CHAPTER 1

EXPLAINING INCOME INEQUALITY TRENDS: AN INTEGRATED APPROACH

Petra Sauer, Narasimha D. Rao and Shonali Pachauri

ABSTRACT

In large parts of the world, income inequality has been rising in recent decades. Other regions have experienced declining trends in income inequality. This raises the question of which mechanisms underlie contrasting 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 between 1981 and 2010, studying a broad set of drivers to investigate their interaction and influence on income inequality. Within this broad approach, we are interested in the heterogeneity of income inequality determinants across world regions and along the income distribution. Our findings indicate the existence of a small set of systematic drivers across the global sample of countries. Declining labour income shares and increasing imports from high-income countries significantly contribute to increasing income inequality, while taxation and imports from low-income countries exert countervailing effects. Our study reveals the region-specific impacts of technological change, financial globalisation, domestic financial deepening and public social spending. Most importantly, we do not find systematic evidence of education's equalising effect across high- and low-income countries. Our results are largely robust to changing the underlying sources of income Ginis, but looking at different segments of income distribution reveals heterogeneous effects.

Keywords: Income inequality; education; developing countries; world regions; comparative analysis; inequality trends

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INTRODUCTION

In large parts of the industrialised world, income inequality has been rising in recent decades (e.g. Morelli et al., 2015). Furthermore, the substantial gains of high-income growth rates have not been equally distributed among the population in some emerging economies such as China and India (e.g. Organisation for Economic Co-operation and Development (OECD), 2011). Conversely, many countries in Latin America, which report some of the highest historical inequality levels, have been experiencing declining income inequality trends (Alvaredo & Gasparini, 2015). This raises the question of which mechanisms underlie contrasting observed trends in income inequality around the globe.

We address this research question with an empirical analysis at the aggregate level, examining a global sample of countries and studying a broad set of drivers to investigate their interaction and influence on income inequality. Within this broad approach, we are interested in the heterogeneity of income inequality determinants across world regions and along the income distribution. We have thus assembled an unbalanced panel dataset gathered from 73 high-, middle- and low-income countries from 1981 to 2010; the dataset combines two variants of income, Gini coefficients and ratios, based on decile income shares with a set of explanatory factors that are derived from existent theoretical contributions and recent empirical findings. These include measures to capture the integrated distributional consequences of technological change, globalisation, financialisation and increasing functional income inequality in conjunction with presumably equalising forces, that is education, labour market institutions and welfare state redistribution.

The empirical literature that investigates the causes of income inequality can be grouped into three categories: studies that concentrate on particular drivers of income inequality, for example, trade (e.g. Meschi & Vivarelli, 2009) or labour market institutions (e.g. Checchi & Garcia-Peñalosa, 2010); studies that look at particular groups of countries, for example, OECD economies (e.g. Roser & Cuaresma, 2016) or Latin American countries (e.g. Lustig et al., 2013); and studies that investigate a broad set of determinants at the global level (e.g. International Labour Organization (ILO), 2008; Jaumotte et al., 2013). Our article bridges these strands of the literature. By compiling a dataset of income inequality measures from the World Income Inequality Database (WIID) with particular focus on consistency of income concepts and underlying sources across countries and over time, we aim to update and revise existing empirical findings based on a global sample of countries. However, estimated effects at the global level can mask which mechanisms are at work in generating particular levels and trends of income inequality in different world regions. This is not only suggested by theoretical and empirical evidence on particular determinants (see, e.g., Goldberg & Pavcnik, 2007, for trade; and Acemoglu, 2003, for technology) but also by contributions which show the relevance of the level of development (Kuznets, 1955) and point the role of institutions (e.g. Huber et al., 2006; Palma, 2019a, 2019b). To infer region-specific effects, we split the full sample into high-income and developing economies and investigate subsamples of the latter group. Looking at different regional splittings enables us to analyse the relative relevance of inequality drivers across country groups and to contribute to the understanding of income inequality determinants in the global South. Income inequality trends have also been shown to be driven by movements at different segments of the income distribution across countries. While Palma (2011, 2014) provides evidence on the relevance of the bottom 40% in conjunction with the top 10%, a large body of the recent literature points to the importance of movements at the very top (Leigh, 2015; Piketty & Saez, 2013). Besides the income Gini, we thus consider inequality measures which capture inequality at the top, the bottom and between the extremes. Finally, we strive to model the education–inequality nexus and thereby add to the concerning more specific literature. Among others, Castelló-Climent and Doménech (2014) have identified the 'puzzle' that educational attainment has been increasing around the globe over recent decades, and the distribution of education has become more equal; however, there has been no effect, not even adverse, on income inequality. By accounting for the distributional dimension of education, separating the effects of different education levels and accounting for public education spending, we examine the possibility of finding the theoretically predicted negative relation between education and income inequality after controlling for confounding factors.

Our findings indicate the existence of a small set of systematic drivers across the global sample of countries. Accordingly, declining labour 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 high-, middle- and low-income countries. Our study reveals the region-specific impacts of technological change, financial globalisation, domestic financial deepening and social policy on income inequality. While technological change exerts a direct equalising impact only in high-income countries, and only until the 1990s, foreign direct investment (FDI) inflows and public debt are particularly relevant to explain income inequality in low-income and Latin American countries. Moreover, public spending on health is equalising in middle- and low-income economies, whereas social protection spending, on the other hand, is regressive. Most importantly, we do not find systematic evidence of education's equalising effect across high- and low-income countries. To a large extent, our results are robust to changing the underlying sources of income Ginis, but looking at different segments of income distribution reveals heterogeneous effects.

The rest of this article is organised as follows: In the first section, we review the theoretical and empirical literature and describe how existing knowledge motivates our analysis. We then introduce our income inequality measures and data sources and discuss descriptive trends of income inequality and its explanatory factors. After justifying our estimation method, we present our empirical results. Finally, we draw conclusions and provide suggestions for further analysis.

WHAT WE KNOW: THEORY AND EMPIRICAL EVIDENCE

The degree of (in)equality in a country's income distribution is a function of the shares of total income from labour 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 derived therefrom. The distribution of labour income depends on the forces of supply and demand and on the relative bargaining power of agents, which is, among other things, shaped by labour market institutions. Beyond that, governments mitigate market risks and essentially play an extensive redistributive role. In this section, we summarise the theoretical mechanisms through which technological change, globalisation, financialisation, education, labour market institutions, taxation and public social spending affect income inequality and discuss the relation between functional and personal income distribution. Due to our interest in explaining diverging outcomes across world regions, we also discuss how the concerning literature gives attention to the particularity of mechanisms in the global South.

Technological Change

Conventionally, analyses of the distributional consequences of technological change have focused on its impact on the earnings distribution. 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 labour. The resulting rise in relative demand puts a premium on high-skilled wages and increases wage inequality. Most literature studying technology-induced skill premiums focuses on high-income countries. However, models that account for the interaction between technology and trade suggest that the inequality increasing effect holds true for low-income countries as well (see the discussion in the subsequent section). For example, Acemoglu (2003) provides a theoretical framework suggesting that skill premiums arise not only in the United States but also in least developed countries (LDCs), where technological adoption and imitation is promoted via trade.

More recently, other dimensions of income distribution gained attention in theoretical and empirical literature. Most importantly, analyses that aim to explain the decline in the labour share since the 1980s also consider technological change to be a decisive factor. According to Karabarbounis and Neiman (2014), progress in information and communication technology (ICT) has significantly reduced the relative prices of investment goods, which has increased the capital intensity of production. As a consequence, the bargaining power of corporations increases relative to their labour force, enabling them to absorb rents (Atkinson, 2015, Chapter 3; Zilian et al., 2016). 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., 2017a, 2017b). Thus, technological change also alters the distribution of profits and capital income. Beyond that, Kim and Brynjolfsson (2009) present evidence indicating that companies' information technology (IT) intensity helps explain increasing remuneration of top executives, thereby contributing to rising inequality at the top of the earnings distribution. Finally, in their literature survey, Tyson and Spence (2017) highlight the central role of ICT in the global integration of markets for goods, services and investment and in the expansion of the financial sector, the distributional consequences of which are discussed in the following sections.

Globalisation

Globalisation is a multidimensional phenomenon including trade in goods and services, cross-border investment and international financial flows.

The characterisation 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 specialise in the factor of production they are relatively abundant in. Accordingly, high-income countries export capital- and skill-intensive goods and import low-skilled, labour-intensive goods from low-income countries. The latter reduces relative prices and wages in import-competing sectors, thereby increasing inequality between labour and capital income and 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 findings of Roser and 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.

The comparative-advantage framework has been criticised for its inability to explain both the inequality effects of intra-industry trade between similar economies and the observed increase in income inequality in most middle- and low-income countries. For example, Meschi and Vivarelli (2009) find that imports from, as well as exports to, high-income countries increase income inequality, especially in middle-income countries. Two strands of the literature fill these gaps with particular relevance. First, theories that account for firm heterogeneity show that exporting firms are more productive and pay higher wages than average firms (see, e.g., Melitz, 2003; Verhoogen, 2008). Second, theories that account for technology indicate that trade liberalisation can provide incentives for innovative activities in exporting sectors (Melitz, 2003) and/or facilitate technological diffusion via technologies embedded in imported capital goods (Acemoglu, 2003).[1] Hence, skill premiums possibly emerge in both high- and low-income countries due to export and import flows from their respective economies. Theories that address the increasing relevance of FDI and outsourcing follow a similar line of argument, indicating that the required skill level of workers in those segments which move from high- to low-income countries is usually higher than the average skill level in receiving economies (Goldberg & Pavcnik, 2007). FDI inflows should therefore increase the dispersion of wages in developing countries. In contrast, if capital flowing out of high-income countries requires a lower skill level of workers than their average, FDI outflows contribute to increasing inequality in these economies. Jaumotte et al. (2013) thus argue that FDI outflows are closely associated with offshore outsourcing and, as such, are an important measure for analysing the impact of globalisation on inequality in industrialised countries. Jaumotte et al. (2013) investigate the effects of financial integration and show the strongest inequality-increasing effect of globalisation to result from inward FDI.

Explanations that go beyond the impact of market forces on the distribution of earnings have also proven to be relevant to understanding the relation between globalisation and income inequality. According to Rodrik (1997), as capital is more mobile than labour, trade integration has increased its relative bargaining power and, thus, its share in total income. Similar effects result from competition between nations aiming to attract foreign investment, which can induce a 'race to the bottom' with regard to regulatory standards (Goldberg & Pavcnik, 2007), labour organisation and corporate taxes (Gross et al., 2016). Moreover, the higher cross-border mobility of capital can affect the redistributive capacity of national tax and transfer systems (Bertola, 2008; Kanbur, 2015). Finally, greater integration with the global economy has been shown to increase income volatility; the impact on sustained income inequality depends on policy responses and financial sector characteristics (Bertola, 2008; Kanbur, 2015). Thus, according to ILO (2008), particularly low-income households in emerging economies with fragile financial systems have been adversely affected by the consequences of increasingly frequent banking crises after financial market liberalisation in the 1990s.

