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# Managing the impact of globalization and technology on inequality

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## ABSTRACT

This article tests the relative importance of globalization and technological change in explaining income inequality at higher and lower development levels. Besides, the article analyses the effectiveness of a set of policy measures for fighting inequality. We use relative pre-tax income shares as a proxy for inequality. Several linear and non-linear threshold panel data models with GDP per capita as the threshold variable are estimated for 42 countries over the period from 1994 to 2016. We find that technology is the most important generator of inequality, while the effect of various globalization measures is weak and often insignificant. We find limited evidence that the effect of globalization differs with respect to the level of GDP per capita. Our results suggest that full employment policies in the low inflation environment are the most efficient solution for the inequality problem. Higher employment and low inflation rate decrease the inequality level. Other than that, we do not find other policy measures that satisfy the one-size-fits-all criteria for tackling inequality. Instead, a set of efficient policy measures against inequality, including expenditures on education, minimum wage policies, and lending rates, depend on the development level and idiosyncratic policies and institutions.

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## 1 Introduction

This article investigates the effects of technological progress and globalization on pre-tax income inequality. Besides, we analyse the effectiveness of a set of policy measures intended for fighting inequality. The article contributes to the literature by differentiating inequality responses at higher and lower levels of development and investigates whether factors that can explain income shares' patterns differ depending on the level of economic development. The focus is on the differences in the inequality response to technology changes, trade and financial openness, and various policy variables. Following Cobham and Sumner (2013), we use the ratio of income shares of the top 10 percent *vis-à-vis* the bottom half of the population as a measure of inequality and

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employ a number of different control variables to capture different policy strategies that countries may have implemented during the globalization process.

Income inequality has increased since the 1970s, as shown by Piketty and Saez (2003, 2014). It called into question a simple model of inverted U-shaped inequality pattern proposed by Kuznets (1955), which suggests that inequality will decrease with higher development levels. Raising inequality poses an important economic and social problem. High inequality of opportunities has deteriorating effects on GDP growth. It will reduce human capital through a negative effect on the educational and occupational choices of individuals, which will lead to lower growth in the long-run. In the short-run, inequality reduces growth through lower aggregate demand, as middle- and lower-income groups spend higher shares of their incomes than the rich. Finally, inequality will slow down social mobility when the children tend to stay in the same income group as their parents (Dabla-Norris et al., 2015).

An increase in inequality observed since the 1970s coincides with the period of intense globalization and technological progress. In recent decades, inequality increased in nearly all countries, but its speed depends on the institutions and economic policy (Alvaredo et al., 2018). However, it is unclear what are the main drivers of such an increase in inequality and which economic policies can be used to prevent it. Extensive studies on inequality often provide mixed results (Goldberg & Pavcnik, 2007). Not only that inequality is determined by different channels, but main channels also differ with the development level. Globalization and international trade, according to the Stolper–Samuelson theorem, will reduce inequality in developing countries by reducing the skill premium, while the opposite will be present in the case of developed countries. Galor and Moav (2004) show that higher inequality will actually increase GDP growth at lower development levels through higher capital accumulation. On the other hand, at higher levels of development, inequality will reduce GDP growth because of unequal opportunity for human capital formation. The theoretical models allow for different outcomes, and it is an empirical question to determine the main drivers of inequality and the effects of different policy measures.

To address all these theoretical and empirical issues, we employ a multi-step methodological approach. First, we start with linear models to examine the determinants of income inequality on the entire sample of countries, regardless of their level of economic development. Specifically, we aim to examine the effects of globalization and technological change on inequality. In the second step, we estimate multiple non-linear models to test our hypothesis that inequality might be differently affected by globalization and technology, depending on the level of development. We thus employ the threshold dynamic two-way fixed effect model to investigate the relative importance of technology and globalization in different groups of countries, depending on their GDP per capita level, i.e., we account for possible differences in the inequality generation process at lower and higher levels of development.

We use GDP per capita as the threshold variable, trade, and financial openness as *de facto* measures of globalization, Freedom to trade internationally index as *de jure* measure of globalization, and total factor productivity (TFP) as a measure of technological change. A wide range of control variables are included as proxies for different

distributional policies and/or alternative measures of globalization (net factor income) or technological change (export of information and communication technology (ICT) goods). The effect of globalization on inequality is often under the influence of various observable factors, including country- and time-specific, such as trade protection before liberalization, the flexibility of domestic markets, or capital and labour mobility. To deal with such problems, we employ a panel data model of international data with time and country fixed effects. To test the robustness of our results and to account for the fact that there are many different ways to measure income inequality in the literature, we use both the ratio of top 10% (90–100 percentiles of income distribution) to bottom 50% income share (1–50 percentiles) and top 10% to middle 40% income share (50–90 percentiles).

Our results suggest that the technological change measured by total factor productivity is the major determinant that increases inequality, both at lower and higher development levels. Globalization has a small and limited effect on inequality. We find some evidence that globalization measured by net factor income from abroad may decrease the inequality between the top and middle-income groups at the lower level of development, while we do not find such an effect at higher development levels. This provides a contribution to the existing literature. Specifically, it highlights the importance of the *skill-based technological change* hypothesis (Berman et al., 1994, 1998; Goldberg & Pavcnik, 2007) in explaining the inequality dynamics.

When it comes to policy measures aimed at decreasing pre-tax inequality, the share of employment in the adult population robustly decreases inequality, while the inflation rate tends to increase it. Contrary to conventional wisdom, the estimated coefficient next to the inflation rate is positive, implying that the quality of institutions could have an influence on inequality. It should be highlighted that we use pre-tax income shares as a measure of inequality. Therefore, we do not explore the role of taxation in income redistribution.

Our results regarding economic policy variables reveal uncertainty regarding the proper policy response to inequality and suggest against a one-size-fits-all policy approach. The minimum wage policy proves to reduce inequality between the top and the bottom of the income distribution, but it does not affect the middle-class inequality. Government expenditure on education and lending rates impact inequality, but their effects are not robust across different development levels. Results suggest that a set of policy measures aimed at decreasing inequality depends on the development level and country-specific policies and institutions.

The remainder of the article is organized as follows. Section 2 brings the literature review on the determinants of income inequality, while section 3 provides an overview of the data and discusses the methodology. In Section 4 we present the empirical results and robustness checks, while Section 5 concludes the article.

## 2 Literature review

The interest in analysing income inequality has increased substantially since Piketty's work, which showed an increasing pattern of inequality in the United States and other developed countries after the 1970s (Piketty & Saez, 2003, 2014). This work

differs from Kuznets (1955), who argued that inequality could be described by an inverse-U pattern with increasing inequality at lower levels of development, but as the economy becomes more developed, inequality decreases. Koh et al. (2020) find that growth and financial depth have an inequality-widening effect in China and tend to increase inequality in the long run. From the perspective of Kuznets' inverted-U hypothesis, the results suggest that China is still on the upward part of the Kuznets' curve, but the authors are not looking for a tipping point. Unlike Kuznets (1955), Piketty and Saez (2003, 2014) argue that inequality is not a deterministic process. They do not explain the reasons behind an upsurge in inequality after the 1970s; however, it overlaps with the globalization process and technological progress, and this article provides a deeper analysis of the issue.

As we will show in the next two subsections, the literature has recognized the importance of both globalization and technological progress as important determinants of inequality (see, e.g., Acemoglu, 1998; Berman et al., 1998; Gozgor & Ranjan, 2017; Kharlamova et al., 2018; Stiglitz, 2018; Wang, 2019). Also, theoretical models differentiate between developing and developed countries as mechanisms through which these determinants may work differ with the level of development. More importantly, from the policy perspective, it is of great interest to recognize efficient policy measures from others less efficient. This article combines these different strains of the literature in comprehensive panel data models.

### ***2.1. Inequality, globalization, and skilled biased technological change***

One of the problems of increasing inequality is that some economic agents cannot fully exploit the opportunities created by technological progress and globalization, which leads to sub-optimal use of capital and labour. This, in turn, limits economic growth. Stiglitz (2018) highlighted the fact that the rise of inequality is the function of redistribution policies employed in the country, as well as of economic openness. He argues that there are negative effects of globalization on blue-collar workers' wages, their jobs, and bargaining power. However, globalization is not the only factor affecting blue-collar workers' wages, as technological progress can be skill-biased. Skill biased technological change (SBTC) represents a shift in production technology that favours more skilled and/or educated people and increases their relative productivity and wages, thus leading to higher inequality.

According to theory, technological change can be the major driver of changes in inequality. In the mainstream growth models, technological change is usually considered as factor-neutral. However, a rapid rise in the relative wage of skilled workers, followed by an upward trend in their relative supply implies that technological change has been skill-biased (Acemoglu, 1998; Berman et al., 1998). The development of information and communication technologies enabled routine tasks to be substituted by technology and/or outsourced offshore. Such routine tasks were previously done by middle-skill workers, but the demand for such skills declined substantially. The SBTC increased the demand for highly educated workers working on abstract tasks, reduced demand for middle-educated workers working on routine tasks, and had no effect on low educated workers engaged in manual tasks that cannot be replaced by

computers (Autor et al., 2003). Such a shift in demand on the labour market led to higher inequality in the upper-tail of the distribution by increasing incomes of highly educated workers and decreasing or stagnating incomes of middle-educated workers, mostly high school graduates.

