The Race Between Education and Technology Revisited

An Integrated Approach to Explaining Income Inequality

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Abstract

We analyze the presumed inequality increasing effect of technological change and the mitigating role of education in this context. In order to do so, we take an integrated approach in two respects. First, we look at a broad set of countries, including Advanced as well as Developing Economies, and analyze global and differential broad regional trends in income inequality. Second, we examine a broad set of determinants besides education and technological progress in order to disentangle the concerning effects. We assembled a unique dataset that combines multiple income inequality indicators, the income Gini coefficient and a ratio of extremes, with the most recent data on multiple drivers. In accordance with theoretical predications, we find that increasing income inequality can be explained by technological progress to a large extent. We were not able to find the strong mediating effect of education which is implied by Tinbergen's and Goldin and Katz's *Race between Technology and Education.* In contrary, we find a more equal distribution of education to increase income inequality in the global sample as well as in Advanced Economies. After accounting for the demographic structure of the population the effect is not significantly different from zero. However, in Developing Economies, the rise in basic schooling has contributed to increasing the share of income accruing to the bottom decile of the income distribution.

Keywords: income inequality, education, technological progress, globalization, trade

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1 Introduction

The notion of a race between technology and education was brought up by Jan Tinbergen (1974) and was, more recently, extensively discussed by Goldin & Katz (2010). It relates, on the one hand, to the skill-biasedness of technological progress with its consequences for income inequality and, on the other hand, to the pivotal role of education in mediating this relation.

Already in the transition from agricultural to industrialized economies, induced by groundbreaking innovations in electricity and transport, among other things, the demand for workers who were able to apply new manufacturing machines increased relative to that for workers with agricultural skills. Thereby increasing the wages of the former relative to that of the latter. Not before the 1950s, this skill premium started to decrease as more and more people attained the required skills through formal education. Observing the resulting decrease in income inequality lead to the famous *Kuznets hypothesis* (Kuznets, 1955) that inequality first increases but after some point decreases in the process of development.

In the US and in Europe, computerization and advancements in information and communication technology induced the transition from industrialized to service sector and knowledge economies in the early 1980s. Technological progress lead, to some degree, to a replacement of routine manufacturing jobs by machines, mace simple jobs more complex and created new jobs requiring higher skills. Thus, again, high-skilled wages increased relative to low skilled wages. Even if secondary and, most importantly, tertiary education increased substantially in the US and even more so in Europe, the premium on high skills continued to increase. Goldin and Katz (2010) infer therefrom, that the skill premium in the 1980s and 1990s has risen in the US, because educational advancements were insufficient in order to countervail demand due to technological progress.

In a nutshell, if technological progress is skill biased, it increases the relative demand for higher skills, thereby increasing inequality in the distribution of wages. In this context, a pivotal equalizing role has been ascribed to education as it increases the supply of skills. Acemoglu & Author (2012) summarize the argument as follows:

> *"Investments in human capital can play a major equalizing role. Under the Tinbergian assumption that technology is skill-biased, technological progress will necessarily widen inequality among skill groups unless it is countered by increases in the supply of human capital. The steady accumulation of human capital has thus been the main equalizer in the U.S. labor market. The rise in inequality over the last three or so decades, in turn, can be understood as the consequence of a slowing rate of accumulation of human capital, which has not kept pace with skill-biased technological change."*

It is not astonishing, that increasing educational attainment in the population has been the prime policy for assuring sustained growth and equality in the Western World over the past fifty years. Even if compelling, revisiting the main arguments in the context of an empirical study on the determinants of income inequality is worthwhile. This work takes this approach in order to address the following issues.

1. Income inequality has been increasing in the developed world since the 1980s. At the same time educational attainment increased and the distribution of education became more equal. Is it possible to trace increasing income inequality only back to a still existing lack of educational advancement?

2. An extensive body of research preceding and following Goldin & Katz (2010) analyzed the dynamics of skill premiums and income inequality in high income countries, while research on the effects of technological progress on income inequality is relatively scarce for middle and low income countries. There, the focus of education policy is to haul people out of poverty by increasing literacy and primary education. These efforts might, however, be offset by technology and trade induced movements in the upper part of the education distribution.

3. Globalization and trade affects the demand for education and the distribution in a similar way as technological progress in Advanced Economies. It is thus hard to disentangle the respective effects. In Developing Economies, on the other hand, the relation between trade and inequality is not equally clear.

4. To what extend did governmental policies mitigate adverse effects of market forces and performed a more or less extinsive redistributive role?

In order to assess the mitigating role of education, this work takes an integrated approach in two respects. First, we look at a broad set of countries, including Advanced as well as Developing Economies, and analyze global and differential broad regional trends in income inequality. Second, we examine a broad set of determinants besides education and technological progress in order to disentangle the concerning effects. We assembled a unique dataset that combines multiple income inequality indicators, the income Gini coefficient and a ratio of extremes, with the most recent data on multiple drivers. We give particular attention to modeling technological progress, as represented by total factor productivity, the distribution of educational attainment but control for population age structure, non-resource trade flows, finance and institutions. Finally, we use a panel estimation method that controls for country-specific effects and corrects for error disturbances, and test the robustness of our findings with respect to income inequality measures, model specifications and regions.

This seminal work is organized as follows. In Section 2 I review the extant literature on determinants of income inequality. In Section 3 I introduce the income inequality measures and data sources, including the considerable processing we undertook to reduce measurement error and test robustness to indicator choice. Section 4 explains and justifies the covariates, and how these are expected to influence inequality. In Section 5 I present descriptive trends for income inequality and the education distribution. In Section 6 I present the estimation method and in section 7 I present and discuss results. Section 8 concludes.

2 What we know: Theory and Empirical Evidence

Fundamentally, income inequality in a country is a function of the distribution of labor and capital and returns to each of these factors. The distribution of labor income, in turn, depends in part on the market forces of supply and demand for labor. Labor supply depends on the composition and size of labor, which is primarily driven by education and demography. In contrast, demand-side factors primary include trade and technology. The distribution of capital income is shaped by historical factors and endowments, but the growing importance of financial markets and global financial integration have implications for the distribution of both capital and labor income. Finally, government interventions and policies can influence all of these factors directly and indirectly.

On the demand side of labor, theory and empirical evidence suggests that increasing technology deployments increases income inequality by substituting capital for labor, and putting a premium on high skills. Acemoglu (2003) provides a theoretical framework which enables to deduce that this is true for the US as well as Developing Economies. The characterization of trade effects is dominated by the Hecksher-Ohlin model, and its corollary, the Stolper-Samuelson theorem (SST) (Stolper & Samuelson, 1941). The theorem posits that trade liberalization has an ameliorating effect on income inequality in exporting countries if nations specialize in goods whose production requires the type of labor they are relatively abundant in. Conversely, imports that compete with domestic markets increase income inequality by driving down prices and wages in these market segments. Beyond that, Acemoglu (2003) show that trade is able to increase income inequality also in Developing Economies where it imports skill-biased technological change. Roser & Cuaresma (2012) provide evidence supporting the implication of SST as they identify non-oil imports from less developed countries as a robust driver of increasing income inequality in OECD countries. However, in general, empirical studies are quite inconclusive. They rather suggest that the mechanisms through which globalization affects inequality are country- and time-specific (UNCTAD, 2012). Results depend on countries' technological development level, the nature of import/export dependency, and whether actual trade flows or indicators of trade openness are examined (Goldberg & Pavcnik, 2007). Jaumotte *et al.* (2013) find trade liberalization and exports to reduce income inequality. Meschi & Vivarelli (2009) provide evidence supporting the skill-enhancing trade (SET) hypothesis, that the technological diffusion embedded in trade can increase skill premiums, and thereby inequality, particularly in middle income countries.