The Economic Relevance of Finance

Since the early 1990s, restrictions on cross-border (financial) capital flows have been relaxed and domestic financial capital markets have been liberalised through various means, including the removal of interest rate ceilings, credit controls and regulations on bank activity (Evans, 2016). The financial sector's increasing economic relevance has been denominated as *financialisation*; its distributional consequences have been analysed in various theoretical and empirical contributions.

One strand of the literature investigates the availability of private credit in developed financial markets as prerequisite for development and long-term growth. Accordingly, the relaxation of borrowing constraints allows for high-return investments, for example, in education, for low-income households, and can 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 vulnerability for uninsurable shocks (Bertola, 2008). Private debt can thus contribute to increasing inequality via increasing macroeconomic instability.[2] According to Claessens and Perotti (2007), whether domestic financial development is actually able to reduce income inequality in developing countries depends on the quality of institutions and whether or not the rich are able to shape them in ways which secure their own interests.

Another strand of the literature looks at the expansion of the financial sector and its consequences for changing corporate behaviour, the rise of executive remuneration and the declining labour share. The gap between high-income earners, especially top executives, and low-income earners has substantially increased since the early 1990s (e.g. Leigh, 2015; Piketty & Saez, 2013). Rising top executive remuneration can, on the one hand, be explained by marginal productivity differentials created by the increasing complexity of managerial tasks in technology-intensive and multinational enterprises. On the other hand, it can be explained by their increasing bargaining power in wage negotiations. This is, among other things, due to the variable income component which has become a major part of top executive's remuneration and has been increasingly linked to companies' stock market value (ILO, 2008). Beyond that, the alignment of corporate goals with financial sector aims – denominated as 'shareholder approach' – has been shown to reduce the bargaining power of trade unions to act as a countervailing force, thereby increasing inequality in the functional income distribution.[3]

Education

Approaches that explain increasing income inequality by the market forces of supply and demand attribute a key role to investment in the future labour force's education. The basic idea is that technological change and globalisation increase the demand for high skills, thus expanding the supply of highly qualified workers counteracts rising skill premiums. A popular exposition of the important role of education in the United States is Goldin and Katz's (2010) book *The Race Between Education and Technology*, which is based on ideas initially brought up by Jan Tinbergen (1974). Goldin and Katz (2010) argue that although secondary and tertiary educational attainment increased substantially in the United States, the premium on high skills continued to increase in the 1980s and 1990s, indicating that educational expansion was unable to meet demand growth due to technological change. An extensive body of research has analysed 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 increased literacy and expanded primary education for poverty alleviation. However, as discussed in the concerning sections, technology and trade can also induce movements in the upper part of the education distribution, and tertiary education has been substantially expanding over recent decades in the global South as well (Sauer, 2019).

Theoretically, the formalisation of the distributional effects 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 relationship between education and inequality in the dispersion of wages depends, however, on the structure of returns to education, and the relative importance of *composition effects* and *wage effects*, respectively (Foerster & Tóth, 2015). The *composition effect* addresses the distribution of education: the income inequality effect depends on the extent to which higher educational attainment simultaneously results in a more equal distribution of education. The *wage effect* addresses how returns respond to changes in the demand for and supply of education. For example, increasing the primary-education share in low-income countries can simultaneously contribute to declining educational and increasing income inequality if returns on low education levels fall. 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. However, income inequality can increase as a result of educational expansion if wages are strictly convex in years of schooling. In that case, shifting the educational structure to higher levels while keeping its distribution unchanged shifts the wage function to a steeper segment, implying that returns to education are distributed more unequally. According to Bourguignon et al. (2005), a fall in income inequality is only possible if educational expansion simultaneously results in a sufficiently large reduction in educational inequality. They show that this was the case in three (Brazil, China and Taiwan) out of the seven countries they have analysed; in Argentina, Colombia, Indonesia, Malaysia and Mexico, their estimated association between average educational attainment and income inequality is positive. Also, Castelló-Climent and Doménech (2014) have observed that large reductions in education inequality (measured by an education Gini coefficient) have not been accompanied by similar reductions in income inequality. Castelló-Climent and Doménech (2014) provide explanations for this 'puzzle', including factors such as technological change which contribute to increasing returns to education or the increasing relevance of movements in top incomes for overall inequality dynamics. However, they do not test for the relative importance of these factors in a multivariate setting.

The extent to which education is able to exert an equalising effect on income distribution also depends on the political economy of education which determines how education policy and educational institutions facilitate educational expansion and react to it. According to Carnoy (2011), the mass expansion of higher education may contribute to increasing income inequality in low-, middle- and high-income countries if public means are distributed unequally across educational institutions, resulting in quality differentials between elite and mass universities.

Labour Market Institutions and Welfare State Redistribution

A wide range of theories from political science, sociology and economics demonstrate the pervasive influence of political institutions and governance on income distribution.[4] The role of public policy can be grouped into the following channels. First are policies that influence the drivers of income inequality such as technological change and trade openness. Second are policies that alter either the primary distribution of income, for example, through labour market regulations or the distribution of disposable household income through transfers and taxation. Third are health or education policies that create in-kind redistribution and affect the level and distribution of human capital.

Labour market institutions such as unions, collective bargaining structures, minimum wages and unemployment benefits aim to mitigate market risks and increase the relative bargaining power of labour. Labour support regulations can therefore simultaneously compress wage gaps and increase the labour share. Trade unions and institutionalised wage bargaining have generally been shown to exert an equalising impact on the dispersion of earnings, even if wage differentials between union and non-union workers rise (ILO, 2008, Chapter 3). This relation also holds for minimum wages and, to a lesser extent, unemployment benefits (e.g. Koeninger et al., 2007). However, the overall effect of labour market institutions on inequality of disposable incomes is not equally clear. Checchi and Garcia-Peñalosa (2010) present a theoretical framework to analyse the distributional effects of labour 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 labour share and contribute to rising unemployment. The net effect on disposable income inequality is positive, while the effect remains negative for greater bargaining coordination and is not significant for unemployment benefits. To a large part, the literature considers high-income countries with large formal labour 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 and Garcia-Peñalosa (2010).[5] In contrast, ILO (2008, Chapter 3) are not able to provide evidence on a direct equalising effect of labour market institutions[6] in a sample that includes high-, middle- and low-income countries. However, they do find an indirect impact via the institutional quality of the welfare state.

Governments' redistributive policies are reflected in the structure of taxes, social insurance and cash transfers. These determine the difference between the distribution of market income and personal disposable income. The extent of redistribution differs across countries and has been changing over time (Causa & Hermansen, 2018). 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.[7] By determining the relative quality of educational institutions, education policies also affect the distribution of returns to education (Carnoy, 2011).

Functional and Personal Income Inequality

As the preceding discussion of income inequality determinants shows, technological change, globalisation, financialisation and labour market institutions are not only directly related to the personal distribution of income but also to the functional distribution between capital and labour. However, the relation between the functional and the personal distribution of income is not straightforward.

Checchi and Garcia-Peñalosa (2010) find a strong negative relation between the labour income share and the income Gini coefficient. They argue that the gap between capital and non-capital owners outweighs inequality within the latter group which is due to gaps between wage earners and the unemployed. The theoretical framework of Milanovic (2016) provides additional insights which enable the identification of situations in which increasing inequality between capital and labour income translates into increasing personal income inequality. First, returns on 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 less equal than the distribution of labour income so that shifts from labour to capital constitute shifts to the less-equally distributed source of income. Third, the correlation between individual capital and labour income should be high. Milanovic (2016) shows that these three conditions prevail in the majority of current societies. He denominates these as *new capitalist* because capital owners and workers are not distinct social groups, as they are in *classical capitalism*, but instead overlap as such income accrues from both sources. It follows that a positive relation between increasing capital income shares and increasing personal inequality can be expected.

Daudey and García-Peñalosa (2007) as well as the more recent contributions of Bengtsson and Waldenstroem (2017) and Francese and Mulas-Granados (2015) provide evidence supporting this hypothesis in different samples with regard to time frame and country coverage. However, the latter two articles find the relation to be weaker, or even insignificant, as further explanatory variables are included.

EMPIRICAL ANALYSIS: MEASURES AND DATA SOURCES

The main inequality measure of our empirical analysis is the income Gini coefficient, which comprehensively measures income differences across an entire population while masking the internal composition of the distribution. We therefore also examine decile ratios, which reveal disparities between different segments of the income distribution, and the top 5% income share. These inequality measures are merged with a set of explanatory variables which we derive from the theoretical mechanisms discussed above. The data we assemble should thus enable us to model the heterogeneous distributional effects of technological change, globalisation, finance, education, welfare state and labour market institutions, and the division between capital and labour.

Our aim is to observe a broad set of countries from various world regions over a reasonably 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 4–6), 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.[8]Generally, we split our sample into high-income OECD members and the remaining group of countries, which we loosely denominate as developing economies. However, we also examine different finer groupings of the latter, quite heterogeneous cluster.

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 cross-country panel datasets has been that of Deininger and Squire (1996), who assembled surveys meeting their desired standard of quality. The internal inconsistency of this dataset has motivated researchers to critically assess the reliability of secondary income inequality datasets (Atkinson & Brandolini, 2001). Recent studies for developing countries have often used 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 the 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., 2015). More recently, large meta-datasets which assemble income inequality measures from a variety of relatively reliable sources have been used more widely. Instead of applying estimation techniques 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).[9]

The most suitable database for our analysis is the UNU-WIDER World Income Inequality Database, Version 3.4 (WIID3.4).[10] It reports not only income Gini coefficients but also decile and quantile income shares and provides extensive documentation which permits to extract data based on a chosen selection criteria in order to maximise consistency of the underlying data. WIID assembles inequality measures from a variety of sources, including OECD, Eurostat and the Luxembourg Income Study (LIS) for high-income countries; Transmonee by UNICEF for Eastern European countries; SEDLAC[11] for Latin American countries; and World Bank sources and household surveys from national statistical offices for other middle- and low-income countries. This compilation 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, WIID provides extensive information, including the income and/or consumption definition, the statistical units to be adopted and the use of equivalence scales and weighting.

An important source of potential inconsistency is variation in 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 (which 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 only occasionally rely on consumption-based measures, but we allow the concept to vary only across countries but not over time. Our measures always cover urban and rural areas, all forms of employment and both males and females. We further address the multitude of underlying databases 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 summarised in the Appendix.

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. Our base case consists of an unbalanced panel with 771 *multi-source* (MS) Gini observations from 73 countries between 1981 and 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).

Table 1. Summary Statistics of Income Inequality Series.