Card and DiNardo (2002) argue that technology cannot be the only explanation for the increase in inequality and show the evidence of labour market policies in the US that can be closely related to an upward trend in inequality. The empirical evidence from the US and Western Europe has also shown that SBTC leads to a change in employment structure or job polarization. Shares of high-paid professionals and managers as well as low-paid service workers are increasing, while on the other hand shares of manufacturing and office workers are decreasing (Acemoglu & Autor, 2011; Goos et al., 2014).<sup>1</sup> Job polarization is shown for the new EU member states as well; for example, in Poland (Arendt & Grabowski, 2019), where relative wages differ with respect to sectors, industries, and even regions. The process of polarization also depends on the business cycle phase. Technological progress can take many different forms, and in this article, we measure it by the total factor productivity (TFP), which is supposed to encompass most of them. Besides, the data on TFP is readily available for many countries.

The divergence of relative wages between skilled and unskilled labour force can also be explained by the process of globalization and trade openness. In the process of globalization, production shifts from developed to developing countries. According to the Stolper–Samuelson theorem, it will decrease inequality in developing countries by increasing the wages of the low-skilled workers and reducing the skill premium. The opposite effect is present in developed countries, leading to higher inequality. Earlier research by Feenstra and Hanson (1996) showed that globalization increases the wages of non-production highly skilled workers through the outsourcing of low-skilled labour. Production activities that require low skill levels are outsourced to countries with lower wages, while the domestic labour market demands more highly skilled workers. International trade has a certain trade-off between lower wages of low-skilled workers and lower domestic prices. This conclusion is also confirmed by Goldberg and Pavcnik (2007). Changes in the skill premium between skilled and unskilled workers can also be explained by technological progress, meaning that the effects of globalization have to be measured together with the technological advances. In terms of the threshold model applied in this article, the Stolper–Samuelson theorem would be confirmed when we would see that globalization decreases inequality in the regime below the estimated level of GDP per capita, while the opposite should be the case in the regime above the threshold level of GDP per capita. As we show later on, that is not the case.

Inequality can also be affected by the level of development. In their theoretical model, Galor and Moav (2004) show that the effect of inequality depends on the development level. According to them, in the early stage, inequality is positively correlated with economic growth. Physical capital formation is more important than human capital formation, and inequality is beneficial for economic growth because it concentrates resources on individuals with a higher marginal propensity to save, thus increasing capital formation. This approach is typical in explaining the positive

correlation of inequality with respect to physical capital accumulation at low levels of development. In the later stage of economic development, the marginal product of human capital increases, and human capital becomes a primary source of economic growth. Unlike physical capital, human capital accumulation is greater when it is widely distributed in the economy. In that regard, inequality is negatively correlated with the level of economic development. Galor and Moav (2004) theoretical model has been empirically verified by Chambers and Krause (2010) and Benos and Karagiannis (2018). In our empirical model, we use GDP per capita as a threshold variable to differentiate between development levels.

Empirical tests of inequality-inducing theories are mixed at best. The Stolper–Samuelson theorem is empirically challenged by the evidence of increasing inequality in developing countries, as shown in Goldberg and Pavcnik (2007). They review a vast literature on the effects of globalization on inequality in developing countries and conclude there is a growing skill-premium which is in conflict with the Stolper–Samuelson theorem.

Jaumotte et al. (2013) analysed the effects of financial and trade openness on inequality using data for 51 countries. Results indicate that trade openness reduces inequality, while financial openness, especially FDI, tends to increase it. However, they note that globalization, measured as financial and trade openness, has a moderate effect on inequality in comparison to technological progress. Technological progress and FDI increase inequality through higher returns on capital and higher incomes of skilled workers, but they do not limit economic opportunities. Real incomes of all income groups have increased, including the poorest ones, but the highest increase is present in the richest group leading to higher inequality.

We have formulated our empirical approach with the theoretical framework that is mostly defined by the skilled-biased technological change (SBTC) hypothesis (Berman et al., 1994, 1998), and the Stolper–Samuelson theorem (Goldberg & Pavcnik, 2007). We also include a range of policy variables that could affect inequality.

## **2.2. The role of economic policy**

Redistribution policies can decrease inequality and keep it under control. Gozgor and Ranjan (2017) develop a simple theoretical model with one sector, and the labour input divided into skilled and unskilled workers. The model captures globalization as a decrease in the price of the imported input. The model shows that globalization increases inequality if the imported inputs can be easily substituted for unskilled labour and are complementary to skilled labour. According to the model, policy-makers redistribute more as a response to higher inequality caused by globalization. Gozgor and Ranjan (2017) test their model empirically using the Gini index as a measure of inequality and the difference between pre-tax and post-tax Gini index as a measure of redistribution. The results show that inequality indeed increases with globalization. However, the redistribution increases as well, confirming the projections of the theoretical model. It suggests that the governments' redistribution policies have mitigated the negative impact of globalization on inequality. Their empirical model proved to be robust; however, it does not take into account technological

progress in any form, therefore excluding SBTC as a potential channel to explain an increasing inequality. Public infrastructure also plays a role in wage inequality. Theoretical models show that an inflow of unskilled workers will have an effect on wage inequality, conditional on the production elasticity of the public intermediate good in the skill using sector. If the production elasticity is small enough, the inflow of unskilled workers will decrease wage inequality. On the other hand, the inflow of skilled workers will decrease wage inequality unconditionally (Wang, 2019). These findings provide inputs for sound migration policies, where countries can plan on the inflow of skilled versus unskilled workers.

Previous literature has looked into the correlations between globalization and inequality, depending on the level of political, financial and economic risk. Lee et al. (2020) found that income distribution can be worsened by the globalization, especially if countries suffer from economic and financial instability (high risk). They also found that the inequality effects of globalization are generally stronger in less developed countries. Huh and Park (2021) offered evidence that globalization may worsen income inequality despite its positive effect on economic growth, however in high-income countries this is much less pronounced than in countries on lower levels of development. Other researchers have focused on the heterogeneity of results in cross-country studies of inequality and presented evidence that this can be explained by the use of different measures of institutional quality, financial liberalization, income inequality, and econometric methods (Ni & Liu, 2019).

A range of policy measures can be used to reduce income inequality. Dabla-Norris et al. (2015) state that the labour market, redistribution, and education policies can reduce inequality if used properly. Labour market policies such as minimum wages, unionization, and/or social security system reduce income inequality and improve the distribution.<sup>2</sup> Redistribution policies such as progressive taxes and social transfers can reduce inequality as well (Alvaredo et al., 2018). Indeed, Gozgor and Ranjan (2017) show that higher inequality is typically followed by stronger redistribution policies by the governments, and Dabla-Norris et al. (2015) show that redistribution policies reduce income inequality, even though tax systems are less progressive in some advanced economies, such as the US. The income share of the global middle-class has reduced in the past 30 years, and it has been crowded out by both the rich and the poor. They have increased their incomes, which has been shown on the famous elephant chart by Lakner and Milanovic (2016) and Alvaredo et al. (2018). Projections by Alvaredo et al. (2018) up to the year 2050 suggest that the middle class will be further crowded out if no actions are taken. On the other hand, if a moderate inequality trajectory of Europe is followed on a global level, inequality will be reduced, the middle class will be preserved, and it will also have positive effects on global poverty. Education is a traditional factor that has typically been considered to reduce inequality since seminal papers by Mincer (1958) and Becker and Chiswick (1966). However, its effect in empirical studies is often unclear due to the imprecise measurement. A typical measure of education is (mean) years of schooling, while its effect on inequality depends on the size of education investments and the rate of return on these investments (Dabla-Norris et al., 2015). Policy measures intended for inequality reduction should be carefully tailored, as there is no one-size-fits-all measure. Dabla-



Norris et al. (2015) report that the effects of policy measures depend on the level of development, while Alvaredo et al. (2018) stress that inequality levels are very different even between countries at the same level of development.

Our empirical models include up to five policy variables to analyse the suitability of different economic policies to fight inequality. We consider government expenditures aimed at human capital formation (health and education), minimum wage as the labour market policy, the rule of law measures, and lending rate to take into account the redistribution effects between lenders and debtors. Instead of a one-size-fits-all economic policy, we consider different strategies against inequality.

### 3. Data and methodology

To analyse the effects of globalization and technological progress on inequality, we first consider the following linear dynamic panel data model estimated by fixed effects (within estimator):

$$y_{i,t} = \alpha_i + \gamma_t + \rho y_{i,t-1} + \beta tfp_{i,t} + \delta'_1 O_{i,t} + \delta'_2 X_{i,t} + e_{i,t}. \quad (1)$$

where  $y_{i,t}$  is the measure of inequality in country  $i$  in year  $t$ , expressed as the ratio of top 10% vs. bottom 50% income share ( $t10b50_{i,t}$ ) or top 10% vs. middle 40% ( $t10m40_{i,t}$ ). Bottom 50% refers to the share of national income between 1st and 50th percentile and middle 40% is the share of national income between 50th and 90th percentile of the pre-tax income distribution.<sup>3</sup>

The key explanatory variables are total factor productivity,  $tfp_{it}$ , as a measure of technological change, and the vector of variables that measure openness,  $O_{it}$ , as a proxy for the level of globalization exposure, respectively. The vector of control variables is given by  $X_{i,t}$ .  $\alpha_i$  and  $\gamma_t$  capture cross-sectional and time fixed effects, respectively.