It has long been recognized that education, through its influence on labor supply, affects income inequality. Based on human capital theory (Becker, 1964), and extensive body of empirical research showed that an additional year of schooling increases wages. Thus, if returns to education are constant, increasing educational attainment, especially if it gives rise to a more equal distribution of education, should reduce income inequality. If returns to education are decreasing, so that an additional year of schooling yields higher returns for lower parts of the education distribution than for higher, the equalizing effect will be stronger. However, if returns to education are increasing due to high skill premiums, the equalizing effect is diminished or might even be offset. Empirical evidence on the relation between education, its distribution and income inequality is inconclusive, though. Studies have focused primarily on OECD countries and on average educational attainment. Some works have examined the distribution of educational attainment, but either in the context of economic growth (Sauer and Zagler, 2012, 2014), or as a consequence - rather than a driver of - income inequality (DiGioacchino & Sabani, 2009). Bussolo *et al.* (2010) derive changes in education attainment primarily through demographic changes, and use these changes to model changes in skilled wage premiums. Castelló-Climent & Doménech (2014) observed that large reductions in education inequality, which are mainly due to a drop in illiteracy in recent decades, have not been accompanied by similar reductions in income inequality. Similarly, Checchi (2000) found that improvements in education reduce inequality only in the case where average education in a nation is low and attainment levels improve rapidly.

Over the last two decades, the share of capital in economies has generally increased with financial liberalization (OECD, 2011, Checchi and Garcia-Peñalosa, 2010). Studies that analyzed the role of financial openness found capital flows (e.g. foreign direct investment) to increase income inequality (Jaumotte *et al.*, 2013) due to the high-skill and technology bias of most foreign investments (Feenstra & Hanson, 2014).

Government interventions of various kinds influence both labor supply and demand. Government labor regulations can alter labor market flexibility to market forces, by setting minimum wages, unemployment benefits, or laying rules for unionization. Labor market policies and institutions are implemented in order to achieve socially desirable redistributive goals and mitigate market risks. Thus, among other things, collective bargaining or unionization, minimum wages and unemployment benefits are generally shown to reduce the dispersion in labor incomes. There is, however, some evidence on unintentional effects of such policies. Checchi & Penalosa (2010) found that labor market institutions indeed reduce income inequality but that this effect is associated with higher unemployment rates. In contrast, Calderón *et al.* (2005) found that minimum wages, if set too high, can reduce employment and increase inequality. Governments' redistributive policies, as it is reflected in the tax structure and social provisions (e.g., social security, basic commodity subsidies), also affect the distribution of personal net disposable income (OECD, 2011). Government's education policies - particularly their relative emphasis on tertiary vs. primary education - can also affect incomes, although this is not sufficient explored in literature (Checchi *et al.*, 2013). One study specifically examines the effect of public education expenditure on income inequality, and finds that greater investments tend to reduce income inequality in the long run, and primarily in developed countries (Sylwester, 2002).

Many works that link governance/regimes to inequality typically examine differences between countries. Some scholars characterize the role of government by the type of political regime. Chakravorty (2006) described governments that divert national resources towards personal gain as extractive (high inequality), and delineates non-extractive regimes into those that redistribute through short-term social transfers (medium to high inequality), or invest in long-term social benefits such as education and health (low inequality). Kemp-Benedict (2011) found empirical support for this, but doesn't disaggregate this effect into between and within effects. Sociologists point to structural features of a society, such as the extent of social cohesion, and historical factors, such as colonization (Chakravorty, 2006; Angeles, 2007).

3 Income Inequality Measures and Data Sources

We examine two conceptually divergent measures of inequality: the Gini coefficient, which is a comprehensive measure of income differences across an entire population, but which masks the internal composition of the distribution; and a ratio of extremes (lowest/highest decile income shares), which reveals the disparity between the tails of the income distribution, but leaves out the rest. We seek the most inclusive measure of income inequality at the individual level in countries. Thus, we seek measures of personal *disposable* income calculated on a per capita basis, covering urban and rural regions, all forms of employment as well as males and females. This restricts us to nationally representative household survey data assembled for a broad panel of countries.

3.1 Data on Income Inequality

Income inequality datasets are notoriously diverse across countries in their underlying estimation methods, measures, units of analysis, data sources and availability of panel data. One of the most widely used and discussed panel dataset is that by Deininger & Squire (1996), who assembled surveys from across countries that meet their desired standard of quality. These data have been shown to be internally inconsistent in ways that are not easily reconcilable.[1] Recent studies use World Bank's POVCAL database for Developing Countries (Chen & Ravallion, 2004). This dataset is, however, quite sparse and unbalanced.

To overcome data sparseness and concept diversity, many studies use parametric extrapolations to calculate Gini indices for years with no survey data. A popular choice is the global Estimated Household Income Inequality (EHII) dataset from the University of Texas Inequality Project (UTIP). It is based on the Deininger and Squire (1996 dataset, but fills in missing data and adjusts for differing

[1] See Atkinson & Brandolini (2001), Galbraith & Kum (2005) and Galbraith (2012).

income concepts by exploiting the relation between manufacturing pay and overall income (Galbraith & Kum, 2005). However, labor in formal markets, let alone manufacturing, represents a small share of employment in poor, particularly agrarian, countries. The estimated income Gini coefficients are thus limited in their ability to predict income inequality in these economies.[2]

We instead develop a self-consistent data set that is derived from the UNU-WIDER World Income Inequality Database, Version 2.0c, May 2008 (WIIDv2). WIIDv2 combines an updated (unpublished) version of the Deininger and Squire dataset with unit data from a variety of other sources, including the Luxembourg Income Study, Transmonee by UNICEF, and Central Statistical Offices of many countries, resulting in a total of over 5,000 observations. While the data still originate from different sources, they are transparent with respect to the income- and/or consumption definition, the statistical units to be adopted and the use of equivalence scales and weighting. Tthe extensive documentation provided with the database enables one to extract data based on a chosen selection criteria and secure a minimum variation of the underlying data.

3.2 Data Processing

We develop selection criteria to ensure that, as far as possible, sources are based on a consistent set of measures and assumptions. We only select sources with comprehensive population coverage, by gender, age and region. We require further consistency with respect to the underlying income concept, and construct individual-, rather than household-based, Gini indices. Finally, we require a minimum of three time observations over one decade and eliminate observations which induce unreasonable jumps in the time series of income Gini coefficients.[3]

The one insurmountable, albeit well-known, source of inconsistency in the dataset is the income measure used across countries. While disposable income would be the ideal basis, many Asian countries report consumption expenditure data. Many others that do use income, only report gross income, which excludes taxes and transfers. As we focus on within-country trends, we allow different concepts across countries but pick sources based on an order of priority in the income measure they use and require consistency of the income concept over time. As a result, we are able to use disposable income for most OECD and Latin American countries, while for many Asian and most African countries we use consumption data.

One novelty in our study is to further refine our income inequality series to enforce source consistency within countries. In the base case we allow multiple sources for a country, but exclude sources in two cases: sources have data for only a single year; and sources whose data are unreasonably incon-

[2]This may explain why we find that estimates for EHII differ considerably from survey data extracted from WIIDv2 for developing countries, both in absolute terms and often in the shape of the Gini series over time.