MSGini	Mean	35.24	Overall SD	10.19	Observations = 771
	Minimum	19.70	Between SD	10.73	$N = 73$
	Maximum	67.60	Within SD	2.04	1981–2010
SSGini	Mean	35.82	Overall SD	10.50	Observations = 630
	Minimum	19.70	Between SD	10.88	$N = 70$
	Maximum	67.60	Within SD	1.97	1981–2010

Our second income Gini series – *single-source* (SS) 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 deciles and percentiles if available. We use this information to compute three decile ratios based on relative income shares: the ratio between the 5th and the 1st deciles captures inequality at the bottom, the ratio between the 9th and the 5th deciles measures inequality at the top and the ratio between the 9th and the 1st deciles reveals inequality at the extremes. This enables us to test whether the influence of income inequality drivers differs along the income distribution. All requirements of the MS Gini with respect to population, regional and time coverage and the income concept also apply to decile ratios, which cover 532 country-time data points. The current literature suggests that top incomes have been particularly relevant for understanding recent income inequality trends. We thus analyse how our model is able to explain movements in the income share accruing to the top 5% of the income distribution. This information is, however, only available for high-income OECD and some European and Central Asian countries (see Table 2). Moreover, this measure is computed from household surveys,[12] which has been shown to not entirely capture incomes at the very top (e.g. Blanchet et al., 2018; Burkhauser et al., 2018).

Descriptive Trends of Income Inequality

The within-country standard deviation of the inequality measures is small in relation to their cross-country variation. This suggests that income distribution changes are slow and that the extent of time-varying drivers' influence is narrowly bounded. Fig. 1 and Table 2 investigate dynamics over time in more detail and depict regional differences in the levels and trends of the income inequality measures we consider in our analysis. In general, the two income Gini series show overlapping time trends. However, eliminating jumps due to different underlying sources – as done for the SS Gini – results in smoother time series and thus reveals significant trends for East Asia and Europe and Central Asia. On the other hand, the time dimension of the SS Gini is smaller than that of the MS Gini for some countries, and the cross-sectional dimension changes, causing the time trends for Latin America and South Asia to become insignificant.[13]

Trends in overall income inequality as measured by the Gini coefficient are generally consistent with trends in different parts of the income distribution.

Table 2. Income Inequality Trends Within Countries by Region.

	Observations				Mean – Trend[a]					
Region[b]	MS	SS	Ratios	T5%	MS	SS	D9/D1	D5/D1	D9/D5	T5%
HI	444	345	248	111	29.88 ⇑	30.11 ⇑	4.82	2.61	1.81 ⇑	14.11 ⇑
ECA	109	93	88	29	33.28	32.79 ⇓	5.73	2.89	1.94	17.48 ⇓
SA	17	13	8	0	33.54 ⇑	33.6	4.51	2.16 ⇑	2.08	
MENA	25	24	20	6	36.26 ⇓	36.14 ⇓	5.73	2.65	2.14 ⇓	12.73 ⇑
EAP	36	24	28	0	40.36	39.53 ⇑	6.65 ⇓	2.61 ⇓	2.54	
LAC	130	123	130	0	52.22 ⇓	52.18	17.88 ⇓	5.68 ⇓	3.01	
SSA	10	8	10	0	55.79	59.36	12.41	3.42	3.63	

[a] Arrows indicate the direction of statistically significant time trends (at the 5% significance level) from a fixed-effect regression of inequality against time.
[b] HI (high-income OECD members), ECA (Europe and Central Asia), LAC (Latin America and Caribbean), EAP (Eastern Asia and the Pacific), SA (South Asia), MENA (Middle East and North Africa and SSA (sub-Saharan Africa).

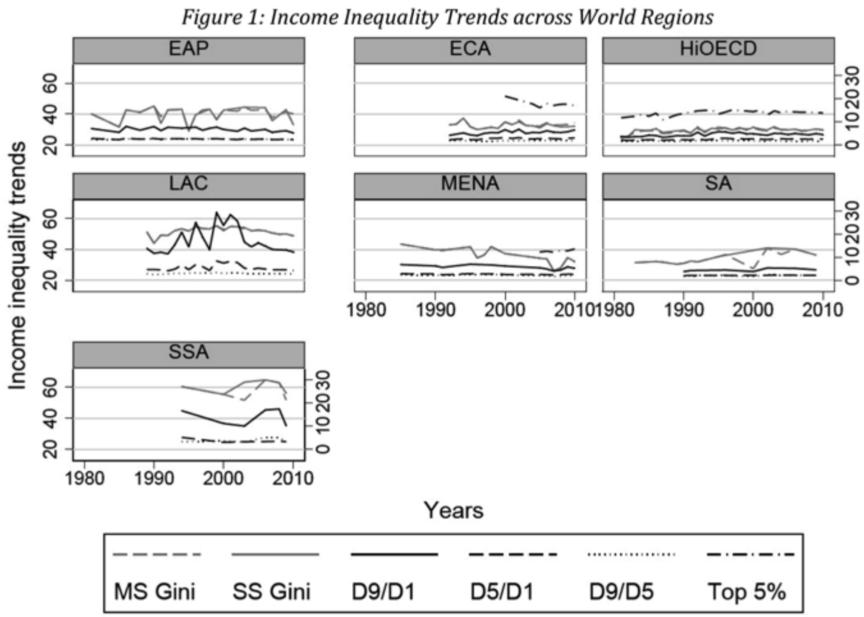

Fig. 1. Income Inequality Trends Across World Regions.
Notes: The left *y*-axis corresponds to the two Gini measures (MS Gini and SS Gini), the right *y*-axis corresponds to the decile ratios and the top 5% income share. HiOECD, high-income OECD members; ECA, Europe and Central Asia; LAC, Latin America and Caribbean; EAP, Eastern Asia and the Pacific); SA, South Asia; MENA, Middle East and North Africa; SSA, sub-Saharan Africa.

Exceptions are countries in East Asia and the Pacific, where income inequality significantly increased with respect to the SS Gini but decreased with respect to the extremes and bottom. In South Asian countries, the significant increase in overall income inequality turns out to be driven by rising gaps between the middle and the bottom segment of the income distribution. In contrast, significantly increasing inequality at the top fostered by a rising share of the top 5% is the dominant force of rising income inequality in high-income OECD countries.

Starting from among the highest inequality levels across world regions, income inequality in Latin America significantly decreased with respect to the MS Gini as well as the two decile ratios which reveal the relative improvement of the bottom, while the gap at the top remained unchanged. Middle Eastern and North African countries show a significantly declining trend with respect to both Gini coefficients in conjunction with an improvement of the middle in relation to the top. We do not observe significant inequality trends over time for sub-Saharan African countries. Yet, the plot in Fig. 1 suggests that inequality was decreasing in the 1990s but has been rising since 2000.

Drivers of Income Inequality

Education

Empirical works have often represented education by an average measure. Rising average attainment might, however, stem from changes in different segments of the education distribution, resulting in differing degrees of educational inequality and affecting the corresponding returns to education differently. Hence, studies which have included, for example, a measure of mean years of schooling as a control variable found that it had either a positive (e.g. OECD, 2011) or insignificant (e.g. Roser & Cuaresma, 2016) effect on income inequality. We disentangle the relation between education and income inequality, controlling for confounding factors, using three methods to capture the distributional dimension of education: the overall education Gini, the Gini for the educated population and population shares at individual attainment levels. For comparison, we also estimate specifications using mean years of schooling to measure average educational attainment. Furthermore, including a measure of public education spending (see below) enables us to test for the relevance of the political economy channel.

As in Sauer (2019) 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:

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

where e_i is the population share for which i is the highest level attained and y_i is the corresponding cumulative duration of formal schooling. MYS, the mean years of schooling in the population aged 15 and over, is given by $\text{MYS} = \sum_{i=1}^{n} e_i * y_i$. An education Gini of 0 means that the entire population attains the same education level. An education Gini of 1, on the other hand, implies that one person completes the tertiary level, but the rest do 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) (Lutz & Samir, 2011; Samir et al., 2010). This dataset, spanning from 1960 to 2010, consists of multistage backward and forward population projections for 175 countries according to five-year age groups, sex and level of educational attainment. 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, e_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).[14]

The strong decline in the share of people without formal education is the predominant driver of decreasing education inequality in developing countries (Cuaresma et al., 2013; Sauer, 2019). The concerning variable is thus 97% correlated with the overall education Gini. In high-income countries, on the other hand, almost universal literacy and schooling was achieved well before the 1980s. To explore the effects of these regional differences, we decompose the education Gini[15] of the total population aged 15 and over, $EducGini_{15+}$, into the share of people without any formal education, (e^{1}_{15+}), and an education Gini for those with at least some formal education (Categories 2–4), $EducGini^{E}_{15+}$. Finally, to test how wage effects differ across education levels, we also model the separate effects of the population shares with primary, secondary and tertiary attainment.*Functional Income Inequality*

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

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 gross domestic product (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 labour 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

$$\mathrm{hc}_{it} = e\varphi * \mathrm{MYS}_{it} \tag{3}$$

where MYS_{it} are the mean years of schooling and φ is the average return to education. We continue along the lines of Inklaar and Timmer (2013)[16] and compute φ as piecewise linear returns to education in accordance with 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 nonetheless lead to the capitalisation of income. Inklaar and Timmer (2013) note that intangible assets such as intellectual property rights are not accounted for in PWT's capital stock measure. The estimated impact of a catchall measure as TFP can thus be biased downwards or upwards, depending on which factor dominates.

The literature summarised in the section on technological change suggests ICT to have been a decisive component of technological change over the last few decades. ICT capital might thus be a more direct measure for capturing the mechanisms that link technology and inequality. 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.

Globalisation

The literature on the distributional effects of globalisation surveyed above indicates that the inequality effects of globalisation vary according to the income level of countries, the quality of institutions and the particular dimension of globalisation considered. Even for trade and financial integration, multiple – and possibly opposing – mechanisms are at work. Hence, aggregate indices have often generated inconclusive results in empirical analysis. In order to reveal the heterogeneous mechanisms of the globalisation–inequality relation, we consider a set of variables measuring trade and financial integration. First, we construct trade flow indicators which 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 therefore fall outside the scope of the SST's 'competing' products. Following Isham et al. (2005), these flows are categorised into those from high-income and low-income countries, as a proxy for high-skilled and low-skilled (manufacturing) imports, respectively. Second, we include the total level of exports in GDP to test whether induced skill biases, inequality between companies or overall employment and wage growth are the dominating effects of exporting. Third, the extent of financial globalisation is captured by inward and outward FDI flows in GDP, taken from the World Development Indicators (WDI).

A thorough analysis of globalisation's effects would also account for measures of portfolio investment and debt. As Jaumotte et al. (2013) show that these factors are 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 liberalisation affects domestic financial deepening, indicators of national financial development can partly absorb and reveal its impact.

Financialisation

We largely follow the literature (e.g. Bertola, 2008; Jaumotte et al., 2013) 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 above, that financial sector-aligned corporate behaviour has contributed to increasing inequality. This driver is measured by the market capitalisation of listed domestic companies in GDP. Both finance variables are from WDI.

Labour Market Institutions and Welfare State Redistribution
We select five measures which 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 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).[17]

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

Descriptive Trends of Covariates

Table 3 provides summary statistics on the levels and time variation (measured by the within-country standard deviation) of all variables we consider in our empirical analysis, separated by the most general regional splitting into high-income OECD and developing economies.

