Explaining Income Inequality Trends: An Integrated Approach

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Abstract

In large parts of the world, income inequality has been rising over the last decades. Other parts have experienced declining trends in income inequality. This raises the question whether similar mechanisms underlie different observed trends in income inequality around the globe. To address this research question in an empirical analysis at the aggregate level, we examine a global sample of 73 countries over a time span from 1981 to 2010 and look at a broad set of drivers to investigate how these interact in their influence on income inequality. Underneath this broad approach, we are interested in the heterogeneity of income inequality determinants across world regions. Our findings indicate the existence of a small set of systematic drivers across the global sample of countries. Declining labor income shares and increasing imports from high-income countries significantly contribute to increasing income inequality while imports from low-income countries and taxation exert countervailing effects. Region specific impacts are revealed for technological change, financial globalization and domestic financial deepening as well as for public social spending. Most importantly, we do not find systematic evidence for an equalizing effect of education across high- and low-income countries. Our article links variants of existing empirical analysis of income-inequality drivers as it provides evidence for a global sample of countries and for regional subsamples while it examines the globalization and the education-inequality nexus in more detail.

JEL-Codes: F62, I24, I28

Keywords: Income Distribution, Education, Globalization

1 Introduction

In large parts of the industrialized world income inequality has been rising over the last decades (e.g. Morelli *et al.*, 2015). Also in some emerging economies, the substantial gains of high income growth rates have not been equally distributed among the population (e.g. OECD, 2011). Conversely, many countries in Latin America, which report among the highest historical inequality levels, have experienced declining income inequality trends (Alvaredo & Gasparini, 2015). This raises the question whether similar mechanisms underlie different observed trends in income inequality around the globe.

We address this research question in an empirical analysis at the aggregate level. Therefore, we examine a global sample of countries and look at a broad set of drivers to investigate how these interact in their influence on income inequality. Underneath this broad approach, we are interested in the heterogeneity of income inequality determinants across world regions. We have thus assembled an unbalanced panel dataset of 73 high-, middle- and low-income countries over a time span from 1981 to 2010, which combines two variants of income Gini coefficients and a ratio of extremes with a set of explanatory factors that are derived from existent theoretical contributions and recent empirical findings. These include measure to capture the integrated distributional consequences of technological change, globalization, finance and increasing functional income inequality in conjunction with presumably equalizing forces, i.e. education, labor market institutions and welfare state redistribution. To infer region specific effects, we split the full sample into high-income and developing economies, but separate effects of subsamples of the latter group.

Our findings indicate the existence of a small set of systematic drivers across the global sample of countries. Accordingly, declining labor income shares and increasing imports from high-income countries significantly contribute to increasing income inequality while imports from low-income countries and taxation exert countervailing effects. However, the majority of determinants differs across subsamples. Region specific impacts are revealed for technological change, financial globalization and domestic financial deepening as well as for public social spending. Most importantly, we do not find systematic evidence for an equalizing effect of education across high- and low-income countries.

The empirical literature that investigates the causes of income inequality can be grouped into three categories: analysis that concentrate on particular drivers of income inequality, e.g. trade (e.g. Meschi & Vivarelli, 2009) or labor market institutions (e.g. Checchi & Penalosa, 2010); analysis that look at particular groups of countries, e.g. OECD economies (e.g. Roser & Cuaresma, 2016) or Latin American countries (e.g. Lustig *et al.*, 2013); and analysis that investigate a broad set of determinants at the global level (e.g. ILO, 2008; Jaumotte *et al.*, 2013). Our paper bridges these groups of existing articles. By examining a broad set of determinants in a global sample of countries, we contribute to the literature of category three. In using most recent available databases for inequality measures and covariates, we aim to update and revise existing empirical findings. Looking at different regional subsamples further enables to infer the relative relevance of inequality drivers across country groups. Finally, we give particular attention to model the linkages that relate globalization and education to income inequality. Thereby we also aim contribute to the more specific literature concerning these drivers. On the one hand, we use disaggregated trade-flow indicators and measures of financial integration to discriminate between the mechanisms suggested by the comparative advantage framework and more recent theoretical approaches. On the other hand, we account for the distributional dimension of education and aim to provide new insights into the heterogeneity in the relation between education and income inequality. Among others, Castelló-Climent & Doménech (2014) have identified the "puzzle" that more people attain at least some formal education and education became more equally distributed, but there has been no or even an adverse effect on income distribution. Within a multivariate framework, we examine if it is possible to find the theoretically predicted negative relation between the education and income inequality after controlling for confounding factors.

The rest of this paper is organized as follows. In Section 2 we review the theoretical and empirical literature, and describe how existing knowledge motivates our analysis. In Section 3, we introduce our income inequality measures and data sources and discuss descriptive trends of income inequality and its explanatory factors. We justify our estimation method in Section 4 and present empirical results in Section 5. Section 6 draws conclusions and provides pointers for further analysis.

2 What we know: Theory and Empirical Evidence

The degree of (in)equality in the distribution of income in a country is a function of the shares of total income from labor and capital (functional income distribution) and their respective distributions among people (personal income distribution). The distribution of capital income results from the underlying wealth distribution and the returns which derive therefrom. The distribution of labor income not only depends on the forces of supply and demand and the relative bargaining power of agents, but also on the extent to which the institutions of the labor market mitigate market outcomes. Beyond that, governments play a more or less extensive redistributive role. In the following, we summarize the theoretical mechanisms through which technological change, globalization, finance, education, labor market institutions and economic policy affect income inequality. We conclude this section by discussing the relation between the functional and the personal distribution of income.

2.1 Technological Change

Conventionally, analysis of the distributional consequences of technological change have focused on its impact on the distribution of earnings. According to the hypothesis that technology is skill-biased (e.g. Acemoglu, 2002), new technologies that require high skills increase the relative productivity of high-skilled workers and cause the replacement of low-skilled labor. The resulting rise in relative demand in turn puts a premium on high-skilled wages and increases income inequality. The "task approach" (Autor, 2013), on the other hand, implies that jobs that involve predominantly manual routine tasks are relatively easily automated, while abstract and manual non-routine tasks continue to require human labor. Hence, employment shares increase in high- and low-skill segments, which pay high and low wages respectively, but decline in the segment that requires medium qualifications and pays medium levels of wages.[1] Routine-biased technological change thus results in

[1] In his subsequent paper, Autor (2015) argues that medium-skill and well remunerated professions complement new technologies if interpersonal interaction, flexibility, adaptability and problem-solving capacity is required, e.g. in medical and health care, trade and repair. Such tasks will thus not be automatized to the extent that is predicted in Autor (2013).

a polarized labor market. Both approaches predict inequality in the distribution of earnings to increase as a result of technological change.

The main focus of the literature on technology-induced skill premiums is on high-income countries. But models that account for the interaction between technology suggest that the general direction of the effect prevails for low-income countries as well (see Section 2.2). For example, Acemoglu (2003) provides a theoretical framework that suggests that skill premiums arise not only in the US, but also in Least Developed Countries (LDCs), where technological adoption and imitation is promoted via trade.

More recently, other dimensions of the income distribution gained attention in the theoretical and empirical literature. Most importantly, analysis that aim to explain the decline in the labor share since the 1980s also consider technological change as decisive factor. According to Karabarbounis & Neiman (2014), progress in information and communication technology (ICT) has significantly reduced the relative prices for investment goods, what has increased the capital intensity of production. Moreover, production and demand economies of scale in ICT-intensive branches have been shown to result in highly concentrated markets with "winner-takes-all"-structures (Autor *et al.*, 2017b,a). As a consequence, the bargaining power of corporations increases relative to their labor force and to public institutions, enabling them to absorb rents (Atkinson, 2015, chapter 3; Zilian *et al.*, 2016). Not only does this alter the distribution between incomes from capital and labor, but also the distribution of profits. Beyond that, Kim & Brynjolfsson (2009) present evidence that indicates companies' IT-intensity to help explaining increasing top executive remuneration. Finally, in their survey, Tyson & Spence (2017) highlight the central role of ICT in the global integration of markets for goods, services and investment as well as for the expansion of the financial sector. Both of which have distributional consequences.

2.2 Globalization

Globalization is a multidimensional phenomenon that includes trade in goods and services, cross-boarder investment and international financial flows. Global integration has substantially deepened over the last 30 years and has been shown to have distributional effects (Kanbur, 2015; Foerster & Tóth, 2015).

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 countries specialize in the factor of production and type of labor in which they are relatively abundant. Accordingly, high-income countries export capital and skill-intensive goods and import low-skilled-labor-intensive goods from low-income countries. The latter reduces relative prices and wages in import-competing sectors, thereby increasing inequality between labor and capital as well as between low- and high-skilled workers. Conversely, the import induced relative reduction of prices and wages in capital- and skill-intensive sectors of low-income countries is predicted to reduce income inequality.

The comparative-advantage framework has been criticized for its inability to explain the inequality effects of intra-industry trade between similar countries and 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 account for firm-heterogeneity show that exporting firms are more productive and pay higher wages than the average firm (see e.g. Melitz, 2003; Verhoogen, 2008). Second, trade liberalization can provide incentives for innovation activities in exporting sectors (Melitz, 2003) and/or facilitate technological diffusion via technologies embedded in imported capital goods (Acemoglu, 2003).[2] Hence, skill premiums possibly emerge in high- as well as low-income countries due to both, export and import flows from different and similar economies respectively. Theories that address the increasing relevance of foreign direct investment (FDI) and outsourcing follow a similar line of argument, indicating that the required skill level of workers in segments that move from high- to low-income countries is usually higher than the average in receiving economies (Goldberg & Pavcnik, 2007). FDI inflows should therefore increase the dispersion of wages in low-income countries but reduce inequality in high-income countries (Kanbur, 2015). In contrast, if the skill level of capital flows out of high-income countries is lower than the average, FDI outflows contribute to increasing inequality in these economies. Jaumotte *et al.* (2013) argue that FDI outflows are closely associated to offshore outsourcing and as such are an important measure for analyzing the impact of globalization on inequality in industrialized countries.

Explanations that go beyond the effects on the distribution of earnings have also been shown to be relevant for understanding the relation between globalization and income inequality. According to Rodrik (1997), trade integration has increased the relative bargaining power capital, which is the more mobile factor, and thus its share in total income. Competition between nations aiming to attract foreign investment can also induce a "race to the bottom" with regards to regulatory standards (Goldberg & Pavcnik, 2007), labor organization and corporate taxes (Gross *et al.*, 2016), while the higher ability of capital and high-income earners to move abroad is able to affect the redistributive capacity of national tax and transfer systems (Kanbur, 2015; Bertola, 2008). Piketty & Saez (2013) argue that lower tax rates on top incomes have provided an incentive to bargain for higher remuneration at the top of the income distribution. To the extent that global capital flows have contributed to this declining trend, they can have an indirect effect on the wage distribution within international as well as domestic firms. Finally, greater integration with the global economy has been shown to increase income volatility. The impact of increasing volatility on sustained income inequality depends on policy responses and financial sector characteristics (Kanbur, 2015; Bertola, 2008). According to ILO (2008), low-income households in emerging economies with fragile financial systems have been adversely affected by the consequences of the increasing number of banking crises after financial market liberalization in the 1990s.

The existing literature reveals heterogeneity in the globalization-inequality relationship. Effects vary, according to the income level of countries, the quality of institutions, and regarding the particular dimension of globalization. Even for trade and financial integration, multiple, possibly opposing mechanisms are at work. Hence, aggregate indices have often generated inconclusive results in empirical analysis. But papers that disentangle globalization effects have provided more detailed insights. For example, the findings of Roser & Cuaresma (2016) support SST as they identify non-oil imports from less-developed countries to be a robust driver of increasing income inequality in OECD countries. Meschi & Vivarelli (2009) find imports from as well as exports to high-income countries to increase income inequality, especially in middle-income countries. Jaumotte *et al.* (2013) also investigate the effects of financial integration and show the strongest inequality increasing effect of globalization to result from inward FDI.

[2] For a short survey and empirical evidence on the relative importance of these mechanisms see Meschi & Vivarelli (2009).

2.3 Education

If technological change and globalization increase the demand for high skills, increasing the supply of highly qualified workers becomes an important equalizing factor. Approaches that explain increasing income inequality by the market forces of supply and demand thus attribute a key role to investing in the education of the future labor force. A popular exposition of the important role of education in the US is Goldin and Katz's (2010) book "The Race between Technology and Education", which is based on ideas initially brought up by Jan Tinbergen (1974). They argue that even if secondary and, most importantly, tertiary education increased substantially in the US, the premium on high skills continued to increase in the 1980s and 1990s. According to Goldin & Katz (2010), educational expansion thus was unable to meet demand growth due to technological change. An extensive body of research has analyzed the dynamics of skill premiums, education and wage inequality in high-income countries (e.g. Peracchi, 2006). Research is relatively scarce for middle- and low-income countries where the focus has been on investigating the role of increasing literacy and primary education for poverty alleviation. However, technology and trade can also induce movements in the upper part of the education distribution (see Sections 2.1 and 2.2). In any case, equal access to education can accelerate intergenerational mobility and provides for a more equal earnings distribution of subsequent generations (Altzinger *et al.*, 2015).

Theoretically, the formalization of the equalizing role of education goes back to the human capital model, which predicts that an additional year of schooling increases individual productivity and wages (Becker, 1964; Becker & Chiswick, 1966). The relation between education and inequality in the dispersion of wages depends, however, on the relative importance of the composition and the wage effect respectively (Foerster & Tóth, 2015). The former addresses the distribution of education. The equalizing impact depends on the extent to which higher educational attainment simultaneously results in a more equal distribution of education. The latter, on the the other hand, addresses how the returns to education respond to changes in the composition. For example, increasing the share of primary education in low-income countries can contribute to decreasing educational but increasing income inequality if the returns to the lowest education level decline. 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. The overall effect of education on income inequality is thus not clear and has to be determined empirically. It depends on the impact on the education distribution and on the returns to education. Moreover, the equalizing effect also depends on the political economy of education. In this vein, Carnoy (2011) argues that mass expansion of higher education may contribute to increasing income inequality in low- middle- and high-income countries equally, if public means are distributed unequally across education institutions, resulting in quality differentials between elite and mass universities.