[3]We dropped all "Quality 4" coded observations, and "Quality 3" coded observations pertaining to unclear and rare income definitions. Over our entire sample, the standard deviation was just under 10 percent (2.8 points with a mean of 33). We considered any jump of over 20 percent in 1-2 years as unreasonable.

Table 1: Income Gini Source Inconsistencies

Country	Year	WB1	WB2	WB3
Ghana	1997	32.7		
Ghana	1998		50.7	
Ghana	1999			40.7
Sri Lanka	2000		27	
Sri Lanka	2002			40.2
Tanzania	1991	58.9		
Tanzania	1993	38		

WB1: World Bank Poverty Monitoring Database 2002; WB2: Deininger and Squire 2004; WB3:World Development Indicators 2004.

sistent for consecutive years with data from other sources. In a second case, we select one source per country that best meet our other selection criteria. The importance of this restriction is illustrated in Figure 1, which shows the difference in Gini trends in consecutive years for Italy from multiple sources, and in Table 1, which reveals inconsistencies in Ginis for Ghana, Sri Lanka and Tanzania even among World Bank sources.

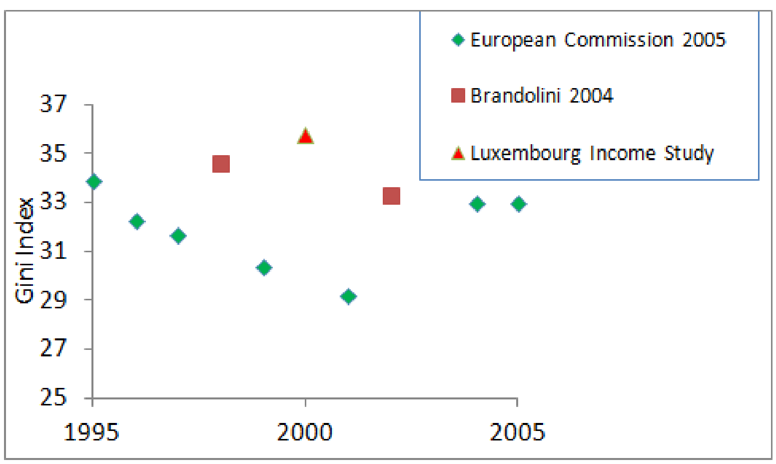

Figure 1: Income Gini Source Inconsistencies. Source: WIIDv2.0

Creating this internally consistent dataset reduces the size of available observations by an order of magnitude, for our base case resulting in an unbalanced panel of 636 observations from 54 countries, including 26 from Advanced Economies (377 observations). Data coverage is more sparse for Developing Countries, with 19%, 16.1% and 5% of total observations in Asian, Latin American and African countries, respectively (see Table 2).

Our data set includes observations from 1960 to 2011, but only 6 percent from 8 countries (of

Table 2: Income Gini Series: Base- and Single-source scenarios

		Mean	Sd	Min	Max	Observations	
Base-case Gini	overall	33.65	10.08	18.00	60.80	Total	636
	between		9.80	21.65	57.78	N	54
	within		2.52	22.60	45.14		
Single-source Gini	overall	34.82	10.15	20.00	62.80	Total	519
	between		9.77	22.50	57.75	N	48
	within		2.37	22.08	44.62		

N refers to the number of countries. Source: WIIDv2.

which 4 percent from 2 countries) are for before 1975, and 2 percent from 4 countries are for after 2006, so we focus our analysis on the period 1975-2006. After accounting for data gaps in independent variables, our most parsimonious model covers 544 observations from 49 countries in this period. The single-source dataset contains 519 observations from 48 countries. More often than not, we use the Luxembourg Income Study (LIS) for western European countries, Transmonee (UNICEF) for countries in transition, the Social and Economic Database for Latin American Countries (SEDLAC) for Latin American countries, and either individual country or World Bank sources (Deininger and Squire, or the Poverty Monitoring Database) for Asian and African countries.

4 Covariates

4.1 Total Factor Productivity

We represent technological change as total factor productivity (TFP). This is a more inclusive indicator than other proxies (Bartel & Sicherman, 1998). Some similar studies use the share of information and communication technology (ICT)in the capital stock (Jaumotte *et al.*, 2013). We prefer a broader productivity measure since our dataset includes poor countries that may benefit from a range of technologies (e.g., assembly lines) other than ICT. The caveat of an economy-wide TFP is that the indicator potentially includes the effect of other factors, such as institutional quality, that mediate between technological change and output. However, the unobserved effect of institutions is pervasive in empirical studies, and partly controlled for by including country-specific effects.

We use a conventional growth accounting framework to estimate TFP (Hall & Jones, 1999). The growth rate of TFP is thus obtained as the unknown part in:

$$\Delta \ln y_{i,t} = \alpha_{it} \Delta \ln k_{it} + (1 - \alpha_{it}) \Delta \ln hc_{it} + \Delta \ln A_{it} \tag{1}$$

where $\Delta \ln y_{i,t}$ is the growth rate of real GDP per worker (at constant 2005 prices, output approach) in country i at time t. $\Delta \ln k_{it}$ is the growth rate of physical capital per worker and α_{it} and $(1-\alpha_{it})$ are the capital and labor shares respectively. All variables are obtained from the most recent version of Penn World Tables (PWT8.0), which provides newly created figures of capital stocks as well as country and time specific labor shares (see Inklaar & Timmer, 2013). However, in order to be consistent with our education variables, we use the IIASA/VID data for computing human capital by worker (hc_{it}) as follows

$$hc_{it} = e^{\phi * s_{it}} \tag{2}$$

where s_{it} are the mean years of schooling (see below) and ϕ is the average return to education. The return has been shown to be not constant but decreasing, though. We thus continue along the lines of Inklaar & Timmer (2013)[4] in allowing for piecewise linear returns to education based on Psacharopoulos (1994) From the resulting growth rates of TFP ($\Delta \ln A_{it}$) we obtain the level of TFP at constant national prices by setting 2005=1.

Based on the literature, we expect that improvements in TFP, reflecting increased technology use, would raise the skill premium and thereby work to increase income inequality.

4.2 Education

Theory predicts that increasing educational attainment acts as a mediating factor between technological progress and trade on the one hand, and income inequality on the other hand. Studies often represent education as an average attainment level (UNCTAD, 2012; Meschi and Vivarelli, 2009; Bergh and Nilsson, 2010). Increases in average attainment might, however, stem from increases within different segments of the education distribution, resulting in differing degrees of inequality in education. We thus argue that it is important to account for a distributional measure of educational attainment. Following Sauer & Zagler (2014) and Cuaresma *et al.* (2013), we calculate an education Gini coefficient which measures the degree of education inequality in the population older than 15 years as follows:

$$\text{EducGini}_{15+} = \frac{1}{MYS} \sum_{i=2}^{4} \sum_{j=1}^{i-1} |y_i - y_j| \; p_i p_j \tag{3}$$

where p_i is the share of concerning population for which i is the highest level attained and y_i is the corresponding cumulative duration of formal schooling. MYS, the mean years of schooling in the population aged 15 and over, is given by $MYS = \sum_{i=1}^{n} p_i * y_i$. As with the income Gini, the education Gini is a measure of mean standardized deviations between all possible pairs of persons. Higher values reflect a less equal distribution. An education Gini of zero means that the entire population attains the same education level, regardless of which. An education Gini of one implies one person has tertiary, and the rest does not attain any education.

[4]Thanks to the extensive documentation along with PWT8.0, we were able to access the stata do file for the calculation of their tfp measure and adjusted this code in order to include the IIASA/VID education data.