In accordance with the literature, we find that the labour share in income declined significantly in both high-income and developing economies. TFP and the ICT capital index increased significantly. Furthermore, all trade variables show a significantly rising trend since the 1980s in both regions, but FDI flows only do so in high-income countries. The significantly increasing trends of private credit and the market capitalisation of listed companies in conjunction with their relatively large within-country standard deviation indicate the expanding economic importance of finance in both regions.

On the public social spending side, all categories gained weight in total government spending in high-income OECD countries, but only education spending increased significantly in developing economies. 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. Due to the small sample size, the trends of labour market institutions can only be interpreted for high-income OECD members. However, the size of this subsample is substantially reduced to 85 observations from nine countries. In line with existing findings, the declining trend of trade union density is visible for this group of countries. Moreover, unemployment benefit coverage has been extended while minimum wages did not change significantly.

As in Sauer (2019) and Cuaresma et al. (2013), we find the distribution of education to have become more equal as education expanded that is 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.

Table 3. Summary Statistics and Trends by Region.

Variable[a]	High-income OECD Mean	High-income OECD Within SD[b]		Developing Mean	Developing Within SD	
L/Y	60.68	2.64	⇓	49.73	2.72	⇓
TFP	0.95	0.06	⇑	0.97	0.08	⇑
ICT	0.98	0.03	⇑	0.99	0.03	⇑
Imp^{high}	23.76	4.37	⇑	23.06	8.63	⇑
Imp^{low}	3.91	1.81	⇑	6.53	3.89	⇑
Exp	28.60	5.01	⇑	29.32	7.92	⇑
FDI^{in}	4.41	7.80	⇑	8.17	23.91	
FDI^{out}	4.66	8.87	⇑	2.91	15.05	
PS_{Edu}[c]	10.22	2.42	⇑	13.59	3.03	⇑
$\text{PS}_{\text{Health}}$	11.58	2.52	⇑	6.65	3.41	
PS_{SP}	34.41	3.96	⇑	12.10	4.17	⇑
TaxesREV	31.36	3.35		20.40	4.22	⇑
MinWage	43.68	22.11		25.63	5.51	⇓[c]
Unemp	54.97	12.32	⇑	15.51	6.00	⇓
UDensity	41.47	5.09	⇓	48.44	32.49	⇓
MCapit	69.85	34.69	⇑	31.12	13.96	⇑
PDebt	89.59	28.73	⇑	44.39	16.39	⇑
MYS_{15+}	12.66	0.40	⇑	9.17	0.53	⇑
EducGini_{15+}	11.27	1.27	⇓	23.85	2.37	⇓
$EducGini^{E}_{15+}$	9.63	0.80	⇓	16.81	0.97	⇓
e^{1}_{15+}	1.87	0.75	⇓	9.23	2.28	⇓
e^{2}_{15+}	15.97	2.89	⇓	33.08	2.68	⇓
e^{3}_{15+}	60.95	2.20	⇑	44.34	2.75	⇑
e^{4}_{15+}	21.20	2.70	⇑	13.36	1.67	⇑

[a] For an explanation of variable abbreviations, see section 'Estimation method'.
[b] Arrows indicate the direction of statistically significant time trends (at the 5% significance level) from a fixed-effect regression of inequality against time.
[c] This estimate is only based on 13 observations from two countries.

ESTIMATION METHOD

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

$$INEQ_t = \gamma Year + \beta_1 \left(\frac{L}{Y}\right)_{i,t-1} + \beta_2 TFP_{i,t-1} + \beta_3 G_{i,t-1} + \beta_5 W_{i,t-1} + \beta_6 F_{i,t-1} + \beta_4 E_{i,t-1} + \alpha_i + \varepsilon_{i,t} \quad (4)$$

with

$G = (\text{Imp}^{\text{high}}, \text{Imp}^{\text{low}}, \text{Exp}, \text{FDIin}, \text{FDIout})$
$W = (\text{PS}_{\text{Educ}}, \text{PS}_{\text{Health}}, \text{PS}_{\text{SP,}}\ \text{IncTaxes})$
$F = (\text{MCapit}, \text{PDebt})$
$E = (\text{EducGini}_{15+}/\text{MYS}_{15+}/e1_{15+}, \text{EducGiniE}_{15+}/e2_{15+}, e3_{15+}, e4_{15+})$

where INEQ_t represents the income inequality measures we use as dependent variables. L/Y is the labour income share and TFP stands for total factor productivity. Globalisation variables, G, include imports from high- ($\mathrm{Imp}^{\mathrm{High}}$) and low-income ($\mathrm{Imp}^{\mathrm{Low}}$) countries, total exports (Exp), and FDI in- and outflows. Measures of welfare state redistribution, W, are the three types of public social spending (PS) on education (educ), health and social protection (SP), as well as income taxes in total revenue (IncTaxes). Market capitalisation (Mcapit) and private debt (PDebt) are the two finance variables. Finally, with regard to education, we include the overall education Gini coefficient ($\mathrm{EducGini}_{15+}$) in our main estimations, but estimate separate specifications which add one of the following: 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 $_{i,t}$ 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 contributions (Galbraith & Kum, 2005; UNCTAD, 2012) is fixed-effect estimation. However, due to the complex error structure we find in our data, our preferred econometric method is a feasible general least squares (GLS) estimator. First, based on a modified Wald Statistic, we reject the null hypothesis that the error variances are equal across panels. Second, we test for panel autocorrelation using a test proposed by Woolridge which is based on the coefficients of a regression of lagged residuals[18] and strongly reject the null hypothesis of no serial correlation in each of our model specifications at the global and regional levels. Furthermore, the feasible GLS model calculates the common AR(1) coefficient to be 0.4 or higher in all model runs. It thus follows that we have to account for first-order autocorrelation (AR1) and groupwise (that is 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 generalised method of moments (GMM) estimator. The lagged dependent variable eliminates AR(1), and the use of lags as instruments accounts for the induced endogeneity, that is a dynamic panel bias. However, system GMM is asymptotically efficient only for very large N. Furthermore, the need to generate instruments from multiple lags reduces the degrees of freedom significantly. A least-squares-dummy-variable approach which corrects for the bias 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 estimation or clustered standard errors in fixed-effect models. For balanced panels which exhibit groupwise heteroskedasticity, Reed and Ye (2011) demonstrate that feasible GLS produces more efficient estimates than ordinary least squares (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.[19] 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 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 allows us to secure stationarity of the time series in Equation (4).

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; these differ according to the composition of regional subsamples, the inequality indicator used as a dependent variable and 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 still retaining a reasonable sample size. This specification accounts for education by adding the education Gini coefficient for the total population aged 15 and over. Even if this measure captures the distributional dimension of education directly, it still masks subjacent effects. We therefore subsequently analyse how unpacking the education distribution reveals its influence on income inequality. Moreover, we test for the robustness of our results to using a more consistent time series of the income Gini and investigate whether different sets of drivers are relevant to explain inequality at different parts of the income distribution. By analysing 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, in the Appendix, we test whether our main results are robust to the econometric method.

Main Results

Tables 4–6 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 labour income share, TFP, variables of trade and financial globalisation, the education Gini and public social spending. Column 2 accounts for nations' tax systems, while Columns 3 and 4 test for the relevance of finance, Column 5 adds ICT capital instead of TFP and Column 6 includes labour 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 labour in total income significantly contributes to reducing the MS Gini coefficient. This is also true for increasing imports from low-income countries, FDI inflows and income taxation. Imports from high-income countries and public education spending contribute to increasing income inequality, measured by the MS Gini, in both regions.[20]

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 capitalisation and the inequality-reducing effect of exports are also driven by their effect in the high-income cluster. Reducing educational inequality and public spending on health, on the other hand, have 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. In contrast, the negative effects we obtain for minimum wages, unemployment benefit coverage and trade union density are based on a small sample of nine high-income countries and are thus hard to generalise.

Regarding ICT capital, the net effect at the global level is insignificant since region-specific impacts point in opposite directions. For high-income OECD members, we find an unexpected negative relation to income inequality.[21] Moreover, the effects of imports from low-income countries and public education spending become insignificant. Retaining TFP in a regression which restricts the sample period, beginning in 1990, reveals these estimator changes are likely due to the shorter time period covered by ICT capital.[22] In developing economies, where TFP is not significant, ICT capital is positively related to the income Gini, and its introduction leaves other effects unchanged.

We balance the trade-off between sample coverage and broadness of considered inequality determinants by choosing the model specification in Column 5 of Tables 4–6 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, Fig. 2 plots the effects of within-country standard deviation changes in each explanatory variable with the corresponding 95% confidence interval for high-income and developing economies.

The MS 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 – 50% – of the Gini's within-group standard deviation (equal to 1.7 in high-income OECD countries). TFP and imports from high-income countries equally add 16% to the time variation of the income Gini. Considering its declining trend, the labour income share significantly contributed to rising income inequality over the sample period (14%). We also find a positive impact (11%) for increasing public spending

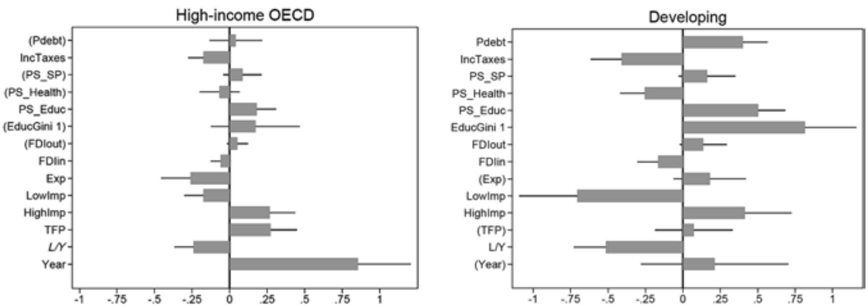

Fig. 2. Magnitude of Effects (Basic Drivers).

Notes: The magnitude of effects is computed as β_i*sd$_i$, where β_i is the estimated effect obtained from Column 4 in Tables 5 and 6 and sd$_i$ is the within-group standard deviation of the concerning explanatory variable obtained from Table 3. Parentheses indicate insignificance. EducGini 1 is the education Gini of the total population aged 15+ (EducGini$_{15+}$).

on education. The largest equalising 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 labour income (20%) as well as imports from high-income countries (17%) and public spending on education (21%) equally exert significant disequalising effects on the income distribution in developing economies (the average within-group standard deviation is equal to 2.43). Beyond these factors, the increasing share of private debt has a large positive impact on income inequality in these economies; it accounts for 17% of the average time variation in the MS Gini. In contrast, the effects of FDI in- and outflows point into different directions and are relatively small. On the equalising side, reducing the degree of inequality in the education distribution (33%) and increasing imports from 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 in the achievement of a more equal distribution of disposable incomes and consumption expenditure.

