-0.000814	-0.00214
			(0.00320)	(0.00476)
L.total_ht			-1.61e-05	0.000216
			(0.000889)	(0.00174)
GDP	-0.0280	0.00243	-0.0258	-0.0183
	(0.0865)	(0.120)	(0.0910)	(0.155)
Education	0.00790	-0.000308	0.00763	0.000818
	(0.0347)	(0.0358)	(0.0353)	(0.0492)
ValAddAgri	-0.000368	-0.000611	-0.000188	0.00127
	(0.00429)	(0.00509)	(0.00463)	(0.00558)
L.fdi	0.00290	0.00290	0.00299	0.00302
	(0.00322)	(0.00349)	(0.00338)	(0.00344)
L.tech	0.244**	0.268***	0.243**	0.265***
	(0.0915)	(0.0831)	(0.0917)	(0.0776)
2.quartile_m	0.0915	0.0806	0.0903	0.149
	(0.085)	(0.101)	(0.0858)	(0.124)
3.quartile_m	0.115	0.122	0.114	-0.0183
	(0.100)	(0.118)	(0.0999)	(0.155)
Observations	903	845	903	845
R-squared	0.679		0.679	
Number of countries	58	58	58	58
Year FE	YES	YES	YES	YES
Number of instruments		56		57
Hansen Test		0.125		0.141
AR(1)		0.00560		0.0115
AR(2)		0.148		0.151

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index of wage inequality. Lags have been restricted to lengths 3-10 in column 2, and 5-13 in column 4. The depth of lag lengths has been guided by the misspecification tests. Similar results emerge with varying lag lengths (results available upon request).

Table 6 contains the estimates obtained when using different versions 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 (corresponding to columns 2 and 4 of table 2), and the original results using the cross-imputed index are displayed in columns 1 and 4 for comparison. The coefficient of the lagged dependent variable and the country group dummies are 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 one using only part of the sectors (columns 3 and 6) is insignificant, which is in line with the fact that it contains fewer sectors and consequently yields less clear results.

Table 6: Robustness of FE results to different labor productivity indices

	(1) Cross-sectoral imputation	(2) Within-sectoral imputation	(3) Cross-sectoral imputation, only sectors with >50% data	(4) Cross-sectoral imputation	(5) Within-sectoral imputation	(6) Cross-sectoral imputation, only sectors with >50% data
L.totaltrade	-0.000105	-0.000107	-0.000114			
	(0.000509)	(0.000509)	(0.000507)			
L.lowtech				0.000747	0.000891	0.000845
				(0.00328)	(0.00327)	(0.00328)
L.medtech				-0.000814	-0.000919	-0.00103
				(0.00320)	(0.00316)	(0.00318)
L.hightech				-1.61e-05	-1.46e-05	5.36e-05
				(0.000889)	(0.000864)	(0.000874)
GDP	-0.0280	-0.0227	-0.0265	-0.0258	-0.0200	-0.0244
	(0.0865)	(0.0869)	(0.0871)	(0.0910)	(0.0915)	(0.0916)
Education	0.00790	0.00931	0.0100	0.00763	0.00903	0.00947
	(0.0347)	(0.0342)	(0.0348)	(0.0353)	(0.0349)	(0.0355)
ValAddAgri	-0.000368	0.000105	-0.000139	-0.000188	0.000320	3.82e-05
	(0.00429)	(0.00435)	(0.00436)	(0.00463)	(0.00471)	(0.00472)
L.fdi	0.00290	0.00293	0.00311	0.00299	0.00302	0.00326
	(0.00322)	(0.00320)	(0.00323)	(0.00338)	(0.00337)	(0.00341)
L.tech	0.244**	0.231**	0.266**	0.243**	0.232**	0.267**
	(0.0915)	(0.0997)	(0.131)	(0.0917)	(0.0998)	(0.132)
Observations	903	903	903	903	903	903
R-squared	0.679	0.679	0.678	0.679	0.679	0.678
No. of countries	58	58	58	58	58	58
Year FE & controls	YES	YES	YES	YES	YES	YES

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index of wage inequality. The lagged dependent variable has been included in the estimation, but is omitted from the output.

Robustness to the TFP technological change index is tested in the following. The estimates in Table 7 correspond to columns 2 and 4 of Table 2 and are displayed again here in columns 1 and 4 for comparison. One can see that the result on the aggregate (total) trade variable does not change substantially. A few control variables change signs, most notably the education variable. However, these are very likely to stem from the smaller sample size rather than the difference in the technological change variable, as the results in columns 4 and 5 as well as 7 and 8 suggest, which show the results for each index when executed on a (substantially smaller) common sample. The same can be said about the observed change in the point estimate of the trade variables, which predominantly stem from the difference in sample composition. In fact, the estimates on the small, constant sample yield very similar coefficients on all variables, with the exception of the technological change index itself. It appears that the TFP index is a little more powerful in capturing movements in the technological frontier, as shown by the larger, and more significant, point estimate in the constant sample and the larger effect it has on the trade variables. The true extent of omitted variable bias might therefore be even slightly larger than what was found in the above estimations.

Table 7: Robustness to the TFP index of technological change (table 2 results,).