Empirical works often represent education by an average measure.Rising 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. Hence, studies that have included a measure of average educational attainment as a control variable found either a negative (e.g. OECD, 2011) or insignificant (e.g. Roser & Cuaresma, 2016) relation to income inequality. Accounting for the distributional dimension of education enables Gregorio & Lee (2002) to find higher average attainment and a lower variance of education to significantly contribute to decreasing income inequality. In contrast, Castelló-

Climent & Doménech (2014) have observed that large reductions in education inequality (measured by an education Gini coefficient), which were mainly due the declining share of people without any formal education, have not been accompanied by similar reductions in income inequality. Castelló-Climent & Doménech (2014) provide explanations for this "puzzle", which include e.g. countervailing effects of returns to education or the increasing relevance of movements in top incomes for overall inequality dynamics. But they do not test for the relative importance of these factors in a multivariate setting.

2.4 Finance

Since the early 1990s, restrictions on cross-boarder (financial) capital flows have been relaxed and domestic financial capital markets have been liberalized e.g. through the removal of interest rate ceilings, credit controls and regulations on bank activity (Evans, 2016). The distributional consequences of the increasing economic relevance of the financial sector have been analyzed in various theoretical and empirical papers.

One strand of the literature investigates the availability of private credit in developed financial markets as prerequisites for development and long-term growth. Accordingly, the relaxation of borrowing constraints allows for high-return investments, e.g. in education, for low-income households. These investments can assist accelerate social mobility. Access to borrowing can also facilitate consumption smoothing and attenuate temporary income shocks. But if credit is provided without contingency, access has also been shown to increase the vulnerability for uninsurable shocks (Bertola, 2008). Private debt can thus contribute to increasing inequality via increasing macro-economic instability.[3] According to Claessens & Perotti (2007), whether domestic financial development is actually able to reduce income inequality in developing countries depends on the quality of institutions and whether the rich are able to shape them in ways that secure their own interests.

Another strand of the literature looks at the expansion of the financial sector and its consequences for changing corporate behavior, the rise of executive remuneration and the declining labor share. The gap between high-income earners, especially executives, and low-income earners has substantially increased since the early 1990s (e.g. ILO, 2008). Increasing top-executive remuneration can, on the one hand, be explained by marginal productivity differentials, e.g. due to the increasing complexity of managerial tasks in technology-intensive and multinational enterprises. However, in particular the variable component which has increasingly been linked to the stock market has become a major part of top executive's income (ILO, 2008). It is, on the other hand, thus argued that the bargaining power of top executives has increased since corporate goals have been aligned with financial sector aims, while the power of trade unions as a countervailing force declined.[4]

[3] Rajan (2010) and Kumhof & Renciére (2010) argue that American low- and middle-income earners tried to keep up with the top by expanding private debt, what fueled the 2007/08 financial crises. VanTreeck & Sturn (2012) refine their findings as they provide evidence that inequality results in higher household indebtedness if, among other things, financial markets are developed, the public social safety net is weak and education systems are predominantly private.

[4] See Palley (2007) for a survey of the underlying mechanisms and Amable *et al.* (2005) for a theoretical model on the relation between finance, industrial bargaining and the functional income distribution.

2.5 Labor Market Institutions & Redistribution

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.[5] The role of public policy can be grouped into the following channels. First, policies influence the drivers of income inequality, such as the direction of technological change or trade openness. Second, policies alter either the primary distribution of incomes, e.g. through labor market regulations, or the distribution of disposable household incomes through transfers and taxation. Third, redistribution in kind through education and health policies affects the level and distribution of human capital.

Labor market institutions, such as unions, collective bargaining structures, minimum wages and unemployment benefits, aim to achieve redistributive goals and mitigate market risks. Labor support regulations therefore contribute to increase the labor share and compress wage gaps. Even if wage differentials between union and non-union workers rise, trade unions and institutionalized wage bargaining have generally have been shown exert an equalizing impact on the dispersion of earnings (ILO, 2008, Chapter 3). This relation also holds for minimum wages and, to a lesser extent, for unemployment benefits (e.g. Koeninger *et al.*, 2007). However, the overall effect of labor market institutions on inequality in disposable incomes is not equally clear. Checchi & Penalosa (2010) present a theoretical framework to analyze the distributional effects of labor market institutions on various dimensions of income inequality simultaneously. In their empirical application to OECD countries, they show that greater union density and a higher minimum wage compress wages and increase the labor share but also contribute to rising unemployment. The net effect on disposable income inequality is positive, while it remains negative for greater bargaining coordination and is not significant for unemployment benefits. The majority of articles considers advanced economies with large formal labor markets. One example that conducts an analysis for a global sample of countries is Calderón *et al.* (2005), who largely confirm the results found in Checchi & Penalosa (2010).[6] In contrast, ILO (2008, Chapter 3) are not able to provide evidence on a direct equalizing effect of labor market institutions[7] in a sample that includes high-, middle- and low-income countries. But they find an indirect impact via the reach of the welfare state.

Governments' redistributive policies are reflected, on the one hand, in the structure of taxes and monetary transfers, such as social security provisions and poverty relief. These determine 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 run, and disposable incomes in the short run.[8] By determining the relative quality of educational institutions, the structure of education spending also affects the distribution of returns to education (Carnoy, 2011).

[5] See e.g. Chakravorty (2006), Angeles (2007) and Huber *et al.* (2006).

[6] Even if they find union density to exert a significant equalizing impact on disposable income inequality, the effect of increasing the minimum wage is positive.

[7] ILO (2008, Chapter 3) looks at trade union density and the degree of coordination in collective bargaining.

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

2.6 Functional and Personal Income Inequality

As the preceding discussion of income inequality determinants shows, technological change, globalization, financialization and labor market institutions are not only directly related to the personal distribution of income, but also to the functional distribution between capital and labor. The increasing number of articles that aim to explain the declining trend in the labor share since the 1980s provide evidence for the importance to account for changes in factor shares.

The relation between the functional and the personal distribution of income is not straightforward. Checchi & Penalosa (2010) find a strong negative relation between the labor income share and the income Gini coefficient, which they explain by the dominance of the gap between capital and non-capital owners over increases in inequality within the latter group, between wage earners and the unemployed. The theoretical framework of Milanovic (2015) provides additional insights which enable to identify situations in which increasing inequality between capital and labor translate into increasing personal inequality. First, returns to capital should predominantly be used for savings and investment so that the capital-output ratio continuously increases. Second, the distribution of capital income should be more unequal than the distribution of labor income, so that shifts from labor to capital are shifts to the more unequally distributed source of income. Third, the higher ones capital income, the higher should ones overall income be. Milanovic (2015) shows these three conditions to prevail in the majority of current/existing societies, which he denominates as *new capitalist* because capital owners and workers are not distinct social groups - as in *classical capitalism* - but overlap so that incomes accrue from both sources. It follows that a positive relation between increasing capital income shares and increasing personal inequality can be expected. Daudey & García-Penalosa (2007) as well as the recent papers of Bengtsson & Waldenstroem (2017) and Francese & Mulas-Granados (2015) provide evidence that supports this hypothesis in different samples with regards to time frame and country coverage. But the latter two articles find the relation to be weaker or even insignificant as further explanatory variables are included.

3 Empirical Analysis: Measures and Data Sources

The main inequality measure of our empirical analysis is the income Gini coefficient, which is a comprehensive measure of income differences across an entire population, but which masks the internal composition of the distribution. We therefore also examine a ratio of extremes, which reveals the disparity between the tails of the income distribution, but leaves out the rest. These inequality measures are merged with a set of explanatory variables which we derive from the theoretical relationships discussed in Section 2. The data we assemble should thus enable to model the heterogeneous mechanisms that underlie technological change, globalization, finance, education, welfare-state- and labor-market institutions as well as the division between capital and labor.

Our aim is to observe a broad set of countries from various world regions over a reasonable long time horizon. This creates a trade-off between sample coverage and accuracy of the econometric model. The basic estimation sample, which includes the least extensive set of determinants (see Column 1 in Tables 4 to 6), covers 73 countries over the time span from 1981 to 2010. In order to reveal heterogeneity across regions, we apply different country groupings based on the World Bank's classification of countries by geographical region and income group.[9] Generally, we split our sample into high-income OECD members and the remaining group of countries, which we loosely denominate as developing economies. But we also examine different finer groupings of the latter, quite heterogeneous cluster.

3.1 Data on Income Inequality

Income inequality datasets are diverse due to their underlying estimation method, income measures and concepts, units of analysis, data sources and availability of panel data. For a long time one of the most widely used and discussed panel dataset has been that by Deininger & Squire (1996), who assembled surveys from across countries that meet their desired standard of quality. The internal inconsistency of this dataset has motivated researchers to critically assess the reliability of secondary income inequality datasets (see e.g. Atkinson & Brandolini, 2001; Galbraith & Kum, 2005; Galbraith, 2012). Recent studies for developing countries often use World Bank's POVCAL database (Chen & Ravallion, 2004), which is, however, quite sparse and unbalanced. To overcome data sparseness and concept diversity, second-generation studies use parametric extrapolations to calculate Gini indices for years with no survey data. For example, the University of Texas Inequality Project (UTIP) provides global Estimated Household Income Inequality (EHII) dataset, which derives Gini indices of gross household income inequality based on an estimated relation between data from Deininger and Squire (1996) and industrial pay inequality (Galbraith & Kum, 2005; Galbraith *et al.*, 2014).

More recently, large meta-datasets that assemble income inequality measures from a variety of relatively reliable sources emerged. Instead of applying estimation techniques in order to correct for differences in the underlying data, these databases make discrepancies explicit as they report survey sources and income concepts, among other things. The *All the Ginis* dataset (Milanovic, 2014) takes this approach and reports Gini coefficients for 166 countries from 1950 to 2012, but does not provide information on decile or quintile income shares. The focus of the World Wealth and Income Database (WID), on the other hand, is top incomes and wealth inequality (Alvaredo *et al.*, 2016).[10]

As it reports not only income Gini coefficients but also decile and quantile income shares and provides extensive documentation that permits to extract data based on a chosen selection criteria in order to maximize consistency of the underlying data, the most suitable database for our analysis is the UNU-WIDER World Income Inequality Database, Version 3.4 (WIID3.4)[11]. It assembles inequality measures from a variety of sources including, among others, data from OECD, Eurostat and the Luxembourg Income Study (LIS) for high-income countries, Transmonee by UNICEF for Eastern European countries, SEDLAC[12] for Latin American countries, and World-bank sources and household surveys from national statistical offices for other middle- and low-income countries. This results in a total of 8,817 observations for 182 countries, with the majority of observations covering the time span from 1960 to 2015. 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

[9] See Appendix B for the classification of countries in our estimation sample. For more information see https://datahelpdesk.worldbank.org/knowledgebase/articles/906519-world-bank-country-and-lending-groups (08/16/2017).
[10] The majority WID measures is based on fiscal data.
[11] The data, a user guide and detailed country documentation can be obtained from *https://www.wider.unu.edu/database/world-income-inequality-database-wiid34*.
[12] Social and Economic Database for Latin American Countries

adopted and the use of equivalence scales and weighting.

An important source of potential inconsistency is variation of the income concept used across countries. While most countries report income-based measures, some countries report only consumption expenditure-based measures. Moreover, income-based measures can be calculated from market income, gross income, which accounts for government transfers. or disposable income, with in addition accounts for taxes. Consumption-based surveys can differ with regard to the inclusion of durables (Jenkins, 2015). We primarily use disposable-income-based Gini indices, and consumption-based measures only exceptionally. The concept is thus allowed to vary across countries, but not over time.[13] We always require our measures to cover urban and rural areas, all forms of employment, males and females. We further address the multitude of underlying 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 sources. The detailed process of data selection is summarized in Appendix A.

In our main model, we allow each country series to be based on different data sources, as long as they conform to our data integrity checks (*multi-source Gini*). Our base case consists of an unbalanced panel with 771 Gini observations from 73 countries over the time span from 1981 to 2010 (see Table 1), including 58% from high-income OECD countries. Data coverage is more sparse for developing economies, with 17%, 14%, 7% and 5% of total observations in Latin American, European and Central Asian, Asian, and African countries, respectively (see Table 2). Our second income Gini series (*single-source Gini*) enforces source consistency within countries over time. Doing so reduces the sample size to 630 observations from 70 countries but leaves the furthest and most recent time observations unchanged. WIID reports income shares of quintiles and deciles if available. We use this information to compute a ratio of extremes as the share of income accruing to the ninth decile in relation to that of the bottom decile of the income distribution (*DecRatio*). A lower value thus implies lower inequality at the extremes. All requirements of the *multi-source Gini* with respect to population, regional and time coverage as well as the income concept also apply to the decile ratio. The decile ratio series covers 532 country-time data points. Not only do we test if our results are robust to modifications of the dependent variable within WIID but we also investigate two conceptually different measures from other datasources. Firstly, we use the gross-income-based Gini from EHII and , secondly, we analyze the extent to which our model enables to explain trends in top-income shares using data from WID.

Table 1 here.

3.2 Descriptive Trends of Income Inequality

The within-country standard deviation of the inequality measures is small in relation to the cross-country variation, and similar across regions. This suggests that income distribution changes are slow at any level of inequality, and that the extent of influence of time-varying drivers is narrowly bounded. Figure 1 and Table

[13]See Section 5.4 for a more detailed discussion about discrepancies between results from different conceptual basis.

