# Explaining Income Inequality Trends in Countries: An Integrated Approach

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# Explaining Income Inequality Trends in Countries: An Integrated Approach*

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**Abstract**

What can we say about systematic trends in the drivers of income inequality in countries? In order to address this question this work gives unprecedented attention to robustness in measures of income inequality, model specifications and determinants. We thus use three income inequality measures, assess determinants such as technological progress and the labor income share, and construct new variations of others, such as non-resource trade flows to test trade theories, education distribution to assess heterogeneity in education levels, and disaggregated public spending to test political influence. We also assess regional variations between Advanced and Developing Economies. Our findings indicate the most robust global drivers of increasing inequality to be technological progress and trade with high-income countries. Trade with low-income countries, public spending on health and decreasing shares of unschooled people have significant equalizing effects on income distribution. The effects of education distribution, public education spending and labor income share are highly region specific and indicate the importance of disentangling global effects.

JEL-Codes: I24, I28, F62

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# 1 Introduction

National income inequality has risen in most parts of the world over the last few decades. This begs the question of whether there are similar factors within countries that explain this common trend. Disentangling income inequality into its main drivers is complex, not only because factors at many scales - global, sub-national and subgroups within nations - affect national income distributions, but also because a range of different drivers interact to influence income inequality. Moreover, the issues of data quality and measurement of income inequality are considerably relevant to any empirical investigation. Aside from the extensive historical accounts of Atkinson, Piketty and their coauthors[1], quantitative studies have either focused on specific regions, due to data availability and reliability especially on OECD economies; or have concentrated on specific drivers, e.g. education, globalization or labor market institutions. These works often rely on a simplified representation of control variables, e.g. education measured as average years of schooling. This leaves open whether one can discern from empirical analysis any robust, systematic global or regional patterns in the drivers of national income inequality.

This study gives unprecedented attention to comprehensiveness and robustness in analyzing within-country income inequality trends. First, we thus look at a broad set of countries, including Advanced as well as Developing Economies, and analyze global and differential broad regional trends. Second, we examine a broad set of determinants in order to disentangle the concerning effects. Third, we examine three measures of income inequality, two Gini coefficients based on differing data bases, and a ratio of extremes. For the fist time, we correct for the multitude of data sources and measurement errors by creating two time series of income Gini coefficients which cover at least one decade and differ with respect to the degree of heterogeneity in the underlying data sources. We thus assembled a unique dataset that combines these multiple income inequality indicators with the most recent data on multiple drivers. Particular attention is given to modeling the distribution of educational attainment but we also analyze technological progress, as represented by total factor productivity, trade between high- and low-income countries, the labor income share and heterogeneity in public social spending. 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.

Our findings indicate the main factors adding to increasing inequality globally to be technological progress and trade with high-income countries. Both market forces contribute to the skill-biasedness of labor demand. Trade with low-income countries, public spending on health and decreasing shares of people without any formal education, on the other hand, had significant equalizing effects on the income distribution. The estimated effects of the education distribution, public education spending and the labor income share are highly region specific. We are also able to provide supplementary insights into the linkages between drivers and inequality by analyzing the decile ratio in addition to the Gini coefficient as dependent variable.

The rest of this paper is organized as follows. In Section 2 we review extant literature, and describe how existing knowledge motivates this study. In Section 3, we introduce our income inequality measures and data sources, including the considerable processing we undertook to reduce measurement error and test robustness to indicator choice. In Section 4, we describe and justify our covariates. Descriptive trends of

[1] See e.g. **?**, **?**, **?**, **?**.

income and education inequality measures are presented in Section 5 while we justify our estimation method in Section 6. In Section 7, we present and discuss our results, and in Section 8 we draw conclusions and provide pointers for further work.

## 2 What we know: Theory and Empirical Evidence

Fundamentally, the degree of (in)equality in the distribution income in a country is a function of the distribution of labor and capital and the individual returns to each of these factors. The distribution of labor income, in turn, depends in part on the market forces of supply and demand. Labor supply is determined by the composition and size of labor, which is primarily driven by education and demography. In contrast, demand-side factors primarily 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 integration have implications for the distribution of both capital and labor income. Finally, government policies and institutions can influence all of these factors directly and indirectly.

In the transition from agricultural to industrialized economies, induced by groundbreaking innovations in electricity and transport, among other things, the demand for skilled workers increased, thereby increasing manufacturing wages relative to that agricultural labor. By 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, made simple jobs more complex and created new jobs requiring higher skills. Thus, again, high-skilled wages increased relative to low skilled wages. 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, implying a positive relation between technological progress and income inequality. Even if technological and sectoral shifts are different, the general direction of the effect prevails for Advanced and Developing Economies. Acemoglu (2003) provides a theoretical framework which enables to deduce that this relationship holds not only for the US, but also for Least Developed Countries (LDCs), where technological adoption and imitation is promoted via trade.

The characterization of trade effects has long been dominated by the Heckscher-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. If industrialized economies export capital- and knowledge-intensive while importing labor-intensive goods, income inequality is predicted to increase. This effect might even be stronger, if the expansion of exporting sectors puts a premium on high skills. The specialization into low-skilled-labor intensive goods, on the other hand, should increase the income share of the lower tail of the income distribution in Developing Economies. The comparative-advantage framework has been criticized, however, due to its inability to explain the inequality effects of intra-industry trade as well as the observed increase in income inequality in most middle- and low-income countries. Two strands of the literature are particularly relevant to fill these gaps. First, theories that address the increasing importance of outsourcing and multinational enterprises indicate that the required skill level of workers in industries that moved from high to low income countries is usually higher than the average in these economies. The resulting skill premium thus increases the dispersion of wages. Second, trade liberalization provides incentives for innovation activities in exporting sectors and facilitates technological diffusion via technologies embedded in imported capital goods (Acemoglu, 2003). Skill premias emerge in high- and low-income countries due to trade with similar and industrialized economies respectively.

In general, empirical studies are quite inconclusive. They 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. Roser & Cuaresma (2014) 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. Also Meschi & Vivarelli (2009) highlight the importance of decomposing trade flows depending on their origin and destination. They provide evidence supporting the hypothesis that the acceleration of technological progress via trade increases skill premiums, thereby inequality, particularly in middle income countries.

It has long been recognized that education has a pivotal equalizing role through its influence on labor supply. Based on human capital theory (Becker, 1964), an extensive body of empirical research showed that an additional year of schooling increases individual wages. Thus, increasing average educational attainment should reduce income inequality. The direction and extent of this effect depends, however, on the distribution of advancement across different education levels and on relative returns at these levels, i.e. on the *composition* and the *wage effect* (Foerster & Tóth, 2015). For a given level of educational attainment, a more equal distribution of education reduces income inequality if returns to education are constant. If returns to education are decreasing, 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. Conversely, increasing higher education might increase the degree of educational inequality but still reduce the skill premium, thereby reducing inequality in the distribution of earnings.

An extensive body of research analyzed the dynamics of skill premiums, education and wage inequality in high income countries, while research 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. In this vein, Carnoy (2011) argues that mass expansion of higher education is able to contribute to increasing income inequality, depending on the return differential between university education and lower levels; and on public education policy. In general, empirical evidence on the relation between education, its distribution and income inequality is inconclusive. Studies that included some measure of average educational attainment as a control variable found either a negative (e.g. OECD, 2011) or insignificant (e.g. Roser & Cuaresma, 2014) relation to income inequality. In a panel dataset covering a broad sample of countries, Gregorio & Lee (2002) find higher average attainment and a lower variance of education to significantly contribute to decreasing income inequality. On the contrary, Castelló-Climent & Doménech (2014) observed that large reductions in education inequality (measured by an education Gini coefficient), which were mainly due to a drop in illiteracy in recent decades, have not been accompanied by similar reductions in income inequality.

Labor supply and demand factors affect not only the personal distribution of income but also the functional distribution between capital and labor. First, technology and trade induced reductions in low-skilled incomes were not countervailed by an increase in the high-skilled income share. The average wage share thus decreased since the 1980s in the majority of economies. Stockhammer (2013) argues that, additionally to its skill-biasedness, technological change has become capital rather than labor augmenting. Second, trade integration has been shown to increase the relative bargaining power of capital, being the more mobile factor (Rodrik, 1997). Beyond that, over the last two decades financial liberalization lead to increasing shares of capital incomes and top-managerial remunerations in economies (OECD, 2011, Checchi and Garcia-Peñalosa, 2010). These factors have weakened the position of labor relative to capital. As capital is held by, and capital income accrues to a few, this contributes to increasing overall income inequality.

A wide range of theories from political science, law and economics, demonstrate the pervasive influence of political institutions and governance on the distribution of income. The level of inequality in societies has been shown to be the result of historical factors, such as colonization, and structural features, such as the extent of social cohesion and ethnic fractionalization (e.g. Chakravorty, 2006; Angeles, 2007). Beyond that, governments with long democratic traditions have implemented extensive civil rights and voting mechanisms in order to reveal the preferences of everybody equally, while decisions in autocratic regimes are taken by and thus benefit a small elite. The ideology of different political parties in democratic regimes in turn determines the degree to which labor movements are supported and redistributive policies are implemented.[2].

Labor market policies are implemented in order to achieve socially desirable redistributive goals and mitigate market risks. Thus, among other things, collective bargaining, 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.[3] Governments' redistributive policies, reflected in the tax structure and provisions as social security and public welfare benefits, determines the difference between the distribution of market and personal disposable income. Education and health policies, on the other hand, alter the level and distribution of human capital, thereby affecting market incomes in the long and disposable incomes in the short run.[4] By determining the relative quality of education institutions, the structure of education spending also affects the distribution of returns to education (Carnoy, 2011). Chakravorty (2006) provides a theoretical framework with implications for the relation between regime types and redistributive policies. He describes governments that divert national resources towards personal gain as extractive (high inequality),

[2]See Huber *et al.* (2006) for a nice discussion of the relevance of political factors and an application to Latin American countries

[3]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.

[4]This is especially true for health care and tertiary education policies which directly alter the costs of health services and tertiary education respectively.

and delineates non-extractive regimes into those that redistribute mainly through short-term social security and welfare benefits (low inequality), or invest in long-term social benefits such as education and health (moderate inequality).

Ample evidence provides support for the vital role of redistribution via social security and transfers in western welfare states (OECD, 2011). However, results on the effects of social spending for a broader set of countries and developing economies are scarce, mainly due to data restrictions. Huber *et al.* (2006) found social security and welfare to have equalizing effects in Latin American and Caribbean countries if they are governed by democratic regimes. Kemp-Benedict (2011) provides empirical support for Chakravorty's (2006) model in a broad sample of countries. Sylwester (2002) examines the effect of public education expenditure on income inequality and finds greater investments to reduce income inequality in the long run, and primarily in high income countries. Carnoy (2011), on the other hand, states that decreasing public spending differences between higher and lower education levels and increasing spending differences between elite and mass universities are able to contribute to increasing inequality not only in emerging economies but also in high income countries.

# 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. Beyond that, we correct for the multitude of data bases and related measurement errors by creating two time series of income Gini coefficients which differ with respect to the degree of heterogeneity in the underlying data sources.

## 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.[5] 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 second-generation 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 income concepts by

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

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.