VARIABLES	(1) Labor	(2) TFP	(3) Labor, constant sample	(4) TFP, constant sample	(5) Labor	(6) TFP	(7) Labor, constant sample	(8) TFP, constant sample
L.tech	0.244**	0.212**	0.449	0.861**	0.243**	0.212**	0.477	0.864**
	(0.0915)	(0.0974)	(0.470)	(0.353)	(0.0917)	(0.0982)	(0.476)	(0.357)
L.totaltrade	-0.000105	-0.000741	0.000959	0.000872				
	(0.000509)	(0.000947)	(0.00155)	(0.00154)				
L.lowtech					0.000747	-0.00310	-0.00302	-0.00273
					(0.00328)	(0.00361)	(0.00484)	(0.00453)
L.medtech					-0.000814	-4.96e-05	0.00326	0.00316
					(0.00320)	(0.00393)	(0.00562)	(0.00579)
L.hightech					-1.61e-05	-0.000604	0.000665	0.000508
					(0.000889)	(0.00119)	(0.00150)	(0.00143)
GDP	-0.0280	-0.00645	-0.210	-0.223	-0.0258	-0.0106	-0.217	-0.229
	(0.0865)	(0.121)	(0.216)	(0.213)	(0.0910)	(0.123)	(0.218)	(0.216)
Edcuation	0.00790	-0.0164	-0.0504	-0.0353	0.00763	-0.0169	-0.0488	-0.0333
	(0.0347)	(0.0439)	(0.0508)	(0.0508)	(0.0353)	(0.0436)	(0.0555)	(0.0551)
ValAddAgri	-0.000368	-0.00312	0.000870	0.00100	-0.000188	-0.00420	-0.000800	-0.000394
	(0.00429)	(0.00547)	(0.00749)	(0.00722)	(0.00463)	(0.00631)	(0.00927)	(0.00891)
L.fdi	0.00290	0.00647	0.00291	0.00357	0.00299	0.00670	0.00264	0.00317
	(0.00322)	(0.00629)	(0.00700)	(0.00711)	(0.00338)	(0.00691)	(0.00774)	(0.00776)
Observations	903	552	386	386	903	552	386	386
R-squared	0.679	0.666	0.629	0.638	0.679	0.667	0.630	0.639
No. of countries	58	37	33	33	58	37	33	33
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The lagged dependent variable has been included in the estimation, but is omitted from the output.

Because results could be more volatile at disaggregated levels, the remaining specifications are checked for robustness as well. Result tables can be found in the appendix. Table A2.1 contains the results for traded composed by the trading partner's relative education classification, and the decomposition by the country group is displayed in table A2.2. The original results are displayed in columns (1) and (3) in both tables. Again, the estimates are qualitatively similar between the TFP and the labor productivity index, but are often less significant with the latter. The overall results of testing the TFP-based versus the labor productivity index indicate that for both exports and imports, the coefficients are similar, with occasional changes in significance as well as magnitude, and very few (insignificant) sign changes, of which at least a fraction can be attributed to the smaller sample.

As another robustness check, the Theil index provided by UTIP is used as the dependent variable. Estimations results can be found in appendix table A3 and A4, with the original results displayed in columns 1 and 3 of each table. The UTIP index provides shorter time coverage of little under 14 years and hence entails a larger dynamic panel bias and less reliable FE estimates. Despite the fact that this would bias coefficients upward, the point estimate for the aggregate (total) trade variable is smaller and less precisely estimated than with the newly constructed Theil index. Of the remaining variables, however, all of those estimated with a certain degree of precision are similar to the original results but slightly larger with the UTIP index. The lagged dependent variable shows a slightly higher degree of intertia, which can be expected to still be downward biased. Notably, the technological change control variable is still strongly associated with the UTIP index, but is slightly smaller and less significant in some of the specifications. This fits well with the fact that the UTIP also uses other data sources to arrive at their index, which naturally cannot be expected to have any association with the technology measure that is intimately connected to the underlying data. The fact that there are no major changes in the results nevertheless lends support to the validity of the newly constructed Theil index.[18]

Finally, and extensive outlier analysis has been conducted, wherein single influential observations have been identified and deleted from the estimation sample. The overall results remain qualitatively and quantitatively unaffected.[19]

[18] The remaining, more disaggregated specification have also been tested on the UTIP index. Results show no qualitative changes between the two measures apart from the already displayed loss in magnitude and significance when using the UTIP index. Results are available from the author upon request.

[19] Added-variable and partial-leverage plots, values of Cook's D, DFBETAs for the trade variables, and regression results with influential observations excluded are available upon request.

6 Conclusion

This paper has attempted to shed some light on the impact of trade on wage inequality in developing countries. It expands on the existing literature in four ways: Firstly, by introducing a newly constructed measure of technological change into the empirical analysis, it addresses concerns of omitted variable bias. Secondly, it employs a comparative advantage-based country classification based on relative skill endowments, thereby incorporating previous findings in the literature which demonstrate the superiority of such a classification over the previously used income-based country categories. Thirdly, it classifies trade flows according to their technology content, measured by the degree of human capital necessary to produce the goods. Lastly, a consistent version of the Theil index of inter-industry wage inequality is used which provides a longer and more consistent time coverage than existing measures.

Results show that the effects of trade are rather heterogeneous once relative endowments are taken into account and technology effects are separated from trade effects. Furthermore, the size of the different impacts increases substantially once this heterogeneity is accounted for.