2 investigate dynamics over time in more detail and depict regional differences in the levels and trends of the multi-source Gini and the decile ratio. In general, both inequality measures move to the same direction, what indicates that changes in the overall income distribution are consistent with changes at the extremes.[14] But the mostly insignificant time trends show that the decile ratio is more persistent than the income Gini. An exception is East Asia, where income inequality significantly increased with respect to the Gini, but decreased at the extremes. In high-income OECD economies, income inequality has been significantly rising since the 1980s. This is also true for both Asian regions. In contrast, starting from the highest inequality level among world regions, income inequality has been significantly decreasing with respect to both measures in Latin American countries. Also Middle Eastern and North African countries show a significantly declining trend with respect to the Gini coefficient. The overall trend in developing economies is thus not significant (see Table 3). We do not observe a significant trend over time for European and Central Asian as well as Sub-saharan countries. But for the latter region, the plot in Figure 1 suggests that inequality has been decreasing in the 1990s but has been rising since 2000.

Table 2 here.

Figure 1 here.

3.3 Drivers of Income Inequality

Labor income share To account for the effects of changes in the distribution between capital and labor income, we use the labor income share from Penn World Tables (PWT) 8.0. Their estimates are based on National Accounts data on the compensation of employees and adjusted for self-employment using information on mixed income, average wages or value added in agriculture, depending on country or region (Inklaar & Timmer, 2013).

Education We use three methods in order to capture the distributional dimension of education: the overall education Gini, the Gini for the educated population and population shares at individual attainment levels.

Following Sauer (2016) and Cuaresma *et al.* (2013), we calculate the education Gini coefficient, which measures the degree of education inequality in the population older than 15 years (15+), as follows:

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

where p_i is the population share for which i is the highest level attained and y_i is the corresponding cumulative

[14]The decile ratio is positively correlated to the Gini, but the extent varies by region. The correlation coefficient ranges from above 0.8 in high-income OECD members, Middle Eastern, North African and South Asian countries to 0.6 in Latin America and East Asia.

duration of formal schooling. MYS, the mean years of schooling in the population aged 15 and over, is given by $MYS = \sum_{i=1}^{n} p_i * y_i$. An education Gini of zero means that the entire population attains the same education level, regardless of which. An education Gini of one, on the other hand, implies that one person completes the tertiary level, but the rest does not attain any education.

In order to measure the average 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. From these data we derive the population shares, 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).[15]

The strong decline in the share of people without formal education is the predominant driver of decreasing education inequality in developing countries (Sauer, 2016; Cuaresma *et al.*, 2013). The concerning variable is thus 97 percent correlated with the overall education Gini. In high-income countries, on the other hand, almost universal literacy and schooling has been achieved well before the eighties. To explore the effects of these regional differences we decompose the education Gini[16] of the total population aged 15 and over, $EducGini_{15+}$, into the share of people without any formal education, (p^1_{15+}), and an education Gini for those with at least some formal education (categories 2-4), $EducGini^E_{15+}$. To test wage effects differ across education levels, we also model the separate effects of the population shares with primary, secondary and tertiary attainment.

Technological Change We represent technological change as total factor productivity (TFP), computed from a conventional growth accounting framework. The growth rate of TFP is thus obtained as the unknown part in:

$$\Delta \ln y_{i,t} = \alpha_{it} \Delta \ln k_{it} + (1 - \alpha_{it}) \Delta \ln hc_{it} + \Delta \ln A_{it} \tag{2}$$

where $\Delta \ln y_{i,t}$ is the growth rate of real GDP per worker (at constant 2005 prices, output approach) in country i at time t. $\Delta \ln k_{it}$ is the growth rate of physical capital per worker and α_{it} and $(1 - \alpha_{it})$ are the capital and labor shares respectively. All economic variables are obtained from PWT 8.0 (Inklaar & Timmer, 2013). However, in order to be consistent with our education variables, we use the IIASA/VID data for computing human capital by worker (hc_{it}) as follows

$$hc_{it} = e^{\phi * MYS_{it}} \tag{3}$$

where MYS_{it} are the mean years of schooling and ϕ is the average return to education. We continue along

[15] 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.

[16] 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.

the lines of Inklaar & Timmer (2013)[17] and compute ϕ as piecewise linear returns to education according to 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.

A caveat of a broad TFP measure is that the indicator potentially includes other factors, such as institutional quality (e.g. Hall & Jones, 1999). In addition, TFP captures variables that are not included in the capital measure used in Equation 2 but lead to the capitalization of income. (Inklaar & Timmer, 2013) note that intangible assets as intellectual property rights are not accounted in PWT's capital stock measure. The estimated impact of TFP can thus be biased upwards.[18] The literature summarized in Section 2.1 suggests ICT to have been the most relevant component of technological change over the last decades. ICT capital might thus be a more direct measure to capture the mechanisms that link technology and inequalty. We therefore test if our main results hold, using a level index based on the growth contribution of ICT capital from the Total Economy Database (TED). This measure is, however, only available from 1990 onwards.

Globalization In order to reveal the heterogeneous mechanisms of the globalization-inequality relation, we consider measures of trade and financial integration. We develop trade flow indicators that enable us to test the differential hypothesis regarding trade with high- and low-income countries. Using the Correlates of War (COW v3.0) bilateral trade database, we 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), these flows are categorized into those from high-income and low-income countries, as a proxy for high-skilled and low-skilled (manufacturing) imports respectively. To test whether skill-bias or overall employment and wage growth is the dominating force of exporting, we include the total level of exports in GDP. The extent of financial globalization is captured by in- and outward FDI flows in GDP, taken from the World Development Indicators (WDI).

A thorough analysis of globalization effects would also account for measures of portfolio investment and debt. As Jaumotte *et al.* (2013) show these factors to be of minor importance in comparison to trade variables and FDI, we omit them for the sake of sample coverage. Moreover, to the extent that international financial market liberalization affects domestic financial deepening, indicators of national financial development can partly absorb and reveal its impact.

Finance We largely follow the literature and account for financial development by including domestic credit to the private sector in GDP. But we also test for the hypothesis, derived from the second strand of literature presented in 2.4, that financial-sector-aligned corporate behaviour has contributed to increasing inequality. This driver is measured by the market capitalization of listed domestic companies in GDP. Both finance variables are from WDI.

Labor Market Institutions & Redistribution We select five measures in order to capture the redistributive capacity of governments. On the revenue side, an ideal measure would capture the progressivity of nations' tax system. In view of the lack of available data for a broad group of countries, we resort to a measure of taxes on income, profits and capital gains relative to total revenue from WDI. On the spending side, we account

[17]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.

[18]We thank the referee for pointing to the relevance of this issue.

for the relative weight of public social spending categories by using data on the shares of education, health and social protection expenditures in total government spending from the Statistics of Public Expenditure for Economic Development (SPEED) database of the International Food Policy Research Institute (IFPRI).

Data on labor market institutions is only available for a relatively small group of countries in our global sample. Since the literature summarized in Section 2.5 shows their relevance for distributional outcomes, we include measures of ratio between minimum and median wages and the unemployment benefit coverage, taken from Schindler (2011), as well as trade union density as percent of paid employment, taken from ILO's Industrial Relations Indicators, in separate specifications.

3.4 Descriptive Trends of Covariates

Table 3 provides summary statistics on the levels and time variation of all measures we consider in our empirical analysis, separated by the most general regional splitting into high-income OECD and developing economies.

Table 3 here.

In accordance with the literature, we find that the labor share in income declined significantly in high-income as well as in developing economies. TFP and the ICT capital index increased significantly. Also all trade variables show a significantly rising trend since the 1980s in both regions, but FDI flows only did so in high-income countries. The significantly increasing trend of both finance variables in conjunction with their relatively large within standard deviation, indicates the substantially expanding economic importance of finance.

On the public social spending side, more or less all categories gained weight in total government spending. But the relative weight of taxes on income, profits and capital gains remained constant in high-income countries. In developing economies, on the other hand, the income tax share increased. The declining trend of trade union density is visible for both world regions and is in line with existing findings. In contrast, unemployment benefit coverage has been extended in high-income OECD countries, but restricted in developing economies.

As in Sauer (2016) and Cuaresma *et al.* (2013), we find the distribution of education to have become more equal as education expanded, i.e. as the mean years of schooling increased. This is true for both education Gini coefficients as well as for both world regions. The shares of unschooled or primary educated people declined significantly while the shares of people with secondary or tertiary education increased.

4 Estimation Method

Our basic model specification is given by Equation (4):

$$IGini_t = \gamma Year + \beta_1 L_{i,t-1} + \beta_2 TFP_{i,t-1} + \beta_3 G_{i,t-1} + \beta_5 W_{i,t-1} + \beta_6 F_{i,t-1} + \beta_4 E_{i,t-1} + \alpha_i + \epsilon_{i,t} \qquad (4)$$

with

$$
\begin{aligned}
G &= (Imp^{high}, Imp^{low}, Exp, FDIin, FDIout) \\
W &= (PS^{Educ}, PS^{Health}, PS^{SP}, TaxesREV) \\
F &= (MCapit, PDebt) \\
E &= (EducGini_{15+}/MYS^{15+}/p^1_{15+}, EducGini^E_{15+}/p^2_{15+}, p^3_{15+}, p^4_{15+})
\end{aligned}
$$

where $IGini_t$ represents one of our three income inequality measures obtained from WIID, the EHII Gini or the top 1% income share. L is the labor income share and TFP stands for total factor productivity. Globalization variables, G, include the two import vectors from high (Imp^{High}) and low (Imp^{Low}) income countries, total exports (Exp), FDI in- and outflows. Measures of welfarestate redistribution, W, consist of the three types public social spending (PS) for education ($educ$), health and social protection (SP) as well as income taxes in total revenue ($taxesREV$). Market capitalization ($Mcapit$) and private debt ($PDebt$) are the two finance variables. Finally, with regards to education, we include the overall education Gini coefficient ($EducGini_{15+}$) in our main estimations, but estimate separate specifications which add either mean years of schooling (MYS^{15+}), the education Gini coefficient for the educated population ($EducGini^E_{15+}$) in combination with the unschooled population share (p^1_{15+}) or the remaining three population shares of primary (p^2_{15+}), secondary (p^3_{15+}) and tertiary (p^4_{15+}) attainment. α_i is the country specific intercept and $\epsilon_{i,t}$ is the time varying error. In order to account for reverse causality, all variables are included lagged one period. Finally, the time trend ($Year$) controls for global macroeconomic factors.

The most widely used econometric method in related empirical papers (UNCTAD, 2012; Galbraith and Kum, 2005) is fixed-effect estimation. However, due to the complex error structure in our data, our preferred econometric method is a feasible general least squares (GLS) estimator. Based on a modified Wald Statistic, we reject the null hypothesis that the error variances are equal across panels. We test for panel autocorrelation using a test proposed by Woolridge which is based on the coefficients of a regression of lagged residuals[19]. We strongly reject the null hypothesis of no serial correlation in each of our model specifications at the global and regional level. Furthermore, the feasible GLS model calculates the common AR(1) coefficient to be 0.4 or higher in all model runs. From this it follows that we have to account for first order autocorrelation (AR1) and groupwise (i.e.country-wise) heteroskedasticity in the errors. Both types of disturbances are likely, as the income Gini is a persistent, path-dependent variable. Moreover, as some countries have more erratic Ginis than others, it is natural to expect the error variances to vary by country.

A typical approach to correct for autocorrelation while accounting for fixed 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

[19] This test is discussed and analyzed in Drukker (2003) and implemented in STATA using the command xtserial.

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 feasible GLS or clustered standard errors in fixed-effects models. For balanced panels which exhibit groupwise heteroscedasticity, Reed & Ye (2011) demonstrate that feasible GLS produces more efficient estimates than OLS in finite samples with N > T. Moreover, although cluster-robust standard errors can correct for serial correlation within panels, they can be less reliable than ordinary standard errors with unbalanced clusters (Kézdi, 2004). There is, thus, a trade-off between feasible GLS and fixed effects with robust standard errors. The former is more efficient but assumes knowledge of the error structure, while the latter is less efficient but does not put a structure on error terms. We select feasible GLS based on its finite sample efficiency properties and the particular error structure present in our data.[20] However, we test the robustness of our results using fixed effects with clustered standard errors.

We apply a Fisher-type unit-root test which is is based on Dickey-Fuller specifications on demeaned data for each panel. Doing so, we can reject the null hypothesis that all panels contain unit roots for all variables except total exports and private debt. Also these covariates become stationary as soon as a time trend is accounted for. Thus, including a time trend or time dummies is able to secure stationarity of the time series in Equation 4.

5 Results and Discussion

The results we obtain from estimating Equation 4 in an unbalanced panel of 73 countries from 1981 to 2010 have various dimensions which differ according to the composition of regional subsamples, the inequality indicator used as dependent variable and on the set of determinants used as independent variables. In order to identify the most robust drivers of income inequality, we start with a parsimonious specification and stepwise expand it to obtain our main model which accounts for the broadest set of explanatory factors while a reasonable sample size is retained. This specification accounts for education by adding the education Gini coefficient for the total population aged 15 and over. Even if this allows for the distributional dimension of education directly, it still masks subjacent effects. We therefore subsequently focus on how unpacking the education distribution reveals its influence on income inequality. By analyzing the results for the global sample and for high-income OECD and developing economies separately, we aim to reveal regional differences in the mechanisms that underlie income inequality trends. More insight into the heterogeneous group of developing economies is obtained by looking at smaller subsamples. Finally, we test if our main results are robust to variations in the dependent variable and the econometric method.

5.1 Main Results

Tables 4 to 6 present the results for the stepwise expansion of the most parsimonious model for the global sample, high-income OECD and developing economies respectively. Column 1 of each table includes a time trend, the

[20] In particular, we implement FGLS using xtgls with the options corr(ar1) and panel(hetero).

labor income share, TFP, variables of trade and financial globalization, the education Gini and public social spending. Column 2 accounts for nations' tax system while columns 3 and 4 test for the relevance of finance, Column 5 adds ICT capital instead of TFP and Column 6 includes labor market institutions.