Most recently, large meta-datasets which assemble income inequality measures from a variety of relatively reliable source emerged. Instead of applying estimation techniques in order to correct for differences in the underlying data, these databases make discrepancies explicit by reporting survey sources and income concepts, among other things. The widely-used *All the Ginis Dataset*, constructed by Branko Milanovic, takes this approach but does not provide information on decile or quintile income shares. We thus develop a self-consistent data set that is derived from the UNU-WIDER World Income Inequality Database, Version 3.0B, September 2014 (WIID V3.0B). WIID 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, SEDLAC[6], World Bank sources and household surveys from national statistical offices, resulting in a total of 7,054 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. The 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 thus 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 per capita-, rather than household-based, Gini indices. Finally, we require a minimum of three time observations over one decade.[7]

The one insurmountable, albeit well-known, source of inconsistency in the dataset is the income concept used across countries. While disposable income would be the ideal basis, many Asian countries report consumption expenditure data. Many others 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-based Gini indices for most Advanced Economies and Latin American countries, while for many Asian and most African countries we use consumption-based measures.

One novelty in our study is to further refine our income inequality series to enforce source consistency within countries at varying degrees. In the most restrictive case (*SingleSource Gini*), we select one source per country that best meets our selection criteria with regards to time coverage, reliability and regional consistency.[8] In a second case (*MultiSource Gini*), we allow multiple sources for a country, but exclude sources

[6] Social and Economic Database for Latin American Countries

[7] We dropped all "Quality 4" coded observations, and "Quality 3" coded observations pertaining to unclear and rare income definitions.

[8] More often than not, we use the Luxembourg Income Study (LIS) and Eurostat measures for Western European countries,

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 |

WB1: World Bank Poverty Monitoring Database 2002; WB2: Deininger and Squire 2004; WB3:World Development Indicators 2004. In each case, WB1 provides the longer time series but WB2 or WB3 appear only once. Source: WIID V3.0B.

in two cases: sources have data for only a single year; and sources whose data are unreasonably inconsistent for consecutive years with data from other sources. The importance of this restriction is illustrated in Table 1, which reveals inconsistencies in Ginis for Ghana and Sri Lanka even among World Bank sources.

Creating this internally consistent dataset reduces the size of available observations by an order of magnitude, in our multi-source case resulting in an unbalanced panel with 945 observations from 74 countries, including 50% from Advanced Economies. Data coverage is more sparse for Developing Economies, with 21%, 14%, 9% and 6% of total observations in Latin American, Central Asian and European, Asian, and African countries, respectively (see Table 2). Our data set includes observations from 1960 to 2013, but only 4 percent of all observations are for before 1975. We thus truncate the dataset in 1975 in order to harmonize th sample period across countries. The time period covered by the multi-source Gini ranges on average from 1980 to 2011 and from 1988 to 2006 in Advanced and Developing Economies, respectively. Strengthening the requirements for data consistency further reduces the sample size. The average time period shrinks, especially in Advanced Economies, now covering the time span from 1985 to 2004.[9] Figures 3 and 4 in the appendix plot the time series of both Gini indices by country in order to visualize the discrepancies w.r.t. time and space.

WIID reports information on incomes by quintiles and deciles if available. We use this information in order to compute a ratio of extremes, the share of income accruing to the bottom decile in relation to that of the top decile of the income distribution (*DecRatio*). A higher value thus implies lower inequality at the extremes. Even if we permit the inclusion of multiple sources, all requirements with respect to population, regional and time coverage as well as the income concept also apply to the decile ratio.

# 4 Covariates

## 4.1 Total Factor Productivity

We represent technological change as total factor productivity (TFP). Some similar studies use the share of information and communication technology (ICT) in the capital stock (Jaumotte *et al.*, 2013). We prefer

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.

[9]This implies that the crises period is captured in the multi-source case for the majority of countries, while it is not in the single-source case.

Table 2: Summary Statistics of Income Inequality Series

| | | Mean | Sd | Min | Max | Observations | |
|---|---|---|---|---|---|---|---|
| *MS Gini* | overall | 35.13 | 10.19 | 18.00 | 66 | Total | 945 |
| | between | | 9.80 | 22.39 | 58.80 | N | 74 |
| | within | | 2.64 | 21.41 | 52.60 | | |
| *SSGini* | overall | 36.57 | 10.78 | 19.10 | 66 | Total | 649 |
| | between | | 10.52 | 20.36 | 58.80 | N | 60 |
| | within | | 2.40 | 25.10 | 48.72 | | |
| *DecRatio* | overall | 10.75 | 6.67 | 0.37 | 32.06 | Total | 691 |
| | between | | 5.87 | 0.70 | 22.09 | N | 71 |
| | within | | 2.15 | 4.34 | 20.99 | | |

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 $\alpha_{it}$ 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 (see section 4.3) 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 $\phi$ is the average return to education. We continue along the lines of Inklaar & Timmer (2013)[10] 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. We test the robustness of our TFP measure by conducting sensitivities using a similar index based on the growth rate of TFP taken from the Conference Board Total Economy Database (de Vries & Erumban, 2015).

[10]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.

### 4.2 Trade

We develop trade flow indicators that enable us to test the differential hypothesis regarding trade with high- and low-income countries. 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 (2014) use a similar trade flow decomposition, but examine inequality in only industrialized countries. Beyond that, we include the total level of exports in GDP in order to account for distributional effects of wage and employment growth in exporting enterprises.

### 4.3 Education

Empirical works 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 and affecting the corresponding returns to education differently (see Section 2). In order to account for the distributional dimension of education, we include an education Gini coefficient and conduct sensitivities with education represented as population shares for different attainment levels.

Following Sauer & Zagler (2014) and Sauer & KC (2012), we calculate the education Gini coefficient measuring 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.

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).[11]

As we discuss in Section 5.2, the strong decline in the share of people without formal education is the predominant driver of decreasing education inequality in Developing Countries. In Advanced Economies, on the other hand, almost universal literacy and schooling has been achieved in the eighties. 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[12] of the total population, $EducGini_{15+}$, into the share of unschooled people, ($p^1_{15+}$), and an education Gini for those with at least some formal education (categories 2-4), $EducGini^E_{15+}$. Moreover, we analyze the separate effects of primary, secondary and tertiary attainment in order to provide a full picture of the relation between education and income inequality.

## 4.4 Labor vs. Capital Income

In order to account for the effects of changes in the distribution between capital and labor which go beyond factors captured by the other covariates, we control for the share of labor income. We use data from PWT 8.0, which for the first time provide labor shares varying over time. Data are limited to after 1980 for Advanced Economies and after 1990 for Developing Economies. Hence, we expect our results to underestimate the influence of the labor share.

## 4.5 Governance

We select four measures in order to capture the redistributive capacity of governments. First, we account for the relative weight of public social spending categories by using data on the shares of education, health and social protection expenditures in total spending from the Statistics of Public Expenditure for Economic Development (SPEED) database of the International Food Policy Research Institute (IFPRI). We also conduct robustness tests accounting for the sum of public social spending relative to GDP, taken from the same database. Second, the propensity of governments to carry out redistributive policies is proxied by the political orientation of the chief executive's party. This measure is taken from the World Bank's Database of Political Institutions (DPI) and is represented by an increasing score from 1 to 3, indicating right, center and left, respectively. The political ideology of the chief executive's party determines the structure and extend, not only of public social provisions, but also of taxation and labor market policies. As we do not control for them separately, we expect the inequality effects of the latter factors to be accommodated by the political orientation variable.

[11] 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.

[12] 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.

# 5 Descriptive Trends - Income and Education Inequality

## 5.1 Income Distribution Trends

Scholars have increasingly been interested in the general rise in inequality since the eighties. More recently, economists started to analyze the role the substantial increase in income inequality has played in the approach of the financial crises. Galbraith (2012) shows that inequality has been increasing since 1987 in low- and middle income non-OECD countries and since 1980 in OECD countries. When grouped by region[13] (see Table 3), we find the multi-source Gini and the decile ratio to reveal that inequality has been rising in Advanced Economies as well as in the Middle East and North Africa. Only in Latin America, the Gini has been declining on average while the share of income accruing to the bottom 10% increased since 1975. However, Latin American countries report the highest average level of inequality. One explanation for this regional difference is that the poorest deciles are benefiting from income gains to a greater extent in Latin America than in other regions. This may be in part due to favorable redistributive policies of recent governments in Latin America (Lustig *et al.*, 2013).

Table 3: Income Inequality Trends within Countries by Region

| | Mean | | Sd | | Trend[a] | |
|---|---|---|---|---|---|---|
| Region | MS Gini[b] | DecRatio | MS Gini | DecRatio | IncGini | DecRatio |
| *AdvEcon* | 28.10 | 0.20 | 2.23 | 0.03 | ⇑ | ⇓ |
| *CAEE* | 34.02 | 0.11 | 3.01 | 0.01 | None | None |
| *LAC* | 50.86 | 0.03 | 2.44 | 0.01 | ⇓ | ⇑ |
| *EAP* | 36.79 | 0.10 | 4.01 | 0.01 | ⇑ | None |
| *SA* | 31.42 | 0.15 | 2.18 | 0.02 | None | None |
| *MENA* | 38.78 | 0.09 | 1.37 | 0.02 | ⇑ | ⇓ |
| *SSA* | 42.05 | 0.07 | 4.45 | 0.02 | None | None |

[a] Statistically significant time trend ($>$ 1975) from a fixed effects regression of inequality against time.
[b] *Multi-source Gini*

At a country level, however, trends in income equality vary over time, and across regions. In both Advanced and Developing economies, many countries (e.g. US, UK, Poland, Bangladesh, China) have experienced steadily rising, while others (e.g. Slovenia, Brazil) have experienced 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 patterns in regional income inequality trends. 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 Decile Ratio explains about 75 percent of the variation in the income Gini within countries.[14] This share is higher in Advanced Economies and Asia,

[13] We categorize countries into regions using the World Bank definition: AdvEcon (Advanced Economies), CAEE (Central Asia & Eastern Europe), LAC (Latin America & Carribean), EAP (Eastern Asia & the Pacific), SA (South Asia), MENA (Middle East & North Africa, SSA (Sub Saharan Africa).

[14] Within $R^2$ of 75.4 in a fixed effects OLS of Gini regressed on DecileRatio for the full sample. Other studies (cited in

where the Decile Ratio is also more volatile. This suggests that, to a large extend, changes in the overall income distribution are consistent with changes 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, ($EducGini_{15+}$) decreased strongly, the education Gini of the educated population ($EducGini^{E}_{15+}$) declined marginally (see Figure 1).