Introducing a new control variable of technological change, empirical findings demonstrate the need to control for this source of potential omitted variable bias, since in particular the export results change substantially with the inclusion of the variable. Some effects appear only when the variable is included, or disappear with its inclusion. In line with the previous findings in the literature on skill-biased technological change, the technological change variable itself is found to significantly and substantially increase wage inequality throughout all specifications. The fact that the medium technology export variables are the most sensitive to the inclusion of the technological change variable suggests that this is also where most of the technological progress seems to be taking place, in particular in the relatively more skill-endowed developing countries. This is in line with the South-South trade hypothesis, stating that this is where the medium-skill endowed country groups should have their comparative advantage.

Regarding technology transfer, the proposition made in the previous literature that trade to and from developed countries is disequalizing due to the introduction of skill-biased technological change can only partly be confirmed. No such effects are found for high-technology trade, neither through exports, nor through imports. In terms of medium technology, exports have positive coefficients and seem to be disequalizing in all but the countries in the lowest education quartile. This finding fits with the South-South trade story as well as the technology transfer hypotheses, in particular the absorptive capacity argument. It is difficult, however, to disentangle technology transfer from comparative-advantage, “trade”-based effects. As for the trade effects, results are generally in line with Heckscher-Ohlin theory for low-technology trade, where equalizing impacts are mostly found. Again, the disequalizing for medium-low technology trade is in line with the predictions of both the South-South trade and the technology transfer hypothesis and it is difficult to isolate these effects in our set-up. More research is needed to investigate the exact magnitude of these effects vis-à-vis one another.

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Appendix Part A

Sample means of main variables

Country	no. of years	Theil index	Total imports (in bn $)	Total Exports (in bn $)	Education quartile (average)[20]	Years of education	Value added in agriculture	FDI (in bn $)	GDP (in mn $)
Argentina	37	0.053	10.86	10.08	3.0	8.2	6.35	5.82	299676
Bangladesh	29	0.040	1.87	0.89	1.0	2.8	29.39	0.09	124108
Bulgaria	16	0.068	8.15	0.00	3.0	9.6	10.80	3.54	70078
Bolivia	37	0.054	0.52	0.34	2.5	5.4	18.69	0.23	13899
Brazil	40	0.123	24.33	26.95	2.0	4.3	8.82	10.86	970292
Barbados	37	0.052	0.14	0.08	3.0	7.4	8.31	0.01	3362
Botswana	11	0.032	2.20	3.18	3.0	7.9	2.11	0.30	17000
Central African Republic	28	0.051	0.04	0.03	1.0	0.9	39.49	0.01	1737
Chile	39	0.062	6.72	8.75	3.0	7.7	6.93	2.86	110627
China	20	0.091	242.30	320.19	2.0	6.6	14.78	59.10	5750470
Côte d'Ivoire	30	0.054	1.07	1.02	1.0	1.3	26.18	0.09	20154
Cameroon	31	0.097	0.58	0.35	1.3	2.9	27.58	0.09	19586
Congo	22	0.077	0.28	0.27	1.5	2.1	13.56	0.03	3303
Colombia	38	0.037	5.21	4.39	2.0	5.4	16.00	2.33	212890
Costa Rica	35	0.042	1.26	1.32	3.0	7.2	11.73	0.35	26220
Cyprus	40	0.026	1.74	0.53	3.0	8.4	6.61	0.56	10973
Dominican Republic	29	0.072	0.34	0.21	2.0	3.8	19.15	0.05	21663
Ecuador	39	0.041	2.05	0.95	2.6	6.1	18.53	0.31	44533
Egypt	35	0.061	6.96	2.97	1.4	3.5	20.05	2.02	168531
Fiji	35	0.053	0.34	0.19	3.0	7.4	19.63	0.07	3147
Gabon	27	0.077	0.97	0.93	1.5	2.5	6.56	0.04	7098
Ghana	31	0.096	0.40	0.27	2.0	3.2	56.72	0.02	17474
Gambia	27	0.013	0.02	0.01	1.0	0.6	29.06	0.00	709
Honduras	35	0.061	0.18	0.11	2.0	3.1	25.15	0.02	9474
Indonesia	40	0.082	41.28	58.98	1.7	5.4	13.99	6.04	812897
India	33	0.085	32.24	25.83	1.0	3.1	26.52	5.57	1616655
Iran	19	0.043	9.67	3.37	1.5	4.1	13.07	1.03	343572
Jordan	39	0.083	2.65	1.41	2.2	5.5	5.80	0.56	13979
Kenya	33	0.078	2.02	1.55	2.0	4.8	31.05	0.06	38707
Kyrgyzstan	15	0.286	0.47	0.38	3.0	9.1	36.53	0.07	10466

[20] Countries classified as “high education”, i.e. being in the 4th quartile at any point in time, and therefore used in the aggregation of the trade data in that year, are: Albania, Argentina, Armenia, Australia, Austria, Belgium, Bulgaria, Belize, Barbados, Canada, Switzerland, Chile, Cuba, Cyprus, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, Fiji, France, Great Britain, Greece, Hong Kong, Croatia, Hungary, Ireland, Iceland, Israel, Japan, Kazakhstan, Sri Lanka, Lithuania, Luxemburg, Latvia, Malta, The Netherlands, Norway, New Zealand, Poland, North Korea, Romania, Russia, Slovakia, Slovenia, Sweden, Tajikistan, Tonga, Trinidad and Tobago, Taiwan, and Ukraine.