Results at the global level can be understood as the average effect across the two broad world regions. On the one hand, a significant relation thus stems from both regional effects pointing into the same direction. In high-income as well as in developing economies, a higher share of labor in total income significantly contributes to reduce the multi-source Gini coefficient. This is also true for increasing imports from low-income countries, FDI inflows and income taxation. Imports from high-income countries, FDI outflows and public education spending contribute to increasing income inequality, measured by the multi-source Gini, in both regions.[21]

On the other hand, some variables show significant effects in the global sample that mask variations between the two regions. Due to its impact in high-income countries, TFP is significant in the global sample. The inequality-increasing effect of market capitalization and the inequality-reducing effect of exports are also driven by their effect in the high-income cluster. Public spending on health, on the other hand, has a net effect of lowering income inequality in some model specifications in the global sample, but its influence is more robust for developing economies. Similarly, increasing private debt significantly contributes to increasing income inequality in developing economies, but does not have a significant effect in high-income countries.

Due to the small sample size, the effects of labor market institutions can only be interpreted for high-income OECD members. However, also for this subsample size is substantially reduced to 85 observations from 9 countries. Thus, even if we find the expected negative effects for minimum wages, unemployment benefit coverage and trade union density, results are hard to generalize. Regarding ICT capital, the net effect at the global level is insignificant since region-specific impacts point into opposite directions. For high-income OECD members, we find an unexpected negative relation to income inequality.[22] Moreover, the effects of imports from low-income countries and public education spending turn insignificant. Retaining TFP in a regression which restricts the sample period to start in 1990 reveals these estimator changes to be likely due to the shorter time period covered by ICT capital. In developing economies, where TFP is not significant, ICT capital is positively related to the income Gini and its introduction leaves other effects unchanged.

Tables 4, 5 and 6 here.

We balance the trade-off between sample coverage and broadness of inequality determinants considered by choosing the model specification in Column 5 of Tables 4 to 6 as the main model for further analysis. Besides the base set of variables, it includes the share of income taxes in total tax revenue and private debt. In order to assess the relative impact magnitude of the main set of drivers, Figure 2 plots the effects of within-standard-deviation changes in each explanatory variable in conjunction with the corresponding 95% confidence interval

[21] In the following we use the terms "inequality" and "(dis)equalizing" interchangeable to refer to (changes in) the multi-source Gini, if not otherwise stated.

[22] In a specification that includes ICT together with total capital, we find this relation to be driven by a negative impact of the latter.

for high-income and developing economies.

Figure 2 here.

The multi-source Gini increased by 0.13 points each year within the sample period in high-income OECD economies. Accumulated over the average deviation from the mean time observation (6.5 years), this accounts for the largest impact of 50% of the Gini's within standard deviation (1.7, see Table 3). TFP and imports from high-income countries equally add 16% to the time variation of the income Gini. Considering its declining trend, the labor income share significantly contributed to rising income inequality over the sample period. We also find a positive impact (11%) of increasing public spending on education. The largest equalizing effects in high-income countries stem from increasing exports (14%), imports from low-income countries (10%) and income taxes (10%), while the impact of FDI inflows (4%) is relatively small.

Even if neither the time trend nor increasing TFP contributes to increasing income inequality, the declining share of labor income (21%) as well as imports from high-income countries (17%) and public spending on education equally (21%) exert significant disequalizing effects on the income distribution in developing economies. Beyond these factors, the increasing share of private debt has a large positive impact on income inequality in these economies, as it accounts for 17% of the average time variation in the multi-source Gini. In contrast, the opposing effects of FDI in- and outflows are relatively small. On the equalizing side, reducing the degree of inequality in the education distribution (33%) and extending the markets for trade in goods and services to low-income countries (29%) are the most important variables in developing economies. Moreover, even if public social protection transfers exert a regressive effect on the income distribution (7%), a higher share of income taxes in total revenue (17%) and spending on health (10%) are significant factors to achieve a more equal distribution of disposable incomes.

5.2 Discussion: Theory & Empirical Evidence

Our results generally confirm the disequalizing influence of technological change, to the extent that TFP and ICT capital adequately measure the intended mechanisms, and with the caveat that each has a different impact in different world regions. Moreover, at this level of analysis it is not possible to discriminate between the two relevant mechanisms, i.e. the skill- and task-biasedness of technological change vs. the increasing concentration and bargaining power of capital.

The evidence concerning trade integration suggests that factors not captured in the theoretical framework of the Heckscher-Ohlin model affect the relation between trade and income inequality. Besides finding trade between similar economies to affect income inequality, we observe inequality increasing (reducing) impacts of imports from high-income (low-income) countries in developing and (high-income OECD) economies respectively. While the former is not captured by the comparative advantage framework, the latter results are counter to its predictions. As discussed in the literature overview, alternative theories account for additional factors that make these results plausible. For example, competition with high-skilled imports can provide incentives for innovation activities and increase the skill premium in high-income countries. Technology embedded in imports from high-income countries, on the other hand, is able to explain increasing inequality in developing economies. Regarding exports, the significantly negative impact in high-income OECD countries can indicate that, after controlling for the adverse distributional consequences of skill-intensive imports, the equalizing effects of wage and employment growth dominate the emergence of skill premiums in exporting sectors. Furthermore, the negative effect of imports from low-income countries in industrialized economies can be due to labor incomes benefiting from lower costs of intermediate imports. OECD (2011) obtain a similar result and show that imports from low-income countries reduce the wage dispersion in countries with stronger employment protection legislation but to widen it in countries with a weaker regulatory framework.

The negative impact of FDI flows to developing countries counters existing findings. However, separating the effects of lower-income and Latin American countries reveals the presumed positive impact of FDI inflows in these subgroups (see Section 5.4). The small negative effect thus seems to be driven by the few higher-income countries in the developing cluster. We do not find evidence that FDI outflows capture the disequalizing effects of outsourcing in high-income countries. The positive effect of FDI outflows in developing economies can, on the other hand, be due to the adverse effects of capital flight.

The relevance of market capitalization in high-income economies is in line with the literature that by now predominantly focuses on the inequality effects of financial-sector-aligned corporate behavior in the industrialized group of countries.[23] Even if theory predicts the equalizing effects of growth-enhancing financial deepening to result from more access to private credit, borrowing constraints of companies can be relaxed by a higher value of their publicly traded shares. However, the positive impact of private debt indicates the simultaneous relevance of disequalizing mechanisms related to higher risk, economic instability and the quality of institutions.

A robust driver across different sample compositions and specifications turns out to be the labor income share. In accordance with the findings of Checchi & Penalosa (2010), the gap between capital and non-capital owners thus seem to dominate inequality within the group of wage earners. An explanation is provided by Milanovic (2015) who identifies the high relevance of capital incomes for total income, high savings out of capital and relatively high inequality in the distribution of capital incomes as conditions to generate a relation between the functional and the personal distribution of income.

5.3 Education & Income Inequality

We present our analysis of the distributional dimension of education using four specifications. Besides the overall education Gini coefficient for the total population aged 15 and over, we estimate specifications that include mean years of schooling in order to compare our results against existing literature, the decomposition into the share of unschooled people and the Gini coefficient of the educated population or the population shares for each education level separately. The results are presented in Tables 7 and 8. For each world region, Figure 3 plots the estimated change in the multi-source Gini that is due to a one within standard deviation change in the concerning education variable in conjunction with the corresponding 95% confidence interval.

[23]Private debt is only relevant in the reduced sample of 9 countries in Column 6 of Table 5. An interesting aspect to note is this group predominantly consists of liberal welfare states (US, Canada, UK, Ireland, Australia, New Zealand, Japan, Chile) where private debt substantially increased in the years before the financial crises.

Figure 3 here.

The benefit of accounting for heterogeneity in the education-inequality relation is revealed by the different results we obtain for high-income OECD and developing economies. Education is almost perfectly equally distributed in high-income countries since a large share of the population attains at least secondary education and tertiary attainment is increasing (Cuaresma *et al.*, 2013). At this stage, further reduction in education inequality can imply that tertiary education does not expand further, what turns out to have adverse effects on income inequality in the high-income sample. The two education Gini coefficients are insignificant but mean years of schooling as well as each education attainment population share - primary, secondary and tertiary - significantly contributes to reduce the income Gini coefficient. The largest impact stems from higher population shares with tertiary education. The simultaneous relevance of tertiary education expansion and TFP in high-income OECD economies suggests the dominance of the wage effect, i.e. declining returns to education as the supply of high-skilled workers rises.

In developing economies, mean years of schooling is the only education variable for which results are consistent with those of high-income OECD members. Both variants of the education Gini coefficient are significantly negative, implying that a more equal distribution of education reduces income inequality. The equalizing impact increasing population shares with secondary attainment on the education as well as the income distribution seems to drive the negative effects of aggregate measures. However, higher population shares with both, primary and tertiary education, increase income inequality. Rising primary education attainment increases the supply of low-skilled workers, thereby reducing their relative wages. The relatively large inequality increasing effect of tertiary education attainment can be explained by the composition effect, i.e. an increase in educational inequality due to increasing higher education levels, excess demand or by increasing segmentation between mass and elite universities, with corresponding divergence in related wages (Carnoy, 2011).

In both world regions we find evidence that public education spending significantly contributes to increasing income inequality. Public education spending would be expected to increase the average level of education if it enables more people to study. But the overall effect on the income distribution also depends on the education level to which spending is targeted, and on the quality of educational institutions. If public means are allocated unequally among institutions, they can intensify quality differentials even within primary, secondary or tertiary education levels, and affect the distribution of returns to education.

Moreover, our findings reveal an interaction between public education and TFP. In Column 6 of Table 7 we find the inequality increasing effect of TFP to be significantly reduced as a larger share of public means is spent on education. This interaction is, however, not relevant for the overall income distribution (see Column 5), but for the the income share of the 9th relative to that of the bottom decile. As opposed to high-income countries, the interaction between public education spending and TFP is an explanatory factor for the overall income distribution, but not for the extremes in developing economies (see Column 5 of Table 8). The estimated impact of TFP becomes significantly positive and declining in education spending as the interaction effect is controlled for. Conversely, the disequalizing effect of public education spending is reduced as TFP rises.

Assuming that the TFP is a reliable measure of technlogical change, an explanation for its interaction with education policy can be found in the literature on the relation between inequality, social mobility and income growth (e.g. Galor & Tsiddon, 1997). Accordingly, technological change increases social mobility and reduces inequality as it provides incentives for people to become educated. More students necessarily increase public means spent for education. The overall effect on income inequality depends on in how far education policies also secure equal access to high-quality schooling and enlarge the pool of talented and thigh-skilled people. On the other hand, following Hall & Jones (1999) in interpreting TFP as a measure of institutional quality, the interaction effect implies the institutional setting to be relevant for equality promoting education policy.

Tables 7 and 8 here.

5.4 Regional Heterogeneity

The subsample of developing economies is a heterogeneous group. It consists e.g. of countries the World Bank classifies as high-income but which are no OECD members[24], middle-income countries of Latin America which experienced declining income inequality as well as Sub-saharan low-income countries. In order to reveal whether our estimation results are driven by particular groups of countries, we interact each explanatory variable with dummy variables indicating different subgroups of the developing economies sample.

The first column of Table 9 reestimates the main model for the global sample. But instead of splitting it, the explanatory factors are interacted with a dummy variable that identifies developing economies. Doing so reveals the previously obtained results that TFP and exports are not relevant but private debt is a significant disequalizing factor in this group of countries. Columns 2 and 3 separate the effects of the low- and lower-middle (LLM) income cluster and Latin America respectively. In both subsamples, inward FDI flows exerts the expected positive impact on income inequality, which is consistent with theories that highlight the interaction of international capital flows, technology and skill bias. The impact of a higher export share in GDP turns positive for the remaining group of developing countries if deviations of LLM countries are controlled for. This result supports findings of Meschi & Vivarelli (2009), who show exports from high-income countries to increase income inequality in middle-income countries.

Latin American countries turn out to drive the positive relation between public education spending and income inequality. At the same time, the negative impact of a more equal distribution of education is significantly larger than in other developing countries. Moreover, TFP is significantly negatively related to income inequality in the Latin American subgroup of middle-income countries. Thus, as discussed in Section 5.3, technological change might either accelerate social mobility via increasing educational attainment, acts as a measure of institutional quality as a basis for equality in the income distribution in developing countries. The large disequalizing impact of public education spending reveals the regressive nature of education policy that e.g. Carnoy (2011) argues to prevail in Latin American countries. For LLM economies, our findings also indicate that welfare state redistribution is less effective since besides social protection transfers, also public spending

[24] Croatia, Cyprus, Latvia, Lithuania, Russia and Venezuela

on health and income taxation show regressive effects.

A different splitting is obtained by separating the effects of countries for which we only observe inequality based on consumption expenditure.[25] For our purpose, the question arises as to whether Ginis from consumption-based and income-based measures can be combined in an estimation sample. Generally, income inequality is higher than inequality in consumption expenditure in absolute terms (Lahoti *et al.*, 2016). Differences in levels are controlled for by the inclusion of country fixed effects. Relevant is, however, if there are systematic differences between income inequality trends that are due to their different conceptual basis. The generally unchanged estimates in Column 4 of Table 9 indicate that our main results are consistent with and driven by countries with income-based. The negative constant term indicates signficant differences in inequality levels. Some variables affect income- and consumption-based Gini coefficients differently. As opposed to other developing economies, income inequality is significantly increasing over time and exports and FDI outflows are additional equalizing factors. The negative effects of public spending on health is significantly larger while spending on social protection is significantly more regressive. Yet, it is not possible to infer the extent to which these effects differ due to their relation to consumption inequality or due to the different sample composition.