In order to measure the aggregate level and the distribution of educational attainment, we use the demographic dataset from the International Institute for Applied Systems Analysis and the Vienna Institute of Demography (IIASA/VID) (KC *et al.*, 2010; Lutz & KC, 2011). This dataset consists of multistage back and forward population projections for 175 countries by five-year age groups, sex and level of educational attainment, spanning the period from 1960 to 2010. Moreover, the dataset gives the full attainment distributions for four education categories: (1) no formal, (2) primary, (3) secondary and (4) tertiary education. These are based on UNESCO's International Standard Classification of Education (ISCED) categories, and are thus strictly consistent over time and across countries. From these data we derive the population attainment levels, p_i. Finally, we obtain country- and year-specific information on the time it takes to reach each education level, y_i, from the UNESCO Institute of Statistics (UIS).[5]

As we discuss in Section 5.2, increasing shares of people with formal education is the predominant driver of education advancements in Developing Countries. In Advanced Economies, the distribution of education within the educated population is the relevant education inequality measure, since almost universal literacy and schooling has been achieved in the eighties.[6] The effects of these regional differences in the education distribution have as yet not been explored separately in the context of income inequality. We fill this gap by decomposing the education Gini of the total population, $EducGini^{15+}$, into the share of unschooled, (*UnSchooled*), and an education Gini for those with at least some formal education (categories 2-4), *EducatedGini*. Since most of the drivers we model affect income inequality within the labor force, we conduct sensitivities with education variables covering the working-age population, aged 15-64.

In general, we expect a more equal distribution of education to increase equality in the income distribution. However, if labor markets respond to changes in the education distribution by adjusting associated returns, a direct relation between the distribution of education and income need not hold. While increases in literacy and primary education may increase the share of low-skilled wages in total income, simultaneous demand effects in tertiary education can drive up the skill premium, making the net effect on income inequality ambiguous.

[5]Since the IIASA/VID dataset includes in each one of the four broad categories of educational attainment individuals who did not complete the respective level, using the total duration for completion would overestimate the years that a representative individual spent in school. We therefore follow the approach proposed by KC *et al.* (2010) in order to account for uncompleted attainment levels when computing the mean duration of each education level.

[6]Morrisson & Murtin (2013) formally show that the positive relation between the education Gini and the share of people with no formal education is mechanical rather than behavioral. Castelló-Climent and Doménech (2014) derive a decomposition of the education Gini coefficient into the share of illiterates and the education Gini coefficient among the literates.

4.3 Age Structure

A populations' age structure - more specifically, the share of elderly - is relevant for both the distribution of income and that of education, particularly in industrialized economies. Pensions are lower, on average, than regular incomes and more unequally distributed. Moreover, educational attainment is typically lower and more unequally distributed among the elderly than among the youth (Cuaresma *et al.*, 2013). We therefore include the dependency ratio (*DepRatio*), i.e. the ratio of people aged 64 and over to those aged 15 and over.

4.4 Trade

We develop trade flow indicators that enable us to test the SST predictions as well as the effect of skill-enhanced trade. We use the Correlates of War (COW v3.0) bilateral trade database to generate import flows from only those countries whose exports are not predominantly natural resources or certain plantation crops, and which therefore fall outside the scope of the SST's 'competing' products. Following Isham *et al.* (2005), we categorize these flows into those from high-income and low-income countries, as a proxy for high-skilled and low-skilled (manufacturing) imports respectively. In comparison, Meschi & Vivarelli (2009) disaggregate exports by source and destination, but do not exclude natural resource trade. Roser & Cuaresma (2012) use a similar trade flow decomposition, but examine inequality in only industrialized countries.

As mentioned earlier, within the narrow boundaries of the SST, imports from low- to high-income countries would increase wage inequality in the latter, and reduce inequality in the former. On the other hand, the skill-enhancing trade theory (Acemoglu, 2003 and Meschi & Vivarelli, 2009) predicts income inequality to increase also in Developing Economies.

4.5 Governance

A wide range of theories from political science, law and economics, demonstrate the pervasive influence of government intervention on income inequality.[7] The various channels of this influence can be grouped into: policies and regulations that directly or indirectly alter household incomes (e.g., direct forms include transfers, while indirect mechanisms include labor support regulations); policies and regulations that influence other channels of influence on income inequality, such as trade openness (which influence the demand for labor of different skill levels), education and health expenditure (which influence human capital); and regime characteristics that reflect the propensity of governments to carry out these policies.

We select the closest possible proxies to redistributive measures,[8] including *de facto* rather than

[7] Kemp-Benedict (2011) for a more detailed review of this literature.

[8] We also analyzed government transfers, using the variable "social contributions" from the World Bank Development Indicators as a revenue proxy, which is the share of government revenues collected by governments towards social security.

de jure indicators for labor regulations.[9] In order to capture the degree of labor support regulations, we use two measures by Schindler (2011), an unemployment benefits (UB) coverage index, which measures the reach of benefits in the unemployed, and a ratio of minimum wage to the mean wage. We combine these two variables using factor analysis into a single covariate, *LaborSupport.* Due to the dominance of informal markets in Developing Economies, this database provides UB data for only 18 advanced economies since 1980, and 29 countries from 1990 onwards. The minimum wage ratio data are available for even fewer country-time combinations.

For regime type,[10] we use the political orientation of the chief executive's party from the World Bank's Database of Political Institutions (DPI), *Political Leaning*, represented by an increasing score from 1 to 2 for right to left.[11] Both theory and empirical studies would suggest an inverse relationship, namely that left-leaning regimes would favor redistributive policies, thereby reducing inequality. However, due to the limited data available, we consider the results with caution, and treat them more as controls than independent variables to be investigated.

4.6 Financial Markets

The share of the top 1 percent in advanced economies and many large developing countries has increased steadily since the seventies (UNCTAD, 2012). Since capital income forms a substantial component of top incomes, and depends, among other things, on the maturity of financial markets in countries, we include private credit, foreign direct investment (FDI), all as shares of GDP. Since these data are likely to have an effect in Developing Countries at most in the last two decades, and because data are in any case sparse, we don't give these variables particular attention, other than to use them as controls.

5 Descriptive Trends - Income and Education Inequality

5.1 Income Distribution Trends

Scholars have been interested in the general rise in inequality since the eighties, and its relation to globalization (UNCTAD, 2012; Galbraith, 2012). More recently, economists started to analyze the role the substantial increase in income inequality has played in the approach of the financial crises.

This is a more direct indicator of redistribution than the more commonly used tax revenues. Unfortunately our dataset becomes much too sparse in order to deduce any reliable inferences. These results are available from the authors upon request.

[9] See Calderón *et al.* (2005) for a discussion of the available *de facto* and *de jure* indicators and their merits.

[10] We attempted to model the theory of regime extractiveness discussed above (Chakravorty, 2006) and operationalized by Kemp-Benedict (2011). However, we found the results to be unreliable when combined with other covariates due to the sparseness of the data, and availability only until 1999.

[11] The original data scored Center as 3 - we recoded this to 1.5, to make the score linear in political orientation.

Table 3: Income Inequality Trends within Countries by Region

		Mean		Sd		Time Trend[a] (> 1980)	
Region	N	IncGini	DecRatio	IncGini	DecRatio	IncGini	DecRatio
Latin America	8	51.5	0.04	2.5	0.01	⇓	None
M.East & N.Africa	6	43.5	0.08	2.6	0.02	None	None
Asia[b]	14	34.3	0.12	2.7	0.01	⇑	⇓
Advanced Econ	26	28.7	0.16	2.3	0.03	⇑	⇓

[a]Statistically significant time trend (t-stat ≥ 2) from a fixed effects regression of inequality against time.
[b]This group comprises South and East Asian countries. Japan is categorized as Advanced Economy.

