Erasmus University Rotterdam

Income Inequality and Economic Growth

The impact of Income Inequalities on Economic Growth

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ABSTRACT

The current paper offers evidence that income inequalities have a little positive effect on GDP *per capita* growth. To study this relationship an improved database is used spanning 49 years from 1971 to 2019 and a set of 170 countries. Panel data estimation allows to control for time-invariant country-specific effects, aiming to lessen the problem of omitted-variable bias. Fixed effects and generalized method of moments estimations are employed for the estimation and results show that a one-point increase in Income Inequalities should lead a 1% increase in the GDP *per capita* growth when exploiting fixed effects and there is no link when using the difference GMM, however the coefficient is positive (0,003). Moreover, redistribution policies seem to negatively impact growth.

Key Words: Net Income Inequalities, Gross Income Inequalities, Economic Growth, Dynamic Panel Models

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Section 1. Introduction

The impact of income inequalities on economic growth has been extensively studied in recent decades. This issue has been attracting increased attention, because of the combination of stagnant growth and the wider gap between the poor and rich groups in many countries. For example, a study from OECD argues that *"We have reached a tipping point. Inequality can no longer be treated as an afterthought. We need to focus the debate on how the benefits of growth are distributed." (OECD[1])*. Even more worrying are the predictions made by Piketty and Zucman (2015), who forecast a continuous increase in inequalities in the following decades, because of the low population and productivity growth.

This increase in income inequalities in the last decades motivated economists to study in detail its potential impact on our societies and economies. In specific, one of the reasons to pay attention to income distribution is its link with poverty, i.e., a more unequal distribution of a certain level of income increases the number people living in poverty. A World Bank report emphasis that it is important to minimize inequalities to make societies fairer and economies stronger: *"Promoting shared prosperity means that we will work to increase the incomes and welfare of the bottom 40 percent of society wherever they are, be it the poorest of nations or thriving middle- or high-income countries"[2]*.

However, it is important to note that this work aims to analyze the impact of income inequality, proxied by the gini coefficient, on GDP *per capita* growth and not how the income inequalities affect welfare and thus, the baseline results themselves are not enough to design policies. The importance of the topic makes of it one of the most economically debated questions. It is essential to comprehend if more income allocation discrepancies lead to greater or smaller rates of economic growth. In case the relationship appears to be negative, being greater levels of inequalities behind lower growth rates, the government should implement policies to improve income allocation, promoting not only general welfare gains but also economic growth. On the other hand, if the studies reveal a positive impact of income inequalities on economic growth, the countries face a trade-off between reducing inequalities to improve welfare or increasing inequalities to promote growth. The last case must be, specially, analyzed in detail by policy makers in order to find a balanced optimal solution.

To study this very crucial question, the current paper makes use of an improved panel of 170 countries between 1971 and 2019. To best of my knowledge there is not any other

[1] OECD Secretary-General; *Source*: OECD (2014)
[2] The World Bank, Oct 07, 2020

previous work on this topic that made use of a panel data as extended as this one, both on the number of countries and the number of years spanned. Thus, it represents a great contribution for the existing literature by increasing external validity. Another appealing characteristic of this broad sample is that it is more likely to offer an accurate empirical assessment of the long-term growth implications from factors such as legal institutions and the degree of income inequality as compared to those samples with fewer countries and years (see Barro 2000). The baseline regression of the current paper uses the GDP *per capita* growth as the main dependent variable, which is computed by doing the logarithm of the ratio of GDP *per capita* in the current year to the lagged GDP *per capita.* The main independent variable is the gini coefficient calculated using the net income, which works as a proxy for income inequalities. Some important controls are added to the main baseline equation: human capital (or years of schooling[3]), investment, labor force participation and government indicators (political stability and control of corruption). Moreover, to deal with the confounding effects of GDP *per capita* growth, the lagged GDP *per capita* is added to the regression accounting for the convergence hypothesis, which states that poorer economies (with lower *per capita* incomes) tend to grow at faster rates than richer economies.[4]

The paper starts by applying a fixed effects model to overcome problems of omitted variables and to eliminate time-invariant country-specific effects[5] that may be correlated with the explanatory variables and produce biased coefficient estimations if omitted. However, more recently many authors argued that the relationship of interest is not linear but is instead dynamic. Because of this, difference generalized method of moments estimation developed by Arellano and Bond (1991) is also performed. It eliminates country-specific effects by computing the first differences of each variable and the Nickell bias which will be discussed in detail after.

The results present a small positive effect of income inequalities on economic growth, which is not significant in all the specifications. The main findings suggest that a one-point increase in income inequalities causes a 1 % increase in the growth of GDP *per capita* when exploiting fixed effects and when using the generalized method of moments, the results are not significant and thus, there should be no link between the two variables, yet the coefficient is positive (0,003). Additionally, the robustness checks performed (Section 6) point a positive

[3] Human Capital and Years of Schooling are added separately to the regression, being its impact evaluated at a time.
[4] Solow Model prediction.
[5] Whether the effect is fixed or not depends on if an individual effect is correlated with the independent variables.

relationship between income inequalities and growth as well: the system GMM offers highly significant coefficients on the gini coefficient calculated using gross income and when splitting the sample into two groups, one with greater levels of corruption and the other with less, the results are also significant and suggest the greater income gaps promote growth *per capita*.

In a nutshell, the statistical significance and the magnitude of the estimated coefficients of the income inequalities seem to differ depending on the model specification chosen. Thus, the positive relationship between the gini coefficient and real GDP *per capita* growth found is not robust to alternative model specifications, meaning that this problem is not solved yet, since there is no evidence of a stable causal effect of inequalities on growth.

Even though most of the previous works found a negative relationship, there are many authors who offered evidence on the positive or null impact of income inequalities on per capita growth (see *Section 2* for more details). With the introduction of the Deininger and Squire's (1996) panel data models the common negative relationship found in cross-sectional regressions changed, opening the possibility to no relationship or a positive one. An example is the one of Barro (2000) who found little association between income inequality and economic growth in a broad panel of countries, finding a positive link in the richer countries and a negative link in the poorer countries. Forbes (2000) finds a strong positive impact of inequalities on growth on the medium and short term, when controlling for fixed effects and using the generalized method of moments developed by Arellano Bond.

It is important to note that the results found in this paper are comparable with other papers since the proxies to both economic growth and income inequalities exploited in this work are the most used ones across different papers and the most common estimation methods employed in previous literature are the fixed effects and the generalized method of moments as well.