Discussion: Theory and Empirical Evidence

A robust driver across different sample compositions and specifications turns out to be the labour income share. This implies that the mechanisms via which technological change, globalisation, financialisation and labour market institutions alter the relative bargaining power of capital and labour and affect the functional income distribution are relevant for explaining overall inequality trends in countries. Beyond that, according to Checchi and Garcia-Peñalosa (2010), this

Table 4. Global Sample – Stepwise Expansion.

	MS 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)
FDI^{in}	−0.007***	−0.006***	−0.006***	−0.006***	−0.005***	0.015
	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.025)
FDI^{out}	0.007**	0.007***	0.011***	0.007***	0.010***	−0.041
	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)	(0.038)
$EducGini_{15+}$	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)
Observations	771	667	478	645	534	88
N	73	64	47	64	57	10

Note: Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

finding indicates that the gap between capital and non-capital owners dominates inequality within the group of wage earners. Moreover, it suggests that the three conditions for generating a relationship between functional and personal income inequality put forward by Milanovic (2016), that is the high impact of capital income on total income, high savings taken out of capital and relatively high inequality in the distribution of capital incomes, are equally fulfilled in high-income OECD economies as well as in the global South.

Table 5. High-income OECD – Stepwise Expansion.

	MS 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)
FDI^{in}	−0.007*	−0.007*	−0.016***	−0.008*	−0.009*	0.022
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.024)
FDI^{out}	0.007*	0.007*	0.006	0.006	0.003	−0.048
	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.038)
EducGini_{15+}	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)
$\text{PS}_{\text{Health}}$	−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)
Observations	444	420	362	401	340	85
N	30	30	28	30	29	9

Note: Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

After controlling for its effect through the labour income share, our results only provide some indication for the presumed disequalising influence of technological change. To the extent that TFP and ICT capital adequately measure the intended mechanisms, the skill-biasedness of technological change seems to have only contributed to increasing income inequality until the 1990s in high-income countries. This contradicts the findings of contributions arguing that particularly more recent advances in technology which have enabled the digitalisation

Table 6. Developing Economies – Stepwise Expansion.

	MS 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)
FDI^{in}	−0.009***	−0.007*	−0.007**	−0.007**	−0.007***
	(0.002)	(0.004)	(0.003)	(0.003)	(0.002)
FDI^{out}	0.017***	0.010	0.019***	0.011*	0.015***
	(0.005)	(0.008)	(0.007)	(0.007)	(0.004)
EducGini_{15+}	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)
$\text{PS}_{\text{Health}}$	−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)
Observations	327	247	116	244	194
N	43	34	19	34	28

Note: Standard errors in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

of production significantly increase skill premiums and thus exert disequalising effects (e.g. Autor, 2014). In developing countries, the diverging results we obtain from using different technology measures suggest that the estimated effect of TFP is biased downwards due to the equalising impact of institutional change (Hall & Jones, 1999). ICT capital, on the other hand, exerts a disequalising impact which goes beyond its effect on functional income inequality.

The evidence concerning trade integration indicates that factors not captured in the theoretical framework of the Heckscher–Ohlin model affect the relationship between trade and income inequality. On the one hand, we find that trade between similar economies affects income inequality. On the other hand, we observe inequality-increasing impacts of imports from high-income countries in developing economies. 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, assuming that imports from other high-income countries compete with high-skilled sectors in these economies, they can provide incentives for innovation activities and increase the skill premium. Technology embedded in imports from high-income countries, on the other hand, is able to explain increasing inequality in developing economies. The significantly negative impact of exports in high-income OECD countries indicates that, after controlling for the adverse distributional consequences of skill-intensive imports, the equalising 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 industrialised economies can be due to labour 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 widen it in countries with a weaker regulatory framework.

The negative impact of FDI flows to developing countries counters theoretical predictions and existing findings. However, separating the effects of low-income and Latin American countries reveals the presumed positive impact of FDI inflows in these subgroups (see the section looking at regional heterogeneity below). The small negative effect thus seems driven by the few high-income countries in the developing cluster. While we do not find the presumed positive relation between FDI outflows and income inequality in high-income countries using the MS Gini, replacing it with the SS Gini provides evidence that FDI outflows capture the disequalising effects of outsourcing. The positive effect of FDI outflows in developing economies could, on the other hand, be due to the adverse effects of capital flight.

One strand of theories on the distributional impact of finance predicts that the equalising effects of growth-enhancing financial deepening result from more access to private credit in developing economies. However, the positive impact of private debt indicates the dominance of disequalising mechanisms related to higher risk, economic instability and the quality of institutions.[23]

The results concerning educational attainment and spending are discussed in detail below. The inequality effects of public spending on health and social protection are not significantly different from 0 in high-income OECD countries, suggesting that progressive and regressive effects even each other out. In developing countries, on the other hand, health spending is equalising while the regressive effect of social protection dominates. Social protection spending is an aggregate measure which is composed of social security transfers such as pensions, sickness, disability and unemployment benefits, universal transfers paid based, for example, on family status, and of social assistance targeted to the poor. Different types of social protection transfers have been shown to affect the secondary distribution of income differently. Causa and Hermansen (2018) provide evidence that social security transfers have become less redistributive since the mid-1990s in high-income countries, while the redistributive effect of social assistance increased.

Yet, the size of the former is substantially larger, what possibly outweighs the equalising impact of the latter. Huber et al. (2006) argue that social security spending, which can make up more than 80% of social protection spending, is regressive in Latin American countries. This is due to payment hinging on participation in the formal sector, being tied to income and privileges existing for social and occupational groups. Moreover, using the same social protection measure as ours, they find a significant equalising effect only in established democracies.

Heterogeneity Across the Income Distribution

Tables 7 and 8 present the results we obtain from substituting the dependent variable. Column 1 replaces the MS Gini with the Gini series that is restricted to be based on one single source. For high-income OECD countries, this significantly reduces the time dimension but leaves the number of countries and the sample period unchanged. Although our results in the high-income sample are largely robust, the estimated impacts of TFP and outward FDI change; while TFP becomes insignificant, outward FDI turns out to be significantly positive.[24] Thus, as it has been highlighted in the concerning literature, differing underlying sources can have substantial effects on results obtained from income inequality analyses using secondary data. In developing economies, on the other hand, changes in the Gini series which predominantly alter the cross-sectional dimension do not affect our results.

The Gini coefficient is particularly sensitive to changes in the middle and thus can mask changes at other segments of the income distribution (e.g. Palma, 2011). Our descriptive evidence reveals significant trends in gaps between the middle and the tails and between the extremes, which need not be consistent with the trend in the income Gini and differ across world regions. This suggests that also the influence of income inequality drivers differs across the income distribution.

Rising income inequality in high-income OECD countries is mainly driven by movements at the top of the income distribution. Declining labour income shares have significantly contributed to this trend by affecting both the 9th-to-5th decile ratio and the top 5% income share. Rising TFP does not affect the very top but magnifies gaps between the other analysed segments of the income distribution. In contrast, exporting and outward FDI are particularly relevant to explain the rising income share of the top 5%. However, exporting also improves the relative position of the middle to the top and thus exerts an overall equalising impact on the income Gini. The counter-intuitive finding that declining educational inequality significantly contributes to rising top income shares can be explained by tertiary educational expansion being the main driver of compositional effects in high-income countries (see the discussion of education results below). The regressive impact of public education spending is relevant at all examined segments of the income distribution. While spending on social protection significantly increases inequality at the top, public spending on health exerts significant countervailing effects. Finally, increasing the weight of taxes on income, profits and capital gains in total revenue significantly contributes to declining income inequality across the distribution but leaves the income share of the top 5% unchanged.

Table 7. High-income OECD – Dependent Variable.

	SS Gini	D9/D1	D5/D1	D9/D5	T5%
Year	0.108***	0.008	0.003	0.001	−0.038
	(0.033)	(0.012)	(0.006)	(0.001)	(0.029)
L/*Y*	−0.101***	−0.007	0.001	−0.003***	−0.129***
	(0.028)	(0.008)	(0.004)	(0.001)	(0.023)
TFP	2.806	1.125*	0.702**	0.156**	−3.253
	(1.770)	(0.657)	(0.299)	(0.068)	(1.978)
Imp^{high}	0.054***	0.008	0.000	0.002**	−0.013
	(0.021)	(0.007)	(0.003)	(0.001)	(0.016)
Imp^{low}	−0.096**	−0.006	−0.002	−0.002	−0.062
	(0.048)	(0.013)	(0.006)	(0.002)	(0.039)
Exp	−0.040*	−0.005	0.001	−0.002**	0.055***
	(0.021)	(0.007)	(0.003)	(0.001)	(0.021)
FDI^{in}	−0.004	−0.002	−0.001	−0.000	0.001
	(0.005)	(0.002)	(0.001)	(0.000)	(0.004)
FDI^{out}	0.009**	−0.001	−0.001	0.000	0.008**
	(0.004)	(0.002)	(0.001)	(0.000)	(0.004)
EducGini_{15+}	−0.094	−0.006	0.012	−0.008*	−0.270***
	(0.132)	(0.041)	(0.020)	(0.005)	(0.089)
PS_{Educ}	0.076**	0.056***	0.023***	0.004***	0.153***
	(0.038)	(0.013)	(0.006)	(0.001)	(0.051)
$\text{PS}_{\text{Health}}$	−0.054*	−0.012	0.001	−0.006***	0.053
	(0.029)	(0.013)	(0.006)	(0.001)	(0.081)
PS_{SP}	0.030*	0.000	−0.003	0.002***	−0.017
	(0.017)	(0.007)	(0.003)	(0.001)	(0.033)
IncTaxes	−0.037**	−0.021***	−0.008**	−0.002**	0.015
	(0.017)	(0.008)	(0.003)	(0.001)	(0.026)
PDebt	0.004	0.001	0.001	−0.000	0.006
	(0.003)	(0.002)	(0.001)	(0.000)	(0.004)
Observations	310	227	227	227	111
N	29	23	23	23	18

Note: Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In developing economies, income inequality trends at different segments of the distribution are more mixed. Our findings reveal that inequality at the top, which is relevant in the Middle East and North Africa, significantly increases due to declining labour income shares, imports from high-income countries, public spending on education and social protection and rising private-debt-to-GDP ratios. Conversely, rising imports from low-income countries, exporting, public spending on health, income taxation and a more equal distribution of education significantly improve the relative position of the 5th decile to the 9th decile. The relative position of the bottom is, on the other hand, the critical factor in other world regions. We find that TFP exerts a significant equalising impact on both the 9th-to-1st and the 5th-to-1st decile ratios, while increasing private debt significantly contributes to rising inequality at the extremes. The results for the top 5% income share only apply to a small sample of Europe and Central Asia, where the share declined over the observed period. In this group of countries, TFP,

Table 8. Developing Economies – Dependent Variable.