5.5 Robustness: Dependent Variable

In order to test if the extremes of the income distribution are affected differently than the overall income distribution, we have estimated the variations of Equation 4 using the decile ratio (see Section 3.1) as dependent variable in Column 1 of Table 10. The drivers of both inequality measures are largely consistent. But the decile ratio being more persistent over time (see Figure 1 and 2), can cause the majority of variables to be not relevant for explaining movements in the extremes. An exception is the TFP-education-spending interaction in high-income countries discussed in Section 5.3.

Movements at the top of the income distribution are not captured in a decile ratio based on survey data but have been shown to be a major contributing factor to increasing income inequality. We analyze to which extent our model is able to explain trends in top incomes by using the top 1% income share from the WID as dependent variable. Their measure is based on fiscal data and thus better able to capture the top, but sample size is substantially reduced. Of our explanatory factors, we find TFP and exports to significantly contribute to increasing top income shares, while FDI inflows and equality in the education distribution are countervailing. The significantly increasing time trend suggests that our model omits variables that are relevant for the explanation of top income shares.

Our more restrictive income Gini series (*single-source Gini*) uses one single source for each country over time. As shown in Column 3 of Table 10, we find our main results to be robust to using this measure as dependent variable. In contrast using the income Gini coefficient from the global EHII dataset does not conform with our findings as several explanatory factors, e.g. imports from low- and high-income countries, are not relevant for their gross-income-based Gini, while TFP significantly reduces income inequality. By securing that both results are based on the same sample, Column 4 shows that discrepancies between estimation results are not due to

[25] In total we observe consumption-based Gini coefficients for 14 countries from Asia (Kazakhstan, Indonesia, Mongolia, Philippines, Thailand, India and Sri Lanka), Middle East and North Africa (Egypt, Iran, Jordan, Morocco and Tunisia), Sub-Saharan Africa (Namibia, Nigeria, South Africa and Swaziland) and Europe (Ukraine).

composition differences across time or space.

5.6 Robustness: Method and Functional Form

Columns 1 and 2 of Table 11 show the results for two- and five-year lags to address further concerns of endogeneity. Reverse causation can apply to trade and private debt being affected by the existing degree of inequality, as well as to redistributive policies and the education distribution. We therefore increase the lag length to two and five years for the concerning variables respectively. Our main results regarding imports, exports and the education Gini coefficient are not affected. But higher private debt and public education spending does not affect overall income inequality five years later.

Including a time trend to the regression equation might not appropriately account for spurious regression and global macroeconomic factors. The more widely used and often considered to be the more suitable approach is to include dummy variable for each year. Column 3 of Table11 shows that our main results are not biased by omitted global dynamics or driven by random simultaneous movement of variables as they remain unchanged regarding the direction and the magnitude of effects. Finally, Column 4 shows the results for FE estimation with robust standard errors. All results except those for trade are consistent with our main evidence. We infer therefrom that the increased efficiency which is gained by applying FGLS contributes to obtain more accurate estimates.

6 Conclusions

The aim of our empirical analysis has been to provide a comprehensive picture of how drivers at the global and regional level interact to influence within-country income inequality. In answer to the research question, our findings provide indication that national income inequality trends can to some degree be explained by similar underlying mechanisms but are to a large extent region specific.

Results based on the global sample capture the average effects across countries. They are thus able to mask regional heterogeneity which, however, provides insights to the causes of income inequality trends. The most robust variables that contribute to rising income inequality across world regions are declining labor income shares and increasing imports from high-income countries. Imports from low-income countries and income taxation are significant factors on the equalizing side. The evidence concerning trade integration suggests the relevance of factors not captured by the comparative advantage framework but by more recent theories which focus on the interaction between technology and trade or the increasing bargaining power and concentration of capital. By splitting the sample into high-income OECD and developing economies, as well as into subsamples of the latter, we find TFP and exports to be robust determinants of income inequality only in high-income countries. In contrast, increasing private debt rises income inequality in middle-income countries but adds to reduce it in low-income countries. Also the theoretically predicted disequalizing impact of FDI inflows is only revealed if we separate the effects of low- and middle-income countries or Latin America. Government redistribution via public health spending is significantly less effective in high-income than in developing economies. However, social protection spending is slightly regressive in the latter group of countries.

Within the broad set of determinants, we have been particularly interested in the relation between education and inequality. We have thus examined the distributional dimension of education by using two variants of education Gini coefficients, allowed for the effects of separate education levels and included a measure of public education spending. We find a large contribution of higher education levels to reduce income inequality in high-income countries. Our results can indicate that particularly increasing tertiary attainment is able to countervail the adverse distributional consequences of technological change and globalization. The relevant factor in developing economies is equality in the education distribution, while increasing attainment at the primary as well as the tertiary level increases income inequality. Beyond that, the finding that public education spending is significantly regressive in both world regions suggests that education inequalities, e.g. regarding quality differentials between education institutions, affect the distribution of returns to education and income inequality. The interaction between education policy with the distribution of the quantity and quality of education and income inequality merits further more detailed research.

We have accounted for endogeneity by including explanatory variables lagged one, two or five time periods. Our main results have also been robust to using different measures of income inequality as dependent variable and various sets of determinants as independent variables. However, some measures might not capture the intended mechanisms adequately, e.g. TFP, or might have been omitted entirely, e.g migration flows, labor market institutions and informal markets in developing economies. Moreover, a caveat of an empirical investigation at the aggregate level is that it is descriptive in nature so that it is not possible to infer causal effects. Nevertheless, our results show correlations that reveal new insights which should feed back to further investigation at the theoretical and micro-econometric level.

Acknowledgment: This research was made possible by support from the IIASA Project SCHEMA, Socio-economic heterogeneity for model applications. The authors thank Jesús Crespo Cuaresma, Stefan Humer, the participants of the BeNA seminar for labor market research (January 2016) as well as this journal's editor and referees for very helpful comments and discussions.

References

Acemoglu, Daron. 2002. Technical Change, Inequality, and the Labor Market. *Journal of Economic Literature*, **40(1)**, 7–72.

Acemoglu, Daron. 2003. Patterns of Skill Premia. *Review of Economic Studies*, **70**, 199–230.

Altzinger, Wilfried, Cuaresma, Jesús Crespo, Rumplmaier, Bernhard, Sauer, Petra, & Schneebaum, Alyssa. 2015. *Education and Social Mobility in Europe: Leveling the Playing Field for Europe's Children and Fuelling its Economy.* WWWforEurope Working Paper no 80.

Alvaredo, Facundo, & Gasparini, Leonardo. 2015. Recent Trends in Inequality and Poverty in Developing Countries. *Pages 697–805 of:* Atkinson, Anthony, & Bourguignon, Francois (eds), *Handbook of Income Distribution*, vol. 2A. Elesvier.

Alvaredo, Facundo, Atkinson, Anthony B., Piketty, Thomas, Saez, Emmanuel, & Zucman, Gabriel. 2016. *The World Wealth and Income Database.* http://www.wid.world, 13/05/2016.

Amable, Bruno, Ernst, Ekkehard, & Palombarini, Stefano. 2005. How Do Financial Markets Affect Industrial Relations: An Institutional Complementarity Approach. *Socio-Economic Review*, **2005**, 311–330.

Angeles, Luis. 2007. Income Inequality and Colonialism. *European Economic Review*, **51(5)**, 1155–1176.

Atkinson, Anthony B. 2015. *Inequality. What Can Be Done.* Cambridge, Massachusetts; London, England: Harvard University Press.

Atkinson, Anthony B., & Brandolini, Andrea. 2001. Promise and Pitfalls in the Use of "Secondary" Data-Sets: Income Inequality in OECD Countries as a Case Study. *Journal of Economic Literature*, **39(3)**, 771–799.

Autor, David H. 2013. The "Task Approach" To Labor Markets: An Overview. *Journal for Labour Market Research*, **46(3)**, 185–99.

Autor, David H. 2015. Why Are There Still So Many Jobs ? The History and Ruture of Workplace Automation. *Journal of Economic Perspectives*, **29(3)**, 3–30.

Autor, David H., Dorn, David, Katz, Lawrence F., Patterson, Christina, & Reenen, John Van. 2017a. *Concentrating on the Fall of the Labor Share.* NBER Working Paper No. 23108.

Autor, David H., Dorn, David, Katz, Lawrence F., Patterson, Christina, & Reenen, John Van. 2017b. *The Fall of the Labor Share and the Rise of Superstar Firms.* https://economics.mit.edu/files/12979.

Becker, Gary S. 1964. *Human Capital: A Theoretical and Empirical Analysis with Special Reference to Education.* Chicago: The University of Chicago Press.

Becker, Gary S., & Chiswick, Barry R. 1966. Education and the Distribution of Earnings. *The American Economic Review*, **56(1/2)**, 358–369.

Bengtsson, Erik, & Waldenstroem, Daniel. 2017. *Captial Shares and Income Inequality: Evidence from the Long Run.* $http://www.uueconomics.se/danielw/Research_{f}iles/BengtssonWaldenstrom_{C}apitalshares_{l}ong.pdf$.

Bertola, Giuseppe. 2008. *Inequality, Globalization, and Financial Development.* EUI Max Weber Programme conference on Globalization and Inequality.

Bruno, Giovanni S.F. 2005. Approximating the Bias of the LSDV Estimator for Dynamic Unbalanced Panel Data Models. *Economics Letters*, **87**, 361–366.

Calderón, César, Chong, Alberto, & Valdés, Rodrigo. 2005. Labor Market Regulations and Income Inequality: Evidence for a Panel of Countries. *Labor Markets and Institutions (Central Bank of Chile)*, **4**, 221–279.

Carnoy, Martin. 2011. As Higher Education Expands, is it Contributing to Greater Inequality? *National Institute Economic Review*, **No. 215**.

Castelló-Climent, Amparo, & Doménech, Rafael. 2014. *Human Capital and Income Inequality: Some Facts and Some Puzzles.* BBVA Research Working Papers No. 12/28.

Chakravorty, Sanjoy. 2006. *Fragments of Inequality: Social, Spatial, and Evolutionary Analyses of Income Distribution.* New York London: Routlege Taylor & Francis Group.

Checchi, Daniele, & Penalosa, Cecilia Garcia. 2010. Labour Market Institutions and the Personal Distribution of Income in the OECD. *Economica*, **77**, 413–450.

Chen, Shaohua, & Ravallion, Martin. 2004. How Have the World's Poorest Fared since the Early 1980s? *World Bank Research Observer*, **19(2)**, 141–169.

Claessens, Stijn, & Perotti, Enrico. 2007. Finance and Inequality: Channels and Evidence. *Journal of Comparative Economics*, **35**, 748–773.

Cuaresma, Jesús Crespo, KC, Samir, & Sauer, Petra. 2013. *Age-Specific Education Inequality, Education Mobility and Income Growth.* WWWforEurope Working Paper no 6.

Daudey, Emilie, & García-Penalosa, Cecilia. 2007. The Personal and the factor Distributions of Income in a Cross-section of Countries. *The Journal of Development Studies*, **43(5)**, 812–829.

Deininger, Klaus, & Squire, Lyn. 1996. A new dataset measuring income inequality. *World Bank Economic Review*, **10(3)**, 565–591.

Drukker, David M. 2003. Testing for Serial Correlation in Linear Panel-data Models. *Stata Journal*, **3(2)**, 168–177.

Evans, Trevor. 2016. The Impact of The Financial Sector On Inequality. A Comparison of the USA, Brazil, Germany and India. *In:* Gallas, Alexander, Herr, Hansjoerg, Hoffer, Frank, & Scherrer, Christoph (eds), *Combating Inequality. The Global North and South.* London, New York: Routledge.

Foerster, Michael F., & Tóth, István Gyoergy. 2015. Cross-Country Evidence of the Multiple Causes of Inequality Changes in the OECD Area. *Pages 1729–1843 of:* Atkinson, Anthony, & Bourguignon, Francois (eds), *Handbook of Income Distribution*, vol. 2B. Elesvier.

Francese, Maura, & Mulas-Granados, Carlos. 2015. *Functional Income Distribution and its Role in Explaining Inequality*. IMF Working Paper 15/244.

Galbraith, James K. 2012. *Inequality and Instability: A Study of the World Economy Just Before the Great Crisis*. Oxford: Oxford University Press.

Galbraith, James K., & Kum, Hyunsub. 2005. Estimating the Inequality of Household Incomes: A Statistical Approach to the Creation of a Dense and Consistent Global Dataset. *Review of Income and Wealth*, **51(1)**.

Galbraith, James K., Halbach, Béatrice, Malinowska, Aleksandra, Shams, Amin, & Zhang, Wenjie. 2014. *The UTIP Global Inequality Data Sets 1963-2008*. UTIP Working Paper 68.

Galor, Oded, & Tsiddon, Daniel. 1997. The Distribution of Human Capital and Economic Growth. *Journal of Economic Growth*, **2**, 93–124.

Goldberg, Pinelopi K., & Pavcnik, Nina. 2007. *Distributional Effects of Globalization in Developing Countries*. NBER Working Paper No. 12885.

Goldin, Claudia, & Katz, Lawrence F. 2010. *The Race bewteen Education and Technology*. Belknap Press.

Gregorio, José De, & Lee, Jong-Wha. 2002. Education and Income Inequality: New Evidence from Cross-country Data. *Review of Income and Wealth*, **48(3)**, 395–416.

Gross, Tandiwe, Hoffer, Frank, & Laliberté, Pierre. 2016. The Rise of Inequality Across the Globe: Drivers, Impacts and Policies for Change. *In:* Gallas, Alexander, Herr, Hansjoerg, Hoffer, Frank, & Scherrer, Christoph (eds), *Combating Inequality. The Global North and South*. London, New York: Routledge.