Lesotho	7	0.247	0.74	0.18	2.0	5.3	9.34	0.04	2348
Latvia	17	0.044	1.77	0.93	3.0	9.1	5.91	0.36	18994
Moldova	17	0.017	0.95	0.50	3.0	9.2	22.47	0.18	9179
Mexico	40	0.055	39.85	12.03	2.1	6.9	5.61	14.14	1032215
Malta	39	0.013	1.35	0.98	3.0	7.8	3.94	0.24	4788
Mongolia	12	0.068	0.47	0.30	3.0	8.1	26.26	0.12	6652
Mozambique	16	0.252	0.24	0.05	1.0	0.8	32.22	0.08	6228
Mauritius	32	0.054	1.56	0.79	2.0	6.1	9.59	0.09	10669
Malawi	37	0.095	0.18	0.09	1.0	2.2	40.58	0.01	5945
Malaysia	41	0.033	31.43	32.69	2.7	6.5	16.99	2.80	157322
Pakistan	26	0.075	6.67	5.86	1.0	3.0	25.52	0.69	261666
Panama	26	0.052	0.59	0.17	3.0	7.8	7.85	0.47	19867
Peru	36	0.276	6.23	6.98	3.0	7.7	8.20	3.11	142417
Philippines	38	0.055	11.92	10.11	3.0	6.9	21.53	0.81	187871
Poland	21	0.033	97.19	88.60	3.0	9.8	4.11	16.40	582449
Senegal	28	0.050	0.89	0.39	1.1	3.3	19.84	0.07	13001
Singapore	40	0.055	52.41	56.26	2.4	6.3	0.63	9.25	96904
El Salvador	35	0.060	1.18	0.82	2.0	5.0	13.95	0.30	5447
Syria	25	0.130	3.77	2.40	1.3	4.5	22.62	0.51	44857
Thailand	41	0.055	21.73	20.56	2.0	4.5	16.20	2.17	260430
Trinidad and Tobago	38	0.189	0.92	0.79	3.0	8.1	1.89	0.55	14581
Tunisia	39	0.166	4.07	2.69	1.4	3.4	15.70	0.47	41407
Turkey	40	0.057	25.16	16.42	2.0	4.3	20.08	2.67	496604
Tanzania	22	0.114	1.47	0.76	1.0	4.6	34.96	0.37	28737
Uganda	18	0.189	0.67	0.39	1.0	3.6	41.07	0.14	18444
Uruguay	35	0.055	1.80	1.62	3.0	7.6	10.17	0.42	29256
Venezuela	39	0.042	4.65	4.03	2.3	4.6	5.32	0.54	131013
Yemen	10	0.073	1.95	0.22	1.0	1.7	11.73	0.21	38228
South Africa	11	0.061	27.80	31.65	2.0	7.8	3.12	3.76	340185
Zambia	27	0.043	1.15	1.06	2.0	3.0	14.97	0.03	11764

Table A1.1: GMM estimates, Table 3 (column 2 and 4) results

	(1)	(2)	(3)	(4)
	Exports		Imports	
VARIABLES	No tech	Tech(-2)	No tech	Tech(-2)
L.ln_Theil_pref	0.780***	0.811***	0.781***	0.838***
	(0.0365)	(0.236)	(0.0362)	(0.257)
L.lowtech	-0.00158	-0.00160	0.000712	0.000799
	(0.00147)	(0.00132)	(0.000498)	(0.000566)
L.medtech	-0.00119	-0.000463	0.00206	0.00353
	(0.00352)	(0.00563)	(0.00864)	(0.00695)
L.hightech	0.00337	0.00245	-0.00512	-0.00622
	(0.00448)	(0.00864)	(0.00583)	(0.00490)
L.totalimp/exp	-1.11e-05	0.000282	-0.000582	-0.000225
	(0.00147)	(0.00305)	(0.00199)	(0.00220)
GDP	-0.0254	-0.00756	-0.0247	-0.00280
	(0.0943)	(0.126)	(0.0903)	(0.118)
Education	0.0110	0.00646	0.00824	0.00643
	(0.0353)	(0.0346)	(0.0348)	(0.0317)
ValAddAgri	-0.00154	-0.00153	-0.00126	-0.00154
	(0.00474)	(0.00436)	(0.00463)	(0.00470)
L.fdi	0.00365	0.00347	0.00435	0.00412
	(0.00329)	(0.00317)	(0.00347)	(0.00341)
L2. tech	0.241**	0.246***	0.243**	0.242***
	(0.0916)	(0.0869)	(0.0914)	(0.0882)
2.quartile (LMEC)	0.0903	0.0851	0.0893	0.0747
	(0.0852)	(0.106)	(0.0844)	(0.103)
3.quartile (UMEC)	0.116	0.111	0.110	0.0929
	(0.0990)	(0.115)	(0.0989)	(0.114)
Observations	903	845	903	845
R-squared	0.679		0.679	
Number of id	58	58	58	58
Year FE	YES	YES	YES	YES
Number of instruments		52		51
Hansen Test		0.856		0.716
Sargan Test		0.753		0.745
AR(1)		0.0168		0.0196
AR(2)		0.163		0.164

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index. Lags have been restricted to lengths 6-8 in column 2, and 6-7 in column 4. The depth of lag lengths has been guided by the misspecification tests, as well as achieving a realistic value for the lagged dependent variable, which should be between the OLS-estimate of 0.904 (0-.893) and the FE estimate of column 1 (3) for column 2 (4). Similar results emerge with varying lag lengths (results available upon request).