	SS Gini	D9/D1	D5/D1	D9/D5	T5%
Year	−0.019	−0.082	−0.028	0.003	−0.505
	(0.046)	(0.058)	(0.017)	(0.003)	(0.355)
L/Y	−0.153***	0.020	0.002	−0.009***	−0.005
	(0.040)	(0.031)	(0.010)	(0.002)	(0.127)
TFP	−2.584	−3.326**	−1.095**	−0.127	−14.738***
	(1.690)	(1.643)	(0.487)	(0.082)	(4.124)
Imp^{high}	0.071***	0.032	0.001	0.006***	−0.123***
	(0.020)	(0.022)	(0.006)	(0.001)	(0.037)
Imp^{low}	−0.281***	−0.055	0.021	−0.011***	0.385***
	(0.058)	(0.053)	(0.016)	(0.003)	(0.091)
Exp	0.009	0.008	−0.002	−0.002**	0.092**
	(0.018)	(0.016)	(0.005)	(0.001)	(0.044)
FDI^{in}	−0.006**	−0.001	−0.001	−0.000	0.003
	(0.003)	(0.004)	(0.001)	(0.000)	(0.003)
FDI^{out}	0.011*	0.005	0.003	−0.000	−0.015**
	(0.006)	(0.009)	(0.003)	(0.000)	(0.008)
$EducGini_{15+}$	0.262***	−0.003	−0.036	0.016***	−2.635**
	(0.068)	(0.078)	(0.025)	(0.004)	(1.266)
PS_{Educ}	0.199***	0.019	0.005	0.010***	0.009
	(0.030)	(0.032)	(0.010)	(0.002)	(0.115)
PS_{Health}	−0.103***	−0.025	−0.000	−0.005***	−0.131
	(0.026)	(0.022)	(0.006)	(0.001)	(0.091)
PS_{SP}	0.038**	0.025	−0.000	0.002**	0.019
	(0.015)	(0.016)	(0.005)	(0.001)	(0.027)
IncTaxes	−0.130***	−0.002	−0.012*	−0.004***	−0.270***
	(0.022)	(0.017)	(0.006)	(0.001)	(0.068)
PDebt	0.033***	0.015**	0.001	0.002***	0.035*
	(0.005)	(0.006)	(0.002)	(0.000)	(0.019)
Observations	211	210	210	210	28
N	33	28	28	28	6

Note: Standard errors in parentheses.
$*p < 0.1$, $**p < 0.05$, $***p < 0.01$.

imports from high-income countries' FDI outflows and income taxation have significantly contributed to this trend, whereas significant disequalising forces are imports from low-income countries and exporting.

Education and Income Inequality

We present our analysis of the distributional impact of education using four specifications. Besides the overall education Gini coefficient for the total population aged 15 and over, we include mean years of schooling to compare our results against existing literature, decompose the education Gini into the share of unschooled people and the Gini coefficient of the educated population and add the population shares for each education level separately. The results using the MS Gini as dependent variable are presented in Columns 1–3 of Tables 9 and 10. Using the three population shares, Columns 4–7 show how educational attainment affects various segments of the income distribution differently.

For each world region, Fig. 3 plots the estimated change in the MS Gini due to a one within-country standard deviation change in the concerning education variable and the corresponding 95% confidence interval.

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, which 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 and each education attainment population share – primary, secondary and tertiary – significantly contribute to reduce the income Gini coefficient. The largest impact stems from higher population shares with tertiary education which accounts for 69% of the MS Gini's within-group standard deviation. However, the estimated equalising effect of education is limited to using the Gini coefficient as dependent variable and seems to be due to its sensitivity to changes at the middle of the income distribution. We find equalising effects of primary, secondary and tertiary education on the 5th-to-1st decile ratio (Column 5 of Table 9) but no significant impacts on the extremes and inequality at the top. In contrast, regressing the top 5% income share on education levels (Column 7 of Table 9) reveals significantly positive effects for each level of educational attainment. This indicates that it is particularly the top in high-income countries benefiting from an upward shift of the educational structure to a segment where wages are more dispersed.

For 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 positive,

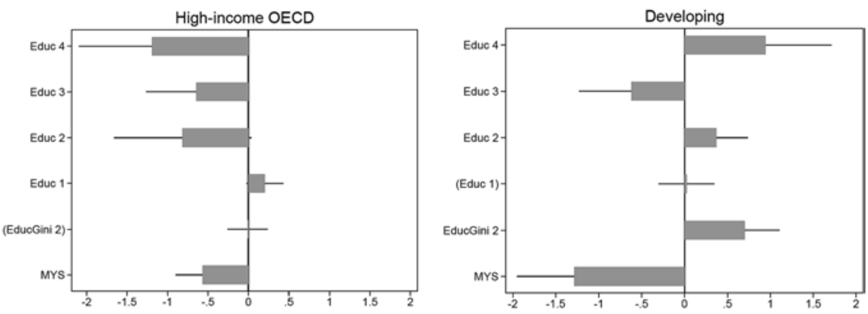

Fig. 3. Magnitude of Effects (Education Variables).

Notes: The effects stem from estimating the different model specifications presented in Tables 9 and 10 (Columns 1–3). The magnitude of effects is computed as β_i * sd$_i$, where β_i is the estimated effect and sd*i* is the within-group standard deviation of the concerning explanatory variable obtained from Table 3. Parentheses indicate insignificance. EducGini 2 is the education Gini of the *educated* population aged 15+ ($EducGini^{E}_{15+}$). Educ 1–4 are the population shares with no, primary, secondary and tertiary education, respectively.

Table 9. High-income OECD – Education.

	MS Gini			D9/D1	D5/D1	D9/D5	T5%
Year	0.182***	0.135***	0.201***	0.019	0.004	0.005***	−0.029
	(0.030)	(0.027)	(0.042)	(0.016)	(0.007)	(0.002)	(0.041)
L/*Y*	−0.096***	−0.090***	−0.088***	−0.002	0.004	−0.003***	−0.135***
	(0.025)	(0.026)	(0.025)	(0.009)	(0.004)	(0.001)	(0.025)
TFP	4.159***	5.191***	4.681***	1.534**	0.927***	0.186**	−3.831*
	(1.537)	(1.595)	(1.615)	(0.670)	(0.294)	(0.076)	(2.085)
Imp^{high}	0.063***	0.057***	0.055***	0.003	−0.001	0.001	−0.010
	(0.019)	(0.019)	(0.019)	(0.007)	(0.003)	(0.001)	(0.016)
Imp^{low}	−0.078**	−0.116***	−0.123***	−0.021	−0.009	−0.004***	−0.053
	(0.036)	(0.039)	(0.038)	(0.015)	(0.007)	(0.002)	(0.039)
Exp	−0.051***	−0.052***	−0.046**	−0.002	0.001	−0.001	0.051**
	(0.020)	(0.020)	(0.020)	(0.008)	(0.003)	(0.001)	(0.022)
FDI^{in}	−0.006	−0.009**	−0.009**	−0.003	−0.001	−0.000	0.002
	(0.004)	(0.005)	(0.004)	(0.002)	(0.001)	(0.000)	(0.004)
FDI^{out}	0.007*	0.005	0.005	−0.002	−0.001	0.000	0.009**
	(0.004)	(0.004)	(0.004)	(0.002)	(0.001)	(0.000)	(0.004)
PS_{Educ}	0.090***	0.088***	0.091***	0.044***	0.017***	0.004***	0.135**
	(0.030)	(0.030)	(0.030)	(0.014)	(0.006)	(0.001)	(0.055)
$\text{PS}_{\text{Health}}$	−0.024	−0.028	−0.031	−0.009	0.003	−0.004***	0.075
	(0.024)	(0.025)	(0.025)	(0.014)	(0.007)	(0.001)	(0.087)
PS_{SP}	0.024	0.021	0.018	−0.005	−0.004	0.001	−0.013
	(0.015)	(0.015)	(0.015)	(0.008)	(0.003)	(0.001)	(0.033)
IncTaxes	−0.047***	−0.050***	−0.053***	−0.018**	−0.007*	−0.001	0.006
	(0.015)	(0.015)	(0.015)	(0.008)	(0.004)	(0.001)	(0.026)
PDebt	0.002	0.001	0.001	−0.000	−0.001	−0.000	0.006
	(0.003)	(0.003)	(0.003)	(0.002)	(0.001)	(0.000)	(0.005)
MYS_{15+}	−1.342***						
	(0.408)						
e^1_{15+}		0.250*	−0.274*	−0.077	−0.067**	0.005	0.369**
		(0.143)					
$EducGini^E_{15+}$		−0.010					
		(0.154)					
e^2_{15+}			(0.146)	(0.053)	(0.028)	(0.007)	(0.157)
e^3_{15+}			−0.288**	−0.036	−0.052*	0.012	0.395***
			(0.141)	(0.053)	(0.028)	(0.007)	(0.136)
e^4_{15+}			−0.435***	−0.084	−0.055*	−0.010	0.381**
			(0.169)	(0.063)	(0.033)	(0.007)	(0.181)
Observations	401	401	401	227	227	227	111
N	30	30	30	23	23	23	18

Note: Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

implying that a more equal distribution of education reduces income inequality. The equalising impact of increasing population shares with secondary attainment on education and income distributions turns out to drive the effects of aggregate measures; the impact amounts to 25% of the MS Gini's average time variation and is particularly due to its effect on inequality at the top. At the same time, higher population shares with both primary (15%) and tertiary (39%) education

Table 10. Developing Economies – Education.