Hall, Robert E., & Jones, Charles I. 1999. Why Do Some Countries Produce So Much More Output Per Worker Than Others? *The Quarterly Journal of Economics*, **114**(1), 83–116.

Huber, Evelyne, Nielsen, Francois, Pribble, Jenny, & Stephens, John D. 2006. Politics and Inequality in Latin America and the Caribbean. *American Sociological Review*, **71**, 943–963.

ILO. 2008. *World of Work Report 2008: Income Inequalities in the Age of Financial Globalization*.

Inklaar, Robert, & Timmer, Marcel P. 2013. *Capital, labor and TFP in PWT 8.0*. PWT8.0 Documentation http://www.rug.nl/research/ggdc/data/penn-world-table.

Isham, Jonathan, Woolcock, Michael, Pritchett, Lant, & Busby, Gwen. 2005. The Varieties of Resource Experience: Natural Resource Export Structures and the Political Economy of Economic Growth. *The World Bank Economic Review*, **19(2)**, 141–174.

Jaumotte, Florence, Lall, Subir, & Papageorgiou, Chris. 2013. Rising Income Inequality: Technology, or Trade and Financial Globalization? *IMF Economic Review*, **61**, 271–309.

Jenkins, Stephen P. 2015. World income inequality databases: an assessment of WIID and SWIID. *Journal of Economic Inequality*, **13**, 629–671.

Kanbur, Ravi. 2015. Globalization and Inequality. *Pages 1845–1881 of:* Atkinson, Anthony, & Bourguignon, Francois (eds), *Handbook of Income Distribution*, vol. 2B. Elesvier.

Karabarbounis, Loukas, & Neiman, Brent. 2014. The Global Decline of the Labor Share. *The Quaterly Journal of Economics*, 61–103.

KC, Samir, Barakat, Bilal, Goujon, Anne, Skirbekk, Vegard, Sanderson, Warren, & Lutz, Wolfgang. 2010. Projection of populations by level of educational attainment, age, and sex for 120 countries for 2005-2050. *Demographic Research*, **22**, 383–472.

Kézdi, Gábor. 2004. Robust Standard Error Estimation in Fixed-effects Panel Models. *Hungarian Statistical Review*, **9**, 95–116.

Kim, Heekyung H., & Brynjolfsson, Erik. 2009. *CEO Compensation and Information Technology.* ICIS 2009 Proceedings. Paper 38. http://aisel.aisnet.org/icis2009/38.

Koeninger, Winfried, Leonardi, Marco, & Nunziata, Luca. 2007. Labor Market Institutions and Wage Inequality. *Industrial and Labor Relations Review*, **60(3)**.

Kumhof, Michael, & Ranciére, Romain. 2010. *Inequality, Leverage and Crises.*

Lahoti, Rahul, Jayadev, Arjun, & Reddy, Sanjay G. 2016. *The Global Consumption and Income Project (GCIP: An Overview*. Available at www.gcip.info.

Lustig, Nora, Lopez-Calva, Luis F., & Ortiz-Juarez, Eduardo. 2013. Declining Inequality in Latin America in the 2000s: The Cases of Argentina, Brazil, and Mexico. *World Development*, **44**, 129–141.

Lutz, Wolfang, & KC, Samir. 2011. Global Human Capital: Integrating Education and Population. *Science*, **333**, 587–592.

Melitz, Mark J. 2003. The Impact of Trade on Intra-industry Reallocations and Aggregate Industry Productivity. *Econometrica*, **71(5)**, 1695–1725.

Meschi, Elena, & Vivarelli, Marco. 2009. Trade and Income Inequality in Developing Countries. *World Development*, **37**, 287–302.

Milanovic, Branko. 2014. *Description of* All the Ginis *Dataset.* $http://www.worldbank.org/en/research/brief/all-the-ginis$.

Milanovic, Branko. 2015. *Increasing Capital Income Share and its Effect on Personal Income Inequality.* MPRA Paper No. 67661.

Morelli, Salvatore, Smeeding, Timothy, & Thompson, Jeffrey. 2015. Post-1970 Trends in Within-Country Inequality and Poverty: Rich and Middle-Income Countries. *Pages 593–696 of:* Atkinson, Anthony, & Bourguignon, Francois (eds), *Handbook of Income Distribution*, vol. 2A. Elesvier.

Morrisson, Christian, & Murtin, Fabrice. 2013. The Kuznets Curve of Human Capital Inequality: 1870-2010. *Journal of Economic Inequality*, **11**(3), 238–301.

OECD. 2011. *Divided We Stand: Why Inequality Keeps Rising.*

Palley, Thomas I. 2007. *Financialization: What It Is and Why It Matters.*

Peracchi, Franco. 2006. Educational Wage Premia and the Distribution of Earnings: An International Perspective. *In:* Hanushek, Eric A., & Welch, Finis (eds), *Handbook of the Economics of Education, Volume 1.* Elesvier B.V.

Piketty, Thomas, & Saez, Emmanuel. 2013. Top Incomes and the Great Recession: Recent Evolutions and Policy Implications. *IMF Economic Review*, **61(3)**.

Psacharopoulos, George. 1994. Returns to Investment in Education: A Global Update. *World Development*, **22**(9), 1325–1343.

Rajan, Raghuram G. 2010. *Fault Lines: How Hidden Fractures Still Threaten the World Economy.* Princeton University Press.

Reed, Robert W., & Ye, Haichun. 2011. Which Panel Data Estimator Should I Use? *Applied Economics*, **43**, 985–1000.

Rodrik, Dani. 1997. *Has Globalization Gone Too Far?* Washington: Institute of International Economics.

Roser, Max, & Cuaresma, Jesus Crespo. 2016. Why is Income Inequality Increasing in the Developed World? *Review of Income and Wealth*, **62(1)**, 1–27.

Sauer, Petra. 2016. *The Role of Age and Gender in Education Expansion: Within- and Between-group Specific Trends in Education (In)equality.* INEQ Working Paper Series #4.

Schindler, Mariya Aleksynskaand Martin. 2011. *Labor Market Regulations in Low-, Middle- and High-income Countries: A New Panel Database.* IMF Working Paper 11/154.

Stolper, Wolfgang F., & Samuelson, Paul A. 1941. Protection and Real Wages. *The Review of Economic Studies*, **9(1)**, 58–73.

Tinbergen, Jan. 1974. Substitution of Graduate by Other Labour. *Kyklos*, **27 (2)**, 217–26.

Tyson, Laura, & Spence, Michael. 2017. Exploring the Effects of Technology on Income and Wealth Inequality. *In:* Boushey, Heather, DeLong, J. Bradford, & Steinbaum, Marshall (eds), *After Piketty. The Agenda for Economics and Inequality.* Cambridge, Massachusetts; London, England: Harvard University Press.

vanTreeck, Till, & Sturn, Simon. 2012. *Income Inequality as a Cause of the Great Recession? A Survey of Current Debates.* ILO Conditions of Work and Employment Series No. 39.

Verhoogen, Eric A. 2008. Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector. *Quaterly Journal of Economics*, **123(2)**, 489–530.

Zilian, Stella, und Timon Scheuer, Maximilian Unger, Polt, Wolfang, & Altzinger, Wilfried. 2016. Technologischer Wandel und Ungleichheit. Zum Stand der empirischen Forschung. *Wirtschaft und Gesellschaft*, **42(4)**.

A WIID3.4 - Data Processing

- We require full area and population coverage and eliminate all observations tagged with the lowest quality rating according to WIID3.4.
- Our preferred income concept is disposable (monetary) income[26] but we use consumption measures if this is the only available concept (see Section 3.1). At this stage we only use income concepts which cover a time span of at least 10 years with a minimum of 3 observations.
- Income-sharing unit is the household but unit of analysis is the individual person. So we either have household-per-capita observations or ones which apply equivalence scales. But we only allow concepts to vary across countries, not over time.
- We select between remaining multiple-time observations by applying a rule to choose between equivalence scales and different sources.
  - For each country, we choose the concept (per capita or different equivalence scales) that appears more often for single-year observations between 1980 and 2010 (as this is the main time span of our analysis) when we have to discriminate between multiple measures per year.
  - For each country we also test not only which source of the inequality measure appears more often in the concerning time frame, but also which source covers the longest time span.
  - We always use this - high frequency/long time span - as the prime criterion to select one single source by country and construct the *single-source-Gini* series. For countries, for which this selection rule does not reveal a single preferred source, we have to discriminate between frequency and time coverage and select sources individually.
  - The selection procedure for the *multi-source-Gini* series follows a similar procedure. First, we choose observations of sources which appear most frequently *and* cover the longest time span if multiple sources per year are available. The remaining observations are again chosen individually, also referring to the graphs of the different gini series in order to detect large differences between Gini series which would result in unreasonable high jumps. We also eliminate all observations of sources which appear only once by country.

B Estimation Sample

[26] Disposable monetary income does not account for imputed rents and home production.

High-income OECD	Australia, Austria, Belgium, Canada, Chile, Czech Republic, Denmark, Estonia, Finland, Germany, Greece, Hungary, Iceland, Ireland, Israel, Italy, Japan, Luxembourg, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, United Kingdom, United States
East Asia & Pacific	China, Indonesia, Mongolia, Philippines, Thailand
Europe & Central Asia	Belarus, Bulgaria, Croatia, Cyprus, Georgia, Kazakhstan, Kyrgyz Republic, Latvia, Lithuania, Moldova, Russia, Turkey, Ukraine
Latin America & Caribbean	Bolivia, Brazil, Colombia, Costa Rica, Dominican Republic, Ecuador, Guatemala, Jamaica, Ecuador, Guatemala, Jamaica, Mexico, Panama, Peru, Uruguay, Venezuela,
Middle East & North Africa	Egypt, Iran, Jordan, Malta, Morocco, Tunisia
South Asia	India, Sri Lanka
Sub-Saharan Africa	Namibia, Nigeria, South Africa Swaziland

Table 1: Summary Statistics of Income Inequality Series

MSGini	Mean	35.24	Overall sd	10.19	Obs	771
	Min	19.70	Between sd	10.73	N	73
	Max	67.60	Within sd	2.04	1981-2010	
SSGini	Mean	35.82	Overall sd	10.50	Obs	630
	Min	19.70	Between sd	10.88	N	70
	Max	67.60	Within sd	1.97	1981-2010	
DecRatio	Mean	8.44	Overall sd	8.98	Obs	532
	Min	2.71	Between sd	10.35	N	59
	Max	85.50	Within sd	3.32	1981-2010	

Table 2: Income Inequality Trends within Countries by Region

	Obs		Mean		Trend[a]	
Region[b]	MS Gini	DecRatio	MS Gini	DecRatio	MS Gini	DecRatio
HI OECD	444	248	29.88	4.83	$\Uparrow$	None
ECA	109	88	33.28	5.73	None	None
LAC	130	130	52.22	17.88	$\Downarrow$	$\Downarrow$
EAP	36	28	40.36	6.65	$\Uparrow$	$\Downarrow$
SA	17	8	33.54	4.51	$\Uparrow$	None
MENA	25	20	36.26	5.73	$\Downarrow$	None
SSA	10	10	55.79	12.41	None	None

[a]Statistically significant time trend from a fixed effects regression of inequality against time.

[b]HI OECD (high-income OECD members), ECA (Europe & Central Asia), LAC (Latin America & Carribean), EAP (Eastern Asia & the Pacific), SA (South Asia), MENA (Middle East & North Africa, SSA (Sub Saharan Africa).

Table 3: Summary Statistics and Trends by Region

	High-income OECD			Developing Economies		
Variable[a]	Mean	Within sd	Trend[b]	Mean	Within sd	Trend
$MSGini$	29.87	1.70	$\Uparrow$	42.52	2.43	None
$DecRatio$	4.82	0.66	None	11.57	4.50	$\Downarrow$
L	60.68	2.64	$\Downarrow$	49.73	2.72	$\Downarrow$
TFP	0.95	0.06	$\Uparrow$	0.97	0.08	$\Uparrow$
ICT	0.98	0.03	$\Uparrow$	0.99	0.03	$\Uparrow$
Imp^{high}	23.76	4.37	$\Uparrow$	23.06	8.63	$\Uparrow$
Imp^{low}	3.91	1.81	$\Uparrow$	6.53	3.89	$\Uparrow$
Exp	28.60	5.01	$\Uparrow$	29.32	7.92	$\Uparrow$
$FDIin$	4.41	7.80	$\Uparrow$	8.17	23.91	None
$FDIout$	4.66	8.87	$\Uparrow$	2.91	15.05	None
PS^{Educ}	10.22	2.42	$\Uparrow$	13.59	3.03	$\Uparrow$
PS^{Health}	11.58	2.52	$\Uparrow$	6.65	3.41	None
PS^{SP}	34.41	3.96	$\Uparrow$	12.10	4.17	$\Uparrow$
$TaxesREV$	31.36	3.35	None	20.40	4.22	$\Uparrow$
$MinWage$	43.68	22.11	None	25.63	5.51	$\Downarrow$[c]
$Unemp$	54.97	12.32	$\Uparrow$	15.51	6.00	$\Downarrow$
$UDensity$	41.47	5.09	$\Downarrow$	48.44	32.49	$\Downarrow$
$MCapit$	69.85	34.69	$\Uparrow$	31.12	13.96	$\Uparrow$
$Pdebt$	89.59	28.73	$\Uparrow$	44.39	16.39	$\Uparrow$
MYS_{15+}	12.66	0.40	$\Uparrow$	9.17	0.53	$\Uparrow$
$EducGini_{15+}$	11.27	1.27	$\Downarrow$	23.85	2.37	$\Downarrow$
$EducGini^{E}_{15+}$	9.63	0.80	$\Downarrow$	16.81	0.97	$\Downarrow$
p^{1}_{15+}	1.87	0.75	$\Downarrow$	9.23	2.28	$\Downarrow$
p^{2}_{15+}	15.97	2.89	$\Downarrow$	33.08	2.68	$\Downarrow$
p^{3}_{15+}	60.95	2.20	$\Uparrow$	44.34	2.75	$\Uparrow$
p^{4}_{15+}	21.20	2.70	$\Uparrow$	13.36	1.67	$\Uparrow$

[a]For an explanation of variable abbreviations see Section 4.
[b]Statistically significant time trend from a fixed effects regression of variable against time.
[c]This estimate is only based on 13 observations from 2 countries.