The same model from equation (1) is estimated by the Arellano and Bond (1991) First Difference GMM (FD-GMM) estimator, and the results are qualitatively similar. However, given the structure of our dataset with a medium-sized  $N$  and a big  $T$  and the size of the model with up to 18 control variables, the model suffers from over-identification. Therefore, the article reports the results of the Fixed Effects model, which is biased but consistent when  $T$  is big, as in our case. The results of the FD-GMM model are available upon request.<sup>4</sup>

To address the differences between higher and lower levels of development, we estimate the following form of a two-way dynamic fixed effect panel threshold model (within estimator) based on equation (1):

$$y_{i,t} = \alpha_i + \gamma_t + \begin{cases} \rho_1 y_{i,t-1} + \beta_{11} tfp_{i,t} + \delta'_{11} O_{i,t} + \delta'_{12} X_{i,t} + e_{1i,t} & \text{if } q_{i,t-d} \leq \theta \\ \rho_2 y_{i,t-1} + \beta_{21} tfp_{i,t} + \delta'_{21} O_{i,t} + \delta'_{22} X_{i,t} + e_{2i,t} & \text{if } q_{i,t-d} > \theta. \end{cases} \quad (2)$$

The threshold variable  $q_{it-d}$  is GDP per capita ( $GDPpc_{i,t}$ ), defined as the natural logarithm of the gross domestic product in constant 2010 US dollars divided by mid-year population and obtained from the World Bank, while  $d$  is the delay parameter. We use  $d=2$  to address the problem with the endogeneity of the threshold variable.

The threshold value ( $\theta$ ) is determined endogenously using a grid search and minimizing the root mean square error (RMSE).<sup>5</sup>

In both models, the ratio of top 10% vs. the middle 40% ( $t10m40_{i,t}$ ) measures the inequality with the emphasis on the middle class. The ratio of top 10% vs. the bottom 50% is a more conventional inequality measure, focusing on the difference between the top and the bottom of the distribution.

Technological change,  $tfp_{i,t}$ , is measured by the index of total factor productivity at constant national prices. Earnings inequality in the US increased between 1963 and 2005, as shown by Autor et al. (2008). A shift in supply and demand for skills on the labour market can be explained by skilled-biased technological change (SBTC) related to ICT technology and the introduction of office computers and the Internet (see also Berman et al. (1994) for the US case and Berman et al. (1998) for international evidence).

Globalization itself is difficult to measure. It includes the mobility of goods and services, physical and financial capital, people, and ideas. Globalization is also characterized by trade and financial account liberalization, international capital flows and investment, increased exposure to foreign shocks, and exchange rate volatility. Goldberg and Pavcnik (2007) use the following indicators of globalization: trade openness and tariff reduction, international capital flows in the form of FDI, and exchange rate shocks.

We measure both *de facto* trade and financial openness of economies in the sample as well as *de jure* openness. The vector that controls for globalization,  $O_{it}$ , has up to four variables: (i) trade openness ( $open_{i,t}$ ) is measured as a sum of exports and imports of goods and services in percent of GDP, (ii) net financial account from the balance of payments in percent of GDP ( $finopen_{i,t}$ ), (iii) net factor income from abroad in percent of GDP ( $NFI_{i,t}$ ) and (iv) *de jure* openness measured using the Freedom to Trade Internationally index ( $FreeTrade_{i,t}$ ). Therefore, we consider the multidimensional nature of globalization, but our focus is on economic globalization. A similar approach is taken to construct the KOF index of globalization, which consists of eight variables.<sup>6</sup> Gozgor and Ranjan (2017) analysed the effects of globalization on inequality using both the KOF index and trade openness (share of import and export in GDP). The results of both measures are qualitatively similar.

The vector of control variables,  $X_{i,t}$ , consists of the following explanatory variables. GDP growth rate ( $growth_{i,t}$ ) to account for the effects that growth-inducing policies have on income distribution. Employment to population ratio ( $Employment_{i,t}$ ) to account for the cyclical behaviour of the bargaining power of labour share of GDP. Inflation rate ( $infl_{i,t}$ ) measured by the GDP deflator to proxy for the quality of institutions, as well as the real interest rate component. Human capital, ( $hc_{i,t}$ ), is used to capture the effect of education on inequality as well. The share of the rural population ( $ruralpop_{i,t}$ ) is used to capture the effect of urbanization on income distribution. The share of value-added in manufacturing ( $manfctr_{i,t}$ ) is used to control for the deindustrialization and the 'outsourcing' effect on inequality. Government expenditure on health ( $Ghealth_{i,t}$ ) and education ( $Geduc_{i,t}$ ) are to control for distributive effects of the public sector, which is dominant in most economies. The Legal System and Property Rights index ( $FreeLegal_{i,t}$ ), as a component of the Freedom index, is

**Table 1.** Variables used in estimated models.

Variable name	Description	Source
t10b50	Ratio of top 10% (90th–100th percentile) and bottom 50% (1st–50th percentile) in income share	WID
t10m40	Ratio of top 10% (90th–100th percentile) and middle 40% (50th–90th percentile) in income share	WID
tfp	Total factor productivity at constant national prices (2011 = 1)	Penn World Table 9.1
GDPpc	GDP per capita (natural logarithm of GDP in constant 2010 US dollars divided by midyear population)	World Bank
open	Trade openness (sum of exports and imports of goods and services in % of GDP)	World Bank
finopen	Financial openness (net financial account in % of GDP)	World Bank
NFI	Net factor income from abroad in % of GDP	World Bank
FreeTrade	Freedom to Trade Internationally index	Fraser Institute
growth	GDP growth rate	World Bank
employment	Employment to population ratio	World Bank
infl	Inflation rate (GDP deflator)	World Bank
hc	Human capital index	Penn World Table 9.1
ruralpop	Share of rural in % of total population	World Bank
manfctr	Share of value added in manufacturing, in % of GDP	World Bank
Ghealth	Government expenditure on health in % of GDP	World Bank
Geduc	Government expenditure on education in % of GDP	World Bank
FreeLegal	Legal System and Property Rights index	Fraser Institute
Lendrate	Lending interest rate	World Bank
ICT	ICT goods exports in % of total goods exports	World Bank
mwage	Statutory gross monthly minimum wage in US dollars (converted using exchange rates and 2017 PPPs)	ILO

Source: authors' calculations.

used to control for the effects of the rule of law on inequality. Lending rate ( $Lendrate_{i,t}$ ) is used to control for the redistribution effects between net lenders and debtors. The share of exported ICT goods in total export ( $ICT_{i,t}$ ) is used to control for the automation effects on the labour market, and minimum wage ( $mwage_{i,t}$ ) to investigate the effects of minimum wage policies on income distribution. Having in mind that our dependent variables are pre-tax national incomes, we do not control for the effect of taxes on income distribution.

Inequality data are from the World Inequality Database, total factor productivity and human capital data are from the Penn World Table 9.1, minimum wage data are from the ILO database, the index measuring the legal system and property rights and the Freedom to Trade Internationally index are from the Fraser Institute. GDP growth rate, trade openness, financial openness, net factor income, employment to adult population ratio, inflation rate, the share of the rural population, the share of manufacturing, government expenditure on health and education, lending rate, and share of ICT export in total export are from the World Bank. Details on variable description and data sources are presented in Table 1.

Depending on the model specification, we estimate our models during the 1994–2016 time period with 16 to 42 cross-sections. Although we have between 1622 and 8664 observations per variable (see Table 2), it is important to have in mind that panel estimators will only use observations that are available for each variable in each country in a given time period.

World Inequality Database has between 1625 and 1661 observations for 51 countries on pre-tax income (20+ adult populations, equal split between spouses). Nevertheless, the number of observations in the estimated models is even smaller