Galbraith (2012) shows that inequality has been rising since 1987 in low- and middle income non-OECD countries and since 1980 in OECD countries. When grouped by geographic region, we find that in Latin America, the Gini has been declining on average since 1980, though the Decile Ratio does not show a statistically significant pattern. However, by both measures inequality has been rising in Advanced Economies and Asia[12] (see Table 3). One explanation for this regional difference that is consistent with the observed trend of increasing incomes at the top of the income ladder in most growing economies is that the poorest deciles are benefiting from these income gains in Latin America to a greater extent than in Europe and Asia. This may be in part due to favorable redistributive policies of recent governments in Latin America (Lustig *et al.*, 2013).

At a country level, however, trends in income equality vary over time, and across regions. In both Advanced and Developing economies, some countries (e.g., US, UK, Poland, Finland, Argentina, Bangladesh) have experienced steadily rising, while others (e.g., Spain, France, Brazil) have experienced steadily falling, inequality. Many countries have experienced reversals in trends, which more often than not took the form of a rise in the eighties into the nineties, followed by a recent decrease either in the nineties or 2000s (e.g., Sweden, Chile, Venezuela, Thailand).

There are other noteworthy regional patterns and differences in income inequality. The within-country standard deviations of Ginis are very similar across regions, suggesting that universally income distribution changes are slow at any level of inequality (see also Table 2), and that the extent of influence of time-varying drivers is narrowly bounded. Moreover, the Decile Ratio is highly (inversely) correlated to the Gini, but the extent varies by region. A simple regression reveals that globally the

[12]The Africa and Asia means are underestimates. Inequality measures in 7 Asian and 4 African countries are based on consumption expenditure, which are known to appear more egalitarian than income surveys. Deininger & Squire (1996) suggest adding 6.6 points to the expenditure Gini to make it comparable to income-based Ginis (Galbraith, 2012). For example India's Gini based on income has been estimated to be 54, based on data from the India Human Development Survey of 2004-05 (Sen and Dreze, 2013). This compares to 36.8 for 2004 in our dataset.

Decile Ratio explains about 75 percent of the variation in the Gini within countries.[13] This share is higher in advanced economies and Asia, where the Decile Ratio is also more volatile. This suggests that, on average, changes in income distribution between 1980 and 2005 have mainly taken place at the extremes.

5.2 Education Distribution Trends

In contrast to the general increasing trend of income inequality, we observe a global trend towards a more equal distribution of education. This finding is consistent with previous evidence pointing to the puzzle (Castelló-Climent & Doménech, 2014) that a universal declining trend of education inequality has not been accompanied by reductions in income inequality. However, while the education Gini for the total population, ($EducGini_{15+}$) has been decreasing, the education Gini of the educated population ($EducatedGini^{15+}$) remained almost constant or increased (see figure 2)[14]

The strong decrease in the education Gini of the total population, especially in Developing Economies, can be attributed in large part to a significant reduction in the share of people who did not attain any formal education. The concerning variable *UnSchooled* is thus 97 percent correlated with $EducGini_{15+}$. The schooled population share has increased by one percentage point every year in Asia, and a tenth of a percentage point per year in Latin America. In contrast, the education Gini of the educated population has been slightly increasing in all regions but Advanced Economies and Central Asian and European[15] countries. Both education inequality measures move almost simultaneously as the share of unschooled people is already very low since the eighties in these two regions (see section 5). Notably, in the last few decades changes in the degree of education inequality within the educated population has been driven by changes at the extremes in Advanced Economies - the share of the population with secondary attainment has remained relatively constant at around 65 percent, while the share with primary (tertiary) has decreased (increased) more dramatically (i.e. 5 percentage points each between 1990 and 2000).

Especially for Developing Economies, we thus expect to provide new insights by decomposing the overall education Gini coefficient and analyzing the effect of a decreasing unschooled population share separately from the impact of changes in the distribution of the educated population on the income distribution. In general, the observation that more people attain at least some formal education and education became more equally distributed but there has been no or even an adverse effect on the income distribution poses the question: Can this be explained by high relative demand for skills? More

[13]Within R^2 of 75.4 in a fixed effects OLS of Gini regressed on DecileRatio for the full sample. Other studies (cited in UNCTAD, 2012) find even stronger dependence of the Gini on income concentration: in the US, the income concentration change in just the top 1 percent explains from half to almost the entire change in the country Gini.

[14]If we look at the education measures for the working-age population (aged 15 to 64), we find die education Gini coefficients to be slightly lower, on average, and decreasing at a faster rate, reflecting generational improvements in education attainment.

[15]These include all European countries which are not categorized as Advanced Economies.

precisely, is it possible to discover the theoretically predicted positive relation between the education and the income distribution after controlling for technological progress and trade?

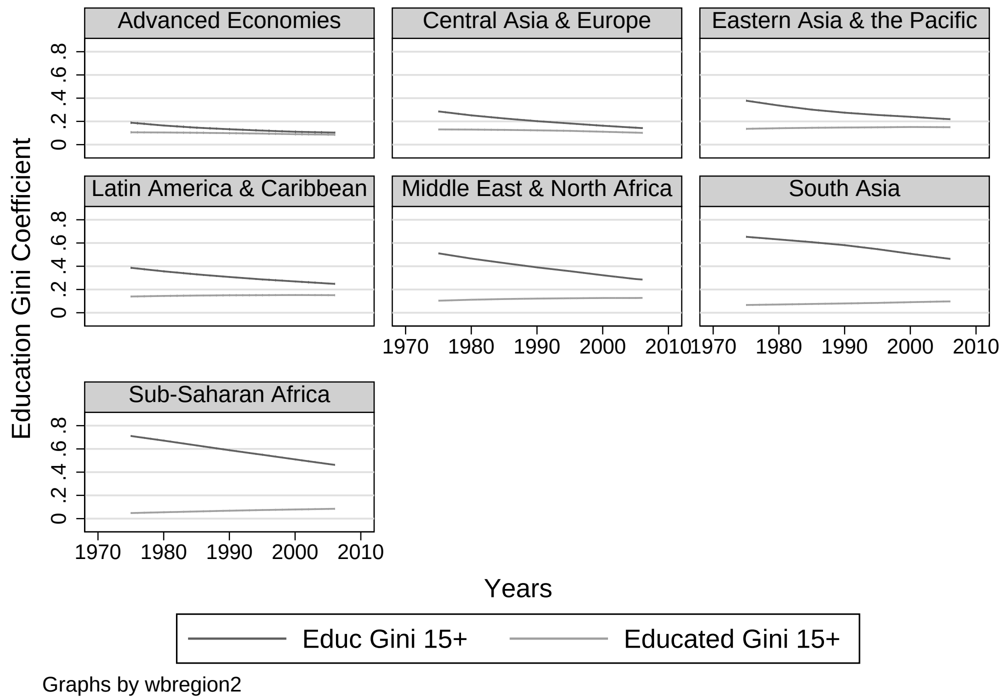

Figure 2: Education Gini Coefficients

6 Methodology

6.1 Estimation Method

Given our primary interest is to examine within-country time trends, a fixed-effect (FE) least squares model would seem appropriate, and has been used in other related works (UNCTAD, 2012; Galbraith and Kum, 2005). However, due to the presence of error disturbances, as described further below, we prefer a feasible GLS (FGLS) estimator with country fixed effects. A similar approach has been used by Kemp-Benedict (2011), but with regional fixed effects .