Table 4: Global Sample - Stepwise Expansion

	Multi-source Gini					
$Year$	0.153***	0.178***	0.188***	0.143***	0.096**	0.112**
	(0.017)	(0.018)	(0.023)	(0.021)	(0.043)	(0.048)
L/Y	-0.143***	-0.118***	-0.069***	-0.133***	-0.140***	-0.070
	(0.020)	(0.020)	(0.024)	(0.020)	(0.026)	(0.074)
TFP	1.715*	1.941*	3.027***	2.370**		-0.192
	(0.887)	(1.005)	(1.105)	(1.031)		(3.018)
ICT					5.424	
					(5.344)	
Imp^{high}	0.052***	0.037***	0.035**	0.045***	0.057***	0.086
	(0.010)	(0.013)	(0.016)	(0.012)	(0.013)	(0.073)
Imp^{low}	-0.168***	-0.148***	-0.174***	-0.154***	-0.113***	-0.451***
	(0.023)	(0.028)	(0.030)	(0.028)	(0.031)	(0.141)
Exp	-0.017*	-0.018	-0.029**	-0.013	-0.026**	0.005
	(0.010)	(0.011)	(0.014)	(0.012)	(0.012)	(0.056)
$FDIin$	-0.007***	-0.006***	-0.006***	-0.006***	-0.005***	0.015
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.025)
$FDIout$	0.007**	0.007***	0.011***	0.007***	0.010***	-0.041
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.038)
$EducGini1$	0.227***	0.373***	0.407***	0.364***	0.340***	0.069
	(0.049)	(0.056)	(0.095)	(0.056)	(0.075)	(0.193)
PS^{Educ}	0.034*	0.096***	0.098***	0.106***	0.099***	-0.028
	(0.019)	(0.021)	(0.025)	(0.021)	(0.026)	(0.112)
PS^{Health}	-0.058***	-0.032*	-0.029	-0.037**	-0.049**	0.068
	(0.015)	(0.017)	(0.020)	(0.017)	(0.019)	(0.057)
PS^{SP}	0.017**	0.017	0.027**	0.019*	0.023**	0.032
	(0.009)	(0.011)	(0.013)	(0.011)	(0.011)	(0.035)
$IncTaxes$		-0.058***	-0.057***	-0.063***	-0.050***	
		(0.013)	(0.012)	(0.013)	(0.014)	
$MCapit$			0.003*			
			(0.002)			
$Pdebt$				0.008***	0.005*	0.012**
				(0.003)	(0.003)	(0.006)
$MinWage$						-0.006**
						(0.002)
$Unemp$						-0.022
						(0.014)
$UDensity$						-0.043
						(0.039)
Obs	771	667	478	645	534	88
N	73	64	47	64	57	10

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5: High-income OECD - Stepwise Expansion

	Multi-source Gini					
$Year$	0.167***	0.147***	0.133***	0.132***	0.236***	0.103**
	(0.027)	(0.025)	(0.027)	(0.028)	(0.053)	(0.049)
L/Y	-0.075***	-0.087***	-0.050**	-0.093***	-0.104***	-0.087
	(0.025)	(0.024)	(0.024)	(0.026)	(0.033)	(0.075)
TFP	3.452**	4.296***	5.518***	4.732***		-0.458
	(1.515)	(1.522)	(1.648)	(1.552)		(3.060)
ICT					-12.699**	
					(6.429)	
Imp^{high}	0.051***	0.050***	0.020	0.059***	0.059***	0.093
	(0.019)	(0.019)	(0.020)	(0.019)	(0.020)	(0.072)
Imp^{low}	-0.119***	-0.104***	-0.138***	-0.095***	-0.016	-0.463***
	(0.038)	(0.036)	(0.037)	(0.036)	(0.043)	(0.141)
Exp	-0.050**	-0.053***	-0.037*	-0.053***	-0.039*	-0.007
	(0.020)	(0.020)	(0.021)	(0.020)	(0.021)	(0.055)
$FDIin$	-0.007*	-0.007*	-0.016***	-0.008*	-0.009*	0.022
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.024)
$FDIout$	0.007*	0.007*	0.006	0.006	0.003	-0.048
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.038)
$EducGini1$	0.194*	0.164	0.054	0.129	0.220	0.035
	(0.108)	(0.112)	(0.122)	(0.112)	(0.155)	(0.197)
PS^{Educ}	0.061**	0.074**	0.052*	0.082***	0.045	0.128
	(0.027)	(0.029)	(0.029)	(0.030)	(0.033)	(0.158)
PS^{Health}	-0.054***	-0.026	-0.030	-0.024	-0.046*	0.054
	(0.021)	(0.024)	(0.024)	(0.025)	(0.024)	(0.059)
PS^{SP}	0.032**	0.021	0.017	0.020	0.019	0.048
	(0.013)	(0.015)	(0.015)	(0.015)	(0.015)	(0.036)
$IncTaxes$		-0.049***	-0.050***	-0.049***	-0.045***	
		(0.015)	(0.014)	(0.015)	(0.017)	
$MCapit$			0.004**			
			(0.002)			
$Pdebt$				0.001	-0.003	0.012**
				(0.003)	(0.003)	(0.006)
$MinWage$						-0.006***
						(0.002)
$Unemp$						-0.025*
						(0.014)
$UDensity$						-0.068*
						(0.041)
Obs	444	420	362	401	340	85
N	30	30	28	30	29	9

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6: Developing Economies - Stepwise Expansion

	Multi-source Gini				
$Year$	-0.035	0.150***	-0.018	0.042	-0.173**
	(0.047)	(0.048)	(0.089)	(0.050)	(0.079)
L/Y	-0.207***	-0.176***	-0.108	-0.175***	-0.207***
	(0.025)	(0.038)	(0.081)	(0.037)	(0.048)
TFP	3.379***	1.824	-2.789	0.847	
	(0.877)	(1.549)	(3.839)	(1.544)	
ICT					35.920***
					(10.034)
Imp^{high}	0.067***	0.041**	0.014	0.048**	0.075***
	(0.014)	(0.019)	(0.038)	(0.019)	(0.025)
Imp^{low}	-0.188***	-0.231***	-0.055	-0.183***	-0.200***
	(0.034)	(0.052)	(0.085)	(0.052)	(0.057)
Exp	0.018	0.010	0.019	0.023	-0.009
	(0.013)	(0.016)	(0.024)	(0.015)	(0.018)
$FDIin$	-0.009***	-0.007*	-0.007**	-0.007**	-0.007***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
$FDIout$	0.017***	0.010	0.019***	0.011*	0.015***
	(0.005)	(0.008)	(0.007)	(0.007)	(0.004)
$EducGini1$	0.077	0.453***	0.559***	0.338***	0.251***
	(0.081)	(0.073)	(0.186)	(0.073)	(0.090)
PS^{Educ}	0.043	0.146***	0.275***	0.158***	0.153***
	(0.029)	(0.030)	(0.044)	(0.029)	(0.039)
PS^{Health}	-0.113***	-0.061**	-0.074	-0.070***	-0.080***
	(0.026)	(0.024)	(0.045)	(0.023)	(0.029)
PS^{SP}	0.024*	0.015	0.045	0.025*	0.029**
	(0.015)	(0.016)	(0.028)	(0.015)	(0.015)
$IncTaxes$		-0.059**	-0.070**	-0.097***	-0.054*
		(0.026)	(0.029)	(0.025)	(0.028)
$MCapit$			-0.015**		
			(0.006)		
$Pdebt$				0.025***	0.022***
				(0.005)	(0.007)
Obs	327	247	116	244	194
N	43	34	19	34	28

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 7: High-income OECD - Education

	Multi-source Gini					DecRatio
$Year$	0.132***	0.182***	0.135***	0.201***	0.154***	0.019
	(0.028)	(0.030)	(0.027)	(0.042)	(0.029)	(0.012)
L/Y	-0.093***	-0.096***	-0.090***	-0.088***	-0.081***	-0.005
	(0.026)	(0.025)	(0.026)	(0.025)	(0.027)	(0.008)
TFP	4.732***	4.159***	5.191***	4.681***	6.496**	6.550***
	(1.552)	(1.537)	(1.595)	(1.615)	(3.022)	(1.460)
Imp^{high}	0.059***	0.063***	0.057***	0.055***	0.062***	0.003
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.007)
Imp^{low}	-0.095***	-0.078**	-0.116***	-0.123***	-0.107***	-0.012
	(0.036)	(0.036)	(0.039)	(0.038)	(0.039)	(0.012)
Exp	-0.053***	-0.051***	-0.052***	-0.046**	-0.054***	0.000
	(0.020)	(0.020)	(0.020)	(0.020)	(0.020)	(0.007)
$FDIin$	-0.008*	-0.006	-0.009**	-0.009**	-0.008*	-0.002
	(0.005)	(0.004)	(0.005)	(0.004)	(0.005)	(0.002)
$FDIout$	0.006	0.007*	0.005	0.005	0.006	-0.001
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.002)
PS^{Educ}	0.082***	0.090***	0.088***	0.091***	0.306	0.458***
	(0.030)	(0.030)	(0.030)	(0.030)	(0.226)	(0.093)
PS^{Health}	-0.024	-0.024	-0.028	-0.031	-0.052**	-0.010
	(0.025)	(0.024)	(0.025)	(0.025)	(0.022)	(0.013)
PS^{SP}	0.020	0.024	0.021	0.018	0.034**	0.001
	(0.015)	(0.015)	(0.015)	(0.015)	(0.014)	(0.007)
$IncTaxes$	-0.049***	-0.047***	-0.050***	-0.053***		-0.017**
	(0.015)	(0.015)	(0.015)	(0.015)		(0.008)
$Pdebt$	0.001	0.002	0.001	0.001	0.001	0.000
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)
$EducGini1$	0.129				0.178	0.048
	(0.112)				(0.110)	(0.042)
MYS		-1.342***				
		(0.408)				
Educ 1			0.250*			
			(0.143)			
EducGini 2			-0.010			
			(0.154)			
Educ 2				-0.274*		
				(0.146)		
Educ 3				-0.288**		
				(0.141)		
Educ 4				-0.435***		
				(0.169)		
$PS^{Educ}*TFP$					-0.262	-0.467***
					(0.251)	(0.108)
Obs	401	401	401	401	425	227
N	30	30	30	30	30	23

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 8: Developing Economies - Education

	Multi-source Gini					DecRatio
$Year$	0.042	0.154**	0.025	-0.110	-0.123***	-0.088
	(0.050)	(0.072)	(0.051)	(0.100)	(0.047)	(0.056)
L/Y	-0.175***	-0.160***	-0.143***	-0.136***	-0.172***	0.023
	(0.037)	(0.038)	(0.039)	(0.037)	(0.025)	(0.031)
TFP	0.847	0.018	1.443	-0.520	5.164***	-3.943
	(1.544)	(1.471)	(1.606)	(1.441)	(1.701)	(2.465)
Imp^{high}	0.048**	0.049***	0.055***	0.070***	0.077***	0.030
	(0.019)	(0.019)	(0.019)	(0.019)	(0.015)	(0.022)
Imp^{low}	-0.183***	-0.142***	-0.190***	-0.111**	-0.191***	-0.064
	(0.052)	(0.050)	(0.052)	(0.050)	(0.035)	(0.054)
Exp	0.023	0.043***	0.011	0.043***	0.033**	0.009
	(0.015)	(0.016)	(0.017)	(0.016)	(0.014)	(0.016)
$FDIin$	-0.007**	-0.008***	-0.007***	-0.007***	-0.008***	-0.001
	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.004)
$FDIout$	0.011*	0.018***	0.014**	0.012*	0.016***	0.004
	(0.007)	(0.006)	(0.006)	(0.007)	(0.005)	(0.009)
PS^{Educ}	0.158***	0.130***	0.154***	0.135***	0.371**	-0.046
	(0.029)	(0.030)	(0.029)	(0.030)	(0.147)	(0.193)
PS^{Health}	-0.070***	-0.059**	-0.072***	-0.054**	-0.117***	-0.024
	(0.023)	(0.024)	(0.023)	(0.025)	(0.024)	(0.023)
PS^{SP}	0.025*	0.033**	0.039***	0.035**	0.029**	0.026*
	(0.015)	(0.015)	(0.015)	(0.014)	(0.013)	(0.016)
$IncTaxes$	-0.097***	-0.091***	-0.116***	-0.070***		0.002
	(0.025)	(0.025)	(0.025)	(0.025)		(0.019)
$Pdebt$	0.025***	0.031***	0.027***	0.021***	0.030***	0.016**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)
$EducGini1$	0.338***				-0.034	-0.026
	(0.073)				(0.070)	(0.069)
MYS		-2.400***				
		(0.642)				
Educ 1			0.009			
			(0.071)			
EducGini 2			0.717***			
			(0.214)			
Educ 2				0.137*		
				(0.071)		
Educ 3				-0.224**		
				(0.113)		
Educ 4				0.572**		
				(0.239)		
$PS^{Educ}*TFP$					-0.324**	0.061
					(0.139)	(0.191)
Obs	244	244	244	244	324	210
N	34	34	34	34	43	28