The paper is structured as follows: Section 2 offers a description and analysis of previous empirical works, Section 3 refers to the data and explains in detail how the database used to draw the results was built and describes all the variables, Section 4 presents the estimation strategies applied, Section 5 contains the baseline results, in Section 6 a set of Robustness Checks are performed and finally, in Section 7 a conclusion is made to clarify the key ideas of the study.

Section 2. Literature Review

In this Section, previous contributions to the analysis of the link between inequality and GDP *per capita* growth are analyzed. In fact, previous literature on this topic is extended.

Table 1 in the *Appendix* summarizes the main points of the most relevant empirical studies. It can be seen that by using different datasets and estimation techniques the findings differ and thus the causal effect of income inequalities on economic growth is ambiguous.

From a theoretical point of view, many transmission channels have been pointed, to explain how inequality may affect growth. On the one hand, a larger concentration of income in a small group of individuals implies a decreased demand by the larger share of the population, which will, consequently, invest less in health care and schooling. Moreover, it is likely to be generated a wave of social and political discontentment, compromising human capital and macroeconomic stability, because of the unfairness in wealth and in the legislative power allocation. Furthermore, income inequalities induce greater levels of leverage and prompt redistribution policies that are frequently accused of moderating growth. Indeed, inequality combined with credit market constraints diminishes the number of entrepreneurial businesses that can be realized, which, in turn, leads to lower GPP growth rates.

On the other hand, some inequality motivates the richer community to start new businesses and make existing ones more productive, therefore expanding economic growth. This is, an unequal income distribution may spur innovation, investment and promote the individual effort, consequently enhancing GDP per capita growth.

Some examples of authors who found a negative relationship are the ones of Stiglitz (2012) that argues that inequality harms the aggregate demand of those individuals at the bottom forcing them to spend a larger share of their income on essential goods, being left with a very small portion of income to spend on those less essential goods; Cingano (2014) claims that income inequalities are economically inefficient, since the lack of access to education by the poorer originates less skilled labour that does not optimally contribute to economic productivity; Aghion et al. (1999) defends that inequality is detrimental to economic prosperity when capital markets are imperfect[6]; Persson & Tabellini (1994) suggest that inequality harms growth in societies where distributional conflict results in political and tax decisions that limit growth; Alesina & Perotti (1993) observe that unequal communities tend to be less politically

[6] The reduced access to credit will limit investment in human capital (education, training, etc), new businesses and insurance mainly among the poorer, who have higher marginal returns to human capital investments than the wealthier, Aghion et al. (1999)

stable because the majority of the society is discontent and has incentives to start revolutions; etc.

More recently, the positive relationship between income inequalities and growth has been highlighted as well in the literature, some examples are the ones of Kaldor’s (1955) who defends that more inequality brings growth if assuming that GDP growth is directly dependent on the saving rate and the rich are those with a great marginal propensity to save; Li and Zou (1998) empirically show that income inequality may be associated with economic growth if public consumption enters the utility function; Benabou (1996a) developed a model that analyses the heterogeneity among individuals and demonstrates that if the level of complementarity between individuals’ human capital is more evident in local than global interactions, then isolated and more unequal societies can experience higher rates of short-run growth; Galor & Tsiddon (1997) noticed that the technological booms coincide with those periods of greater inequality and improved mobility, in which high-skilled workers are allocated in high-tech sectors and this promotes long-run growth; Partridge (1997) defends that states with more income inequality at the beginning of the period actually experience greater subsequent economic growth; Forbes (2000) observed that some degree of income inequality promoted growth in the short and medium-term, not excluding the possibility that income concentration may reduce growth; etc.

Knowles (2005) and Voitchovsky (2005) state that it is plausible that the considerable difference in the outcomes obtained depends on the diversity in data quality, in the model used to estimate or in the time horizon considered. Another potential explanation for the variation in the findings is the lack of robustness checks performed in most of the literature.

One of the biggest concerns in estimating the relationship between income inequalities and economic growth is the high likelihood that the inequality variable is endogenous. It is reasonable that the development level of each country influences its Income Inequalities level. This path of the analysis has been investigated by various studies following Kuznets' (1955) hypothesis. Kuznets hypothesizes that, in the early stages of the development process, when GDP *per capita* is still low, inequality levels are reduced, too. However, as economies get more developed, inequality typically rises to generate capital accumulation through savings. Kuznets recalls the Keynesians hypothesis that the individuals on the top levels of income have a greater marginal propensity to save. The increase in inequality is in part due to worker's transition from the primary to the secondary sector. The author assumes that the agricultural sector has a lower average income and less wages discrepancies than the manufacturing sector and when the last one expands, the gini coefficient typically increases. However, when a certain income benchmark is reached in the manufacturing sector, inequalities shrink, establishing a positive relationship between development and inequality, because of the introduction of a progressive tax system, the introduction of capital, inheritance or capital revenue taxes, favoring the career of young entrepreneurs. Kuznets exploits time-series data relative to United Kingdom, France and U.S. and hypothesizes a non-linear relationship between the inequality level and the *per capita* GDP, which takes the form of an inverted "U". Based on his theory, Easterly (2007) states that only countries with a certain degree of development can yield a redistributive system to reduce inequality.

The hypothesis formulated by Kuznets (1955) has been tested by many researchers, i.e., Ravallion (1995) proposes that there is not a systematic impact of growth on inequality and in the same direction Adams (2004) presents evidence that the link between inequalities and growth is not statistically significant. Piketty (2003) challenges Kuznets' hypothesis as well, showing that between the end of the 19th and the beginning of the 20th centuries, the US, the UK and France experienced an obvious increase in wealth concentration, but no evidence of a systematic downward trend of inequality in Western economies during the 20th century was encountered. The three above-presented examples suggest that the obstacle of inequalities endogeneity in the growth regression might be not so severe.

To circumvent possible data quality issues, the present paper makes use of the more recent and accurate available dataset on worldwide gini indices, which is the Standardized World Income Inequality Database (SWIID), Version 9.1, May 2021 constructed by Frederick Solt and that works as a proxy to Income Inequalities. The estimation relies on yearly data. On the topic of time-frequency, Pagano (2004), Wan, Lu and Chen (2006) and Herzer and Vollmer (2012) state that the length of the interval is essentially arbitrary and the averaging technique eliminates short-term fluctuations and much annual data is dissipated.

Concerning the model formulation of the baseline equation, there is also no general agreement. Some studies rely on a linear model and others on dynamic models, such as GMM or VAR estimations.

Barro (2000) suggests that the relationship between inequality and growth is non-linear. Another dynamic but different understanding is the one of Banerjee and Duflo (2003) who find an inverted "U" shape between the two variables. They present evidence that changes in inequality (both decreases and increases) lead to a reduction in the growth rate of an economy. In the same line, Chen (2003) proposes that redistribution policies may harm growth for greater equality degrees, but the opposite happens for more unequal levels.