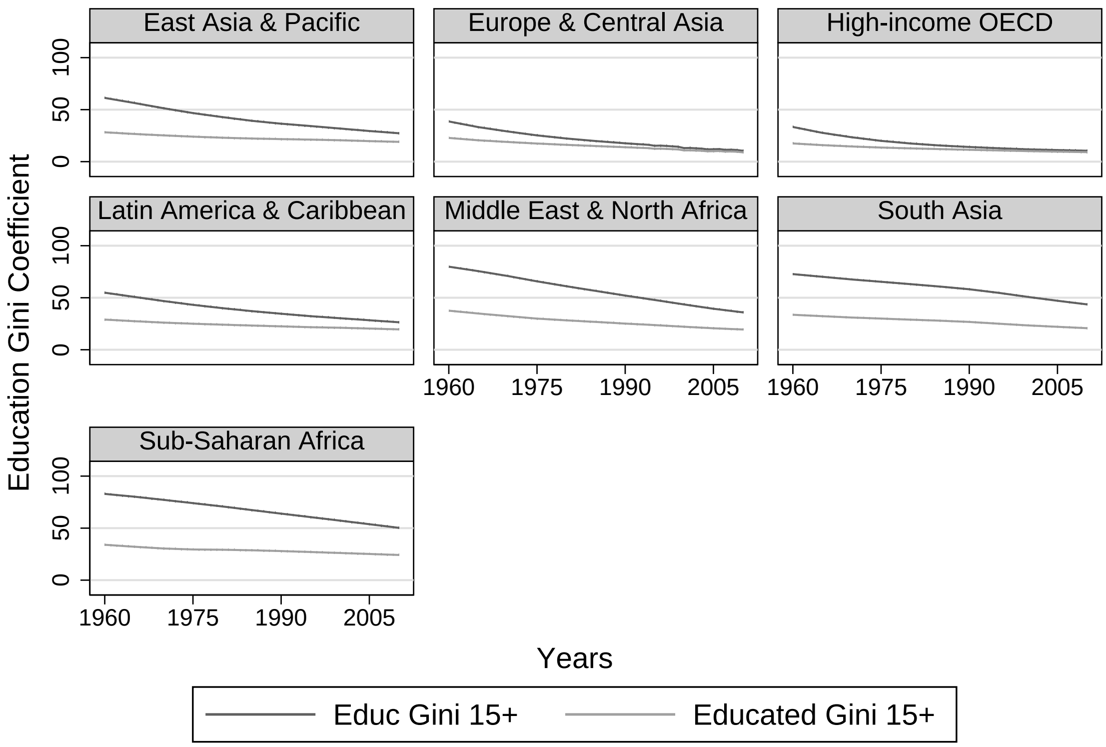


Figure 1: Education Gini Coefficients

The strong decrease in the education Gini of the total population, especially in Developing Economies, can in large part be attributed to a significant reduction in the share of people who did not attain any formal education. The concerning variable is thus 97 percent correlated with the overall education Gini, $EducGini_{15+}$. In regions with a relatively high number of unschooled people in 1975 (see Figure 2), the trends in education inequality measures differ substantially. The reduction in the respective population share was most modest in the highest inequality regions, South Asia and Sub-Saharan Africa. However, primary schooling does not necessarily increase if simultaneous movements to secondary attainment dominate. In Advanced Economies as well as Central Asia and Europe[15], both education inequality measures move almost simultaneously as the share of unschooled people is already very low since the eighties (see section 5). Notably,

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.

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

changes in the degree of education inequality within the educated population have been driven by changes at the extremes in Advanced Economies. The share of the population with secondary attainment has remained relatively constant at 60% since 1990, while the share with primary (tertiary) decreased (increased) more dramatically (i.e. 5 percentage points each between 1990 and 2000).

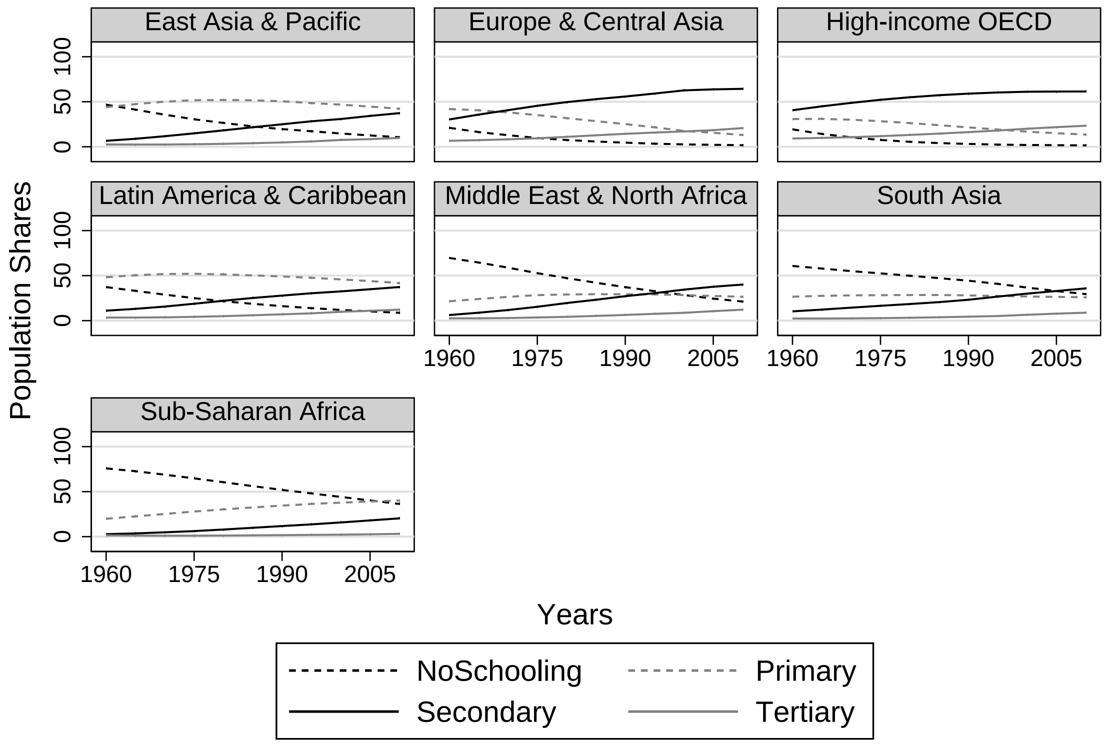


Figure 2: Education Population Shares

# 6 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 we prefer a feasible GLS (FGLS) estimator combined with country fixed effects. A similar approach has been used by Kemp-Benedict (2011), but with regional fixed effects. We describe our justification for this choice below.

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 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

[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 the null that the country-wise variances in standard errors are equal in each specification. In order to test for AR(1), we use the test by 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 in each of our model specifications at the global and regional level. Furthermore, the FGLS model calculates the common AR(1) coefficient to be 0.4 or higher in all the model runs.

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 the system GMM estimator. 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 combined with unobserved country fixed effects in order to estimate the long-term, global and broad regional effects of income-inequality drivers within countries. Our model specification is thus given by Equation (4):

$$IGini_t = \beta_1 TFP_{t-1} + \boldsymbol{\beta_3}\mathbf{T}_{t-1} + \boldsymbol{\beta_4}\mathbf{E}_{t-1} + \beta_5 L_{t-1} + \boldsymbol{\beta_5}\mathbf{P}_{t-1} + \gamma Year + \alpha_i + \epsilon_{i,t} \tag{4}$$

with

$$\mathbf{T} = [Imp^{high}, Imp^{low}, Exp]$$
$$\mathbf{E} = [MYS^{15+}; EducGini_{15+}; p^1_{15+}, EducGini^E_{15+}; p^2_{15+}, p^3_{15+}, p^4_{15+}]$$
$$\mathbf{P} = [PO, PS^{Educ}, PS^{Health}, PS^{SP}]$$

where $IGini_t$ represents one of our three income inequality measures. Total factor productivity ($TFP$) proxies for technological progress, trade matrix, $\mathbf{T}$, consists of the two import vectors from high ($Imp^{High}$) and low ($Imp^{Low}$) income countries and total exports ($Exp$). $L$ is the labor income share. From the education matrix, $\mathbf{E}$, either mean years of schooling ($MYS^{15+}$), the education Gini coefficient ($EducGini_{15+}$), the education Gini coefficient for the educated population ($EducGini^E_{15+}$) and the unschooled population share ($p^1_{15+}$) or the remaining three population shares of primary, secondary and tertiary attainment enter the model specification. In our governance specifications we add the matrix of political factors, $\mathbf{P}$, which includes the political orientation of the chief executive's party ($PO$) and the three types public social spending. $\alpha_i$ 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. Using Fisher-type unit-root tests we find some[18] indication for our

[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.

[18] Depending on the mothod for combining country-wise p-values, four test statistics can be computed, differing with respect to

income inequality measures to be trend-stationary in Dickey-Fuller specifications which account for AR(1). This is also true for TFP and the labor income share. The population share with tertiary attainment and imports from low income countries, on the other hand, follow a unit root process. For tackling the issue of stationary, at least with respect to the dependent variables, TFP and the labor share, we include a time trend ($Year$).

# 7 Results and Discussion

Tables 5 to 10 report the main results of our analysis. We provide results for each of three income inequality measures (see Sections 3.2 and 5.1) and education variables (see Sections 4.3 and 5.2). Moreover, we present our findings separately for the global level, for Advanced and for Developing Economies as well as excluding (Tables 5 to 7) and including (Tables 8 to 10) political factors as doing so reduces the number of countries and time periods. In order to provide some sense of the relative impact magnitude of multiple income inequality drivers, we report regional specific summary statistics and the average trends over time for each variable in Table 4 and interpret the effects as percentage contribution to the within standard deviation of the concerning inequality measure in the relevant region.

Table 4: Summary Statistics and Trends by Region

| | Advanced Economies | | | Developing Economies | | |
|---|---|---|---|---|---|---|
| Variable[a] | Mean | Within sd | Trend[b] | Mean | Within sd | Trend |
| $MSGini$ | 28.09 | 2.23 | ⇑ | 42.18 | 2.99 | ⇑ |
| $SSGini$ | 28.39 | 2.03 | ⇑ | 42.90 | 2.65 | None |
| $DecRatio$ | 15.61 | 2.88 | ⇓ | 6.50 | 1.21 | None |
| $TFP$ | 0.94 | 0.07 | ⇑ | 0.95 | 0.10 | ⇓ |
| $Imp^{high}$ | 25.71 | 5.62 | ⇑ | 20.26 | 7.82 | ⇑ |
| $Imp^{low}$ | 4.14 | 2.29 | ⇓ | 6.04 | 3.84 | ⇑ |
| $Exp$ | 30.05 | 5.89 | ⇑ | 26.80 | 7.32 | ⇑ |
| $L$ | 61.32 | 2.81 | ⇓ | 50.52 | 3.70 | ⇑ |
| $PS^{Educ}$ | 10.28 | 2.43 | ⇑ | 13.39 | 3.14 | ⇑ |
| $PS^{Health}$ | 12.07 | 2.56 | ⇑ | 6.56 | 3.47 | ⇑ |
| $PS^{SP}$ | 35.19 | 4.21 | ⇑ | 11.48 | 4.75 | ⇑ |
| $MYS_{15+}$ | 12.13 | 0.63 | ⇑ | 8.50 | 0.61 | ⇑ |
| $EducGini_{15+}$ | 12.76 | 2.20 | ⇓ | 27.72 | 3.18 | ⇓ |
| $EducGini^{E}_{15+}$ | 10.70 | 1.28 | ⇓ | 18.01 | 1.24 | ⇓ |
| $p^{1}_{15+}$ | 2.39 | 1.34 | ⇓ | 12.79 | 3.06 | ⇓ |
| $p^{2}_{15+}$ | 18.69 | 4.50 | ⇓ | 35.07 | 2.69 | ⇓ |
| $p^{3}_{15+}$ | 59.53 | 3.26 | ⇑ | 35.07 | 2.69 | ⇑ |
| $p^{4}_{15+}$ | 19.41 | 3.09 | ⇑ | 11.96 | 1.54 | ⇑ |

[a]For an explanation of variable abbreviations see Section 6.
[b]Statistically significant time trend (> 1975) from a fixed effects regression of inequality against time.