Table A1.2: GMM estimates, Table 4 (column 2, 4, and 6) results

	(1)	(2)	(3)	(4)	(5)	(6)
	Total trade		Exports		Imports	
VARIABLES	FE	GMM	FE	GMM	FE	GMM
L.ln_Theil	0.778***	0.803***	0.778***	0.844***	0.778***	0.819***
	(0.0364)	(0.263)	(0.0360)	(0.207)	(0.0365)	(0.272)
L.ht_trade	0.0121	0.0102	-0.0146	-0.0112	-0.0383	-0.0305
	(0.0154)	(0.0273)	(0.0147)	(0.0151)	(0.0353)	(0.0571)
LMEC*L.ht_trade	-0.0140	-0.0119	-0.0132	-0.0182	0.0166	0.0131
	(0.0154)	(0.0295)	(0.0296)	(0.0352)	(0.0203)	(0.0284)
UMEC *L.ht_trade	-0.0120	-0.00991	0.00279	0.00955	-0.0165	-0.0127
	(0.0158)	(0.0297)	(0.0318)	(0.0411)	(0.0200)	(0.0300)
L.mt_trade	-0.0196	-0.0186	0.0127	0.0187	-0.0166	-0.0128
	(0.0128)	(0.0224)	(0.0300)	(0.0382)	(0.0205)	(0.0300)
LMEC*L.mt_trade	0.0263*	0.0245	-0.0124	-0.00919	-0.0338	-0.0287
	(0.0137)	(0.0274)	(0.0178)	(0.0208)	(0.0252)	(0.0382)
UMEC*L.mt_trade	0.0170	0.0150	0.0401	0.00955	0.0299	0.0243
	(0.0130)	(0.0302)	(0.0259)	(0.0411)	(0.0269)	(0.0419)
L.lt_trade	0.0178*	0.0177	0.0101	0.00435	0.0253	0.0187
	(0.00973)	(0.0128)	(0.0178)	(0.0272)	(0.0269)	(0.0482)
LMEC*L.lt_trade	-0.0229**	-0.0222	0.0181	0.0171	0.0359	0.0304
	(0.0109)	(0.0163)	(0.0125)	(0.0105)	(0.0304)	(0.0430)
UMEC*L.lt_trade	-0.0163	-0.0150	-0.0310**	-0.0283*	-0.0387	-0.0329
	(0.0111)	(0.0199)	(0.0153)	(0.0147)	(0.0328)	(0.0458)
L.totalimp/exp			-0.000270	-0.000460	0.000958	0.00106
			(0.00169)	(0.00147)	(0.000785)	(0.000984)
GDP	-0.0219	-0.00783	-0.0209	0.00973	-0.0313	-0.0139
	(0.0943)	(0.133)	(0.0967)	(0.102)	(0.0910)	(0.136)
Education	0.00764	0.00440	0.0114	0.00454	0.0101	0.00780
	(0.0364)	(0.0348)	(0.0361)	(0.0286)	(0.0373)	(0.0348)
ValAddAgri	-9.47e-06	7.53e-05	-0.000925	-0.00113	-0.000881	-0.00129
	(0.00474)	(0.00446)	(0.00498)	(0.00456)	(0.00462)	(0.00502)
L.fdi	0.00322	0.00314	0.00354	0.00335	0.00430	0.00397
	(0.00363)	(0.00348)	(0.00360)	(0.00316)	(0.00382)	(0.00412)
L2. tech	0.252***	0.256***	0.255***	0.261***	0.242**	0.243***
	(0.0937)	(0.0881)	(0.0927)	(0.0870)	(0.0936)	(0.0894)
2.quartile (LMEC)	0.129	0.124	0.0917	0.0745	0.122	0.106
	(0.0908)	(0.145)	(0.0936)	(0.102)	(0.0872)	(0.134)
3.quartile (UMEC)	0.141	0.132	0.0908	0.0728	0.156	0.136
	(0.113)	(0.170)	(0.113)	(0.117)	(0.108)	(0.166)
Observations	903	845	903	845	903	845
R-squared	0.680		0.681		0.680	
Number of id	58	58	58	58	58	58
Year FE	YES	YES	YES	YES	YES	YES
Control variables	YES		YES		YES	
No. of instruments		57		57		56
Hansen Test		0.852		0.635		[21]

[21] The Hansen test of overidentification is omitted for this equation since the instrument lag length is restricted to one lag, meaning that the model is exactly identified. No well-behaved model could be found with lag lengths deeper than 1. Results using alternative lag lengths and depths are available upon request.

AR(1)	0.0267	0.00924	0.0253
AR(2)	0.171	0.152	0.169

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index. Lags have been restricted to lengths 6-8 in column 2, 7-8 in column 4, and 6 in column 6. The depth of lag lengths has been guided by the misspecification tests, as well as achieving a realistic value for the lagged dependent variable, which should be between the OLS- and the FE estimate. Similar results emerge with varying lag lengths (results available upon request).