	MS Gini			D9/D1	D5/D1	D9/D5	T5%
Year	0.154**	0.025	−0.110	−0.343***	−0.068**	−0.003	1.283***
	(0.072)	(0.051)	(0.100)	(0.115)	(0.031)	(0.006)	(0.388)
L/*Y*	−0.160***	−0.143***	−0.136***	−0.013	−0.001	−0.007***	−0.455***
	(0.038)	(0.039)	(0.037)	(0.034)	(0.011)	(0.002)	(0.135)
TFP	0.018	1.443	−0.520	−3.659**	−1.240**	−0.100	−21.119***
	(1.471)	(1.606)	(1.441)	(1.864)	(0.535)	(0.082)	(4.086)
Imp^{high}	0.049***	0.055***	0.070***	0.042*	0.003	0.006***	−0.075*
	(0.019)	(0.019)	(0.019)	(0.023)	(0.007)	(0.001)	(0.043)
Imp^{low}	−0.142***	−0.190***	−0.111**	0.017	0.021	−0.009***	0.474***
	(0.050)	(0.052)	(0.050)	(0.061)	(0.018)	(0.003)	(0.064)
Exp	0.043***	0.011	0.043***	−0.008	−0.006	−0.000	0.036
	(0.016)	(0.017)	(0.016)	(0.018)	(0.005)	(0.001)	(0.057)
FDI^{in}	−0.008***	−0.007***	−0.007***	−0.001	−0.001	−0.000	0.003
	(0.003)	(0.003)	(0.003)	(0.005)	(0.001)	(0.000)	(0.002)
FDI^{out}	0.018***	0.014**	0.012*	−0.001	0.001	−0.000	−0.029***
	(0.006)	(0.006)	(0.007)	(0.011)	(0.003)	(0.000)	(0.010)
PS_{Educ}	0.130***	0.154***	0.135***	0.076**	0.009	0.009***	0.039
	(0.030)	(0.029)	(0.030)	(0.035)	(0.011)	(0.002)	(0.116)
PS_{Health}	−0.059**	−0.072***	−0.054**	−0.017	−0.000	−0.004***	0.042
	(0.024)	(0.023)	(0.025)	(0.025)	(0.007)	(0.001)	(0.110)
PS_{SP}	0.033**	0.039***	0.035**	0.013	0.000	0.001	−0.105***
	(0.015)	(0.015)	(0.014)	(0.016)	(0.005)	(0.001)	(0.038)
IncTaxes	−0.091***	−0.116***	−0.070***	−0.040*	−0.013*	−0.003**	−0.220***
	(0.025)	(0.025)	(0.025)	(0.021)	(0.007)	(0.001)	(0.050)
PDebt	0.031***	0.027***	0.021***	0.007	0.000	0.002***	−0.006
	(0.005)	(0.005)	(0.006)	(0.007)	(0.002)	(0.000)	(0.020)
MYS_{15+}	−2.400***						
	(0.642)						
e^1_{15+}		0.009	0.137*	0.207***	0.043**	0.008*	−9.699***
		(0.071)					
$EducGini^E_{15+}$		0.717***					
		(0.214)					
e^2_{15+}			(0.071)	(0.080)	(0.021)	(0.005)	(2.861)
e^3_{15+}			−0.224**	0.140	0.062*	−0.022***	−10.760***
			(0.113)	(0.134)	(0.037)	(0.006)	(2.856)
e^4_{15+}			0.572**	1.031***	0.176**	0.044**	−8.850***
			(0.239)	(0.287)	(0.078)	(0.018)	(3.142)
Observations	244	244	244	210	210	210	28
N	34	34	34	28	28	28	6

Note: Standard errors in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

increase income inequality. Rising primary education attainment increases the supply of low-skilled workers, thereby reducing their relative wages. This effect is thus particularly relevant to explain inequality at the bottom and the extremes (Columns 5 and 6 of Table 10). From this, it follows that the declining trend of primary attainment has contributed to reduce income inequality in developing economies by improving the relative position of the bottom. Increasing educational attainment at the tertiary level exerts a relatively large disequalising effect, particularly by improving the position of the top and the middle, relative to the bottom. This is in line with the evidence provided in Bourguignon et al. (2005), which shows that in the majority of low- and middle-income countries, reductions in educational inequality have not been sufficiently large to offset the increasing spread of returns to education. In the six mostly Eastern European countries for which information on top 5% incomes is available, expanding education at all levels significantly contributes to reduce the income share.

In both world regions, we find evidence that public education spending significantly contributes to increasing income inequality. In high-income OECD countries, this is true for all segments of the income distribution. In developing economies, where this effect is additional to the disequalising impact of higher attainment levels, public education spending particularly improves the relative position of the 9th decile. Public education spending increases the average level of education if it enabled more people to study, the inequality effects of which are controlled for by including quantity-based measures of education, such as the education Gini and population shares. However, the overall effect on the income distribution also depends on the relative 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. For example, according to Carnoy (2011), tertiary education expansion in Asia and Latin America has resulted in increasing segmentation between mass and elite universities, what contributes to diverging wages within the higher education segment.

Regional Heterogeneity

The subsample of developing economies is a heterogeneous group. For instance, it consists of countries the World Bank classifies as high income but which are not OECD members,[25] middle-income countries in Latin America which experienced declining income inequality and sub-Saharan low-income countries. In order to reveal whether our estimation results are driven by particular groups of countries, we cause each explanatory variable to interact with dummy variables indicating different subgroups of the developing-economies sample. The estimates provided in Table 11 are based on the developing-economies sample (upper panel) and separate the effects of the low- and lower-middle (LLM)-income cluster and Latin America, respectively (lower panel).

Significantly positive time trends indicate that income inequality increased due to factors we do not observe in our model. Among other things, this is true for political aspects not captured in our public policy measures, labour market institutions and the relevance of informal markets in developing economies. Concerning inequality at the bottom and between the extremes, the time trend is stronger in LLM countries as opposed to the remaining developing-economies cluster. In contrast, the relative position of the 1st decile significantly improved in Latin America. At the same time, the 9th decile gained relative to the median, so that overall inequality as measured by the MS Gini increased. This finding provides support for the argument in Palma (2011, 2014) that political and institutional factors have helped Latin American elites to continue to appropriate a significant share of income growth.

While the labour income share is equally relevant in Latin America as in the rest of the developing sample, it is more important to explain movements at the bottom and the extremes in LLM countries. TFP has equalising effects along the income distribution in both subsamples, but the estimated effect with respect to the income Gini is particularly large in Latin America. Assuming that TFP is a reliable measure of technological change, an explanation for its equalising effect 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. In contrast, following Hall and Jones (1999), the negative effect can be interpreted as revealing improvement in institutional quality.

Concerning trade in goods and services, estimated effects are relatively homogeneous across the developing-economies sample. Cross-border investment flows have a more heterogeneous impact on income inequality. The expected disequalising effect of inward FDI flows is revealed in both subsamples we consider. This is true with respect to the income Gini as well as to the relative position of the 1st decile, suggesting that the middle and top benefit from FDI inflows equally, leaving gaps at the top unchanged. As opposed to other developing economies, FDI outflows significantly reduce inequality at the bottom and between the extremes in LLM countries, and deteriorate the relative position of the 9th decile in Latin America. Accounting for heterogeneity within the developing cluster also shows that the inequality-increasing effect of private debt is mainly driven by its impact in Latin America, where the increasing incidence of private sector borrowing significantly deteriorates the relative position of the bottom. In contrast, private debt exerts a small equalising effect on overall income inequality, measured by the MS Gini, in LLM countries.

In accordance with our education findings discussed above, separating the effects of LLM countries and Latin America reveals that a more equal distribution of education need not be associated with smaller disparities along the income distribution. While lower education inequality significantly reduces income inequality at the bottom and between the extremes in LLM countries, it contributes to increase inequality at the bottom in Latin America, what seems to drive the positive effect on the income Gini in the developing cluster. Public spending on education is almost equally regressive across the developing sample, but it is able to reduce gaps between the 9th and the 5th decile in LLM countries.

Among the public spending policies we consider in our model, spending on health has the strongest equalising effects in developing economies. This is true for different subsamples; only in LLM countries, public health spending turns out to be regressive with respect to the income Gini. On the other hand, social protection spending is particularly regressive in both LLM and Latin American countries. Yet, in Latin America, it significantly reduces inequality at the top, while it contributes to deteriorate the relative position of the bottom. This is in line with the discussion in Huber et al. (2006) and can imply that social security

Table 11. Regional Heterogeneity.

	Low and Lower-middle Income				Latin America			
	MS Gini	D9/D1	D5/D1	D9/D5	MS Gini	D9/D1	D5/D1	D9/D5
Year	0.020	−0.040	−0.016**	0.002	0.014	0.034**	0.018***	−0.001
	(0.048)	(0.026)	(0.007)	(0.003)	(0.066)	(0.017)	(0.006)	(0.003)
L/Y	−0.174***	−0.046**	−0.001	−0.011***	−0.204***	−0.026*	−0.002	−0.011***
	(0.038)	(0.018)	(0.005)	(0.002)	(0.041)	(0.015)	(0.005)	(0.002)
TFP	0.623	−2.109***	−1.125***	−0.017	1.107	−2.359***	−0.881***	−0.084
	(1.536)	(0.779)	(0.211)	(0.099)	(1.882)	(0.479)	(0.182)	(0.081)
Imp^{high}	0.039**	0.018*	−0.001	0.005***	0.030	0.020***	0.002	0.006***
	(0.019)	(0.009)	(0.003)	(0.001)	(0.023)	(0.007)	(0.002)	(0.001)
Imp^{low}	−0.205***	0.006	0.023***	−0.013***	−0.192***	−0.006	0.007	−0.009***
	(0.049)	(0.023)	(0.005)	(0.003)	(0.055)	(0.014)	(0.005)	(0.002)
Exp	0.041***	−0.010	−0.003	−0.002*	0.029	−0.018***	−0.003**	−0.003***
	(0.015)	(0.007)	(0.002)	(0.001)	(0.020)	(0.005)	(0.002)	(0.001)
$FDIi^{in}$	−0.007**	−0.002	−0.001***	0.000	−0.007*	−0.001	−0.001*	−0.000
	(0.003)	(0.001)	(0.000)	(0.000)	(0.004)	(0.001)	(0.000)	(0.000)
FDI^{out}	0.011*	0.006**	0.003***	−0.000	0.009	0.003*	0.002**	0.000
	(0.006)	(0.003)	(0.001)	(0.000)	(0.008)	(0.002)	(0.001)	(0.000)
$EducGini_{15+}$	0.355***	−0.014	−0.025***	0.015***	0.213**	0.041*	0.014*	0.009**
	(0.071)	(0.029)	(0.008)	(0.005)	(0.096)	(0.021)	(0.007)	(0.004)
PS_{Educ}	0.185***	0.104***	0.020***	0.013***	0.070	0.046*	0.021***	0.006
	(0.028)	(0.019)	(0.006)	(0.002)	(0.084)	(0.024)	(0.007)	(0.004)
PS_{Health}	−0.070***	−0.016	0.003	−0.006***	−0.059	−0.055**	−0.030***	−0.001
	(0.023)	(0.015)	(0.004)	(0.001)	(0.069)	(0.025)	(0.009)	(0.003)
PS_{SP}	0.032**	−0.005	−0.004**	0.003**	0.046*	0.002	−0.002	0.004***
	(0.014)	(0.008)	(0.002)	(0.001)	(0.024)	(0.006)	(0.003)	(0.001)
IncTaxes	−0.139***	−0.051***	−0.015***	−0.008***	−0.109***	−0.039***	−0.012***	−0.004***
	(0.024)	(0.011)	(0.002)	(0.001)	(0.029)	(0.007)	(0.003)	(0.001)
Pdebt	0.030***	0.008***	0.001	0.002***	0.021***	0.003*	−0.001	0.002***
	(0.005)	(0.002)	(0.001)	(0.000)	(0.006)	(0.002)	(0.001)	(0.000)