## 7.1 Total Factor Productivity

In general, we find a tendency of technological progress, measured by TFP, to increase inequality in the distribution of income within countries. However, the relationship strongly varies depending on the inequality

their asymptotic behavior. While the inverse chi-squared statistic and its modification indicate that the multi- and single-source Gini are stationary, the inverse- normal and inverse logit t statisitc indicate trend-stationarity.

measures used, the observed region and whether political factors are accounted for. At a global level, we find indication that accelerating technological progress increases inequality w.r.t. the Gini coefficient as well as the ratio of extremes in our basic specification. For the income Gini coefficients, the relationship becomes more significant in the governance specification, with the magnitude being generally bigger for the multi-source Gini. A large part of this effect stems from the sizable impact in Developing Economies where the estimator ranges around 10, implying that an increase of TFP by one unit equal to 0.1 contributes approximately 35% to the within variation of the multi-source Gini.

In Advanced Economies, in contrast, an increase in TFP by 0.1 accounts for roughly 34% to the within variation of the single-source Gini. Truncating the sample in 2005 shows TFP to signficantly affect also the multi-source Gini, indicating distortions due to the inclusion of the crises period in the latter case. TFP becomes less relevant if we account for the distributional dimension of education and political factors. The most robust result w.r.t. its impact in an education distribution specification is its relation to the decile ratio: an increase of 0.1 decreases the relative share of incomes accruing to the bottom decile by 0.59, i.e. 18% of the respective within variation.

## 7.2 Trade

The decomposition of imports provides region specific insights into the inequality effects related to trade. We find imports from low-income countries to have an equalizing effect in Advanced Economies. If political factors are accounted for, this impact is larger and visible for all three inequality measures. Moreover, it is generally higher for the single-source than for the multi-source Gini, fluctuating around 0.13 in the latter case. Thus, an increase in the share of imports from low-income countries in GDP by one percentage point accounts for roughly 6% to the within variation of the multi-source Gini. Our evidence thus contradicts the implication of the Stolper-Samuelson theorem that imports from low-income countries compete with goods produced in low-skilled sectors of high-income countries, thereby increasing income inequality.

In Developing Economies, the effect of trade with other low-income countries is much larger but only significant in the multi-source case where the impact ranges from 11% to 14%, controlling for political factors. On the contrary, trade with high-income countries significantly increases income inequality, contributing by about 3% to the within variation of the multi-source Gini. Beyond that, importing goods from high-income countries also slightly affects single-source Gini and the extremes of the income distribution. Trade between high-income countries, on the other hand, significantly increases income inequality only in our basic specification.

Our results indicate the positive distributional impacts of wage and employment growth in exporting enterprises, captured by the share of total exports in GDP, to be only relevant for the income distribution in the parsimonious specification for Advanced Economies. This might be due to the interference of disequalizing effects of skill premiums simultaneously emerging in relevant industries. In Developing Economies, on the other hand, the inequality effects of exporting to other low and middle or to high income countries have been shown to work in opposite directions and are thus able to confound each other.

In general, our findings provide indication that factors not captured in the theoretical framework of the Heckscher-Ohlin model affect the relation between trade in goods and services and income inequality in

Advanced as well as in Developing Economies. Trade between similar economies turns out to be relevant for the income distribution. Moreover, even after controlling for TFP, we find the technology embedded in imports from high-income countries to significantly contribute to increasing income inequality, especially in the developing world.

### 7.3 Education

We capture the distributional dimension of education using three methods: the overall education Gini coefficient, the decomposition into the share of unschooled people and the Gini coefficient of the educated population and the population shares with each education level separately. In order to compare our results to the existing literature, the first three columns of each table report estimates on the inequality effects of average educational attainment, measured by mean years of schooling. In our most parsimonious models, average attainment matters marginally for income inequality, slightly affecting the decile ratio globally and in Developing Economies. While accounting for political factors substantially increases the significance of the equalizing effect of mean years of schooling at a global level as well as for Advanced Economies, the impact on the ratio of extremes disappears for Developing Economies.

Exploring the distributional dimension of educational attainment provides a more nuanced picture of the relation between education and inequality. Reducing educational inequality, measured by the overall education Gini coefficient, significantly contributes to decreasing income inequality in Advanced Economies. This effect penetrates to the global level, is true for the two income Gini coefficients as well as the decile ratio, and becomes larger as political factors are accounted for: based on column 5 of Table 9, a reduction in the education Gini coefficient by one point decreases the multi-source Gini by 0.4 points and increases the decile ratio by one percentage point, thereby contributing for 18% and 35% to the within variation of the concerning variables respectively.

For Developing Economies the education effect w.r.t. the overall education Gini coefficient vanishes if we account for political factors. However, the predominant driver of decreasing education inequality is the strong decline in the share of people without formal education (see section 5.2). The inequality relevance of this observation is supported by the decomposition into the share of unschooled people and the education Gini coefficient for the educated population. Decreasing the respective population share by one percentage point increases the relative income share of the bottom decile by 0.16 percentage points, i.e. 13% of the within variation, in the governance specification. With a magnitude of 0.7 points, this effect is even larger in Advanced Economies. The extend of the reduction in the unschooled population share was, however, much larger in Developing Economies (see Figure 2).

In Advanced Economies, the distribution of education among the educated population does not deviate much from the overall distribution, its relation to income inequality is thus similar. In contrast, the slight decrease in the degree of educational inequality among the educated population has contributed to decrease the relative share of income accruing to the bottom decile in Developing Economies. This effect is reflected in the negative impact of primary and tertiary education population shares on the ratio of extremes, implying that the slight decrease in primary education, observed in Central and Eastern Asia as well as in Latin America, the Middle East and North Africa had an equalizing effect at the extremes while the respective increase in South Asia and Sub-Saharan Africa contributed to worsen the relative position of the bottom decile (see Figure 2. In each case the impact magnitude is 14% of the within variation. Both situations imply a dominance of the wage effect, intensifying and relaxing the pressure on low-skilled wages in the latter and former situation respectively. The inequality increasing effect of tertiary education attainment, on the other hand, is much larger as it contributes 36% to the within variation of the decile ratio. This outcome might result from the composition effect, i.e. an increase in educational inequality induced by higher education levels, from excess demand or from increasing segmentation between mass and elite universities.

In Advanced Economies, increasing the population shares in any education category significantly contributes to decreasing income inequality. The effect is strongest for tertiary education attainment where an increase by one percentage point accounts for 14% as compared to 11% for secondary and 6% for primary attainment of the within variation in the multi-source Gini. Interestingly, higher education is not only relevant for the overall distribution but also for the extremes in Advanced Economies, revealing the importance of the wage effect at this stage of educational development.

The fit of our model, given by the correlation between the dependent variable and its prediction, is neither heavily affected by switching from the mean years of schooling to the overall education Gini specification, nor by moving to models which include single elements the education distribution. At this stage it is thus not straightforward to discriminate between the two aggregate measures of educational attainment. But the importance of accounting for heterogeneity in the education-inequality relation is revealed by differential regional results. In Advanced Economies, the coefficients of all elements in columns (7) to (12) point into the same, inequality decreasing, direction. We thus find a similarly strong relation between the aggregate measures and income inequality. In Developing Economies, on the other hand, the estimates of the effects of separate categories point into different directions, this precludes finding a significant relation between aggregate measures and income inequality.

### 7.4 Governance

Our evidence suggests the most significant redistributive effects of governments to work through health policies. Globally and in both regions as well as across almost all education specifications and income inequality measures, increasing the share of public spending on health significantly contributes to reducing income inequality. However, the magnitudes are quite small as it does not explain more than 4% and 5% of the within variation of the income Gini coefficients and the decile ratio respectively.

In contrast, increasing the relative weight of social protection expenditures does not turn out to have any distributional impacts. This result might be due to the dominance of social security spending in this category.[19] Social security is tied to labor market participation, thus population coverage is smaller the larger informal markets, and exerts regressive effects if pay offs are strongly income dependent and contributions are capped. Especially in Developing Economies, such conditions are able to countervail the equalizing effects of direct income transfers.

Public education spending would be expected to increase the average level of education if it enables

[19] The main underlying sources of the SPEED database are the IMF Government Financial Statistics Yearbook and IMF Statistical Annexes. Huber *et al.* (2006) note that more than 80 percent of expenditures in the social protection category goes to social security.

more people to study but its effects on the education distribution depend on where it is targeted. It also affects the quality of educational institutions if resources per student increase. If quality related means are allocated unequally among institutions, even within primary, secondary or tertiary education levels, public education policy exerts disequalizing effects on the returns to education, thus income inequality increases. Our results indicate such conditions to prevail in Advanced Economies where, after controlling for the strong equalizing effect of the quantitative dimension of educational attainment, increasing the relative weight of public education spending increases income inequality generally and at the extremes. Even if the magnitude is small, not contributing more than 7% and 9% to the within variation of the income Ginis and the decile ratio respectively, it exceeds the equalizing effects of public spending on health. In Developing Economies, on the other hand, we do not find any education policy effects which go beyond the impact on the quantity of educational attainment.

Accounting for the political orientation of the chief executive's party reduces the sample size for Developing Economies substantially. The fit of the model, measured by the correlation between the actual and the predicted value of the dependent variable, is thus impaired. Nevertheless, the propensity of governments to carry out redistributive policies is significantly relevant for the extremes of the income distribution in Developing Economies. A shift from a right or central to a left government increases the relative income share of the bottom decile by 0.4 and 0.2 percentage points respectively, accounting for 20% of the concerning within variation. To some extend, this impact is indirect as it captures the inequality effects of redistributive policies we are not accounting for.

### 7.5 Labor Income Share & Time Trend

Our basic specification reveals a decline in the labor income share to significantly contribute to increasing income inequality w.r.t. all measures globally and in Developing Economies. This effect entirely changes as political factors are controlled for in Developing Economies. In Advanced Economies, in contrast, the functional income distribution is more relevant after accounting for redistributive policies. This is especially true for the single-source Gini and the ratio of extremes. In these cases, a decline in the labor share by one percentage point accounts for almost one half and at most 83% of the respective within variation. We thus find support for the hypothesis that changing power relations between capital and labor which go beyond the market forces and political conditions we are accounting for are highly relevant also for the personal income distribution in Advanced Economies.

Further evidence for the importance of inequality increasing conditions we are not capturing in our model for Advanced Economies is provided by the significantly positive time trend. This may proxy for factors such as the increasing role of financial capital and neoliberal policies of changing tax structures and labor market liberalization, among other things, as they are extensively discussed for the US in Stiglitz (2012), and have in general contributed to strengthen the relative position of capital owners and top-income earners. In the governance specifications, the single- and multi-source Gini coefficients increased by roughly 0.2 points a year while the relative share of income accruing to the bottom decile decreased by 0.3 percentage points. This accounts for about 7% and 15% of the concerning within variations respectively.