**Table 2.** Descriptive statistics.

		Mean	Std. Dev.	Min	Max	N/n/T – bar
t10b50	overall	2.127578	2.125328	.2935455	15.50499	1622
	between	.	2.237694	.661193	12.09514	51
	within	.	.5209085	-.7930256	5.537426	31.80392
t10m40	overall	.8913048	.4769726	.3022745	3.276733	1622
	between	.	.5031696	.4949912	2.346859	51
	within	.	.1275874	.3996976	1.821179	31.80392
tfp	overall	1.004594	.3586246	.2890339	7.107444	5435
	between	.	.2381635	.6673017	2.005242	106
	within	.	.2736157	-.0877144	6.106796	51.27358
growth	overall	.0190972	.0597415	-1.049717	.8018594	6869
	between	.	.0162068	-.0216974	.0902649	147
	within	.	.0578025	-1.057576	.831119	46.72789
NFI	overall	-.0214063	.2650826	-20.57895	.9976932	6603
	between	.	.0827809	-.7913226	.4554631	150
	within	.	.2533528	-19.80903	.7699162	44.02
employment	overall	57.92728	11.89497	30.601	88.994	4200
	between	.	11.65307	34.95979	84.91193	150
	within	.	2.563114	44.7376	69.69686	28
infl	overall	39.22684	481.5698	-98.70383	26765.86	6976
	between	.	96.14672	1.583083	713.4419	150
	within	.	471.1707	-677.052	26091.64	46.50667
hc	overall	2.050977	.7370055	1.007038	3.974208	7454
	between	.	.6833003	1.063435	3.522766	129
	within	.	.3533096	1.031159	3.789032	57.78295
ruralpop	overall	51.34667	24.1451	0	97.923	8664
	between	.	22.58206	0	93.67483	150
	within	.	8.657285	16.99836	94.79018	57.76
manfctr	overall	14.31378	7.082958	0	56.6507	5424
	between	.	6.66689	2.21763	45.48239	148
	within	.	3.594991	-1.111384	38.79686	36.64865
Geduc	overall	4.333344	1.873544	0	44.33398	3094
	between	.	1.568695	1.211527	10.31332	146
	within	.	1.183163	-4.146684	38.35401	21.19178
Ghealth	overall	128.729	103.2595	0	504.982	3581
	between	.	73.90071	6.070389	313.8441	149
	within	.	72.96099	-171.3999	370.6121	24.03356
FreeLegal	overall	5.086372	1.745265	.9337595	9.138119	2657
	between	.	1.543806	1.892605	8.423666	141
	within	.	.7075768	-.6048092	8.404012	18.84397
Lendrate	overall	59.40217	2172.892	.5	121906	3153
	between	.	391.4422	2.756744	4097.034	109
	within	.	2136.353	-4027.094	117868.3	28.92661
ICT	overall	3.369824	9.205465	.0025579	89.70885	1916
	between	.	8.268446	.0155589	61.3244	126
	within	.	2.981269	-31.01689	35.7823	15.20635
mwage	overall	1646.594	14367.43	.39	280154.8	1487
	between	.	12525.94	5.475	129316.3	106
	within	.	7158.229	-106504.5	152485.1	14.0283
open	overall	68.8531	45.9336	0	442.62	6774
	between	.	39.43264	13.34745	330.3475	148
	within	.	21.32111	-170.562	272.0581	45.77027
finopen	overall	-1.841227	10.98852	-340.3469	106.6386	4876
	between	.	5.672626	-34.88508	20.33268	144
	within	.	9.734824	-359.0224	108.1904	33.86111
FreeTrade	overall	6.721236	1.706019	0	10	2687
	between	.	1.207434	2.875292	9.46939	141
	within	.	1.207994	.0631205	11.94185	19.05674

Source: authors' calculations.

because we work with an unbalanced panel, and available observations do not overlap between variables, countries, and years in the database. For example, data for minimum wage is available on average for 14.02 years per country, while human capital data is available for 57.78 years per country on average (see Table 2). Due to these limitations, we have used three different datasets in each estimation. First, we used all available data to control for all mentioned effects. After that, we omitted the variables for ICT share and minimum wage to increase the number of observations in estimated models. In the end, we also omitted the variables for government expenditure on health, education, data on lending rates, and the rule of law index ( $FreeLegal_{i,t}$ ) to increase the number of countries and observations used in estimations.

Figure 1 presents the number of observations per country that are available for each of the three estimated threshold models. Depending on the vector of control variables, the number of countries goes from 16, in the estimation with full vector of control variables (Figure 1a), to 42 countries in the estimation with the smallest vector of control variables (Figure 1c). In terms of the total number of observations, models with the largest number of variables are estimated with 142 observations, while using the smallest vector of control variables increases the number of observations up to 628 in non-linear models and 832 in the linear model (Tables 4–7).<sup>7</sup>

Table 3 shows the correlation coefficients for all variables to check if there is a multicollinearity problem with independent variables. Except for dependent variables, we can find correlation coefficients that are above .6 in absolute terms only for openness and ICT share in export; the free trade index *vis-à-vis* human capital; share of the rural population and the Legal System and Property Rights index; human capital *vis-à-vis* share of the rural population and government health expenditure; and government health expenditure *vis-à-vis* the Legal System and Property Rights index. Since the highest correlation coefficient is 0.8, but mostly it is much lower, we conclude that the panel data model does not suffer from multicollinearity problem.

Figure 2 represents the data within a selected group of six countries (out of 52 countries in total in our analysis). Figure 2a compares the movement of the *t10b50* ratio and TFP, while Figure 2b compares inequality with trade openness. These six countries are taken as an example to observe both some similarities and differences within the sample. As can be seen in Figure 2a, countries at the lower level of development have a mostly positive, while the USA and France have a negative correlation between inequality on the one hand and TFP and openness on the other. Having in mind the differences between countries over time, we have tried to include a wider number of control variables into our estimations and also to control for a potential non-linear relationship between different groups of countries by estimating the non-linear threshold model in the next section.

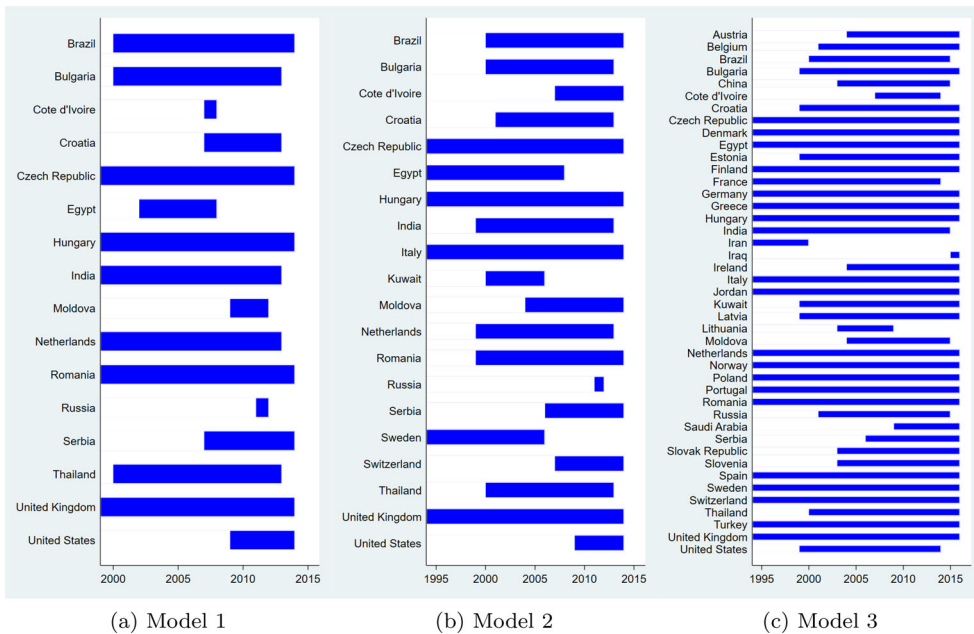
## 4 Results

We present the results of our analysis by following economic intuition in several steps. First, we acknowledge that the pre-tax income inequality within countries changes over time, even without the redistribution policies implemented by the policymakers. Second, we aim to test how much of these changes can be explained by the

**Table 3.** Correlation matrix.

	t10b50	t10m40	tfp	growth	open	finopen	FreeTrade	NFI	employment	infl	hc	ruralpop	manfctr	Geduc	Ghealth	FreeLegal	Lendrate	ICT	mwave	
t10b50	1.00																			
t10m40	0.94	1.00																		
tfp	0.03	0.06	1.00																	
growth	0.09	0.13	0.20	1.00																
open	-0.42	-0.47	-0.04	-0.07	1.00															
finopen	0.23	0.21	-0.11	-0.32	0.12	1.00														
FreeTr	-0.56	-0.65	-0.07	-0.25	0.29	-0.02	1.00													
NFD	0.00	-0.02	0.03	-0.02	-0.37	0.18	0.04	1.00												
empl	0.54	0.41	-0.20	-0.04	-0.01	0.40	0.10	-0.07	1.00											
infl	0.03	0.09	-0.07	0.37	-0.24	-0.28	-0.34	0.04	-0.14	1.00										
hc	-0.61	-0.72	-0.10	-0.28	0.30	-0.12	0.79	-0.01	-0.09	-0.32	1.00									
rural	0.25	0.29	0.13	0.27	-0.01	-0.06	-0.70	-0.03	-0.13	0.29	-0.62	1.00								
manuf	0.20	0.15	-0.03	0.23	0.43	0.09	-0.26	-0.56	0.27	0.10	-0.18	0.50	1.00							
Geduc	-0.01	-0.03	-0.02	-0.28	0.03	0.03	0.24	0.37	-0.00	-0.21	0.23	-0.36	-0.45	1.00						
Ghealth	-0.52	-0.60	-0.10	-0.19	0.18	-0.09	0.74	0.13	0.04	-0.20	0.66	-0.59	-0.25	0.28	1.00					
FreeLe	-0.31	-0.40	-0.07	-0.21	0.18	0.24	0.73	0.27	0.33	-0.38	0.55	-0.44	-0.27	0.31	0.62	1.00				
Lendrt	0.37	0.45	-0.16	0.12	-0.47	-0.07	-0.33	-0.06	0.02	0.57	-0.44	-0.08	-0.06	-0.05	-0.25	-0.48	1.00			
ICT	-0.13	-0.17	-0.11	-0.10	0.80	0.27	0.22	-0.43	0.21	-0.28	0.14	0.03	0.50	0.09	0.15	0.34	-0.36	1.00		
mwave	-0.24	-0.37	-0.06	-0.42	0.18	0.30	0.70	0.26	0.34	-0.47	0.61	-0.60	-0.42	0.43	0.57	0.83	-0.45	0.18	1.00	

Source: authors' calculations.