Year	0.120	1.330***	0.381***	0.002	0.278**	−0.684***	−0.271***	0.029***
	(0.210)	(0.402)	(0.107)	(0.013)	(0.139)	(0.258)	(0.073)	(0.010)
L/*Y*	0.007	−0.618**	−0.187***	0.016**	0.044	−0.091	−0.011	−0.004
	(0.125)	(0.258)	(0.068)	(0.008)	(0.095)	(0.176)	(0.049)	(0.007)
TFP	−3.964	−14.294	−3.380	−0.624***	−24.689***	−12.636	−1.643	−1.371***
	(3.835)	(9.459)	(2.453)	(0.242)	(5.979)	(9.811)	(2.763)	(0.423)
	(0.256)	(0.458)	(0.124)	(0.020)	(0.200)	(0.342)	(0.102)	(0.018)
EducGini_{15+}	−0.255	2.175***	0.633***	0.006	0.897***	−0.994*	−0.484***	0.078***
	(0.300)	(0.633)	(0.166)	(0.017)	(0.282)	(0.599)	(0.170)	(0.024)
PS_{Educ}	0.007	−0.558	−0.124	−0.036***	0.176*	0.049	−0.016	0.010
	(0.220)	(0.352)	(0.095)	(0.012)	(0.098)	(0.105)	(0.029)	(0.006)
$\text{PS}_{\text{Health}}$	0.340**	0.630	0.174	0.035	−0.004	−0.029	0.010	−0.003
	(0.141)	(0.417)	(0.117)	(0.023)	(0.075)	(0.050)	(0.015)	(0.004)
PS_{SP}	0.024	0.403**	0.132***	−0.005	−0.042	0.188***	0.061***	−0.006**
	(0.090)	(0.171)	(0.046)	(0.005)	(0.038)	(0.066)	(0.018)	(0.003)
IncTaxes	0.241***	−0.222	−0.091**	0.025***	−0.083	−0.159	−0.011	−0.015***
	(0.083)	(0.166)	(0.046)	(0.005)	(0.066)	(0.110)	(0.031)	(0.006)
PDebt	−0.055**	0.014	0.006	−0.001	−0.027	0.163***	0.054***	−0.002
	(0.023)	(0.042)	(0.011)	(0.001)	(0.026)	(0.059)	(0.016)	(0.003)
Observations	244	210	210	210	244	210	210	210
N	34	28	28	28	34	28	28	28

Note: Standard errors in parentheses.
$^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

transfers particularly benefit the (upper) middle class in the formal segment of the labour market and improve their position relative to the top.

SUMMARY AND CONCLUSIONS

The aim of our empirical analysis has been to provide a comprehensive picture of how drivers at the global, broad regional and national levels interact to influence within-country income inequality. In answer to the research question, our findings indicate that national income inequality trends can only to a small degree be explained by similar underlying mechanisms but are better understood in their variability across world regions. Uncovering regional heterogeneity and variation along the income distribution has proven to provide valuable insights regarding the causes of income inequality trends around the globe.

The most robust factor across different sample compositions and specifications contributing to rising income inequality is declining labour income shares. This implies that besides their direct impact on personal income inequality, technological change, globalisation, financialisation and labour market institutions – as measured in our model – also exert an indirect influence via their effect on the functional distribution of income. Following Milanovic (2016), the low-, middle- and high-income countries we observe thus share the characteristics of *new capitalist* economies. While increasing imports from high-income countries contributes to rising income inequality around the globe, imports from low-income countries and income taxation are significant factors on the equalising 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 firm heterogeneity, the interaction between technology and trade, and the increasing bargaining power and concentration of capital.

By splitting the sample into high-income OECD and developing economies, we find technological change, as measured by TFP and ICT capital, to exert the presumed direct disequalising impact only in the former group of countries and only until the 1990s. Increasing borrowing to the private sector reduces income inequality in low-income countries but increases it in the middle-income sample. This indicates the dominance of disequalising mechanisms related to higher risk, economic instability and the quality of institutions in this group, consisting particularly of Latin American, Eastern European and Central Asian countries. Furthermore, the theoretically predicted disequalising impact of FDI inflows is revealed for the two subgroups of the developing cluster we consider, that is LLM-income and Latin American countries. Government redistribution via public health spending is significantly less effective in high- and low-income countries, respectively, than it is in middle-income countries. Social protection spending is regressive in all compositions of the developing cluster, which, following the discussion in Huber et al. (2006), is presumably due to the relative importance of social security benefits.

Mostly, our results are robust to changing the underlying sources of income Ginis, but looking at different segments of the income distribution reveals heterogeneous effects which are masked by composite indices. In accordance with the recent literature, we find movements at the top to be relevant for explaining income inequality dynamics in high-income countries and so are the major factors that contribute to this trend, such as labour income shares and imports from high-income countries. In developing economies, income inequality trends are more mixed, with inequality at the top being relevant in the Middle East and North Africa, while the relative position of the 1st decile is the decisive factor in the other countries of the sample.

Within the broad set of determinants, we have been particularly interested in the relation between education and inequality. Thus, we have done the following: 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 that higher education levels significantly reduce income inequality in high-income countries. Our results suggest that increasing tertiary educational attainment countervails the adverse distributional consequences of technological change and globalisation in high-income countries. However, tertiary education expansion also increases the income share of the top 5%, indicating a shift towards a steeper segment of the wage function (Bourguignon et al., 2005). The relevant factor in developing economies is equality in the education distribution, while increasing attainment at the primary as well as the tertiary levels increases income inequality. Beyond that, the finding that public education spending is significantly regressive in both world regions is in line with recent evidence from Pritchett and Sandefur (2020) and Pritchett and Viarengo (2021), suggesting that education inequalities which result from quality differentials affect the distribution of returns on education and income inequality. Our findings point to the complexity of the education–inequality relationship. The interaction between education policy, the distribution of the quantity and quality of education and income inequality thus merits further research.

Our results suggest that an analysis of income inequality should transcend explanations based on the market forces of supply and demand, which rely on productivity differentials between factors of production and across workers with different skills, and acknowledge the contextual variability across world regions and the relevance of power relations, political factors and institutional settings for income inequality levels and trends. However, a detailed analysis of these factors goes beyond the scope of this article and is restricted by its methodological approach. 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 variables and various sets of determinants as independent variables. However, some measures might not capture the intended mechanisms adequately, for example, TFP, or might have been omitted entirely, for example, migration flows, labour 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 it is not possible to infer causal effects. Nevertheless, our results show correlations which reveal new insights which should inform further theoretical reasoning as well as empirical investigation at the country level and based on different more refined regional splittings.

NOTES

1. For a short survey and empirical evidence on the relative importance of these mechanisms, see Meschi and Vivarelli (2009).

2. Rajan (2010) and Kumhof and Rancière (2010) argue that American low- and middle-income earners tried to keep up with the top by expanding private debt, which fuelled the 2007/2008 financial crisis. Van Treeck and 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.

3. See Palley (2007) for a survey of the underlying mechanisms and Amable et al. (2005) for a theoretical model on the interactions among finance, industrial bargaining and the functional income distribution.

4. See, for example, Palma (2014), Chakravorty (2006), Angeles (2007) and Huber et al. (2006).

5. Even though they find union density to exert a significant equalising impact on disposable income inequality, the effect of increasing the minimum wage is positive.

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

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

8. See Appendix for the classification of countries in our estimation sample. For more information, see https://datahelpdesk.worldbank.org/knowledgebase/papers/906519-world-bank-country-and-lendinggroups (16 August 2017).

9. The majority of WID measures is based on fiscal data.

10. The data, a user guide and detailed country documentation can be obtained from https://www.wider.unu.edu/database/world-income-inequality-database-wiid34.

11. Social and economic database for Latin American countries.

12. Luxembourg Income Study (LIS) or European Survey of Income and Living Conditions (EUSILC) for the countries in our sample.

13. The multi-source Gini trends for EAP and ECA, and the single-source Gini trends for LAC and SA would be significant at the 10% level.

14. Since the IIASA/VID dataset includes individuals who, in each of the four broad categories of educational attainment, 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 Samir et al. (2010) in order to account for uncompleted attainment levels when computing the mean duration of each education level.

15. Morrisson and 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 behavioural. 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.

16. Thanks to the extensive documentation along with PWT 8.0, we were able to access the stata do file for the calculation of their TFP measure; we adjusted this code in order to include the IIASA/VID education data.

17. Education spending includes public spending at each education level and for subsidiary services. Health spending includes spending on medical products and equipment, outpatient, hospital and public health services. Social protection spending includes social assistance transfers, benefits due to sickness, disability, old age as well as for survivors, families, housing and unemployment.

18. This test is discussed and analysed in Drukker (2003) and implemented in STATA using the command xtserial.
19. In particular, we implement Feasible generalized least squares (FGLS) using xtgls with the options corr(ar1) and panel(hetero).
20. In the following, we use the terms 'inequality' and '(dis)equalising' interchangeably to refer to (changes in) the multi-source Gini, if not otherwise stated.
21. In a specification that includes ICT together with total capital, we find this relation to be driven by a negative impact of the latter.
22. These results are available from the authors upon request.
23. Private debt is only relevant in the reduced sample of nine countries in Column 6 of Table 5. An interesting aspect to note is that this group predominantly consists of liberal welfare states (USA, Canada, UK, Ireland, Australia, New Zealand, Japan, Chile) where private debt substantially increased in the years before the financial crises.
24. Changes for other variables as public spending on social protection and health are relatively small and hard to interpret as they happen only at the 10% significance level.
25. Croatia, Cyprus, Latvia, Lithuania, Russia and Venezuela.
26. Disposable monetary income does not account for imputed rents and home production.

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APPENDIX

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. At this stage, we only use income concepts which cover a time span of at least 10 years with a minimum of three 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* (SS) 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.

Estimation Sample

This Appendix lists all 73 countries included in the most parsimonious specification (see Column 1 of Tables 4–6). *B* indicates that they are also included in our main model. *S*, *D* and *T* indicate that they are included in the estimation samples using the SS Gini, decile ratios and the top 5% income share, respectively.

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

Low- and Lower-middle-income Countries

This Appendix lists the countries in our sample are categorised as low- and lower-middle-income countries.

East Asia and Pacific	Indonesia, Philippines^{BSD}
Europe and Central Asia	Georgia^{BSD}, Kyrgyz Republic^{BSD}, Moldova^{BS}, Ukraine^{BSD}
Latin America and Caribbean	Bolivia^{BSD}, Guatemala
Middle East and North Africa	Egypt, Morocco^{BSD}
South Asia	India^{BS}, Sri Lanka^{BSD}
Sub-Saharan Africa	Nigeria, Swaziland

Robustness: Method and Functional Form

Columns 1 and 2 of Table A1 show the results for two- and five-year lags to address further concerns of endogeneity. Reverse causation can apply to trade and private debt, which may be 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 concerned variables, respectively. Our main results regarding imports, exports and the education Gini coefficient are not affected. However, 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 likely more suitable, approach is to include dummy variable for each year. Column 3 of Table A1 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 fixed effects (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 more accurate estimates.

Table A1. 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)
FDI^{in}	−0.006***	−0.005**	−0.004***	−0.005**
	(0.002)	(0.002)	(0.002)	(0.002)
FDI^{out}	0.008**	0.007**	0.010***	0.011***
	(0.004)	(0.003)	(0.002)	(0.004)
EducGini_{15+}	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)
$\text{PS}_{\text{Health}}$	−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)
Observations	627	570	645	653
N	61	61	64	72

Note: Standard errors (SEs) in parentheses.
$^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.