Table A2.1: Robustness to the TFP index of technological change, Table 3:(column 2, 4 and 6) results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exports				Imports			
VARIABLES	Labor	TFP	Labor constant sample	TFP constant sample	Labor	TFP	Labor constant sample	TFP constant sample
L.total_ht_exp	-1.11e-05	0.00128	0.00556	0.00520	-0.000582	-0.00240	-0.00733	-0.00713
	(0.00147)	(0.00337)	(0.00447)	(0.00435)	(0.00199)	(0.00349)	(0.00600)	(0.00574)
L.total_mt_exp	0.00337	0.000352	0.00554	0.00464	-0.00512	0.00212	0.0120	0.0127
	(0.00448)	(0.00563)	(0.0107)	(0.0107)	(0.00583)	(0.00895)	(0.0114)	(0.0108)
L.total_lt_exp	-0.00119	0.00187	0.0130	0.0130	0.00206	-0.0126	-0.0280*	-0.0282**
	(0.00352)	(0.00808)	(0.0130)	(0.0124)	(0.00864)	(0.0103)	(0.0140)	(0.0129)
L.totalimp/exp	-0.00158	-0.00301	-0.00569	-0.00525	0.000712	0.000463	0.00527	0.00479
	(0.00147)	(0.00305)	(0.00549)	(0.00532)	(0.000498)	(0.00273)	(0.00479)	(0.00466)
GDP	-0.0254	-0.0126	-0.224	-0.234	-0.0247	-0.00867	-0.216	-0.226
	(0.0943)	(0.124)	(0.224)	(0.221)	(0.0903)	(0.125)	(0.224)	(0.221)
Education	0.0110	-0.0163	-0.0489	-0.0347	0.00824	-0.0168	-0.0426	-0.0267
	(0.0353)	(0.0433)	(0.0537)	(0.0540)	(0.0348)	(0.0427)	(0.0551)	(0.0545)
ValAddAgri	-0.00154	-0.00422	-0.00100	-0.000359	-0.00126	-0.00488	-0.00363	-0.00316
	(0.00474)	(0.00658)	(0.00973)	(0.00923)	(0.00463)	(0.00632)	(0.00906)	(0.00858)
L.fdi	0.00365	0.00894	0.00848	0.00861	0.00435	0.00802	0.00487	0.00504
	(0.00329)	(0.00774)	(0.00855)	(0.00823)	(0.00347)	(0.00779)	(0.00858)	(0.00824)
L2.tech	0.241**	0.210**	0.379	0.834**	0.243**	0.214**	0.529	0.874**
	(0.0916)	(0.0976)	(0.460)	(0.342)	(0.0914)	(0.0970)	(0.475)	(0.357)
Constant	-0.576	-0.721	1.134	1.166	-0.574	-0.748	1.065	1.102
	(0.864)	(1.111)	(2.032)	(1.987)	(0.827)	(1.121)	(2.013)	(1.966)
Observations	903	552	386	386	903	552	386	386
R-squared	0.679	0.667	0.631	0.640	0.679	0.667	0.632	0.641
Number of id	58	37	33	33	58	37	33	33
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The dependent variable is the log of the Theil index.