**Figure 1.** Time span of observations per country used in estimation in Tables 6 and 7 (a) Model 1, (b) Model 2, and (c) Model 3. Source: authors' calculations.

globalization and technological change processes. In other words, we aim to test if there is a secular trend in income inequality driven by these two variables that cannot be explained by active policy measures. Finally, we test what economic policy tools can be used to mitigate this trend of rising inequality and present the results of their potential effect on income inequality.

Results of the econometric analysis are organized in four tables. There is a table for each dependent variable in both the linear and non-linear model. Estimates for the ratio of top 10 deciles relative to the bottom half of population ( $t10b50_{i,t}$ ) as the dependent variable are presented in Table 4 for the linear model and in Table 6 for the non-linear model. On the other hand, estimates that employ the income ratio of top 10% of population vs. the middle 40% ( $t10m40_{i,t}$ ) are presented for linear models in Table 5 and for the threshold model in Table 7.

In total we present 12 estimated models for each dependent variable: nine linear (Tables 4 and 5) and three non-linear models (Tables 6 and 7). Due to the nature of the threshold models (two different regimes), we provide up to 15 estimated coefficients for variables that are present in these models. In each threshold model, there are coefficients for the regime above the threshold value and coefficients for the rest of the sample.

The main motivation for estimating as many as 24 models (12 for each dependent variable) is to check the robustness of results since the choice of independent variables changes the number of observations quite drastically. For example, an increase in the number of regressors from 12 to 17 reduces the number of observations from 628 to 142 and the number of countries from 42 to 15. It is thus important to investigate whether the results are driven by an internal economic mechanism of the inequality

**Table 4.** Top 10% vs bottom 50% – Fixed Effect linear model results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	t10b50	t10b50	t10b50	t10b50	t10b50	t10b50	t10b50	t10b50	t10b50
L.t10b50	0.794*** (17.65)	0.813*** (11.93)	0.763*** (10.99)	0.794*** (16.60)	0.813*** (12.76)	0.776*** (11.42)	0.881*** (19.91)	0.816*** (11.13)	0.763*** (11.34)
open	0.001 (1.52)	0.002 (1.56)	0.003*** (3.01)				0.001** (2.12)	0.002 (1.63)	0.003** (2.78)
finopen	-0.002 (-0.82)	0.002 (1.08)	-0.000 (-0.26)				0.000 (0.00)	0.002 (0.98)	-0.000 (-0.27)
FreeTrade	-0.014 (-0.57)	0.029 (0.86)	-0.004 (-0.08)	0.017 (0.55)	0.084** (2.83)	0.008 (0.17)			
tfp	0.757** (2.03)	0.293** (2.13)	0.406* (1.98)	0.756* (1.95)	0.238* (1.90)	0.466** (2.25)	0.244 (1.03)	0.318** (2.31)	0.405* (1.96)
growth	-0.495 (-0.66)	0.516 (1.67)	0.324 (0.86)	-0.227 (-0.34)	1.140** (2.11)	0.349 (1.12)	-0.081 (-0.26)	0.539* (1.81)	0.321 (0.90)
NFI	1.156** (2.38)	-0.295 (-0.55)	0.684 (0.81)	0.909*** (2.70)	0.008 (0.02)	0.250 (0.32)	0.649* (1.91)	-0.384 (-0.68)	0.681 (0.82)
employment	-0.011* (-2.02)	-0.011** (-2.62)	-0.015** (-2.33)	-0.009* (-1.81)	-0.011** (-2.79)	-0.011* (-1.79)	0.000 (0.04)	-0.010** (-2.40)	-0.015** (-2.36)
infl	0.005** (2.31)	0.007*** (3.71)	0.004 (1.56)	0.004* (1.80)	0.004 (1.68)	0.006* (1.97)	-0.001 (-0.64)	0.007*** (3.05)	0.005 (1.14)
hc	0.083 (0.57)	-0.065 (-0.50)	-0.067 (-0.34)	-0.075 (-0.50)	-0.216 (-1.52)	-0.113 (-0.62)	0.116 (1.06)	-0.022 (-0.15)	-0.067 (-0.34)
ruralpop	-0.001 (-0.21)	-0.000 (-0.03)	0.004 (0.47)	0.000 (0.05)	-0.002 (-0.30)	-0.001 (-0.19)	-0.006* (-1.69)	-0.000 (-0.04)	0.003 (0.46)
manfctr	0.006 (0.69)	0.003 (0.30)	0.007 (0.54)	0.005 (0.66)	-0.003 (-0.26)	0.010 (0.76)	0.006 (1.10)	0.006 (0.62)	0.007 (0.57)
Geduc		-0.035* (-1.85)	-0.016 (-0.61)		-0.031* (-1.74)	-0.032 (-1.43)		-0.039* (-2.06)	-0.016 (-0.62)
Ghealth		0.000 (0.61)	0.000 (1.00)		-0.000 (-0.67)	0.000 (0.48)		0.000 (0.75)	0.000 (0.93)
FreeLegal		-0.014 (-0.46)	0.030 (0.83)		-0.028 (-0.98)	0.015 (0.40)		-0.003 (-0.13)	0.029 (0.92)
Lendrate		0.001 (0.31)	0.005 (1.49)		0.004 (1.57)	0.004 (1.25)		0.001 (0.25)	0.005 (1.32)
ICT			-0.011 (-1.60)			-0.002 (-0.20)			-0.011 (-1.19)
mwage			-0.000* (-1.95)			-0.000 (-1.14)			-0.000** (-2.34)
_cons	-0.071 (-0.13)	0.488 (0.67)	0.302 (0.31)	0.088 (0.16)	0.940 (1.28)	0.582 (0.61)	-0.268 (-0.48)	0.417 (0.55)	0.290 (0.33)
N	628	194	142	659	205	142	832	194	142
N_g	42	19	15	42	20	15	42	19	15
rmse	0.186	0.081	0.088	0.183	0.086	0.089	0.209	0.081	0.088
r2	0.784	0.871	0.860	0.782	0.859	0.855	0.815	0.870	0.860
r2_a	0.773	0.846	0.819	0.772	0.836	0.815	0.807	0.846	0.821
hausman_p	0.000	0.001	0.000	0.000	0.000	0.028	0.000	0.026	0.000

Notes: Standard errors in parentheses, \*\*\*, \*\*, and \* mark statistical significance at 1%, 5%, and 10% level. Prefix 'L.' denotes a lagged variable.  $N$  is number of observation,  $N_g$  is number of countries and hausman p represents Hausman's test p-value.

Source: authors' calculations.

generation process, captured by the estimated model, or by the changes in the sample of countries, due to data availability.

Results for the linear estimations have six additional models to capture the effect of globalization proxies on inequality. Models 4–6 exclude trade and financial openness variables from the vector of control variables  $O_{i,t}$ , while models 7–9 exclude only  $FreeTrade_{i,t}$  from vector  $O_{i,t}$ . The number of observations and countries in models 4–6 and 7–9 are the same as in models 1–3, and the only difference is in the number of observations that climbs up to 832 in model 7.