A simple approach to deal with nonlinearity consists in including squared and interaction terms. Noh and Yoo (2008) defend that interaction terms between inequality and the other independent variables allow us to understand if the influence of inequality on economic growth is impacted by another factor. However, the impact of nonlinearities on the estimation might be not so problematic, since most of the interaction terms are not statistically significant (De La Croix and Doepke, 2003). Furthermore, Sukiassyan (2007) exploiting transition economies confirms that the estimated coefficients of the squared Gini variables are not statistically significant in all model specifications.

Countries are heterogeneous and thus the findings may suffer from omitted variable bias (OVB). Because of this, a Fixed Effects estimate should be favored since it deletes unobserved time-invariant and country-specific effects that can be correlated with the independent variables.

A term with the lagged *per capita* GDP has been extensively included among the explanatory variables in previous empiric works. This variable accounts for the so-called "knowledge gap" (“convergence hypothesis”) between richer and poorer countries. This gap refers to the fact that the less developed countries can grow faster and be more productive by learning from the most developed economies (Solow Growth Model). Also, to account for conditional convergence, Fallah and Partridge (2007) suggest including a logarithm of the lagged GDP *per capita.*

When adding the variable that accounts for the lagged level of income, the model is not linear anymore, it becomes dynamic and thus, the Fixed Effects estimate becomes inconsistent (Nickell Bias[7]).

To solve the problem of endogeneity, many previous works made use of instrumental variables (IV). However, it is very difficult to find a suitable instrument. For example, Bagchi and Svejnar (2015) instrument the gini coefficient with the exchange rate, however, this variable fluctuates a lot and might be correlated with the economy's performance (GDP growth), thus it is likely to be endogenous. Another example is the one of De La Croix and Doepke (2003) who used life expectancy and fertility rate to instrument the inequalities coefficient, but again these variables are likely to be endogenous since they are correlated with GDP growth.

Also, Easterly (2007) builds on a body of work by Engerman and Sokoloff (1997, 2000) and states that factor endowments are a central determinant of inequality, so he suggests

[7] Nickell bias features are explained in Section 4

instrument the gini coefficient with the ratio between the extent of land suitable for wheat and that available for sugarcane cultivation. But again, this innovative instrument is not optimal, since it is not so relevant in the most developed economies that rely less on agriculture.

Find an appropriate is a very hard challenge, thus the generalized method of moments has been preferred as compared to the IV estimation. Because of this and to increase comparability with previous literature the current paper exploits the GMM methods.

Dominicis et al. (2008) and Neves et al. (2016) developed a meta-analytic reassessment of the impact of inequality on growth. Dominicis et al. (2008) argue that the magnitude and direction of the estimated effect of inequality on growth found in previous works depends on the estimation method, data quality and the sample coverage. With respect to the methodology, Dominicis et al. (2008) states that fixed effects estimators tend to offer a stronger effect of inequality on economic growth. Neves et al. (2016) extended the meta-analytic reassessment to more recent works and proved that the empirical literature is biased towards statistically significant results, and this makes the link between inequalities and growth be greater than it is actually. Additionally, the negative effect was found to be stronger in cross-section studies than in panel data studies.

Section 3. Data

The sample

An annual panel that encompasses a set of 170 countries (List 1, *Appendix*) with observations from 1971 to 2019 is constructed, including countries at vastly different levels of economic development.

Some countries were left out from the sample because their data was not available in all of the used databases[8].

This extended panel represents a contribution for the existing literature in the sense that most of the previous work used a database encompassing less countries and spanning less years. The increased sample size implies that the standard errors on the mean outcome are lower and that the confidence intervals become narrower. Another attractive feature of the sample is that it encompasses a considerable variation in the government policies and other variables that will be assessed. One shortcoming of this type of broad samples is that it is more difficult to measure variables consistently across countries and over time; in particular, developing countries are

[8] SWIID, WDI, WGI and Schooling databases (discussed next)

likely to have measurement errors in their national reports, however Barro (2000) believes that the convincing signal from the variation is stronger and dominates the noise.

The variables

The existing literature has been restricted by the lack of good quality data on income allocation since most of the data collected is based on heterogeneous national sources, being likely to have measurement error.

Despite its known weaknesses, the gini index is the most generally used measure of income inequality, since it is the variable with greater data availability compared to other inequalities indices (see Solt (2016) to a better understanding of the trade-off between comparability and coverage).

This paper makes use of the same database as the one adopted by Solt (2016) using the Standardized World Income Inequality Database (SWIID), which indexes the Luxemburg Income Study (LIS) and the gini indexes in the source data. In specific, I make use of SWIID 9.0, which encompasses a set of 198 countries and has data available from 1960 to 2019, in a yearly time frequency.

Penn World Table version 10.0 is exploited to collect yearly data relative to the levels of income, output, input and productivity. It covers 183 countries between 1950 and 2019.

The World Development Indicators database (WDI) is a combination of relevant high-quality statistics about worldwide development in distinct areas. It contains 1,400 time series indicators for 217 economies, which goes back more than 50 years. The indicators available allow to control for a set country-specific characteristics. Many economists have emphasized the importance of human capital, specifically the education attainment to economic progress (Lucas, 1988, Barro, 1991 and Mankiw, Romer and Weil, 1992), so schooling represents a relevant control to the specification of interest, however the WDI database is missing too many observations on schooling variables, thus it is used a new updated and expanded data on the average total years of schooling for adult population that combines three databases: Lee-Lee (2016), Barro-Lee (2018) and UNDP (2018), which provides educational attainment estimates for 193 countries from 1970 to 2017.

The 2020 updated World Governance Indicators (WGI) project is used to analyze if the causal relationship of interest goes in the same direction in those countries with greater governance quality and those with worst governance performance. This database covers over 200 countries and territories spanning the years of 1996-2019 and reports data on six dimensions: Voice and Accountability, Political Stability and Absence of Violence, Government Effectiveness, Regulatory Quality, Rule of Law and Control of corruption.

The main dependent variable is the annual GDP growth *per capita,* and the main explanatory variable is the gini index with respect to disposable income.

Economic Growth

GDP *per capita* growth[9] (g_t) is the change in value of all final goods and services produced divided by the number of inhabitants:

$$g_t = \frac{GDP\ per\ capita_t - GDP\ per\ capita_{t-1}}{GDP\ per\ capita_{t-1}}$$

To calculate the growth rate, data from the Pen World Tables is used. And the description of the variables used to compute growth is presented below:

GDP	Real GDP at constant 2017 national prices (2017US$), PWT
GDP *per capita*	Real GDP / Population, PWT

Deaton (2013) states that in the 1980s and 1990s, there was a broad increase in world incomes on average. He described an improvement in the material living standards around the world, but he found no evidence that growth is linked with poverty levels reduction.