Unlike a pooled regression, a FE model would prevent omitted variable bias related to country-specific time-invariant factors that distinguish country's historical levels of inequality. However, we observe first order autocorrelation (AR1) and groupwise (i.e. country-wise) heteroskedasticity in the errors.[16] The observed complex structure of error disturbances makes a basic FE model unsuitable

[16]For groupwise heteroskedasticity, we calculate a modified Wald Statistics using the STATA command xttest3 in a fixed effect model. The test results strongly rejects ($p > Chi2 = 0.0000$, $Chi2(49) = 8301$) the null that the country-wise variances in standard errors are equal. We demonstrate autocorrelation AR(1) in several ways. We use the test by

for drawing inferences on statistical significance. Both types of disturbances are likely, as the Gini is a persistent, path-dependent variable. Moreover, as some countries have more erratic Ginis than others, it is natural to expect the error variances to vary by country. Notably, with the exception of studies that use dynamic panel models, many empirical works of income inequality, including those that use FE models, do not report tests of error disturbances.

A typical approach to correct for autocorrelation while accounting for individual effects is to include the lagged dependent variable and use system GMM (Calderón *et al.* (2005); Roser and Cuaresma, 2012). The lagged dependent variable eliminates AR(1), and the use of lags as instruments accounts for the induced endogeneity, i.e. dynamic panel bias. However, system GMM is asymptotically efficient only for very large N. Furthermore, the need to generate instruments from multiple lags reduces the degrees of freedom significantly. The least squares dummy variable bias correction approach in dynamic models is an alternative to system GMM (Meschi & Vivarelli, 2009), but offers no straightforward way to deal with groupwise heteroskedasticity (Bruno, 2005).

Estimation methods that correct for complex error structures include FGLS or clustered standard errors in FE models. We select FGLS based on its finite sample efficiency properties and the particular error structure present in our data. In samples as ours, with N > T, that exhibit groupwise heteroskedasticity, FGLS is likely to be more efficient than OLS (Reed & Ye, 2011).[17] Moreover, although cluster robust standard errors can correct for serial correlation within panels, and can be weighted on groupwise heteroskedasticity, they can be less reliable than ordinary standard errors with unbalanced clusters (Kézdi, 2004).

To sum up, we apply a FGLS estimator in order to estimate the long-term, global and broad regional effects of income-inequality drivers within countries. Our most parsimonious model specification is thus given by Equation (4):

$$IncGini_{i,t} = \beta TFP_{i,t-1} + \boldsymbol{\delta} E_{i,t-1} + \boldsymbol{\gamma} T_{i,t-1} + \mu_i + \epsilon_{i,t} \tag{4}$$

with

$$E = UnSchooled, EducatedGini \tag{5}$$

$$T = Imp^{High}, Imp^{Low}, Exp \tag{6}$$

Woolridge, which is discussed and analyzed in Drukker (2003) and implemented in STATA using the command xtserial. The null hypothesis of no serial correlation (based on the coefficient of a regression of lagged residuals) is strongly rejected ($F(1, 34) = 41.5$, $p > F = 0.0000$). Furthermore, the FGLS model calculates the common AR(1) coefficient to be 0.4 or higher in all the model runs.

[17] In particular, we implement FGLS using xtgls with the options corr(ar1) and panel(hetero). Reed and Ye (2009) demonstrate (in balanced panels) that this method produces more efficient estimates than OLS in finite samples with N > T.

where the total factor productivity (TFP) proxies for technological progress, the education matrix, E, includes the share of people without any formal education (*UnSchooled*) and the education Gini coefficient of the educated population aged 15 and over (*EducatedGini*). The trade matrix, T, consists of the two import vectors from high (Imp^{High}) and low (Imp^{Low}) income countries and total exports (Exp). μ_i is the country specific intercept and $\epsilon_{i,t}$ is the time varying error. We include all variables lagged one period in order to account for reverse causality.

In addition, we report results accounting for the age structure in Advanced Economies.[18] We also present evidence from additional model specifications with institutional (*LaborSupport* and *PoliticalLeaning*) and finance (*PrivateCredit* and FDI) covariates and conducted other sensitivities as described below.

7 Results and Discussion

Tables 4 to 10 provide the key results of our analysis. Table 4 presents results corresponding to the most parsimonious model for the global sample. In tables 5, 6, 7 and 8 we split our sample into Advanced, Developing and Highly Unequal Economies. Evidence on institutional and financial variables for the global sample is provided in tables 9 and 10.

[18]Due to the collinearity with the unschooled population share, we cannot include the dependency ratio in the base model. However, we do include it in the advanced economy sensitivities, where the correlation is much weaker (< 0.3).

Table 4: Global Sample - Parsimonious Model

	Base-Case	Single-Source	DecRatio	Ehii
TFP	8.10	11.29	-0.02	-0.00
	(1.31)***	(1.54)***	(0.01)*	(0.60)
UnSchooled	-6.17	-3.06	0.05	-28.76
	(4.03)	(4.73)	(0.03)**	(1.95)***
EducatedGini	-24.46	-29.54	0.48	-81.78
	(10.03)**	(12.68)**	(0.15)***	(7.27)***
Imp^{High}	0.72	2.51	-0.04	1.00
	(1.77)	(2.11)	(0.02)**	(0.98)
Imp^{Low}	-11.34	-19.02	0.11	-3.11
	(3.91)***	(5.26)***	(0.03)***	(1.66)*
Exp	1.46	0.54	-0.01	-0.36
	(1.44)	(1.75)	(0.01)	(0.87)
Obs	544	455	371	1,143
N	49	44	40	47
$\bar{T}$	11.10	10.34	9.28	24.32
$Chi2$	11,957.13	10,238.98	6,382.75	6,215.29

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 5: Advanced Economies - Parsimonious Model

	Base-case	Single-source	DecRatio	Ehii
TFP	10.79	15.56	-0.23	2.51
	(2.04)***	(2.37)***	(0.04)***	(0.96)***
UnSchooled	-21.86	-18.73	-0.01	-23.35
	(10.68)**	(13.47)	(0.15)	(3.52)***
EducatedGini	-22.65	-36.43	0.29	-84.39
	(13.76)*	(17.82)**	(0.30)	(9.52)***
Imp^{High}	4.07	1.49	-0.11	0.33
	(2.74)	(2.94)	(0.04)**	(1.15)
Imp^{Low}	-9.54	-24.45	0.11	-2.70
	(5.36)*	(7.75)***	(0.08)	(1.75)
Exp	-4.56	-3.22	0.09	-1.75
	(2.64)*	(2.84)	(0.04)**	(1.10)
Obs	339	278	207	690
N	26	23	22	26
$\bar{T}$	13.04	12.09	9.41	26.54
$Chi2$	1,301.11	1,147.56	1,198.40	1,610.03

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 6: Advanced Economies - Age Structure