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regional Heterogeneity

	Dev	LLM	Latin America	Consumption
$Year$	0.123***	0.020	0.014	0.124*
	(0.026)	(0.048)	(0.066)	(0.069)
L/Y	-0.101***	-0.174***	-0.204***	-0.137***
	(0.025)	(0.038)	(0.041)	(0.045)
TFP	5.120***	0.623	1.107	-0.811
	(1.478)	(1.536)	(1.882)	(1.916)
Imp^{high}	0.059***	0.039**	0.030	0.060***
	(0.019)	(0.019)	(0.023)	(0.020)
Imp^{low}	-0.094***	-0.205***	-0.192***	-0.242***
	(0.035)	(0.049)	(0.055)	(0.065)
Exp	-0.049**	0.041***	0.029	0.015
	(0.020)	(0.015)	(0.020)	(0.019)
$FDIin$	-0.009**	-0.007**	-0.007*	-0.005
	(0.005)	(0.003)	(0.004)	(0.004)
$FDIout$	0.005	0.011*	0.009	0.008
	(0.004)	(0.006)	(0.008)	(0.008)
$EducGini1$	0.129	0.355***	0.213**	0.708***
	(0.104)	(0.071)	(0.096)	(0.163)
PS^{Educ}	0.086***	0.185***	0.070	0.176***
	(0.029)	(0.028)	(0.084)	(0.030)
PS^{Health}	-0.020	-0.070***	-0.059	-0.056**
	(0.024)	(0.023)	(0.069)	(0.025)
PS^{SP}	0.019	0.032**	0.046*	0.028*
	(0.015)	(0.014)	(0.024)	(0.017)
$IncTaxes$	-0.057***	-0.139***	-0.109***	-0.090***
	(0.015)	(0.024)	(0.029)	(0.031)
$Pdebt$	0.002	0.030***	0.021***	0.036***
	(0.003)	(0.005)	(0.006)	(0.007)
$Year$	-0.084	0.120	0.278**	0.459***
	(0.061)	(0.210)	(0.139)	(0.140)
L/Y	-0.073	0.007	0.044	-0.141*
	(0.047)	(0.125)	(0.095)	(0.075)
TFP	-4.286*	-3.964	-24.689***	-2.266
	(2.210)	(3.835)	(5.979)	(3.431)
Exp	0.065**	-0.003	-0.053	-0.085**
	(0.026)	(0.046)	(0.036)	(0.039)
$FDIin$	0.002	0.406**	0.260**	-0.136
	(0.005)	(0.188)	(0.103)	(0.132)
$FDIout$	0.006	-0.005	-0.078	-0.928*
	(0.008)	(0.256)	(0.200)	(0.521)
$EducGini1$	0.198	-0.255	0.897***	0.039
	(0.133)	(0.300)	(0.282)	(0.210)
PS^{Educ}	0.066	0.007	0.176*	-0.034
	(0.043)	(0.220)	(0.098)	(0.098)
PS^{Health}	-0.048	0.340**	-0.004	-0.298**
	(0.034)	(0.141)	(0.075)	(0.124)
PS^{SP}	0.005	0.024	-0.042	0.154***
	(0.022)	(0.090)	(0.038)	(0.043)
$IncTaxes$	-0.028	0.241***	-0.083	0.036
	(0.030)	(0.083)	(0.066)	(0.060)
$Pdebt$	0.023***	-0.055**	-0.027	-0.049***
	(0.007)	(0.023)	(0.026)	(0.012)
Consumption				-898.859***
				(280.620)
Obs	645	244	244	244
N	64	34	34	34

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10: Robustness - Dependent Variable

	DecRatio	Top 1%	SS Gini	MS Gini	EHII
$Year$	0.017	0.001***	0.110***	0.169***	0.194***
	(0.023)	(0.000)	(0.032)	(0.027)	(0.015)
L/Y	-0.002	0.000	-0.194***	-0.130***	-0.007
	(0.016)	(0.000)	(0.024)	(0.021)	(0.014)
TFP	-0.278	0.070***	0.517	0.866	-6.637***
	(1.045)	(0.010)	(1.459)	(1.266)	(0.645)
Imp^{high}	0.028**	-0.000	0.066***	0.060***	0.010
	(0.012)	(0.000)	(0.014)	(0.016)	(0.009)
Imp^{low}	-0.037	0.000	-0.146***	-0.109***	-0.025
	(0.029)	(0.000)	(0.046)	(0.034)	(0.018)
Exp	-0.009	0.000***	-0.011	-0.032**	-0.022***
	(0.011)	(0.000)	(0.013)	(0.013)	(0.007)
$FDIin$	0.000	-0.000*	-0.004**	-0.008	0.005
	(0.001)	(0.000)	(0.002)	(0.007)	(0.005)
$FDIout$	0.001	0.000	0.009***	0.004	0.006
	(0.002)	(0.000)	(0.003)	(0.013)	(0.005)
$EducGini1$	0.162***	-0.002***	0.459***	0.272***	0.084***
	(0.053)	(0.001)	(0.064)	(0.051)	(0.025)
PS^{Educ}	0.012	0.000	0.176***	0.125***	0.029**
	(0.017)	(0.000)	(0.026)	(0.024)	(0.012)
PS^{Health}	-0.025	0.000	-0.072***	-0.051***	0.001
	(0.016)	(0.000)	(0.021)	(0.020)	(0.013)
PS^{SP}	0.021**	0.000	0.028**	0.020*	0.006
	(0.010)	(0.000)	(0.013)	(0.012)	(0.007)
$IncTaxes$	-0.028**	0.000	-0.094***	-0.080***	-0.061***
	(0.012)	(0.000)	(0.019)	(0.016)	(0.009)
$Pdebt$	0.010***	0.000	0.014***	0.006*	-0.001
	(0.003)	(0.000)	(0.004)	(0.003)	(0.002)
Obs	350	408	350	446	446
N	45	23	45	55	55

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 11: Robustness - Method

	2 lags	5 lags	Year	FE-SE
$Year$	0.134***	0.163***		0.111**
	(0.021)	(0.023)		(0.042)
L/Y	-0.101***	-0.058**	-0.123***	-0.142***
	(0.024)	(0.024)	(0.021)	(0.042)
TFP	1.890	0.688	2.191**	1.623
	(1.225)	(1.300)	(1.102)	(2.079)
Imp^{high}	0.048***	0.023*	0.037***	0.027
	(0.011)	(0.013)	(0.014)	(0.021)
Imp^{low}	-0.133***	-0.118***	-0.075**	-0.071
	(0.027)	(0.029)	(0.034)	(0.070)
Exp	-0.005	-0.005	-0.017	0.000
	(0.009)	(0.008)	(0.012)	(0.026)
$FDIin$	-0.006***	-0.005**	-0.004***	-0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
$FDIout$	0.008**	0.007**	0.010***	0.011***
	(0.004)	(0.003)	(0.002)	(0.004)
$EducGini1$	0.382***	0.388***	0.431***	0.335***
	(0.054)	(0.062)	(0.056)	(0.097)
PS^{Educ}	0.095***	-0.017	0.103***	0.119***
	(0.020)	(0.017)	(0.022)	(0.037)
PS^{Health}	-0.016	-0.060***	-0.040**	-0.049**
	(0.015)	(0.014)	(0.017)	(0.019)
PS^{SP}	0.015	0.022**	0.022**	0.031
	(0.010)	(0.010)	(0.011)	(0.018)
$IncTaxes$	-0.074***	-0.037***	-0.058***	-0.085***
	(0.013)	(0.013)	(0.014)	(0.028)
$Pdebt$	0.011***	0.004	0.009***	0.013**
	(0.003)	(0.003)	(0.003)	(0.005)
Obs	627	570	645	653
N	61	61	64	72

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

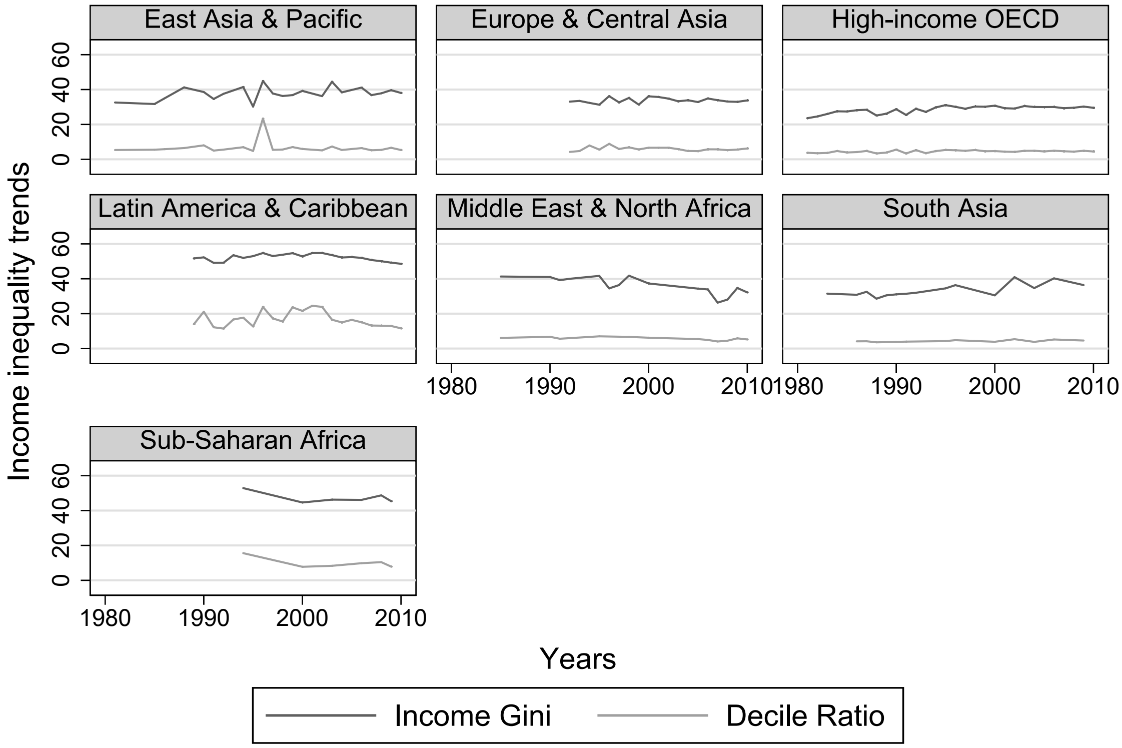

Figure 1: Income Inequality Trends across World Regions

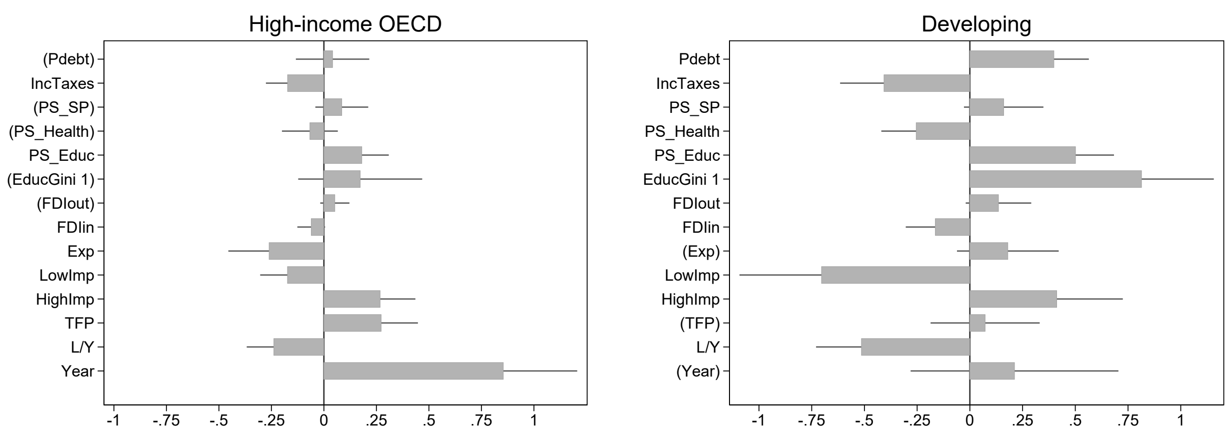

Figure 2: Magnitude of effects (basic drivers)

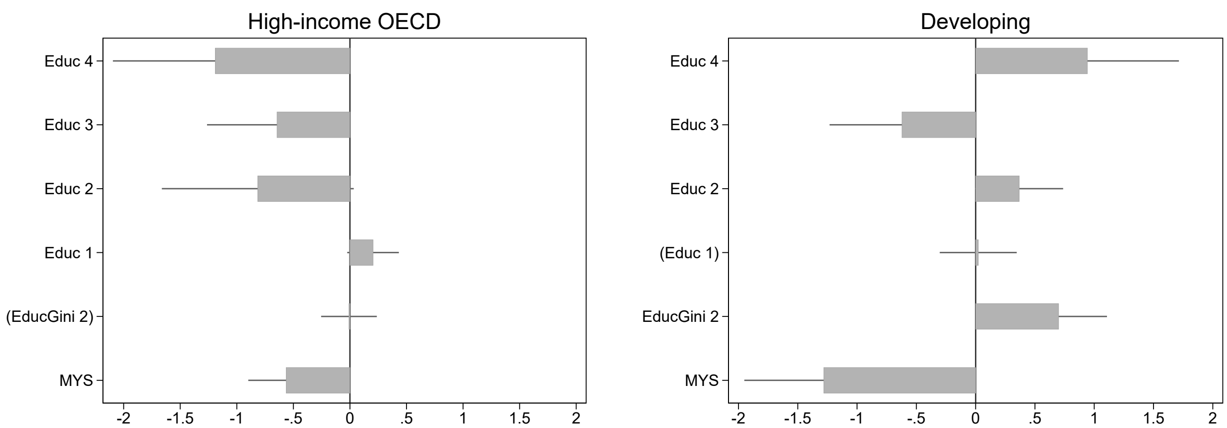

Figure 3: Magnitude of effects (education variables)