Regarding, the lagged level of GDP *per capita* it is not yet clear whether it affects the relationship between inequalities and growth. For example, Barro (2000 and 2008) and Grijalva (2011) defend that more equability stimulates growth in poorer countries, whereas it harms growth in the richer ones. Bleaney and Nishiyama (2004) on the other hand, found no significant difference for the gini between rich and poor countries. To make sure this lagged level of income does not affect the estimations, it will be added to the model to provide further evidence on that subject.

[9] Represented by Y_t in the following sections.

The Gini Index

The increase in income inequalities in the last decades motivated economists to study in detail its potential impact on our societies and economies. It is important to minimize inequalities to make societies fairer and economies stronger.

The gini index, or gini coefficient, is a measure of the income distribution across a population, which was created in 1912 by the Italian statistician Corrado Gini. The coefficient ranges from 0 (or 0%) to 1 (or 100%), with 0 representing perfect equitable societies and 1 denoting perfect inequality.

The SWIID database offers data on the gini coefficient, both on income pre-taxes and transfers (net inequalities) and on income post-taxes and transfers (gross inequalities). Note that to increase readability, through the paper gini coefficient calculated with the net income will be mentioned as net inequalities and when referring to the gini coefficient calculated with gross income the term gross inequalities will be used.

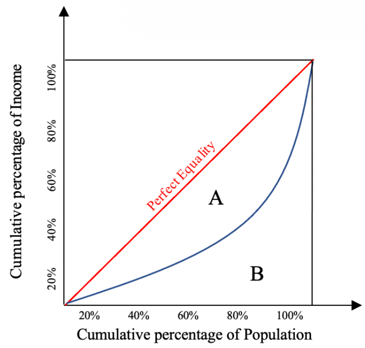
It is expected that gini coefficient values are lower after taxes and transfers, since these aim in part to redistribute wealth. Indeed, it is visible in the Summary Statistics table (Table 3 below) in the *Appendix* that net inequalities mean (38,61) is lower than the gross inequalities mean (45,80).

Gini Index (gross)	Estimate of gini index of inequality in equivalized (square root scale) household market (pre-tax, pre-transfer) income, using Luxembourg Income Study data as the standard, SWIID.
Gini Index (disposable)	Estimate of gini index of inequality in equivalized (square root scale) household disposable (post-tax, post-transfer) income, using Luxembourg Income Study data as the standard, SWIID.
Redistribution	The difference between the gini coefficient calculated with gross income and the gini coefficient calculated with net income (gross inequalities – net inequalities) represents a proxy to redistribution policies.

The present work focuses mainly on ex-post inequality, looking to the actual income gaps and not on ex-ante inequality, which relates to inequality in the opportunities and the starting points. The Lorenz curve (blue line in Figure 1) that accounts to gross income should be to the right (below) of the line calculated with disposable income, which should theoretically be closer to the perfect equality line (red line).

Mathematically, the gini coefficient (G) is the ratio of the area between Lorenz Curve[10] (blue line) and the perfect equality line (red line); i.e., G = $\frac{A}{A+B}$ (*See Figure 1 below*).

Figure 1: Lorenz Curve

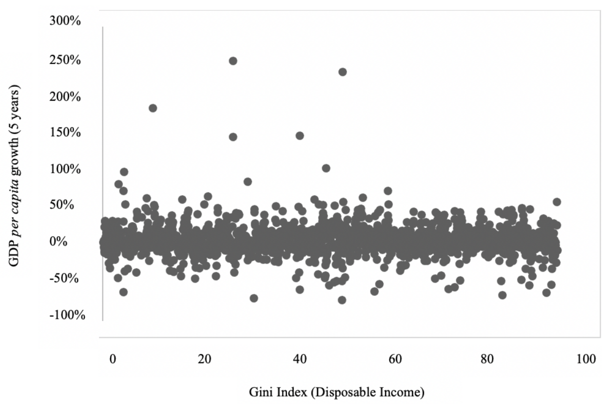


Source: Author's own elaboration

In the figures below, the relationship between the average gini index (calculated with net income) and real GDP growth *per capita* in the long run is presented.

Figure 2 offers a comparison between the average gini index in 5 years and the GDP *per capita* growth in those 5 years. On the other hand, figure 3 illustrates the relationship between GDP *per capita* growth in 10 years and the average gini index in those 10 years.

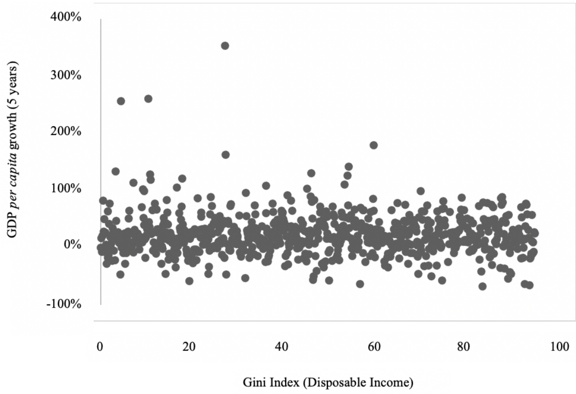
Figure 2: Scatterplot of Gini Index (Net Income) vs Real *Per Capita* 5 years Growth (*Long-run*), 170 countries, 1971-2019



Note: The last growth rate encompasses only 4 years (2016-2019), because data from 2020 is not available. *Source*: author's own elaboration on the basis of PWT and SWIID databases

[10] Lorenz curve represents the way in which wealth is cumulatively distributed- the wealth held by each individual is put in ascending order.

Figure 3: Scatterplot of Gini Index (Net Income) vs Real *Per Capita* 10 years Growth (*Long-run*), 170 countries, 1971-2019



***Note**:* The last growth rate encompasses only 9 years (2011-2019), because data from 2020 is not available. *Source*: author's own elaboration on the basis of PWT and SWIID databases

The figures 2 and 3 above provide some evidence of the large level of dispersion in the annual GDP *per capit*a growth. This is because the used sample encompasses 170 countries for 49 years. Thus, these fluctuations are reasonable because of the extended time span, during which wars and radical economic and political changes took place.

In figure 2 the three outliers refer to the 253,2%, 238,5% and 190% GDP *per capita* growth from 1976 to 2000 experienced by Equatorial Guinea, Liberia and Bosnia and Herzegovina, respectively. In figure 3 there is as well an evident outlier which refers to the 353,1% GDP *per capita* growth experienced by Equatorial Guinea between 1971 and 2000.