Table A2.2: Robustness to the TFP index of technological change, Table 4: (column 4 and 6) results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Exports				Imports			
VARIABLES	Labor	TFP	Labor constant sample	TFP constant sample	Labor	TFP	Labor constant sample	TFP constant sample
L.tech	0.255***	0.226**	0.559	0.874**	0.242**	0.214**	0.626	0.891**
	(0.0927)	(0.0965)	(0.488)	(0.357)	(0.0936)	(0.0988)	(0.454)	(0.362)
L.ht_trade	-0.0132	0.0193	-0.0141	-0.0164	0.0166	0.0329	0.0216	0.0205
	(0.0296)	(0.0560)	(0.0655)	(0.0584)	(0.0203)	(0.0247)	(0.0239)	(0.0216)
LMEC*L.ht_trade	0.00279	-0.0419	-0.0116	-0.0105	-0.0165	-0.0360	-0.0337	-0.0334
	(0.0318)	(0.0609)	(0.0684)	(0.0604)	(0.0200)	(0.0283)	(0.0282)	(0.0261)
UMEC *L.ht_trade	0.0127	-0.0170	0.0295	0.0297	-0.0166	-0.0380	-0.0354	-0.0346
	(0.0300)	(0.0566)	(0.0689)	(0.0602)	(0.0205)	(0.0262)	(0.0268)	(0.0246)
L.mt_trade	-0.0124	-0.0231	0.0403	0.0390	-0.0338	-0.0471	-0.0462	-0.0400
	(0.0178)	(0.0323)	(0.0434)	(0.0370)	(0.0252)	(0.0305)	(0.0304)	(0.0258)
LMEC*L.mt_trade	0.0401	0.0988*	0.123**	0.119**	0.0299	0.0538	0.0707*	0.0655*
	(0.0259)	(0.0565)	(0.0495)	(0.0458)	(0.0269)	(0.0338)	(0.0361)	(0.0339)
UMEC*L.mt_trade	0.0101	0.0209	-0.0461	-0.0420	0.0253	0.0558*	0.0774*	0.0736*
	(0.0178)	(0.0346)	(0.0496)	(0.0412)	(0.0269)	(0.0320)	(0.0412)	(0.0386)
L.lt_trade	0.0181	0.0247	0.00804	0.00625	0.0359	0.0289	0.0296	0.0198
	(0.0125)	(0.0250)	(0.0203)	(0.0173)	(0.0304)	(0.0322)	(0.0333)	(0.0304)
LMEC*L.lt_trade	-0.0310**	-0.0473	-0.0362	-0.0318	-0.0387	-0.0482	-0.0739	-0.0603
	(0.0153)	(0.0300)	(0.0243)	(0.0208)	(0.0328)	(0.0364)	(0.0445)	(0.0414)
UMEC*L.lt_trade	-0.0146	-0.0241	0.0229	0.0228	-0.0383	-0.0648	-0.113*	-0.101*
	(0.0147)	(0.0245)	(0.0301)	(0.0272)	(0.0353)	(0.0398)	(0.0586)	(0.0534)
L.totalimp	-0.000270	-0.00340	-0.0146*	-0.0137*	0.000958	0.00220	0.00875	0.00812
	(0.00169)	(0.00351)	(0.00831)	(0.00778)	(0.000785)	(0.00294)	(0.00629)	(0.00594)
GDP	-0.0209	0.0102	-0.157	-0.162	-0.0313	-0.0227	-0.204	-0.202
	(0.0967)	(0.127)	(0.225)	(0.223)	(0.0910)	(0.120)	(0.227)	(0.221)
Education	0.0114	-0.00929	-0.0397	-0.0268	0.0101	-0.0223	-0.0370	-0.0240
	(0.0361)	(0.0494)	(0.0571)	(0.0568)	(0.0373)	(0.0481)	(0.0608)	(0.0600)
ValAddAgri	-0.000925	-0.00383	-0.000461	6.14e-05	-0.000881	-0.00444	-0.00296	-0.00248
	(0.00498)	(0.00658)	(0.00963)	(0.00904)	(0.00462)	(0.00616)	(0.00898)	(0.00837)
L.fdi	0.00354	0.00525	0.0112	0.0119	0.00430	0.00982	0.00882	0.00922
	(0.00360)	(0.00917)	(0.0119)	(0.0113)	(0.00382)	(0.00848)	(0.0100)	(0.00951)
Observations	903	552	386	386	903	552	386	386
R-squared	0.681	0.670	0.641	0.650	0.680	0.670	0.639	0.648
Number of id	58	37	33	33	58	37	33	33
Year FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes. Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1. The lagged dependent variable has been included in the estimation, but is omitted from the output.

Table A3.1: Robustness to the UTIP measure of inter-industry wage inequality, Table 2: (column 2 and 4) results

VARIABLES	(1) Theil	(2) UTIP	(3) Theil	(4) UTIP
Lagged dep. var.	0.781***	0.787***	0.781***	0.784***
	(0.0365)	(0.0533)	(0.0368)	(0.0543)
L2.as_cross_tech_lab	0.244**	0.199**	0.243**	0.199**
	(0.0915)	(0.0927)	(0.0917)	(0.0928)
L.totaltrade	-0.000105	-0.000742		
	(0.000509)	(0.000493)		
L.lowtech			0.000747	-0.00324
			(0.00328)	(0.00285)
L.medtech			-0.000814	0.00269
			(0.00320)	(0.00335)
L.hightech			-1.61e-05	-0.00154
			(0.000889)	(0.00106)
GDP	-0.0280	-0.0219	-0.0258	-0.0238
	(0.0865)	(0.0863)	(0.0910)	(0.0886)
Education	0.00790	-0.0227	0.00763	-0.0205
	(0.0347)	(0.0393)	(0.0353)	(0.0397)
L.fdi	-0.000368	0.00115	-0.000188	0.00112
	(0.00429)	(0.00383)	(0.00463)	(0.00395)
ValAddAgri	0.00290	0.00559*	0.00299	0.00438
	(0.00322)	(0.00304)	(0.00338)	(0.00272)
Constant	-0.563	-0.571	-0.587	-0.568
	(0.780)	(0.817)	(0.837)	(0.841)
Observations	903	805	903	805
R-squared	0.679	0.700	0.679	0.700
Number of id	58	58	58	58
Year FE	YES	YES	YES	YES

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

Table A3.2: Robustness to the UTIP measure of inter-industry wage inequality, Table 3:(column 2 and 4) results