	Base-case	Single-source	DecRatio	Ehii
TFP	9.37	14.35	-0.20	0.75
	(2.07)***	(2.46)***	(0.04)***	(0.99)
UnSchooled	-17.79	-10.05	-0.11	-24.98
	(11.55)	(15.99)	(0.18)	(4.14)***
EducatedGini	37.92	5.40	-1.48	-19.44
	(26.30)	(31.63)	(0.75)**	(14.27)
DepRatio	37.86	30.51	-0.90	42.11
	(10.68)***	(11.44)***	(0.32)***	(6.53)***
$EducatedGini * DepRatio$	-305.28	-204.36	9.31	0.74
	(140.31)**	(180.42)	(3.71)**	(1.15)
Imp^{High}	3.96	1.31	-0.11	-2.08
	(2.77)	(2.96)	(0.04)**	(1.80)
Imp^{Low}	-9.06	-23.55	0.06	-2.49
	(5.50)*	(8.00)***	(0.09)	(1.11)**
Exp	-4.96	-3.62	0.12	
	(2.62)*	(2.82)	(0.04)***	
Obs	339	278	207	690
N	26	23	22	26
$\bar{T}$	13.04	12.09	9.41	26.54
$Chi2$	1,366.65	1,128.28	1,072.06	1,601.10

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 7: Developing Economies - Parsimonious Model

	Base-case	Single-source	DecRatio
TFP	6.32	6.35	0.02
	(1.91)***	(2.33)***	(0.01)**
UnSchooled	2.92	7.18	-0.04
	(5.46)	(5.70)	(0.02)**
EducatedGini	5.82	-18.07	-0.03
	(24.14)	(26.54)	(0.13)
Imp^{High}	-1.22	7.99	-0.02
	(2.60)	(4.28)*	(0.01)
Imp^{Low}	1.09	-6.59	0.01
	(7.12)	(8.90)	(0.03)
Exp	2.32	3.29	0.01
	(1.72)	(2.43)	(0.01)
Obs	205	177	164
N	23	21	18
$\bar{T}$	8.91	8.43	9.11
$Chi2$	4,244.99	2,755.46	11,053.22

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 8: Highly Unequal Economies - Parsimonious Model

	Base-case	Single-source	DecRatio
TFP	7.22	6.60	0.01
	(2.28)***	(2.71)**	(0.01)
UnSchooled	19.21	22.08	-0.04
	(9.78)**	(10.26)**	(0.02)*
EducatedGini	99.12	86.59	-0.11
	(54.08)*	(58.26)	(0.18)
Imp^{High}	7.34	12.12	-0.02
	(5.52)	(6.28)*	(0.02)
Imp^{Low}	-14.47	-19.99	0.03
	(10.25)	(12.87)	(0.03)
Exp	2.72	3.01	-0.00
	(2.53)	(2.88)	(0.01)
Obs	161	145	129
N	19	18	14
$\bar{T}$	8.47	8.06	9.21
$Chi2$	1,699.83	1,600.06	4,701.58

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 9: Global Sample - Governance Model

	Base-case	Single-source	DecRatio	Ehii
TFP	6.80	9.67	-0.01	-7.19
	(2.25)***	(2.64)***	(0.02)	(1.12)***
UnSchooled	0.89	-9.51	0.06	-36.12
	(7.50)	(9.81)	(0.05)	(5.11)***
EducatedGini	-23.47	-35.72	0.76	-131.51
	(13.84)*	(18.89)*	(0.22)***	(11.89)***
Imp^{High}	8.81	6.93	-0.09	6.04
	(3.00)***	(3.41)**	(0.03)***	(1.70)***
Imp^{Low}	-13.87	-4.21	0.27	-0.60
	(6.28)**	(3.11)	(0.07)***	(3.44)
Exp	-4.63	-33.14	0.01	-4.01
	(2.72)*	(9.43)***	(0.02)	(1.34)***
LaborSupport	0.16	-0.01	-0.00	0.00
	(0.20)	(0.23)	(0.00)	(0.12)
PoliticalLeaning	0.66	0.67	-0.00	-0.30
	(0.34)*	(0.37)*	(0.00)	(0.15)**
Obs	273	232	189	531
N	29	26	23	30
$\bar{T}$	9.41	8.92	8.22	17.70
$Chi2$	8,698.28	6,127.88	3,485.14	3,535.29

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table 10: Global Sample - Finance Model

	Base-case	Single-source	DecRatio	Ehii
TFP	7.15	9.66	-0.03	-0.24
	(1.41)***	(1.58)***	(0.01)**	(0.58)
UnSchooled	-0.54	11.38	0.04	-21.05
	(4.47)	(5.09)**	(0.03)	(1.82)***
EducatedGini	-8.43	-7.59	0.33	-61.08
	(11.13)	(11.64)	(0.19)*	(7.29)***
Imp^{High}	2.55	5.43	-0.05	2.22
	(1.96)	(2.18)**	(0.02)**	(0.92)**
Imp^{Low}	-14.25	0.04	-0.01	-2.41
	(4.46)***	(1.85)	(0.01)	(1.60)
Exp	2.14	-17.19	0.13	-1.90
	(1.54)	(4.82)***	(0.05)***	(0.78)**
FDI	0.01	0.01	-0.00	0.00
	(0.01)	(0.00)**	(0.00)	(0.00)
PrivateCredit	0.00	0.02	0.00	0.00
	(0.01)	(0.00)***	(0.00)	(0.00)*
Obs	454	378	290	967
N	46	41	36	45
$\bar{T}$	9.87	9.22	8.06	21.49
$Chi2$	12,316.00	12,070.46	5,846.80	9,457.87

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

7.1 Total Factor Productivity

TFP is the most robust predictor of income inequality in our analysis, for all income inequality measures, and for different regions. Consistent with the literature on skill-biased technological change, TFP is positively related to the Gini coefficient, and therefore to income inequality. This result is more relevant in Advanced Economies. There, an increase in TFP by one standard deviation (0.1) is associated with an increase in the income Gini by 1.0 and 1.5 points for the base- and single-source case respectively. This effect is stronger for the Decile Ratio, where a standard deviation increase in TFP would decrease the Decile Ratio also by a standard deviation. The EHII also shows a significant effect for Advanced Economies, but not for the global sample, which may be because of the unreliable data for Developing Economies.

7.2 Education and Age Structure

The relation between education and the income distribution is region dependent. Reducing the unschooled population share reduces income inequality in Developing Countries. This effect manifests across all income inequality measures in the subset of *highly unequal* countries (Table 8). The Decile Ratio shows the most robust effect across Developing Economies in general (Table 7) This is a reasonable finding, since the benefits of improving basic education opportunities are likely felt by the poorest. The magnitude of the effect seems rather small, however. At the rate this group of countries has improved schooling (5 percentage points per decade), these improvements would account for an increase in at most a tenth of the standard deviation of the Decile Ratio. At a global level and in Advanced Economies, the effect of schooling is ambiguous. In any case, in Advanced Economies with a few exceptions[19] unschooled population shares were well below 5 percent by the nineties, making them relatively unimportant for explaining income inequality trends.

In contrast, education inequality appears to be inversely related to income inequality. This is true for all inequality measures in the global sample and Advanced Economies. This rather counter-intuitive result is consistent with recent trends, wherein income inequality in Advanced Economies has been increasing since 1980, while education inequality has been falling.[20] This relationship may reflect the confounding effect of demographic shifts rather than a causal effect. This is evidenced by the inclusion of the dependency ratio (Table 6), wherein the coefficients of education inequality become insignificant with respect to the income Gini measures. In this case, however, a more equal distribution of education among the educated population contributes to increasing the share of income accruing to the bottom 10%. Higher dependency ratios are associated on their own with increasing income inequality - presumably because pensioners' incomes on average are lower than those in the

[19] Portugal and Greece

[20] Since 1980, the income Gini has increased by 0.2 percentage points, while the educated Gini has reduced by 0.1 percentage points a year in Advanced Economies.

labor force but more unequally distributed. Moreover, the positive effect might absob the pressure of pensions on governments budgets in aging societies. Also, the interaction between education inequality and the dependency ratio is significant, indicating that the negative relation between education and income inequality is present only at higher levels of aging.The interaction manifests in countries with higher education inequality and dependency ratios, such as Spain or Portugal, where the net effect of both on income inequality is small. However, in countries such as Germany, with low education inequality and an older population, the income inequality-increasing effect of the dependency ratio dominates. One possible explanation for this is that newer generations of retirees are both richer and better educated, so that the education inequality among the retired population is lower, but income inequality is higher due to higher returns to higher level education compared to earlier decades.