Only by looking at the scatterplots above it is expected that there is no or a low association between average income inequalities and long-run growth, since no clear upwards or downwards trend can be identified in the scatterplots. Note that however, this is only a preliminary result, and a final conclusion cannot be driven yet.

To comprehend how the gini index and the GDP *per capita* growth are linked, some dependence measures are computed. The results are reported in the Table 2 below and show a weak correlation between both gini coefficients and GDP *per capita* growth, showing that the indices have a low level of co-movement. Kendall's Tau coefficient and Spearman's rank correlation coefficients measure statistical associations based on the ranks of the data. Both the measures present weak negative results for the correlation between *per capita* growth and inequalities, suggesting that inequalities and growth do not co-move, this is likely to be because of a third variable that influences this relationship, and thus these findings need further econometric investigation.

Table 2: Co-movement measure between Inequalities and GDP *per capita* growth

	Correlation	Kendall's Tau	Spearsman's Rho
Net Gini Index vs GDP *per capita* growth	0.0131	-0.0192	-0.0303
Gross Gini Index vs GDP *per capita* growth	0.0044	-0.0429	-0.0633

Source: author's own elaboration on the basis of PWT and SWIID databases

Other explanatory variables

A set of other controls of interest is included in the regressions to increase the predictive power of the model[11]:

Labour Force Participation (15-64)	(% of total population ages 15-64) (modeled ILO estimate) Labor force participation rate is the proportion of the population ages 15-64 that is economically active: all people who supply labor for the production of goods and services during a specified period.
Gross Fixed Capital Formation (GFCF)	(Constant 2010 US$) GFCF or formerly gross domestic fixed investment includes land improvements (fences, ditches, drains, and so on); plant, machinery, and equipment purchase; and the construction of roads, railways, and the like, including schools, offices, hospitals, private residential dwellings, and commercial and industrial buildings.
Human Capital Index	Based on years of schooling and returns to education, PWT.
Schooling	Average Total Years of Schooling for Adult Population (Lee-Lee (2016), Barro-Lee (2018) and UNDP (2018)).
Political Stability and Absence of Violence/ Terrorism	Political Stability and Absence of Violence/Terrorism measures perceptions of the likelihood of political instability and/or politically motivated violence, including terrorism. Estimate of governance (ranges from approximately -2.5 (weak) to 2.5 (strong) governance performance), WGI.
Control of Corruption	Reflects perceptions of the extent to which public power is exercised for private gain, including both petty and grand forms of corruption, as well as "capture" of the state by elites and private interests. Estimate of governance (ranges from approximately -2.5 (weak) to 2.5 (strong) governance performance).

[11] In the baseline regression all the variables described appear with a logarithm except the ones that account for the institutions' quality.

Putting together, the improved data not only aims to reduce measurement error but also allows to employ panel estimation to control for time-invariant omitted variables.

The summary statistics for all variables used in the estimation are presented in the Table 3 below. The table refers to the sample of the 170 countries between 1971 and 2019. In all the estimations shown in Section 4 the variables are lagged and defined as logarithms. However, in Table 3, the descriptive statistics are mostly illustrated on current levels are without logarithms to increase readability from an economic point of view.

The main takeaways from Table 3 are that the average GDP *per capita* growth in all the countries throughout the 49 years being studied is approximately 0,06%. The average GDP *per capita* is $14 701 per year. The mean of the gross inequalities (45,8) is greater than the one of net inequalities (38,61), suggesting that taxes and transferences (proxy to redistribution policies) smooth the income allocation discrepancies. At a first sign the mean value of labor force participation seem very low, however this is likely to be because in the early years and in developing countries these measure was/ is not properly reported, i.e., it is likely that many people employed are not officially registered.[12]

[12] It is very hard to lessen measurement error when the samples are as extended as this one and encompassing so many years. However, the databases used are actualized and improved. Note also that the same happens with the report of the GDP.

Table 3: Descriptive Statistics

	Obs.	*Mean*	*Std. Dev.*
GDP per capita growth	7 815	0,000646	0,246
GDP per capita	7 841	14 701	18 854
Real GDP	7 841	392,3 *B*	1 398 *B*
Gini Index (Net Income)	5 009	38,61	8,791
Gini Index (Gross Income)	5 009	45,80	6,643
Redistribution	5 009	7,191	6,923
Years of Schooling	4 736	7,186	3,248
Human Capital	6 557	2,198	0,730
GFCF	5 182	84,510 *B*	275 *B*
Labor Force Participation	4 889	67,63	10,29
Political Stability and No Violence	3 475	-0,0918	0,952
Control Of Corruption	3 482	-0,0290	1,008
Palma ratio	2 630	1, 418	1,876

Note: The number of observations, the mean, the standard deviation, the minimum and the maximum values of each variable used in the model are presented above. B stands for billions.

Section 4. Empirical Specification

The Model

In this Section, the econometric models are presented. This paper's baseline specification has been developed on the basis of the existing literature, presented on Section 2. The added controls follow the empiric works of Barro (1999, 2008), Forbes (2000), Alesina e Rodrik (1994), to minimize possible omitted variable bias.

The baseline specification takes the form of:

$$Y_{i,t} = \alpha \; lny_{i,t\text{-}1} + \beta \; Ineq_{i,t\text{-}1} + \gamma \; X_{i,t\text{-}1} + \mu_i + \mu_t + \epsilon_{i,t} \quad (1)$$

$Y_{i,t}$ represents the annual GDP growth rate *per capita*, which is computed according to the following equation:

$$Y_{i,t} = \ln\left(\frac{y_{i,t}}{y_{i,t-1}}\right) = ln(y_{i,t}) - ln(y_{i,t-1}) \quad (2)$$

where i denotes a particular country and t is the time period. The left-hand side of equation (1) is the *per capita* GDP growth in a country each year. On the right hand-side, *Ineq* is a summary measure of inequality (the gini index). Panel data allows to control for fixed effects, μ_i presents country-specific effects, μ_t period-specific effects, and ε_{it} the idiosyncratic error term. Finally, vector *X* contains a set of controls and *per capita* GDP ($\ln y_{t-1}$) is included as a measure of the initial state of growth, allowing to account for the convergence hypothesis[13]. However, this variable is also used to calculate the main dependent variable (GDP *per capita* growth), so this variable might suffer from problems that are comparable to those of a lagged dependent variable.