Table 5: Global Sample - Basic

| | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Year$ | 0.110** | 0.104*** | -0.163*** | 0.111*** | 0.071*** | -0.143*** | 0.121*** | 0.073*** | -0.116*** | 0.155*** | 0.043 | -0.209*** |
| | (0.045) | (0.033) | (0.028) | (0.032) | (0.023) | (0.020) | (0.031) | (0.024) | (0.019) | (0.051) | (0.039) | (0.038) |
| $TFP$ | 4.482*** | 3.010** | 0.541 | 4.025*** | 3.151*** | 1.314* | 3.872*** | 3.140*** | 1.194 | 3.826** | 3.584*** | 1.701* |
| | (1.453) | (1.201) | (0.768) | (1.468) | (1.197) | (0.770) | (1.463) | (1.199) | (0.770) | (1.564) | (1.258) | (0.918) |
| $Imp^{high}$ | 0.046*** | 0.037*** | -0.029*** | 0.047*** | 0.036*** | -0.034*** | 0.049*** | 0.036*** | -0.030*** | 0.037*** | 0.033*** | -0.030*** |
| | (0.011) | (0.011) | (0.008) | (0.011) | (0.011) | (0.009) | (0.012) | (0.011) | (0.009) | (0.012) | (0.011) | (0.009) |
| $Imp^{low}$ | -0.189*** | -0.130*** | 0.068*** | -0.194*** | -0.129*** | 0.082*** | -0.199*** | -0.129*** | 0.075*** | -0.179*** | -0.122*** | 0.074*** |
| | (0.026) | (0.023) | (0.020) | (0.026) | (0.023) | (0.020) | (0.027) | (0.023) | (0.020) | (0.027) | (0.024) | (0.020) |
| $Exp$ | 0.007 | -0.010 | 0.016** | 0.003 | -0.011 | 0.024*** | 0.003 | -0.012 | 0.021*** | 0.001 | -0.012 | 0.019** |
| | (0.012) | (0.012) | (0.007) | (0.012) | (0.011) | (0.007) | (0.012) | (0.011) | (0.007) | (0.012) | (0.012) | (0.008) |
| $L$ | -0.072** | -0.053** | 0.068*** | -0.077** | -0.058** | 0.079*** | -0.071** | -0.059** | 0.083*** | -0.074** | -0.051* | 0.089*** |
| | (0.035) | (0.026) | (0.015) | (0.035) | (0.026) | (0.014) | (0.035) | (0.026) | (0.013) | (0.036) | (0.027) | (0.013) |
| $MYS_{15+}$ | -0.595 | -0.396 | 1.289*** | | | | | | | | | |
| | (0.478) | (0.358) | (0.307) | | | | | | | | | |
| $Gini^E_{15+}$ | | | | 0.152** | 0.000 | -0.252*** | | | | | | |
| | | | | (0.077) | (0.062) | (0.047) | | | | | | |
| $p^1_{15+}$ | | | | | | | 0.046 | 0.007 | -0.199*** | | | |
| | | | | | | | (0.075) | (0.058) | (0.045) | | | |
| $EducGini^E_{15+}$ | | | | | | | 0.311** | 0.007 | -0.048 | | | |
| | | | | | | | (0.146) | (0.118) | (0.114) | | | |
| $p^2_{15+}$ | | | | | | | | | | -0.336*** | -0.045 | 0.273*** |
| | | | | | | | | | | (0.086) | (0.067) | (0.053) |
| $p^3_{15+}$ | | | | | | | | | | -0.173** | 0.026 | 0.308*** |
| | | | | | | | | | | (0.084) | (0.065) | (0.059) |
| $p^4_{15+}$ | | | | | | | | | | -0.496*** | -0.002 | 0.503*** |
| | | | | | | | | | | (0.133) | (0.111) | (0.114) |
| $Obs$ | 575 | 795 | 580 | 575 | 795 | 580 | 575 | 795 | 580 | 575 | 795 | 580 |
| N | 52 | 60 | 55 | 52 | 60 | 55 | 52 | 60 | 55 | 52 | 60 | 55 |
| $\bar{T}$ | 11.06 | 13.25 | 10.55 | 11.06 | 13.25 | 10.55 | 11.06 | 13.25 | 10.55 | 11.06 | 13.25 | 10.55 |
| $Corr(y,\hat{y})$ | 0.981 | 0.977 | 0.363 | 0.981 | 0.977 | 0.385 | 0.981 | 0.977 | 0.449 | 0.982 | 0.978 | 0.939 |

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

Table 6: Advanced Economies - Basic

| | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Year$ | 0.108 | 0.146 | -0.103 | 0.192 | 0.114 | -0.233 | 0.194 | 0.111 | -0.199 | 0.272 | 0.091 | -0.247*** |
| | (0.065)* | (0.038)*** | (0.061)* | (0.044)*** | (0.031)*** | (0.049)*** | (0.049)*** | (0.032)*** | (0.049)*** | (0.075)*** | (0.051)* | (0.075) |
| $TFP$ | 9.954 | 2.398 | -5.445 | 7.162 | 2.424 | -2.926 | 6.455 | 2.450 | -3.455 | 6.799 | 3.351 | -8.036*** |
| | (2.586)*** | (1.904) | (2.693)** | (2.582)*** | (1.926) | (2.710) | (2.979)** | (2.026) | (2.773) | (2.719)** | (2.053) | (2.636) |
| $Imp^{high}$ | 0.059 | 0.034 | -0.064 | 0.064 | 0.032 | -0.080 | 0.067 | 0.031 | -0.075 | 0.039 | 0.026 | 0.002 |
| | (0.023)*** | (0.022) | (0.034)* | (0.023)*** | (0.022) | (0.034)** | (0.023)*** | (0.023) | (0.035)** | (0.023)* | (0.023) | (0.034) |
| $Imp^{low}$ | -0.254 | -0.144 | 0.131 | -0.241 | -0.139 | 0.152 | -0.226 | -0.136 | 0.146 | -0.256 | -0.130 | 0.191*** |
| | (0.068)*** | (0.044)*** | (0.060)** | (0.067)*** | (0.044)*** | (0.059)*** | (0.071)*** | (0.045)*** | (0.061)** | (0.065)*** | (0.045)*** | (0.059) |
| $Exp$ | -0.056 | -0.016 | 0.040 | -0.061 | -0.017 | 0.043 | -0.061 | -0.018 | 0.042 | -0.049 | -0.014 | -0.016 |
| | (0.026)** | (0.024) | (0.035) | (0.025)** | (0.024) | (0.034) | (0.026)** | (0.024) | (0.035) | (0.025)* | (0.025) | (0.034) |
| $L$ | -0.052 | 0.037 | 0.102 | -0.064 | 0.029 | 0.130 | -0.063 | 0.028 | 0.114 | -0.092 | 0.037 | 0.071 |
| | (0.054) | (0.043) | (0.051)** | (0.051) | (0.042) | (0.053)** | (0.051) | (0.043) | (0.048)** | (0.049)* | (0.044) | (0.053) |
| $MYS_{15+}$ | -0.079 | -0.519 | -0.062 | | | | | | | | | |
| | (0.702) | (0.447) | (0.714) | | | | | | | | | |
| $Gini^E_{15+}$ | | | | 0.284 | 0.031 | -0.508 | | | | | | |
| | | | | (0.114)** | (0.096) | (0.173)*** | | | | | | |
| $p^1_{15+}$ | | | | | | | 0.153 | 0.022 | -0.401 | | | |
| | | | | | | | (0.131) | (0.116) | (0.174)** | | | |
| $EducGini^E_{15+}$ | | | | | | | 0.385 | 0.014 | -0.281 | | | |
| | | | | | | | (0.255) | (0.164) | (0.253) | | | |
| $p^2_{15+}$ | | | | | | | | | | -0.584 | -0.105 | 0.596*** |
| | | | | | | | | | | (0.127)*** | (0.123) | (0.165) |
| $p^3_{15+}$ | | | | | | | | | | -0.333 | -0.014 | 0.353** |
| | | | | | | | | | | (0.121)*** | (0.112) | (0.167) |
| $p^4_{15+}$ | | | | | | | | | | -0.830 | -0.085 | 0.968*** |
| | | | | | | | | | | (0.185)*** | (0.147) | (0.238) |
| $Obs$ | 281 | 436 | 294 | 281 | 436 | 294 | 281 | 436 | 294 | 281 | 436 | 294 |
| N | 23 | 26 | 25 | 23 | 26 | 25 | 23 | 26 | 25 | 23 | 26 | 25 |
| $\bar{T}$ | 12.22 | 16.77 | 11.76 | 12.22 | 16.77 | 11.76 | 12.22 | 16.77 | 11.76 | 12.22 | 16.77 | 11.76 |
| $Corr(y, \hat{y})$ | 0.946 | 0.909 | 0.878 | 0.947 | 0.910 | 0.883 | 0.947 | 0.910 | 0.882 | 0.955 | 0.914 | 0.900 |

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

Table 7: Developing Economies - Basic

| | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Year* | 0.038 | -0.014 | -0.051 | -0.003 | -0.071 | 0.014 | 0.013 | -0.031 | 0.003 | -0.039 | -0.032 | -0.068* |
| | (0.082) | (0.080) | (0.034) | (0.052) | (0.052) | (0.023) | (0.048) | (0.049) | (0.021) | (0.116) | (0.103) | (0.038) |
| *TFP* | 0.753 | 3.349** | 2.603*** | 0.848 | 3.888** | 2.186*** | 1.071 | 4.343*** | 2.305*** | 0.303 | 3.754** | 3.042*** |
| | (1.836) | (1.564) | (0.709) | (1.835) | (1.530) | (0.756) | (1.943) | (1.601) | (0.743) | (1.960) | (1.631) | (0.775) |
| $Imp^{high}$ | 0.052*** | 0.026 | -0.016* | 0.053*** | 0.022 | -0.017* | 0.054*** | 0.025 | -0.019** | 0.046** | 0.023 | -0.018* |
| | (0.018) | (0.019) | (0.009) | (0.018) | (0.018) | (0.009) | (0.018) | (0.018) | (0.009) | (0.020) | (0.019) | (0.009) |
| $Imp^{low}$ | -0.192*** | -0.100** | 0.037* | -0.194*** | -0.091** | 0.038* | -0.197*** | -0.100** | 0.042** | -0.173*** | -0.090** | 0.040* |
| | (0.040) | (0.041) | (0.021) | (0.040) | (0.040) | (0.021) | (0.040) | (0.041) | (0.021) | (0.044) | (0.042) | (0.021) |
| *Exp* | 0.027* | 0.002 | 0.001 | 0.024 | 0.007 | 0.003 | 0.023 | 0.004 | 0.006 | 0.019 | 0.004 | 0.004 |
| | (0.015) | (0.015) | (0.006) | (0.015) | (0.015) | (0.007) | (0.016) | (0.015) | (0.007) | (0.016) | (0.015) | (0.006) |
| $L$ | -0.091* | -0.094*** | 0.060*** | -0.098** | -0.097*** | 0.049*** | -0.093** | -0.089*** | 0.046*** | -0.100** | -0.094*** | 0.062*** |
| | (0.047) | (0.034) | (0.014) | (0.046) | (0.033) | (0.015) | (0.047) | (0.034) | (0.015) | (0.049) | (0.035) | (0.014) |
| $MYS_{15+}$ | -0.373 | 0.264 | 0.657* | | | | | | | | | |
| | (0.853) | (0.803) | (0.352) | | | | | | | | | |
| $Gini^E_{15+}$ | | | | -0.014 | -0.186* | 0.015 | | | | | | |
| | | | | (0.117) | (0.107) | (0.049) | | | | | | |
| $p^1_{15+}$ | | | | | | | -0.019 | -0.162* | 0.046 | | | |
| | | | | | | | (0.121) | (0.093) | (0.047) | | | |
| $EducGini^E_{15+}$ | | | | | | | 0.085 | 0.108 | -0.131 | | | |
| | | | | | | | (0.256) | (0.230) | (0.116) | | | |
| $p^2_{15+}$ | | | | | | | | | | -0.141 | 0.148 | -0.033 |
| | | | | | | | | | | (0.132) | (0.111) | (0.047) |
| $p^3_{15+}$ | | | | | | | | | | 0.075 | 0.135 | 0.126** |
| | | | | | | | | | | (0.170) | (0.141) | (0.064) |
| $p^4_{15+}$ | | | | | | | | | | -0.223 | 0.101 | 0.027 |
| | | | | | | | | | | (0.325) | (0.286) | (0.097) |
| *Obs* | 294 | 359 | 286 | 294 | 359 | 286 | 294 | 359 | 286 | 294 | 359 | 286 |
| N | 29 | 34 | 30 | 29 | 34 | 30 | 29 | 34 | 30 | 29 | 34 | 30 |
| $\bar{T}$ | 10.14 | 10.56 | 9.53 | 10.14 | 10.56 | 9.53 | 10.14 | 10.56 | 9.53 | 10.14 | 10.56 | 9.53 |
| $Corr(y, \hat{y})$ | 0.968 | 0.963 | 0.478 | 0.968 | 0.964 | 0.958 | 0.968 | 0.964 | 0.964 | 0.969 | 0.964 | 0.382 |