7.3 Trade

Our results show that low-skilled (i.e., from low-income countries), non-resource imports reduce income inequality in importing countries. The statistically significant negative sign for low-skilled imports is robust to different income inequality measures as well as regional sensitivities. The influence is, however, very small. The coefficient ranges from -3 to -25 percentage points for a 100 percent change in imports (as a share of GDP), but the standard deviation of the latter within countries is only about 2 percentage points.

This negative effect is contrary to the theoretical predictions of the SST for industrialized economies. There is a plausible explanation, considering the long time frame of the panel. If labor supply reacts to skill premiums in the long run, lowering wages for low-skilled manufacturing jobs in Advanced Economies may induce shifts in labor towards services, which command higher wages, thereby working to reduce inequality. The net effect of observed rising income inequality, however, would depend on other factors that increase concentration of income within the service sector, such as executive compensation or IT entrepreneurship.

Imports from high-income countries, on the other hand, serve to increase income inequality in Developing Economies. Increasing the share of high-skilled imports in GDP by one percentage point increases the Single-source Gini by 1.2. This finding is consistent with the SET hypothesis that the technological diffusion embedded in trade can increase skill premiums, and thus income inequality. In Advanced Economies, imports from other high-skilled countries significantly increase income inequality by affecting the income share at the bottom of the distribution.

Total exports have a significant effect of reducing income inequality in advanced economies, which is also consistent with literature. This manifests in the income Gini and the Decile Ratio, and is of comparable magnitude to the effect of imports.

7.4 Governance and Finance

We don't find conclusive evidence for the effect of political institutions on income inequality (Table 9). Left-orientated governments tend to be related to a more equal distribution of incomes at global level. But we do not find any statistically significant effect of labor market institutions. However, we interpret this as a limitation of data, rather than an evidence of no effect. The limitation is on three grounds: first, very sparse data availability, particularly for Developing Countries. The available sample is less than 30 countries, without any clear geographic pattern. Second, we consider the indicators themselves inadequate to capture the nuances of government redistributive tendencies or policies in particular countries, as revealed by Calderón *et al.* (2005) (labor market regulations) and Lustig *et al.* (2013). Third, the methodology of this study is suited for examining less volatile, structural changes in the economy - however, shifts in redistributive policies and regime are often short-lived, and therefore not picked up in decadal trends.

Consistent with previous work, we find an expected positive relationship between both income inequality and FDI as well as private debt. The effects are relatively small but stronger for Advanced Economies (see Appendix A).

7.5 Robustness

From the perspective of our primary interest to identify statistically significant drivers, we see fairly robust results across income inequality measures for TFP, schooling, and trade variables. In most cases, the significance and signs are consistent for the Decile Ratio and Gini coefficients. A notable exception is for Developing Countries alone, where only the effect of basic formal schooling appears significant. There are, however, differences of up to 50 percent in the magnitude of coefficients between the Base-case and Single-source Gini, and sometimes significance observed for one and not the other. For the most part, the EHII corroborates the results with the WIID-sourced measures, notwithstanding some differences. For instance, TFP does not show as significant with the EHII, even though it does in all three other measures. These discrepancies give some sense of the margin of errors in coefficients related to different sources, and suggest caution in drawing conclusions from analyses that are based on single income inequality measures.

Regarding space and time sensitivities, we have already seen that the influence of basic schooling, education inequality, imports and aging vary in the significance and magnitude of their influence between Advanced Economies and Developing Countries. TFP is the only driver whose influence is pervasive across regions, but also has a stronger impact in Advanced Economies.

8 Conclusions and Further Research

Income inequality has been rising in most parts of the world, with the exception of some Developing Economies in Latin America and Africa with high levels of absolute inequality. In accordance with theoretical predications, this increase in income inequality can be explained by technological progress to a large extent. We were not able to find the strong mediating effect of education which is implied by Tinbergen's and Goldin and Katz's *Race between Technology and Education.* In contrary, we find a more equal distribution of education to increase income inequality in the global sample as well as in Advanced Economies. After accounting for the demographic structure of the population the effect is not significantly different from zero. However, in Developing Economies, the rise in basic schooling has contributed to increasing the share of income accruing to the bottom decile of the income distribution.

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A Advanced Economies

Table A.1: Advanced Economies - Governance Model

	Base-case	Single-source	DecRatio	Ehii
TFP	18.40	23.25	-0.30	3.64
	(2.86)***	(3.04)***	(0.05)***	(1.82)**
UnSchooled	8.99	-23.04	-0.18	-100.44
	(20.20)	(24.73)	(0.43)	(16.12)***
EducatedGini	23.32	23.57	0.54	18.94
	(9.47)**	(10.40)**	(0.34)	(6.11)***
Imp^{High}	14.00	9.72	-0.36	2.99
	(3.89)***	(3.95)**	(0.06)***	(2.22)
Imp^{Low}	-7.99	-28.77	0.17	-1.59
	(7.45)	(10.01)***	(0.13)	(3.85)
Exp	-14.85	-12.83	0.28	-7.63
	(3.81)***	(3.97)***	(0.05)***	(2.03)***
LaborSupport	0.06	-0.22	-0.00	0.02
	(0.25)	(0.26)	(0.00)	(0.17)
PoliticalLeaning	0.62	0.69	-0.01	0.06
	(0.45)	(0.46)	(0.01)	(0.18)
Obs	179	149	103	323
N	16	14	12	16
$\bar{T}$	11.19	10.64	8.58	20.19
$Chi2$	867.21	784.35	571.97	651.60

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Table A.2: Advanced Economies - Finance Model

	Base-case	Single-source	DecRatio	Ehii
TFP	7.93	10.83	-0.20	2.26
	(1.99)***	(2.05)***	(0.04)***	(0.91)**
UnSchooled	-6.67	-13.05	0.56	-43.08
	(15.16)	(16.85)	(0.42)	(9.61)***
EducatedGini	21.57	9.55	-0.22	25.36
	(7.80)***	(7.38)	(0.18)	(3.68)***
Imp^{High}	8.22	7.78	-0.17	0.63
	(2.67)***	(2.93)***	(0.04)***	(1.23)
Imp^{Low}	-19.62	-18.38	0.04	-4.50
	(5.03)***	(6.24)***	(0.08)	(2.06)**
Exp	-5.90	-5.84	0.17	-1.67
	(2.63)**	(2.84)**	(0.04)***	(1.13)
FDI	0.01	0.01	-0.00	0.00
	(0.00)***	(0.00)***	(0.00)*	(0.00)
PrivateCredit	-0.00	0.01	0.00	0.01
	(0.01)	(0.01)***	(0.00)***	(0.00)***
Obs	287	234	158	600
N	26	23	20	26
$\bar{T}$	11.04	10.17	7.90	23.08
$Chi2$	1,903.18	1,974.13	1,594.65	2,885.23

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$