Both fixed effects and GMM estimations are performed, being the second one the preferred one. The problem with fixed effects estimates is the so-called Nickell bias that occurs when panel data models with fixed effects and lagged dependent variables are determined by the standard within the estimator and the time dimension (T) is finite. This bias is of the order 1/T, meaning that as T increases the bias decreases (Nickell 1981, Alvarez and Arellano 2003). Considering that the time dimension in the paper's database is usually considered large enough (49 years), the standard within the estimator should have a less problematic bias. However, to prevent possible bias, the present paper makes use of the difference generalized method of moments (GMM) estimator (Arellano and Bond 1991), because it uses lags of the independent variables as instruments and like this, it reduces the bias. Indeed, the GMM method accounts for the possible "Nickell-bias"[14], since this approach uses a set of internal instruments, built from past observations of the instrumented variables, providing several tests for the validity of such instruments.[15] Previous works also applied the system GMM (Blundell and Bond 1998), which yields similar results, but offers less clear results. Both approaches are useful because they can deal with endogenous regressors and reverse causality.

The difference generalized method of moments (GMM) estimator developed by Arellano and Bond (1991) excludes the country-specific effect by differencing model presented in equation 1 and instruments the independent variables with its lagged values. They point that

[13] The poorer economies' *per capita* GDP grows faster than richer economies, until both reach the "steady state".
[14] the lagged dependent variable ($\ln y_{i,t-1}$) cannot be distributed independently of the error term
[15] Including the Arellano-Bond that tests for possible endogeneity caused by autocorrelation in the residuals.

by consistently employing first differences implies no serial correlation in the error term, $e_{i,t}$. However, it encompasses a shortcoming: in this context gini coefficient exhibits persistence (tends to remain quite stable within a country), thus when taking the first differences most of the variation in the panel is eliminated, meaning that the lagged variables are not good instruments for the independent variables, moreover the variables of the current period may offer little information on future changes (Blundell and Bond 1998; Bond et al. 2001). Hence, one must assume that first differences and country fixed effects are not correlated. Blundell-Bond (1998) suggests that in growth regressions it is necessary to assume that the divergence of initial values from their steady states is not correlated with the country-specific fixed effects.

A possible concern with the proposed model is endogeneity due to reverse causality, since many previous empirical works studied the relationship of interest in the opposite direction, finding a significant impact of economic growth on the inequalities level, meaning that the reverse causality problem cannot be ignored. Saint-Paul and Verdier (1993) and Forbes (2000) state that economic growth increases wealth and thus the investment in human capital accumulation, reducing income allocation discrepancies. To account for this, some previous studies made use of lagged controls. Two examples are the ones of Keefer and Knack (2002) who lagged around 10 years the human capital and inequalities data and the one of Fallah and Partridge (2007) that analyze the growth rates over 1990-2000 using independent variables relative to the years of 1989-90. However, lagged endogenous variables impact the lagged economic growth, which in turn affect the current economic growth (Mo, 2000).

This paper focuses on a dynamic model, i.e., the Arellano-Bond GMM estimation technique to deal with the possible endogeneity of the explanatory variables.

Section 5. Results

In this section, the baseline results for the fixed effects and the difference generalized method of moments are presented.

Section 5.1 Linear Regression exploiting Fixed Effects

The first results presented below exploit a fixed effects linear estimation that should minimize possible distortions created by omitted variables by eliminating unobserved time-invariant country-specific effects.[16]

A problem with fixed effects is that equation (1) contains a lagged endogenous variable (the lagged GDP *per capita*) and might generate inconsistent results. As explained before, the bias is of the order 1/T and assuming that the period studied is long enough (49 years), this should not be so problematic. However, in the Table 6 (*Appendix*) the results when the lagged GDP per capita control is not included are presented and the coefficient of interest does not differ much from the one of Table 4. For the estimations in Table 6, the following equation is used:

$$Y = \alpha\ Ineq_{i,t\text{-}1} + \beta\ X_{i,t\text{-}1} + \mu_i + \mu_t + \epsilon_{i,t} \quad (3)$$

In Table 4 below, the results of the estimation of equation (1) can be seen and withing parentheses the cluster standard errors are presented. The latter allow for intra-country correlation, allowing to relax the usual prerequisite that the observations are independent. This means that the observations should be independent between clusters (countries) but not necessarily within each country.

[16] Noh and Yoo (2008) and Forbes (2000)

Table 4: Impact of Income Inequalities on *per capita* GDP Growth – *Fixed Effects estimation*

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
GDP per capita (t-1)	-0.184**	-0.068***	-0.118*	-0.185*	-0.068***	-0.113*	-0.114*
	[0.093]	[0.014]	[0.061]	[0.099]	[0.014]	[0.064]	[0.059]
Net Inequalities (t-1)	0.013	0.001	0.010*				0.010
	[0.009]	[0.001]	[0.006]				[0.006]
Gross Inequalities (t-1)				0.009	0.000	0.006	
				[0.007]	[0.001]	[0.005]	
GFCF (t-1)	0.048*	0.007	0.027	0.048	0.007	0.026	0.026
	[0.028]	[0.007]	[0.018]	[0.031]	[0.007]	[0.019]	[0.017]
Labor Force Participation (t-1)	-0.068	-0.044	0.068	-0.074	-0.044	0.041	0.106
	[0.074]	[0.041]	[0.147]	[0.070]	[0.041]	[0.147]	[0.157]
Human Capital (t-1)	0.169*		0.075	0.113*		0.046	0.095
	[0.086]		[0.135]	[0.061]		[0.137]	[0.126]
Political Stability and No Violence (t-1)	-0.004	0.001		-0.004	0.001		
	[0.006]	[0.004]		[0.006]	[0.004]		
Control Of Corruption (t-1)	-0.011	0.008		-0.008	0.008		
	[0.018]	[0.006]		[0.016]	[0.006]		
Schooling (t-1)		0.055***			0.053***		
		[0.017]			[0.017]		
Redistribution (t-1)							-0.013*
							[0.006]
Constant	0.248	0.506***	-0.280	0.417	0.547***	-0.026	-0.331
	[0.357]	[0.187]	[0.798]	[0.310]	[0.183]	[0.758]	[0.795]

Note: The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. Cluster adjusted (Country) standard errors are in parentheses; ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

To analyze the impact of income inequalities on economic growth *per capita*, a preliminary fixed effects estimation is performed, even though it is likely to yield biased results[17]. The main results are presented in the Table 4 above, where net inequalities are added from columns 1 to 3, gross inequalities from olcumns 4 to 6 and the impact of redistribution is analyzed in the column 7.

Not surprisingly the lagged GDP *per capita* presents a significant coefficient in all the specifications. This happens because of the convergence hypothesis that states that those less

[17] Previous works suggest different strategies to deal with the bias. In this paper the bias is minimized by estimating the baseline regression, exploiting the GMM as well.

developed and less wealthy economies tend to grow faster and learning from the most developed ones.