VARIABLES	(1) Theil	(2) UTIP	(3) Theil	(4) UTIP
L.ln_Theil_pref	0.780***	0.784***	0.781***	0.783***
	(0.0365)	(0.0545)	(0.0362)	(0.0550)
L.total_lt_exp	-0.00119	-0.00255	0.00206	-0.00540
	(0.00352)	(0.00393)	(0.00864)	(0.00562)
L.total_mt_exp	0.00337	0.00350	-0.00512	0.00332
	(0.00448)	(0.00603)	(0.00583)	(0.00585)
L.total_ht_exp	-1.11e-05	-0.000972	-0.000582	-0.00235
	(0.00147)	(0.00199)	(0.00199)	(0.00209)
L.totalimp	-0.00158	-0.00162	0.000712	-0.000380
	(0.00147)	(0.00188)	(0.000498)	(0.000755)
L2. tech	0.241**	0.198**	0.243**	0.199**
	(0.0916)	(0.0927)	(0.0914)	(0.0925)
GDP	-0.0254	-0.0240	-0.0247	-0.0173
	(0.0943)	(0.0915)	(0.0903)	(0.0885)
Education	0.0110	-0.0201	0.00824	-0.0223
	(0.0353)	(0.0403)	(0.0348)	(0.0394)
L.fdi	0.00365	0.00514*	0.00435	0.00510*
	(0.00329)	(0.00282)	(0.00347)	(0.00286)
ValAddAgri	-0.00154	0.000493	-0.00126	0.00135
	(0.00474)	(0.00404)	(0.00463)	(0.00404)
2.quartile (LMEC)	0.0903	0.0710	0.0893	0.0711
	(0.0852)	(0.117)	(0.0844)	(0.118)
3.quartile (UMEC)	0.116	0.107	0.110	0.110
	(0.0990)	(0.131)	(0.0989)	(0.132)
Observations	903	805	903	805
R-squared	0.679	0.700	0.679	0.700
Number of id	58	58	58	58
Year FE	YES	YES	YES	YES

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

Table A3.3: Robustness to the UTIP measure of inter-industry wage inequality, Table 4: (columns 2 and 4) results

	(1)	(2)	(3)	(4)	(5)	(6)
	Total		Exports		Imports	
VARIABLES	Theil	UTIP	Theil	UTIP	Theil	UTIP
Lagged dep. var.	0.778***	0.778***	0.778***	0.784***	0.778***	0.778***
	(0.0364)	(0.0562)	(0.0360)	(0.0555)	(0.0365)	(0.0564)
L.ht_trade	0.0121	0.0200	-0.0132	0.0456	0.0166	0.0252
	(0.0154)	(0.0223)	(0.0296)	(0.0377)	(0.0203)	(0.0432)
LMEC*L.ht_trade	-0.0140	-0.0239	0.00279	-0.0537	-0.0165	-0.0288
	(0.0154)	(0.0224)	(0.0318)	(0.0393)	(0.0200)	(0.0430)
UMEC *L.ht_trade	-0.0120	-0.0223	0.0127	-0.0470	-0.0166	-0.0303
	(0.0158)	(0.0228)	(0.0300)	(0.0391)	(0.0205)	(0.0443)
L.mt_trade	-0.0196	-0.0326	-0.0124	-0.0402*	-0.0338	-0.0474
	(0.0128)	(0.0197)	(0.0178)	(0.0224)	(0.0252)	(0.0414)
LMEC*L.mt_trade	0.0263*	0.0435**	0.0401	0.0626**	0.0299	0.0551
	(0.0137)	(0.0202)	(0.0259)	(0.0301)	(0.0269)	(0.0416)
UMEC*L.mt_trade	0.0170	0.0367*	0.0101	0.0417	0.0253	0.0590
	(0.0130)	(0.0208)	(0.0178)	(0.0257)	(0.0269)	(0.0441)
L.lt_trade	0.0178*	0.0304**	0.0181	0.0299*	0.0359	0.0507
	(0.00973)	(0.0146)	(0.0125)	(0.0163)	(0.0304)	(0.0388)
LMEC*L.lt_trade	-0.0229**	-0.0404***	-0.0310**	-0.0421**	-0.0387	-0.0663
	(0.0109)	(0.0150)	(0.0153)	(0.0190)	(0.0328)	(0.0404)
UMEC*L.lt_trade	-0.0163	-0.0333**	-0.0146	-0.0306	-0.0383	-0.0583
	(0.0111)	(0.0149)	(0.0147)	(0.0186)	(0.0353)	(0.0396)
L.imp/exp			-0.000270	-0.00127	0.000958	-0.000162
			(0.00169)	(0.00255)	(0.000785)	(0.00126)
L2,tech	0.252***	0.206**	0.255***	0.205**	0.242**	0.200**
	(0.0937)	(0.0971)	(0.0927)	(0.0964)	(0.0936)	(0.0965)
GDP	-0.0219	-0.0316	-0.0209	-0.0274	-0.0313	-0.0292
	(0.0943)	(0.0934)	(0.0967)	(0.0938)	(0.0910)	(0.0939)
Education	0.00764	-0.0191	0.0114	-0.0164	0.0101	-0.0215
	(0.0364)	(0.0422)	(0.0361)	(0.0410)	(0.0373)	(0.0428)
ValAddAgri	-9.47e-06	0.00122	-0.000925	0.000765	-0.000881	0.00150
	(0.00474)	(0.00417)	(0.00498)	(0.00425)	(0.00462)	(0.00424)
L.fdi	0.00322	0.00398	0.00354	0.00522*	0.00430	0.00429
	(0.00363)	(0.00290)	(0.00360)	(0.00309)	(0.00382)	(0.00282)
Observations	903	805	903	805	903	805
R-squared	0.680	0.703	0.681	0.702	0.680	0.702
Number of id	58	58	58	58	58	58
Year FE	YES	YES	YES	YES	YES	YES

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

Appendix Part B: Potential caveats of the sector-based approach for the measure of wage inequality.

Table B1. 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).