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

Table 8: Global Sample - Governance

| | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Year$ | 0.119** | 0.210*** | -0.199*** | 0.107** | 0.134*** | -0.144*** | 0.103** | 0.124*** | -0.120*** | 0.194*** | 0.152*** | -0.256*** |
| | (0.057) | (0.037) | (0.039) | (0.042) | (0.030) | (0.025) | (0.041) | (0.029) | (0.025) | (0.065) | (0.047) | (0.048) |
| $TFP$ | 5.753*** | 5.605*** | -1.288 | 4.729** | 5.832*** | -1.356 | 4.857** | 5.803*** | -1.079 | 4.185* | 5.413*** | -1.006 |
| | (2.227) | (1.439) | (1.153) | (2.223) | (1.495) | (1.109) | (2.229) | (1.493) | (1.148) | (2.331) | (1.560) | (1.166) |
| $Imp^{high}$ | 0.046** | 0.028* | -0.026** | 0.048** | 0.028 | -0.034** | 0.045** | 0.026 | -0.034** | 0.031 | 0.026 | -0.024* |
| | (0.019) | (0.017) | (0.013) | (0.019) | (0.017) | (0.014) | (0.019) | (0.017) | (0.014) | (0.019) | (0.017) | (0.014) |
| $Imp^{low}$ | -0.220*** | -0.156*** | 0.097*** | -0.223*** | -0.160*** | 0.113*** | -0.224*** | -0.162*** | 0.111*** | -0.229*** | -0.166*** | 0.118*** |
| | (0.057) | (0.039) | (0.036) | (0.057) | (0.039) | (0.036) | (0.057) | (0.040) | (0.037) | (0.057) | (0.040) | (0.035) |
| $Exp$ | 0.008 | 0.002 | 0.005 | 0.005 | -0.005 | 0.009 | 0.005 | -0.004 | 0.006 | 0.009 | -0.003 | 0.000 |
| | (0.018) | (0.015) | (0.010) | (0.018) | (0.015) | (0.011) | (0.018) | (0.015) | (0.011) | (0.018) | (0.016) | (0.011) |
| $L$ | -0.040 | -0.015 | 0.089*** | -0.052 | -0.020 | 0.105*** | -0.054 | -0.020 | 0.098*** | -0.039 | -0.012 | 0.084*** |
| | (0.046) | (0.033) | (0.028) | (0.047) | (0.034) | (0.028) | (0.047) | (0.034) | (0.028) | (0.047) | (0.035) | (0.030) |
| $PO$ | 0.026 | 0.007 | 0.020 | 0.019 | 0.001 | 0.029 | 0.019 | 0.002 | 0.019 | 0.037 | 0.011 | 0.045 |
| | (0.084) | (0.078) | (0.075) | (0.086) | (0.079) | (0.072) | (0.085) | (0.079) | (0.071) | (0.083) | (0.080) | (0.071) |
| $PS^{Educ}$ | 0.106*** | 0.093*** | 0.012 | 0.098*** | 0.082*** | 0.012 | 0.099*** | 0.081*** | 0.010 | 0.084*** | 0.091*** | 0.016 |
| | (0.029) | (0.029) | (0.016) | (0.029) | (0.030) | (0.016) | (0.029) | (0.030) | (0.016) | (0.029) | (0.031) | (0.016) |
| $PS^{Health}$ | -0.059*** | -0.065*** | -0.006 | -0.064*** | -0.074*** | -0.002 | -0.065*** | -0.076*** | 0.004 | -0.077*** | -0.077*** | 0.005 |
| | (0.020) | (0.022) | (0.013) | (0.020) | (0.022) | (0.014) | (0.021) | (0.022) | (0.014) | (0.020) | (0.022) | (0.014) |
| $PS^{SP}$ | 0.020 | -0.005 | 0.016* | 0.023* | -0.003 | 0.003 | 0.024* | -0.001 | 0.002 | 0.025* | -0.001 | 0.012 |
| | (0.013) | (0.014) | (0.008) | (0.013) | (0.014) | (0.007) | (0.013) | (0.014) | (0.007) | (0.013) | (0.015) | (0.009) |
| $MYS_{15+}$ | -0.923 | -2.021*** | 1.713*** | | | | | | | | | |
| | (0.673) | (0.448) | (0.427) | | | | | | | | | |
| $Gini^E_{15+}$ | | | | 0.219* | 0.282*** | -0.321*** | | | | | | |
| | | | | (0.131) | (0.101) | (0.073) | | | | | | |
| $p^1_{15+}$ | | | | | | | 0.210 | 0.260*** | -0.299*** | | | |
| | | | | | | | (0.135) | (0.096) | (0.080) | | | |
| $EducGini^E_{15+}$ | | | | | | | 0.152 | 0.168 | -0.029 | | | |
| | | | | | | | (0.202) | (0.154) | (0.173) | | | |
| $p^2_{15+}$ | | | | | | | | | | -0.432*** | -0.245** | 0.341*** |
| | | | | | | | | | | (0.143) | (0.103) | (0.082) |
| $p^3_{15+}$ | | | | | | | | | | -0.334** | -0.318*** | 0.386*** |
| | | | | | | | | | | (0.141) | (0.103) | (0.078) |
| $p^4_{15+}$ | | | | | | | | | | -0.650*** | -0.342** | 0.701*** |
| | | | | | | | | | | (0.190) | (0.149) | (0.156) |
| $Obs$ | 375 | 548 | 401 | 375 | 548 | 401 | 375 | 548 | 401 | 375 | 548 | 401 |
| N | 42 | 49 | 44 | 42 | 49 | 44 | 42 | 49 | 44 | 42 | 49 | 44 |
| $\bar{T}$ | 8.93 | 11.18 | 9.11 | 8.93 | 11.18 | 9.11 | 8.93 | 11.18 | 9.11 | 8.93 | 11.18 | 9.11 |
| $Corr(y,\hat{y})$ | 0.987 | 0.980 | 0.961 | 0.986 | 0.981 | 0.962 | 0.984 | 0.981 | 0.962 | 0.978 | 0.980 | 0.960 |

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

Table 9: Advanced Economies - Governance

| | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Year$ | 0.161** | 0.277*** | -0.215*** | 0.174*** | 0.184*** | -0.267*** | 0.169*** | 0.185*** | -0.255*** | 0.323*** | 0.234*** | -0.380*** |
| | (0.070) | (0.036) | (0.055) | (0.059) | (0.041) | (0.050) | (0.060) | (0.040) | (0.049) | (0.080) | (0.057) | (0.079) |
| $TFP$ | 4.862* | 2.399 | -5.967** | 3.537 | 1.837 | -3.911 | 3.272 | 1.642 | -3.716 | 0.326 | 1.757 | -5.871** |
| | (2.621) | (1.755) | (2.484) | (2.858) | (2.037) | (2.493) | (3.050) | (2.061) | (2.488) | (2.849) | (2.016) | (2.386) |
| $Imp^{high}$ | 0.020 | 0.009 | 0.001 | 0.030 | 0.013 | -0.013 | 0.034 | 0.014 | -0.014 | 0.000 | 0.004 | 0.037 |
| | (0.025) | (0.023) | (0.032) | (0.026) | (0.024) | (0.031) | (0.026) | (0.025) | (0.031) | (0.025) | (0.024) | (0.031) |
| $Imp^{low}$ | -0.204*** | -0.126*** | 0.132** | -0.214*** | -0.126*** | 0.165*** | -0.196*** | -0.123** | 0.163*** | -0.218*** | -0.133*** | 0.214*** |
| | (0.066) | (0.045) | (0.057) | (0.066) | (0.047) | (0.055) | (0.070) | (0.048) | (0.057) | (0.066) | (0.048) | (0.058) |
| $Exp$ | -0.024 | 0.020 | -0.024 | -0.031 | 0.012 | -0.015 | -0.031 | 0.010 | -0.014 | -0.008 | 0.018 | -0.052* |
| | (0.027) | (0.024) | (0.031) | (0.027) | (0.025) | (0.030) | (0.027) | (0.025) | (0.030) | (0.027) | (0.025) | (0.032) |
| $L$ | -0.104* | 0.005 | 0.234*** | -0.109** | 0.001 | 0.253*** | -0.107** | 0.001 | 0.252*** | -0.104** | 0.017 | 0.134** |
| | (0.054) | (0.040) | (0.046) | (0.053) | (0.042) | (0.047) | (0.053) | (0.042) | (0.047) | (0.053) | (0.043) | (0.057) |
| $PO$ | 0.035 | 0.049 | 0.046 | 0.045 | 0.003 | 0.033 | 0.049 | 0.007 | 0.031 | 0.045 | 0.021 | -0.001 |
| | (0.087) | (0.080) | (0.120) | (0.086) | (0.086) | (0.116) | (0.087) | (0.086) | (0.118) | (0.085) | (0.086) | (0.123) |
| $PS^{Educ}$ | 0.171*** | 0.171*** | -0.179*** | 0.153*** | 0.135*** | -0.112** | 0.158*** | 0.135*** | -0.109* | 0.136*** | 0.162*** | -0.051 |
| | (0.038) | (0.040) | (0.059) | (0.037) | (0.040) | (0.054) | (0.037) | (0.041) | (0.056) | (0.039) | (0.043) | (0.061) |
| $PS^{Health}$ | -0.072** | -0.081** | 0.061 | -0.079** | -0.098*** | 0.082** | -0.076** | -0.096*** | 0.083** | -0.107*** | -0.100*** | 0.120*** |
| | (0.034) | (0.032) | (0.042) | (0.034) | (0.035) | (0.041) | (0.034) | (0.035) | (0.039) | (0.034) | (0.036) | (0.036) |
| $PS^{SP}$ | 0.023 | -0.004 | -0.002 | 0.025 | -0.009 | -0.018 | 0.022 | -0.011 | -0.014 | 0.023 | -0.015 | -0.007 |
| | (0.017) | (0.019) | (0.027) | (0.017) | (0.020) | (0.027) | (0.018) | (0.020) | (0.027) | (0.017) | (0.020) | (0.027) |
| $MYS_{15+}$ | -1.170 | -2.798*** | 2.286*** | | | | | | | | | |
| | (0.849) | (0.500) | (0.696) | | | | | | | | | |
| $Gini^{E}_{15+}$ | | | | 0.383* | 0.397** | -0.997*** | | | | | | |
| | | | | (0.200) | (0.156) | (0.193) | | | | | | |
| $p^{1}_{15+}$ | | | | | | | 0.193 | 0.325* | -0.868*** | | | |
| | | | | | | | (0.243) | (0.189) | (0.234) | | | |
| $EducGini^{E}_{15+}$ | | | | | | | 0.457 | 0.405** | -0.855*** | | | |
| | | | | | | | (0.281) | (0.201) | (0.263) | | | |
| $p^{2}_{15+}$ | | | | | | | | | | -0.363 | -0.186 | 0.993*** |
| | | | | | | | | | | (0.231) | (0.196) | (0.240) |
| $p^{3}_{15+}$ | | | | | | | | | | -0.296 | -0.315* | 0.962*** |
| | | | | | | | | | | (0.222) | (0.187) | (0.228) |
| $p^{4}_{15+}$ | | | | | | | | | | -0.762*** | -0.419** | 1.566*** |
| | | | | | | | | | | (0.268) | (0.212) | (0.295) |
| $Obs$ | 239 | 381 | 262 | 239 | 381 | 262 | 239 | 381 | 262 | 239 | 381 | 262 |
| N | 22 | 26 | 25 | 22 | 26 | 25 | 22 | 26 | 25 | 22 | 26 | 25 |
| $\bar{T}$ | 10.86 | 14.65 | 10.48 | 10.86 | 14.65 | 10.48 | 10.86 | 14.65 | 10.48 | 10.86 | 14.65 | 10.48 |
| $Corr(y, \hat{y})$ | 0.958 | 0.930 | 0.920 | 0.958 | 0.929 | 0.922 | 0.958 | 0.929 | 0.922 | 0.961 | 0.929 | 0.926 |