Starting by analyzing the first three columns, it is visible that the coefficient of interest (net inequalities) is positive across all the estimations, however its magnitude is quite small. It is only significant in the third column where institutions quality and schooling are not added.

Human capital and years of schooling are added separately, since if both are added in the same regression estimation, it is likely to suffer from multicollinearity, since the human capital includes not only training, intelligence, skills and health, but also educational attainment. Because of its completeness estimations using human capital are the preferred ones. Moreover, when human capital is not included (moving from column 1 to column 2), the magnitude coefficient of interest becomes considerably smaller. In both columns 1 and 2 the coefficient of interest is not significant suggesting that there is no causal effect between inequalities and growth, however in column 3 when years of schooling and the governmental indicators are not added the results are significant at a 10% level and indicate that if the gini coefficient increases by one-point, economic growth *per capita* increases by 1%. The lower magnitude might suggest that there is an external factor driving the results. It can be that for certain set of countries the relationship of interest is positive and for another subset it is negative and thus the overall net effect is very low or even null.[18]

Gross fixed capital formation (GFCF), also called "investment", is always positive and significant in column 1 indicating that the more a country invests on its fixed assets the greater will be the growth the following year. Contrarily, the greater the labor force participation the lower the growth will be. Assuming that less unemployment (greater labor force participation) is associated with more households obtaining a salary and thus reducing the gap between poor and rich, this result is not surprising. This is less labor force participation increases inequalities and an increase in inequalities increases growth.

Looking to the institutions' quality controls (political stability and control of corruption), none of them is statistically significant and its magnitude is very low. It also surprising that the direction of the estimation varies depending on whether *Human Capital* or *Years of Schooling* are used. Its impact is not yet clear and thus as a robustness check (see Section 6) is performed to comprehend how the institutions heterogeneity may affect the link between inequalities and economic *per capita* growth.

[18] A robustness check that accounts for country heterogeneity will be conducted in Section 6.

The gini coefficient that accounts for the income before transfers and taxes should not be so important, because the income used for the calculations is not the real income households face, however from columns 4 to 6, its impact on economic growth *per capita* is analyzed as well. The coefficient on gross inequalities is never statistically significant and the coefficient is much lower when compared to the one of net inequalities. In column 4, a one-point increase in the gini coefficient only leads to 0,9% in *per capita* economic growth (not significant).

The great difference between net and gross inequality coefficients motivated the study of the impact of redistribution on economic growth and the results can be seen on the last column of Table 4. The coefficient of redistribution is significant at a 10% level, and it is negative. This implies that redistribution policies decrease economic growth. Again, the intuition is similar to the one of labor force participation. If one assumes that less redistribution policies increase inequalities, which in turn increase economic growth. Moreover, the control of Redistribution was calculated as the difference between the gini calculated using the gross income and net income. Thus, since gross inequalities has a lower coefficient than net inequalities it is logical that the coefficient on redistribution is negative.

As mentioned previously, the fixed effects method is inconsistent because of the lagged income term (predictor variable), which is endogenous, since it has values that are determined by the other variables in the main equation. Thus, the identifying assumption is that the lagged level of income is not pre-determined by the other explanatory variables. [19]

Section 5.2 Difference Generalized Method of Moments (GMM)

Now, the estimation results when the generalized method of moments, presented by Arellano and Bond (1991), is applied are presented. The difference GMM lags the variables one year and calculates the first differences of all the variables and like this it deletes country-specific effects. One can thus, re-write the baseline equation for the GMM as follows:

$$\Delta Y = \alpha\, \Delta\, lny_{i,t-1} + \beta\, \Delta\, Ineq_{i,t-1} + \gamma\, \Delta\, X_{i,t-1} + \delta\, \Delta\, \epsilon_{i,t-1} \quad (4)$$

Rewriting, we have equation (5) [20] :

$$Y_{it} - Y_{i,t-1} = \alpha\, (lny_{i,t-1} - lny_{i,t-2}) + \beta\, (Ineq_{i,t-1} - Ineq_{i,t-2}) + \gamma\, (X_{i,t-1} - X_{i,t-2}) + \delta\, (\epsilon_{i,t-1} - \epsilon_{i,t-2})$$

[19] This assumption is very unlikely to hold; for example, human capital and investment directly impact the lagged level of income.

[20] Forbes (2000)

All variables are now expressed as deviations from lagged values. For example, for period 3, Arellano and Bond use Y_{i1} as an instrument for (Y_{i2} - Y_{i1}), for period 4 they use Y_{i1} and Y_{i2} as instruments for (Y_{i3} - Y_{i2}), etc., and this procedure continues creating instruments for each differenced variable. Thus, two assumptions must be fulfilled to guarantee the consistency and efficiency of the estimator. The first one is that the lagged dependent variables ($X_{i,\ t-s}$) must be pre-determined by at least one period: $E(X'_{it}\, u_{is}) = 0$ for all $s > t$. The second assumption is that the error terms cannot be serially correlated: $E(u_{i,t}\, u_{i,t-s}) = 0$ for all $s \geq 1$.

Indeed, first difference GMM creates a correlation between the error term and the lagged dependent variable ($\Delta\ lny_{i,t-1}$), which bias the results. To circumvent this shortcoming, as a robustness check the estimation is made using the system generalized method of moments, which account for this correlation (see Section 6.2 for more details on *Sys*-GMM and the results are presented in the Table 8 in the *Appendix*)

Concerning the standard errors, a two-step estimate with the Windmeijer bias-corrected robust VCE is performed. Arellano and Bond suggest that using the two-step estimator with bias-corrected robust standard errors instead of using the two-step nonrobust results for inference on the coefficients because the standard errors are likely to be biased downwards (see Arellano and Bond 1991). The Table 5 use the Windmeijer bias-corrected robust VCE, proposed by Windmeijer (2005).

Moreover, instead of one step estimator, two step estimator is used for the growth regressions, since it is more robust than the one-step system GMM and it is more efficient and robust to heteroskedasticity and autocorrelation (*Roodman, 2009*).

Arellano and Bond's estimators are consistent if the explanatory variables are exogenous If the explanatory variables are not exogenous, only the Arellano and Bond estimator is consistent.