**Table 5.** Top 10% vs middle 40% – Fixed Effect linear model results.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.t10m40	t10m40 0.816*** (10.46)	t10m40 0.840*** (9.45)	t10m40 0.716*** (5.81)	t10m40 0.816*** (10.51)	t10m40 0.858*** (10.30)	t10m40 0.725*** (6.03)	t10m40 0.883*** (13.18)	t10m40 0.842*** (8.91)	t10m40 0.719*** (6.01)
open	0.000 (0.40)	0.001 (1.29)	0.001 (1.16)				0.000 (1.26)	0.001 (1.33)	0.001 (0.98)
finopen	0.000 (0.10)	0.000 (0.35)	−0.000 (−0.53)				0.000 (0.76)	0.000 (0.34)	−0.000 (−0.50)
FreeTrade	−0.001 (−0.09)	0.005 (0.30)	−0.012 (−0.59)	0.003 (0.57)	0.012 (1.70)	−0.009 (−0.43)			
tfp	0.039* (1.92)	0.141* (2.08)	0.198** (2.37)	0.040* (1.94)	0.128** (2.43)	0.208** (2.55)	0.022 (1.25)	0.145** (2.29)	0.197** (2.30)
growth	0.091 (0.89)	0.246* (2.01)	0.209 (1.21)	0.098 (1.06)	0.339** (2.41)	0.227 (1.36)	0.109 (1.57)	0.250* (2.09)	0.201 (1.25)
NFI	0.211 (1.66)	0.037 (0.18)	0.366 (1.31)	0.193* (1.95)	0.058 (0.33)	0.206 (0.95)	0.061 (0.58)	0.021 (0.09)	0.359 (1.34)
employment	−0.003** (−2.54)	−0.003** (−2.33)	−0.007** (−2.52)	−0.002** (−2.65)	−0.003** (−2.56)	−0.006** (−2.17)	−0.001 (−1.06)	−0.003* (−2.07)	−0.007** (−2.59)
infl	0.001* (1.85)	0.002*** (3.15)	0.002 (1.39)	0.001* (1.77)	0.002** (2.27)	0.003 (1.61)	0.000 (1.40)	0.002** (2.43)	0.003 (1.24)
hc	−0.009 (−0.26)	0.016 (0.28)	0.063 (0.72)	−0.028 (−0.97)	−0.019 (−0.36)	0.053 (0.62)	−0.004 (−0.12)	0.022 (0.38)	0.060 (0.69)
ruralpop	0.001 (0.59)	0.002 (0.65)	0.005 (1.31)	0.001 (0.80)	0.001 (0.47)	0.004 (1.07)	−0.000 (−0.62)	0.002 (0.65)	0.005 (1.29)
manfctr	0.001 (0.51)	0.004 (0.74)	0.008 (1.07)	0.001 (0.68)	0.004 (0.86)	0.009 (1.21)	0.000 (0.23)	0.004 (0.98)	0.008 (1.06)
Geduc		−0.010 (−1.27)	−0.002 (−0.15)		−0.009* (−1.96)	−0.005 (−0.50)		−0.011 (−1.62)	−0.001 (−0.13)
Ghealth		0.000 (1.10)	0.000* (1.90)		0.000 (0.22)	0.000 (1.53)		0.000 (1.25)	0.000* (1.99)
FreeLegal		0.003 (0.26)	0.020 (1.34)		−0.000 (−0.02)	0.017 (1.10)		0.004 (0.59)	0.016 (1.13)
Lendrate		0.001 (1.16)	0.004* (2.05)		0.002* (1.95)	0.003* (1.87)		0.001 (1.13)	0.003* (1.82)
ICT			−0.005* (−2.03)			−0.003 (−1.27)			−0.004 (−1.14)
mwage			−0.000** (−2.95)			−0.000** (−2.59)			−0.000* (−2.00)
_cons	0.231 (1.39)	−0.133 (−0.49)	−0.227 (−0.57)	0.249 (1.58)	−0.032 (−0.12)	−0.176 (−0.45)	0.143 (1.02)	−0.144 (−0.53)	−0.264 (−0.64)
N	628	194	142	659	205	142	832	194	142
N_g	42	19	15	42	20	15	42	19	15
rmse	0.043	0.035	0.039	0.042	0.034	0.039	0.041	0.035	0.039
r2	0.731	0.838	0.840	0.731	0.834	0.838	0.811	0.838	0.839
r2_a	0.718	0.807	0.793	0.720	0.807	0.794	0.802	0.808	0.794
hausman_p	0.000	0.437	0.020	0.000	0.187	0.024	0.000	0.016	0.001

Notes: Standard errors in parentheses, \*\*\*, \*\*, and \* mark statistical significance at 1%, 5%, and 10% level. Prefix 'L.' denotes a lagged variable.  $N$  is number of observation,  $N_g$  is number of countries and hausman\_p represents Hausman's test p-value.

Source: authors' calculations.

Given that the number of countries in 24 estimated models fluctuates between 15 and 42, we interpret the results with caution. To make more general conclusions, we are looking for robust effects through the majority of estimated models. On the other hand, for the variables that have significant effects only in a smaller number of estimated models, we highlight that the identified effect might be group-specific and/or apply to a specific institutional or policy environment. Having that in mind, in [Figure 1](#) we provide names of countries and the number of observations per country used in each model.

**Table 6.** Top 10% vs bottom 50% – FE threshold model (GDP per capita as threshold variable).

	(1)		(2)		(3)	
	t10b50		t10b50		t10b50	
L.t10b50_1	0.523***	(4.17)	0.793***	(9.79)	0.844***	(13.27)
tfp_1	0.774**	(2.90)	0.499**	(2.37)	0.102	(0.60)
growth_1	0.610	(0.82)	0.184	(0.45)	0.127	(0.38)
FreeTrade_1	-0.045	(-1.16)	-0.040	(-0.74)	0.002	(-0.15)
open_1	0.002	(1.06)	0.004**	(2.57)	-0.001	(-0.40)
finopen_1	0.000	(0.23)	0.002	(0.96)	0.002	(1.35)
NFI_1	0.504	(0.74)	0.690	(0.55)	0.138	(0.22)
employment_1	-0.015	(-1.58)	-0.014**	(-2.25)	-0.005	(-1.04)
infl_1	0.012**	(2.88)	0.008**	(2.79)	0.006**	(2.59)
hc_1	0.984*	(2.11)	-0.203	(-1.14)	-0.131	(-0.44)
ruralpop_1	-0.056***	(-3.12)	0.002	(0.20)	0.002	(0.34)
manfctr_1	-0.017	(-0.87)	0.013	(0.66)	0.012	(1.31)
Geduc_1	0.076**	(2.40)	-0.010	(-0.50)		
Ghealth_1	0.000	(0.11)	0.000	(0.28)		
FreeLegal_1	-0.037	(-1.01)	-0.018	(-0.44)		
Lendrate_1	-0.005	(-0.80)	0.002	(0.86)		
ICT_1	0.170**	(2.79)				
mwage_1	-0.001***	(-3.14)				
L.t10b50_2	0.042	(0.19)	0.304	(1.62)	0.679***	(18.43)
tfp_2	1.251	(1.74)	0.318*	(1.75)	1.995***	(3.94)
growth_2	-0.295	(-0.75)	0.756	(1.58)	-2.460	(-1.28)
FreeTrade_2	0.005	(0.07)	0.063	(1.50)	0.032	(0.56)
open_2	0.002	(0.74)	-0.001	(-0.73)	-0.001	(-0.86)
finopen_2	0.004	(0.65)	0.005	(1.63)	0.001	(1.21)
NFI_2	0.103	(0.13)	-0.761	(-1.43)	-0.315	(-0.24)
employment_2	0.004	(0.48)	-0.005	(-1.12)	-0.020**	(-2.58)
infl_2	-0.006	(-1.03)	0.014***	(5.73)	-0.016**	(-2.68)
hc_2	0.140	(0.72)	0.091	(0.51)	-0.531	(-0.93)
ruralpop_2	-0.028***	(-3.15)	-0.011*	(-1.93)	-0.004	(-0.64)
manfctr_2	-0.007	(-0.45)	-0.008	(-0.75)	0.002	(0.20)
Geduc_2	-0.032	(-0.59)	-0.119***	(-3.64)		
Ghealth_2	-0.001	(-1.12)	-0.000	(-0.06)		
FreeLegal_2	0.013	(0.26)	0.032	(0.91)		
Lendrate_2	0.015***	(4.61)	0.009**	(2.67)		
ICT_2	-0.008	(-1.26)				
mwage_2	-0.000	(-0.21)				
_cons	0.859	(0.89)	0.881	(0.85)	0.814	(0.83)
N	142		194		628	
Tr_variabl	GDPPc		GDPPc		GDPPc	
Tr_value	8.930		9.060		10.146	
rmse	0.065		0.073		0.170	

Notes: Standard errors in parentheses, \*\*\*, \*\*, and \* mark statistical significance at 1%, 5%, and 10% level. Prefix 'L.' denotes a lagged variable. Suffix '\_1' indicates that the coefficient is estimated for cases below the threshold value  $\theta$  (low levels of development), while suffix '\_2' corresponds to the cases with GDP per capita above  $\theta$  (high level of developments). Tr\_value represents endogenously selected threshold value.

Source: authors' calculations.

In the non-linear estimation (Tables 6 and 7) we use GDP per capita as the threshold variable to split the sample. Our goal here is to investigate the differences in the underlying mechanisms that may drive inequality at various development levels.<sup>8</sup>

Estimated threshold values,  $\theta$ , for the models with the ratio of top 10% vs. bottom 50% are between 8,930 and 10,146 PPP USD per capita (Table 6), while threshold estimates for the model with the ratio of the income share of top 10% vs. middle 40% are between 8,184 and 8,503 PPP USD (Table 7). We do not find major differences for the drivers of inequality at the lower and higher levels of development, although there is some evidence that the expenditure for education, net factor income, inflation, and minimum wage affect inequality in a non-linear fashion.