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

Table 10: Developing Economies - Governance

| | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio | SSGini | MSGini | DecRatio |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $Year$ | 0.238* | 0.057 | 0.014 | 0.096 | 0.079 | 0.037 | 0.100 | 0.082 | 0.051** | 0.134 | -0.157 | 0.051 |
| | (0.129) | (0.113) | (0.049) | (0.075) | (0.063) | (0.024) | (0.070) | (0.059) | (0.021) | (0.180) | (0.139) | (0.052) |
| $TFP$ | 0.285 | 11.449*** | 0.556 | 2.245 | 11.005*** | -0.608 | 1.361 | 9.631*** | 0.522 | 0.611 | 10.296*** | 2.552** |
| | (4.165) | (2.441) | (1.019) | (3.926) | (2.294) | (0.880) | (4.039) | (2.703) | (0.928) | (4.437) | (2.485) | (1.089) |
| $Imp^{high}$ | 0.097*** | 0.069** | -0.024* | 0.100*** | 0.071** | -0.024* | 0.104*** | 0.078** | -0.041*** | 0.113*** | 0.089*** | -0.031*** |
| | (0.036) | (0.033) | (0.013) | (0.037) | (0.033) | (0.012) | (0.037) | (0.035) | (0.013) | (0.037) | (0.034) | (0.011) |
| $Imp^{low}$ | -0.153 | -0.359*** | -0.048 | -0.204 | -0.338*** | -0.016 | -0.231 | -0.351*** | 0.015 | -0.218 | -0.404*** | -0.011 |
| | (0.144) | (0.115) | (0.050) | (0.142) | (0.114) | (0.047) | (0.144) | (0.115) | (0.042) | (0.152) | (0.113) | (0.052) |
| $Exp$ | 0.023 | 0.038 | 0.011 | 0.021 | 0.034 | 0.004 | 0.028 | 0.039 | -0.004 | 0.030 | 0.039* | 0.012 |
| | (0.029) | (0.024) | (0.009) | (0.028) | (0.024) | (0.010) | (0.029) | (0.024) | (0.009) | (0.029) | (0.024) | (0.009) |
| $L$ | 0.137 | -0.019 | 0.004 | 0.104 | -0.018 | -0.004 | 0.119 | -0.011 | -0.026 | 0.113 | -0.007 | 0.021 |
| | (0.093) | (0.057) | (0.028) | (0.093) | (0.057) | (0.029) | (0.093) | (0.058) | (0.030) | (0.094) | (0.057) | (0.023) |
| $PO$ | -0.257 | -0.169 | 0.238*** | -0.240 | -0.155 | 0.247*** | -0.216 | -0.113 | 0.190** | -0.196 | -0.045 | 0.099 |
| | (0.225) | (0.209) | (0.072) | (0.232) | (0.209) | (0.070) | (0.230) | (0.210) | (0.076) | (0.236) | (0.211) | (0.070) |
| $PS^{Educ}$ | 0.010 | 0.028 | -0.006 | 0.022 | 0.023 | 0.002 | 0.028 | 0.021 | -0.002 | 0.004 | 0.034 | -0.011 |
| | (0.055) | (0.044) | (0.012) | (0.054) | (0.044) | (0.012) | (0.054) | (0.044) | (0.012) | (0.056) | (0.044) | (0.013) |
| $PS^{Health}$ | -0.053* | -0.066** | 0.020** | -0.063* | -0.063** | 0.021** | -0.073** | -0.070** | 0.034*** | -0.049 | -0.070** | 0.008 |
| | (0.032) | (0.030) | (0.009) | (0.033) | (0.030) | (0.009) | (0.034) | (0.031) | (0.010) | (0.034) | (0.030) | (0.010) |
| $PS^{SP}$ | 0.001 | -0.004 | -0.011* | 0.012 | -0.002 | -0.011 | 0.013 | -0.001 | -0.013 | 0.011 | 0.011 | -0.011** |
| | (0.022) | (0.021) | (0.006) | (0.024) | (0.021) | (0.007) | (0.024) | (0.021) | (0.008) | (0.024) | (0.021) | (0.005) |
| $MYS_{15+}$ | -2.197 | -0.567 | 0.086 | | | | | | | | | |
| | (1.372) | (1.178) | (0.498) | | | | | | | | | |
| $Gini^E_{15+}$ | | | | 0.172 | 0.175 | 0.060 | | | | | | |
| | | | | (0.185) | (0.146) | (0.060) | | | | | | |
| $p^1_{15+}$ | | | | | | | 0.390 | 0.303 | -0.159** | | | |
| | | | | | | | (0.270) | (0.199) | (0.074) | | | |
| $EducGini^E_{15+}$ | | | | | | | -0.393 | -0.233 | 0.651*** | | | |
| | | | | | | | (0.541) | (0.468) | (0.159) | | | |
| $p^2_{15+}$ | | | | | | | | | | 0.002 | -0.038 | -0.167*** |
| | | | | | | | | | | (0.255) | (0.168) | (0.063) |
| $p^3_{15+}$ | | | | | | | | | | -0.284 | -0.033 | 0.027 |
| | | | | | | | | | | (0.234) | (0.188) | (0.080) |
| $p^4_{15+}$ | | | | | | | | | | 0.099 | 0.588 | -0.426*** |
| | | | | | | | | | | (0.503) | (0.401) | (0.138) |
| $Obs$ | 136 | 167 | 139 | 136 | 167 | 139 | 136 | 167 | 139 | 136 | 167 | 139 |
| N | 20 | 23 | 19 | 20 | 23 | 19 | 20 | 23 | 19 | 20 | 23 | 19 |
| $\bar{T}$ | 6.80 | 7.26 | 7.32 | 6.80 | 7.26 | 7.32 | 6.80 | 7.26 | 7.32 | 6.80 | 7.26 | 7.32 |
| $Corr(y,\hat{y})$ | -0.052 | 0.614 | 0.850 | 0.195 | 0.384 | 0.802 | 0.189 | 0.952 | 0.765 | 0.091 | 0.366 | 0.552 |

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

### 7.6 Robustness

We assessed the robustness of our findings w.r.t. income inequality measures, regional heterogeneity, data sources and model specifications. All explanatory variables exhibit some differences in magnitude and significance with different income Gini indices as dependent variable. The single- and multi-source Gini results reflect a trade-off between volatility that confounds pattern discernment and increasing sample size. For Advanced Economies, we find a tendency of the single-source Gini to yield more frequent occurrences of variable significance as the recent crises period is included in the multi-source Gini series. For Developing Economies, on the other hand, the larger sample size of the multi-source Gini produces more significant results as compared to the single-source series. In most cases, the significance and signs are consistent for the decile ratio and Gini indices. Discrepancies are likely due to inequality drivers affecting the overall income distribution differently than its tails.

From the regional sensitivities we learn that drivers of income inequality vary between Advanced and Developing Economies. On the one hand, global results are based on a larger sample size and can thus be considered as more reliable. On the other hand, they show the average effect across regions. Drawing inferences from only a global analysis would thus give false confidence in a claim, e.g., that increasing population shares of educational attainment has served to reduce income inequality in Developing Economies.

Beyond the tests already included in our main results, we addressed robustness by varying sample sizes and data sources, modeling political governance differently and by accounting for the importance of international capital flows. These results are available from the authors upon request.

In order to evaluate whether the discrepancies between our basic and governance specifications can be attributed to the inclusion of political factors or to the shrinking sample size w.r.t. time and space, we compare the concerning results, restricting the basic model to the governance sample size. Doing so reveals a part of the reduced influence of TFP and the increasing importance of education and the labor share in Advanced Economies to be due to the varying sample size. This is also true for the increasing significance of TFP, education and imports from high-income countries in Developing Economies.[20] We also estimated the governance specifications excluding the political orientation of the chief executive's party as this variable drives the sample size reduction; without any additional effects on our main results. Besides analyzing the heterogeneity in public social spending, we tested the sum of public health, education and social protection expenditures in GDP. Doing so reveals a positive relation between public social spending and the single-source Gini in Advanced Economies which may be driven by the inequality increasing effect of education spending. Interacting the sum of public spending with the political orientation variable provides some evidence that this positive relation is strongest if a right party is in office and decreases in magnitude when changing to center and left parties. Consistent with the inequality reducing effect of health spending, we find public social spending to reduce income inequality in Developing Economies. Except for the overall education Gini coefficient being significant in these specifications for Developing Economies, remaining results are unchanged.

In order to test whether our estimates of trade effects are robust to accounting for international capital flows, we add foreign direct investment (FDI) inflows in GDP, taken from the World Development Indica-

[20] In Advanced Economies mainly Eastern European Countries (Czech Republic, Poland, Slovakia, Slovenia) drop out of the sample while this group larger and more mixed in Developing Economies.

tors (WDI). Interestingly, while FDI itself is neither significant in Advanced, nor in Developing Economies, imports from other high-income countries and total exports significantly increase and decrease income inequality w.r.t. the single-source Gini in Advanced Economies respectively. In general, using conference board TFP data does not affect our main results even though the sample period is reduced to range from 1990 to 2010. Finally, our sensitivities truncating the sample size in 2005 reveal fluctuations due to the crises period to affect our results in the basic specification, turning TFP to be significant also w.r.t. the multi-source Gini. In contrast, the results in the governance specification are not similarly affected.

## 8 Conclusions and Further Research

The novelty of this study has been in the design and choice of indicators of income inequality and its drivers. We provided a comprehensive picture of global and broad regional drivers interacting to influence within-country income inequality and identified factors which explain the common trend of increasing income inequality in most parts of the world over the last few decades.

Our findings indicate the main factors adding to increasing inequality globally to be technological progress and trade with high-income countries. Trade with low-income countries, public spending on health and decreasing shares of people without any formal education, on the other hand, had significant equalizing effects on the income distribution. The estimated effects of other income inequality drivers are highly region specific. In Advanced Economies, the general decline in the share of labor incomes and increasing public education spending added to increase income inequality, while reducing the degree of education inequality and increasing educational attainment had substantial equalizing effects. In contrast, in Developing Economies, the role of education is not equally clear as we find increasing population shares with primary and tertiary education to have disequalizing effects. While some variables, such as technological change and trade only affect the comprehensive measure of income inequality, others, such as the labor income and the unschooled population share, are only relevant for the extremes of the income distribution. Analyzing the decile ratio in addition to the Gini coefficient as dependent variable thus provided supplementary insights into the region-specific linkages between drivers and inequality. The additional examination of two income Gini time series once more reveals the importance of dealing with issues of data quality in an empirical study of income inequality. Even if we provided evidence on the heterogeneity of inequality determinants across space, the division between Advanced and Developing Economies is quite rough and leaves an investigation of differential regional splittings an important issue for further research.

In summary, our results provide evidence supporting the hypothesis of skill-bias being induced by technological progress and trade with high-income countries; but the strong equalizing role of increasing the skill level of labor supply by increasing years of schooling and providing for a more equal distribution of education is only present in Advanced Economies. Political governance has important equalizing but also disequalizing effects on the income distribution. Moreover, changing power relations between capital and labor are relevant for the personal income distribution. Although we examined multiple drivers, there are still factors which we were not able to capture in our model. Data limitations are especially stringent with respect to political factors in Developing Economies where national indicators of public sector redistribution and labor market institutions lack in coverage across time and space. Also the causes and effects of variations at the top of the income ladder, such as capital incomes and executive compensation, are only accounted for insofar they affect the labor income share. A thoroughly examination of the direct and indirect inequality effects of fiscal policies and regulations in western welfare states as well as Developing Economies is thus a highly relevant for understanding income inequality but probably goes beyond the scope of large panel studies in their ability to infer causal effects.

## References

# A Income Gini Time Series

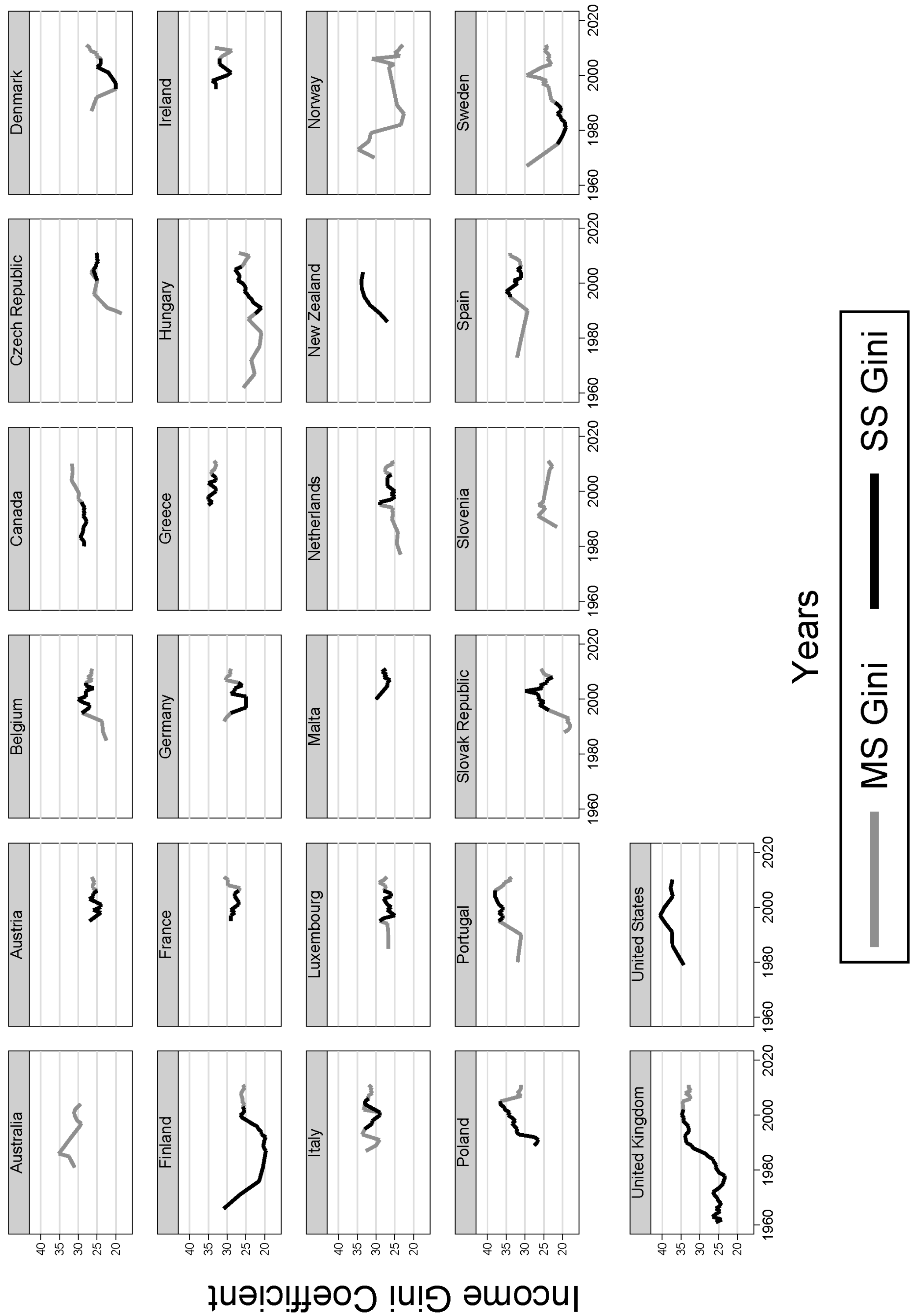


Figure 3: MultiSource Gini vs. SingleSource Gini Advanced Economies

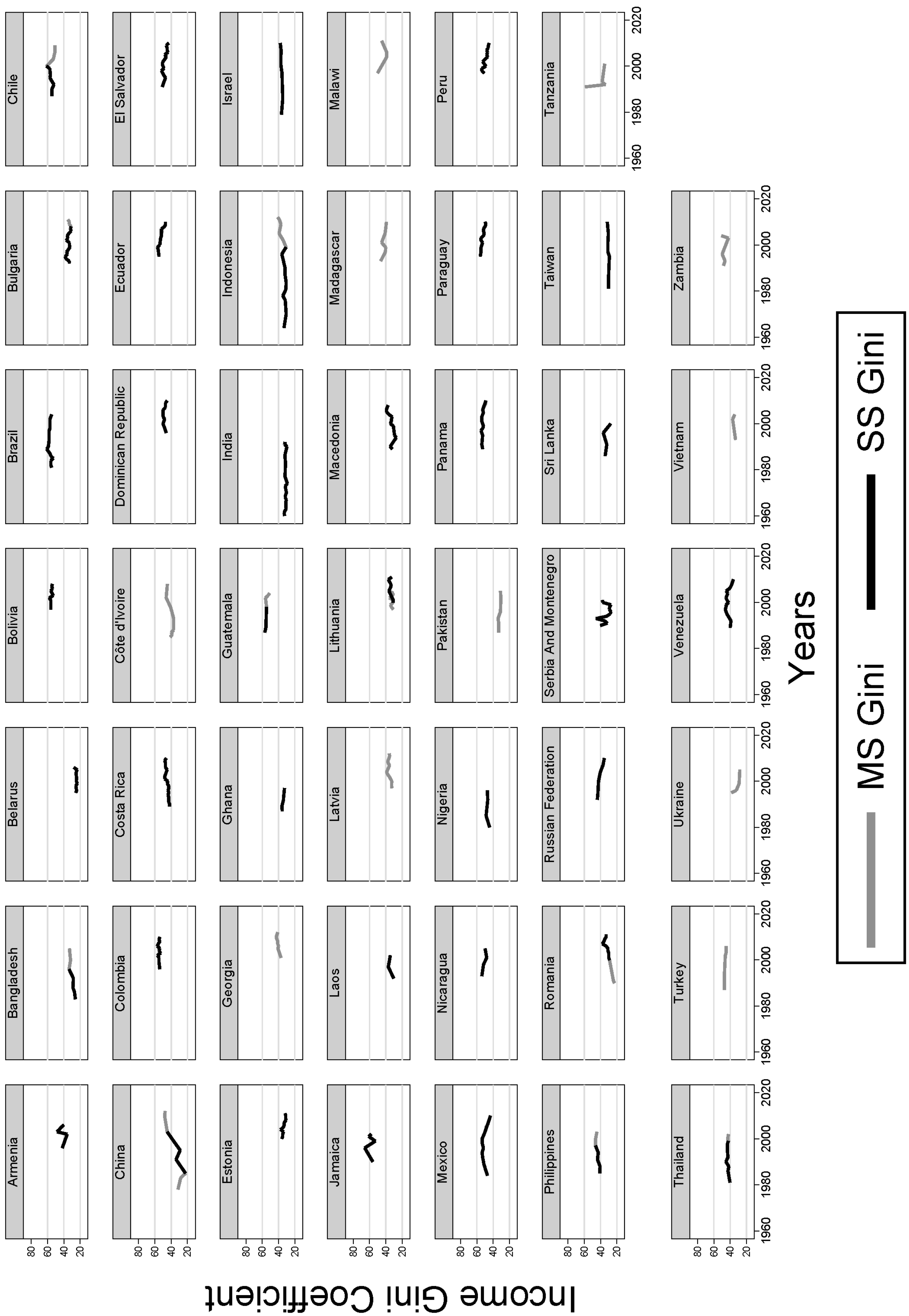


Figure 4: MultiSource Gini vs. SingleSource Gini Developing Economies