**Table 7.** Top 10% vs middle 40% – FE threshold model (GDP per capita as threshold variable).

	(1)		(2)		(3)	
	t10m40		t10m40		t10m40	
L.t10m40_1	0.723***	(10.43)	0.889***	(19.84)	0.991***	(24.32)
tfp_1	1.269*	(2.13)	0.232**	(2.17)	-0.241***	(-3.98)
growth_1	0.050	(0.23)	-0.253	(-0.99)	0.409	(1.51)
FreeTrade_1	-0.014	(-0.94)	0.013	(1.44)	0.030**	(2.17)
open_1	0.000	(0.26)	0.001	(1.02)	-0.001**	(-2.67)
finopen_1	-0.013	(-1.70)	0.002	(0.58)	-0.000	(-0.21)
NFI_1	-2.211**	(-2.18)	0.324	(0.54)	-0.720*	(-1.73)
employment_1	-0.016**	(-2.96)	-0.004	(-0.64)	-0.014***	(-5.99)
infl_1	0.006*	(1.86)	0.006***	(3.54)	0.002*	(1.72)
hc_1	0.325	(1.30)	0.155*	(1.92)	-0.088**	(-2.38)
ruralpop_1	-0.002	(-0.31)	-0.017**	(-2.13)	0.005***	(3.79)
manfctr_1	0.009	(1.63)	-0.005	(-0.63)	0.017***	(4.35)
Geduc_1	-0.061	(-1.58)	0.000	(0.01)		
Ghealth_1	0.000	(0.62)	-0.000	(-0.60)		
FreeLegal_1	-0.013	(-0.64)	-0.025	(-0.80)		
Lendrate_1	0.007**	(2.37)	0.005	(1.60)		
ICT_1	-0.013	(-0.75)				
mwage_1	-0.001	(-1.58)				
L.t10m40_2	-0.100	(-0.93)	0.268	(1.55)	0.648***	(8.76)
tfp_2	0.348**	(2.78)	0.177**	(2.43)	0.031	(1.48)
growth_2	-0.043	(-0.25)	0.332**	(2.25)	0.078	(0.64)
FreeTrade_2	-0.021	(-0.73)	0.006	(0.43)	0.001	(0.18)
open_2	0.001	(0.69)	0.000	(0.67)	0.000	(1.11)
finopen_2	0.001	(1.36)	0.002***	(2.89)	0.000	(0.40)
NFI_2	0.377	(0.89)	-0.281	(-1.10)	0.249	(1.68)
employment_2	0.006	(1.26)	0.001	(0.40)	-0.003**	(-2.54)
infl_2	0.000	(0.26)	0.003**	(2.82)	0.001*	(1.81)
hc_2	0.400***	(4.08)	0.127	(1.65)	0.007	(0.13)
ruralpop_2	-0.004	(-1.61)	-0.005**	(-2.22)	0.001	(0.61)
manfctr_2	-0.002	(-0.34)	-0.005	(-1.54)	0.001	(0.46)
Geduc_2	0.030*	(1.79)	-0.015	(-1.29)		
Ghealth_2	-0.000	(-1.68)	-0.000**	(-2.55)		
FreeLegal_2	0.052**	(2.38)	0.017	(1.43)		
Lendrate_2	0.006**	(2.90)	-0.002	(-1.17)		
ICT_2	-0.003	(-0.78)				
mwage_2	-0.000	(-1.34)				
_cons	-0.982	(-1.54)	0.301	(1.01)	0.288	(1.52)
N	142		194		628	
Tr_variabl	GDPpc		GDPpc		GDPpc	
Tr_value	8.503		8.425		8.184	
rmse	0.026		0.029		0.041	

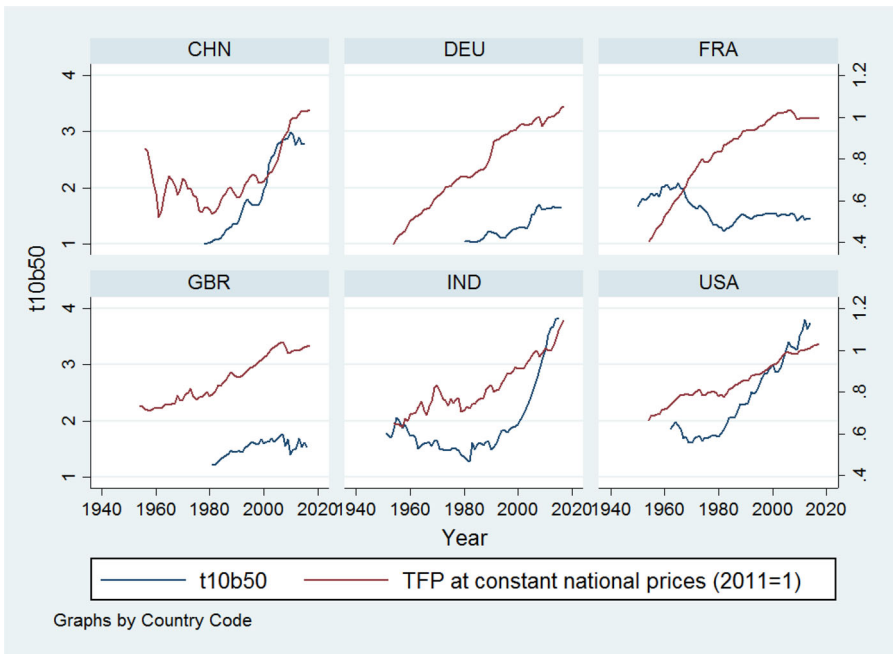
Notes: Standard errors in parentheses, \*\*\*, \*\*, and \* mark statistical significance at 1%, 5%, and 10% level. Prefix 'L.' denotes a lagged variable. Suffix '\_1' indicates that the coefficient is estimated for cases below the threshold value  $\theta$  (low levels of development), while suffix '\_2' corresponds to the cases with GDP per capita above  $\theta$  (high level of developments). Tr value represents endogenously selected threshold value.

Source: authors' calculations.

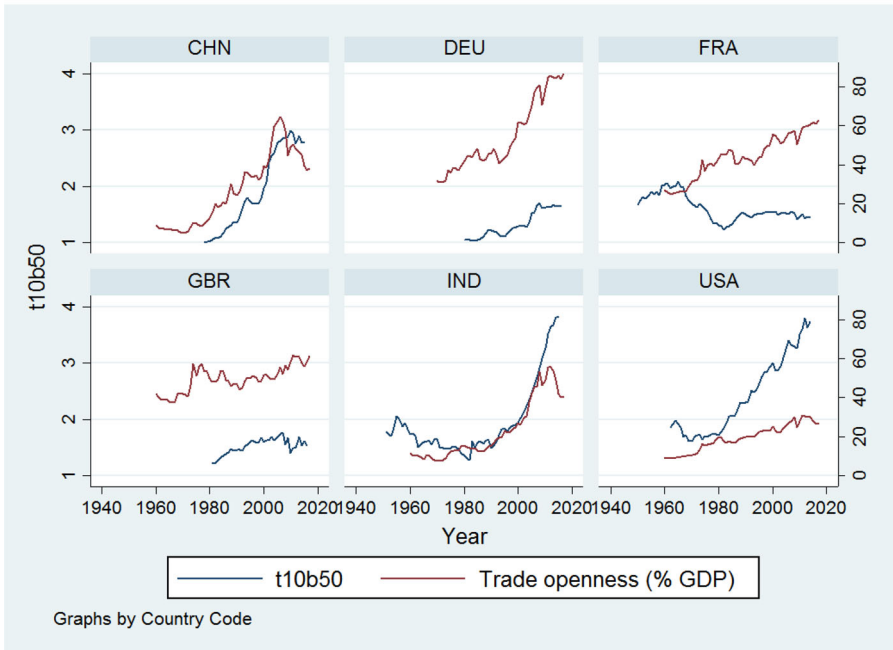
As expected, results indicate that inequality is highly persistent. The lagged dependent variable is significant in all nine linear models in Tables 4 and 5, thus justifying the choice of the dynamic panel model.

#### 4.1. Globalization and technological change as determinants of inequality

We start by presenting the results focusing on technological change and globalization as potential drivers of inequality. Total factor productivity,  $tfp_{i,t}$ , is statistically significant in all linear models except model 7, with the coefficient ranging between .2 and .8, indicating a robust and positive effect on inequality (Tables 5–6).



(a) Ratio of share of top income decile and. bottom 50 percentiles vs. TFP (TFP on the right axis)



(b) Ratio of share of top income decile and. bottom 50 percentiles vs. openness (Openness on the right axis)

**Figure 2.** Inequality vs. TFP and openness in selected group of countries (a) Ratio of share of top income decile and bottom 50 percentiles vs. TFP (TFP on the right axis) (b) Ratio of share of top income decile and bottom 50 percentiles vs. openness (Openness on the right axis).

Source: WID, World Bank, Penn World Table 9.1.

The effect of the technological progress prevails in non-linear models as well, confirming the robustness of results. Technological change has a positive and significant effect on inequality in almost all specifications. The overall effect is mostly positive even in the non-linear model, suggesting that the effect of technological progress on inequality does not change with development and higher levels of GDP per capita. This further confirms that technology is among the most important determinants of inequality, which is in line with the findings of Jaumotte et al. (2013) and the related skilled-biased technological change (SBTC) hypothesis.

On the other hand, the effect of globalization is rather weak. We have estimated 102 coefficients in 24 models overall that proxy for the effects of globalization (trade openness, financial openness, Freedom to Trade Internationally index, and net factor income). Only 14 of them are statistically different from zero, indicating that the effects of globalization on inequality are not robust (Tables 4–7).

The majority of statistically significant coefficients have been estimated for the effect of net factor income,  $NFI_{i,t}$ , but three are positive, and three are negative. The other globalization proxies are found to be statistically different from zero in a smaller number of estimated models.

We do not find that technology and globalization have different effects on inequality conditional on development level. We find only limited evidence of a negative effect of net factor income on inequality at lower levels of development (regime 1) for the top 10% vs. middle 40% income ratios (Table 7) and of trade openness for the top 10% vs. bottom 50% in the linear model (Table 4). This result partially supports findings of Jaumotte et al. (2013), who conclude that trade openness reduces inequality. We contribute to their conclusion by showing that this may be true only at lower levels of GDP per capita (below the development threshold) and does not hold for all countries and/or income groups.

#### **4.2. Economic policy variables as determinants of pre-tax inequality**

The employment-to-adult-population ratio, inflation rate, and the minimum wage are economic policy variables with the most robust results overall. The lending rate is an important inequality determinant which is robust when the top 10% vs. the middle 40% income share ratio ( $t10m40_{i,t}$ ) is considered. Furthermore, the government education expenditures are important for the top 10% vs. the bottom 50% income share ratio ( $t10b50_{i,t}$ ).

The ratio of employed-to-adult-population has negative and significant coefficients in 22 out of 30 estimated models, especially in linear models (Tables 4–7). Since high employment is related to lower inequality, it supports the policy recommendation that full employment economic policy should be an effective remedy for inequality. In the linear estimates, only one model has statistically insignificant coefficients for the employment variable, while in the non-linear models, we do not find evidence that the employment effects on inequality are conditional to the level of development. The robustness of non-linear models is lower when compared to linear estimates, but without a statistically significant difference in estimated signs at the lower and higher levels of development.

Inflation rate has a robust and positive effect on inequality in the majority of linear and non-linear models (Tables 4–7). Together with technology, the inflation rate effect is the most robust result in our study. Given that estimated signs are positive, the inflation rate can be interpreted as a proxy for the quality of institutions and governance transparency. This result does not surprise as it confirms that lower institutional quality (higher inflation) exacerbates income inequality. It also suggests that the quality of institutions is more important than inflationary effects on the debt and liabilities of households. In terms of the non-linear model, regimes differ only in the case of top 10% vs. the bottom 50% income share ratio at the higher level of development, where we find inconclusive results in terms of the sign of coefficient between models 2 and 3 (Table 6).

The lending rate,  $Lendrate_{i,t}$ , appears to have a positive and significant effect on inequality, but its effect might depend on development level. The estimated coefficient next to the lending rate is positive and statistically significant in four out of six linear models for middle percentiles (Table 5). In the non-linear model, we find evidence of differences between development levels in models with bottom 50 percentiles, where the lending rate affects inequality positively only at higher levels of development (Table 6). This suggests a different role of financial capital between development stages. Also, this is an intuitive result having in mind that people at the bottom half of income distribution might face liquidity constraints in lower-income countries (regime 1) with underdeveloped financial systems.

Estimated coefficients for the minimum wage,  $mwage_{i,t}$ , are negative and robust overall. Out of 10 estimated coefficients, six of them are statistically significant and negative – almost all coefficients in linear models (Tables 4 and 5) and the coefficient for regime 1 in the non-linear model ( $t10b50_{i,t}$ ). This suggests that minimum wage policies are most efficient for reducing inequality of the least fortunate income groups in countries at lower development levels (Table 6).

Government expenditure on education,  $Geduc_{i,t}$ , is important for reducing the income inequality between the top 10 and the bottom 50 percent of the income distribution. In four out of 10 models, estimated coefficients are negative and statistically different from zero (Tables 4 and 6). At higher levels of development (Table 6), we find a theoretically expected result, where expenditures on education decrease inequality. However, at lower levels of development, the effect of education expenditures on inequality is positive. The results for education expenditure, coupled with the results for minimum wage, imply that both policies are important for the inequality, but that the relative importance of these measures changes with economic development.

Other control variables such as the share of the rural population and ICT share in exports are also significant in non-linear models, but results are not robust across different specifications.

## 5. Conclusion

Although vast in volume, the previous literature has not reached a consensus on the effects of globalization and technological progress on income inequality. This article

contributes to that discussion by empirically testing these effects in a threshold panel framework, allowing us to simultaneously measure the globalization and technology effects on inequality at higher and lower levels of development.

One of the most interesting conclusions often neglected both in the literature and public discussions is that economic progress is not neutral *vis-à-vis* the changes in the income shares of top income groups. Our results confirm the expectation that technology is the most important generator of inequality and that full employment policies, coupled with low inflation, are the best remedy for the problem. In non-linear models, the effect of technology on income inequality is negative and robust in both development regimes. This finding highlights the importance of the *skill-based technological change* hypothesis (Berman et al., 1994, 1998; Goldberg & Pavcnik, 2007).

Furthermore, our findings indicate that globalization (as measured by trade openness, financial openness, net factor income, and/or *de jure* openness) does not affect the ratio of the income share of top 10% *vis-à-vis* bottom 50% or middle 40%. The majority of these variables are insignificant in linear models. We do not find evidence that proxies for economic globalization have different impacts at the lower and higher development levels. We confirm only a limited negative effect of net factor income on inequality at the lower level of development, contrary to Lakner and Milanovic (2016). These results differ somewhat from the previous literature (Gozgor & Ranjan, 2017), where the effect of globalization is found to be strong. These differences can be attributed to the skill-biased technological change, which is explicitly included in our model. Our findings stress the importance of controlling for both SBTC and globalization to properly differentiate their effects, which is in line with Jaumotte et al. (2013).

Employment and inflation play an important role in reducing inequality regardless of the country's level of development or sample used in estimation. Other policy variables suggest that government expenditures on education, minimum wage, and the lending rate seem to be important tools in fighting inequality, but their effects depend on the development level and institutional and policy environment. This finding highlights the fact that there is no one-size-fits-all economic policy against income inequality, which is in line with the findings of Dabla-Norris et al. (2015) and Alvaredo et al. (2018) who report substantial differences in inequality even between countries at the same level of development.

Robust results for the effects of the inflation rate are interesting from a theoretical standpoint. In all estimated models but one, the estimated coefficient for the inflation rate was positive. Conventional wisdom would expect a negative effect working through the real interest rate channel (a higher inflation rate would lower the real interest rate, leading to lower inequality). However, the fact that stable prices create less inequality may imply that the quality of institutions and governance transparency play a role in this result. Stable and low inflation quite often indicates that a country has an independent institutional framework (at least a monetary one), which might be a good proxy for institutional quality and fiscal transparency in a wider sense.

The empirical result that low inflation and high employment rates are compatible with low inequality might be at odds with the original Phillips curve framework. But, if we analyse these results within the Neo-Keynesian model (for example Erceg et al.,

2000), the economy with high employment levels and stable prices will necessarily have a lower price and/or wage mark-ups relative to other economies. By definition, a low mark-up economy (more competition in the product market) will have a higher real income share for wage-earning households. This further emphasizes the difference between development stages and justifies the use of non-linear models in this context.

In terms of policy recommendations, our results indicate that protectionism does not reduce inequality (at least not in all countries). Without appropriate inequality remedies, technological progress *per se* might increase inequality in the long run to socially unsustainable levels. Considering the importance of technological progress for economic growth in the long run, it is very important to control for biased effects of technology on various income groups and make growth more inclusive.

In order to do that, according to our results, policymakers should focus on investments in the education sector, minimum wage policies, and lending rates (e.g., credit guarantee schemes). Additionally, they should insist on the product market, financial market, and the labour market regulation policies that result in sustainable increases in employment-to-population ratios. Furthermore, contrary to traditional views, our findings suggest that the quality and transparency of formal institutions (organizations) might be an important remedy for the rise in inequality trends.

In this article, we consider pre-tax inequality and its determinants. Thus we do not discuss policy recommendations or policy efficiency when it comes to reducing inequality in post-tax income shares. Following a recent strand of literature (e.g., Alavuotunki et al., 2019; Troiano, 2018), future research could also consider post-tax inequality and the role of tax policies in mitigating inequality. That would be an area of research that could yield precisely targeted policy recommendations to mitigate inequality and to evaluate current economic policies in different countries with respect to the inequality level.

We acknowledge that there are many other dimensions of globalization, not only the economic one. For instance, social and political globalization is certainly an interesting topic worthy of exploring (see, e.g., Dalton, 2017; Schäfer and Schwander, 2019). However, these aspects of globalization are beyond the scope of this article but remain a potentially fruitful topic for future research.

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## Disclosure statement

No potential conflict of interest was reported by the authors.



## Notes

- 1.. See Acemoglu and Autor (2011) for a theoretical labour market model and a review of the theoretical and empirical literature on skilled biased technological change.
2. For example, Zhan et al. (2020) show that an increase in minimum wage will increase labour income share and will not cause overwork. Card and DiNardo (2002) relate an increase in inequality in the US from the 1980s to a decrease in the minimum wage.
3. Pre-tax national income is the sum of all pre-tax personal income flows accruing to the owners of the production factors, labour and capital, before taking into account the operation of the tax/transfer system, but after taking into account the operation of the pension system. The population is comprised of individuals over age 20 and we use equal-split adults data (i.e., income or wealth divided equally among spouses).
4. We thank anonymous referees for an insightful comment.
5. For an application and overview of similar models refer to Chudik et al. (2017) and Arčabić et al. (2018).
6. See Potrafke (2015) for the literature review that uses KOF index.
7. In the linear model (7)  $FreeTrade_{i,t}$  as a measure of openness is excluded as well.
8. We split observations (not countries) into two groups. Once we select the threshold value, the sample is split into observations that are below and above the threshold value. For example, if a certain country moves from being below to being above the threshold value of GDP per capita during the time period used in estimations, one part of the observations for that country will be in the sample below the threshold, and the remaining observations in the sample above it.

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