Table 5: Impact of Income Inequalities on *per capita* GDP Growth –*Generalized Method of Moments estimation with the Windmeijer bias-corrected robust VCE*

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
GDP per capita (t-1)	-0.162**	-0.189***	-0.113**	-0.160**	-0.195***	-0.114***	-0.113***
	[0.065]	[0.035]	[0.047]	[0.068]	[0.036]	[0.038]	[0.043]
Net Inequalities (t-1)	0.001	0.000	0.003				0.003
	[0.006]	[0.004]	[0.003]				[0.004]
Gross Inequalities (t-1)				0.000	0.000	0.002	
				[0.005]	[0.005]	[0.002]	
GFCF (t-1)	-0.007	-0.002	-0.019	-0.010	-0.003	-0.020	-0.020
	[0.029]	[0.017]	[0.022]	[0.027]	[0.016]	[0.021]	[0.019]
Labor Force Participation (t-1)	0.045	0.102	-0.138	0.056	0.106	-0.157	-0.123
	[0.222]	[0.118]	[0.132]	[0.199]	[0.119]	[0.126]	[0.116]
Human Capital (t-1)	0.291*		0.360***	0.301*		0.369***	0.377***
	[0.171]		[0.078]	[0.172]		[0.100]	[0.086]
Political Stability and No Violence (t-1)	-0.004	-0.005		-0.004	-0.005		
	[0.014]	[0.015]		[0.013]	[0.014]		
Control Of Corruption (t-1)	0.022	0.017		0.024	0.017		
	[0.018]	[0.016]		[0.020]	[0.017]		
Schooling (t-1)		0.196***			0.192***		
		[0.063]			[0.062]		
Redistribution (t-1)							-0.005
							[0.015]
Constant	1.201	0.996*	1.666***	1.245	1.067**	1.814***	1.657***
	[0.922]	[0.521]	[0.602]	[0.791]	[0.486]	[0.586]	[0.611]

Note: The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. The two-step Generalized Method of Moments is used and Windmeijer bias-corrected (WC) robust VCE standard errors are in parentheses**;** ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

The Table 5 above shows the results when the generalized method of moments estimation is used. From columns 1 to 3, it is estimated the impact of net inequalities and from columns 4 to 6 the impact of gross inequalities is estimated instead. The last column is useful to comprehend how redistribution policies affect economic growth.

Again, the coefficient on the lagged income level is negative, confirming the Solow model predictions.

Since the coefficients on the inequality variables are never significant, income inequalities themselves should not directly impact economic *per capita* growth. Yet, the results hint a positive direction of the relationship of interest: there is little evidence of a small positive impact of income inequalities on economic growth, even though the coefficients of interest are not statistically significant. In fact, both income inequalities calculated with net and gross income the coefficients are not significant and are close to zero. When, schooling and institutions quality are not added (columns 3 and 6) the coefficients on net inequalities and gross inequalities are 0,003 and 0,002, respectively.

The only controls that are significant are the lagged level of income, the human capital and schooling.

Again, the magnitude of the coefficient is greater when the quality of institutions is not included, this might be because the variable on inequalities is taking part of the predictive power of the government indices and if it is the case the impact of inequality on growth is even lower.

When the linear regression estimation was performed the impact of GFCF on growth was significantly positive and now, with a dynamic estimation, the predictions point to the opposite effect. A one percent increase in investment should decrease GDP *per capita* growth by around 1,9%[21] (column 3). Since different estimations generate distinct results the impact of investment on growth in this context is ambiguous. Barro (2000), states theoretically that indeed inequalities and investment move in opposite direction. He starts by declaring that a greater degree of inequality motivates more redistribution through the political process and more distortions are created and thus investment is lower. During the transition until the steady state, economic growth declines accordingly.

The labor force participation presents again a negative coefficient, when inequalities present a magnitude that is greater than zero (columns 3 and 6) and positive when the opposite

[21] Note that this result is not statistically significant, however it is curious that the direction of the relationship is inverted, being investment harmful for growth in this model.

happens (magnitude of the coefficient of the inequality variables is close to zero). In column 3, a one percent increase in labor force participation decreases economic *per capita* growth by approximately 13,8% and in column 6 by approximately 15,7% (not statistically significant).

Finally, in column 7 the impact of redistribution[22] on economic *per capita* growth is negative but not significant, being the coefficient -0,005. The possible argument for this is again, that redistribution should decrease inequalities, which leads to a decrease in growth, so redistribution should present the opposite sign of inequalities.

Section 6. Robustness Checks

Section 6.1 Palma Ratio

The gini index has been found to have a number of limitations. The first is related to the broad concept of "income", which can take into account the household size or simply analyze the individual level and might consider financial holdings or just wage earnings. Moreover, the income of the informal sector is not included in the inequality measurement and in the majority of the developing countries, the informal sector represents almost 90% of employment. In agricultural subsistence-driven economies, income is likely to take different forms other than money. Also, each economy applies different income tax regimes (regressive, proportional and progressive). Additionally, the gini index violates the Pareto improvement principle[23]. The index does not account for social benefits or interventions that shrink the gap between rich and poor. Demographic changes or characteristics of the population are not reflected by the gini index. However, despite its shortcomings it is the most commonly used measure of inequality, since it is the variable that covers a greater amount of data.

To check if the gini index is indeed a bad proxy for income inequalities, as a robustness check the Palma ratio is used instead. The Palma ratio is na inequalities measure that analyses the differences between the individuals on the top and on the bottom of the income levels. In specific, this ratio divides the richest 10% of the population's share of Gross National Income (GNI) by the poorest 40% of the population.

The data is gathered from the World Income Inequality Database (WIID)[24] and the results can be seen in Table 7 of the *Appendix*. The coefficient on the Palma ratio is close to

[22] Recall, that Redistribution is proxied by the difference between gini coefficient calculated with gross and net income, i.e. gross inequalities – net inequalities

[23] A Pareto improvement is a change in allocation that does not harms anyone and helps at least one person, given a certain initial goods allocation.

[24] UNU-WIDER, World Income Inequality Database (WIID). Version 31 March 2021.

zero confirming again the small impact of inequalities on growth itself. It is not statistically significant in none of the specifications and thus, again income inequalities themselves do not impact *per capita* GDP growth. Except in column 1, where the fixed effects estimator is used and no governance indicators are added, the relationship between the Palma ratio and *per capita* economic growth is negative. This result does not go in accordance with the previous findings where inequalities were expected to slightly improve growth.

Different inequality measures offer different results, not leaving clear what is the actual impact of inequalities on economic growth. Again, these findings open space to future research.

Section 6.2 System Generalized Method of Moments with the Windmeijer bias-corrected robust VCE

The system GMM estimator developed by Bundell and Bond (1998) has been commonly used in recent studies to overcome the shortcomings of the first differences GMM, namely the correlation created between the lagged dependent variable and the error term when performing the first differences. It works as an extension of the difference GMM estimator, which instruments first differences with lagged levels of the respective variables to circumvent the dynamic panel bias. Difference GMM estimation performs a poor work when the variables are highly persistent, like the inequalities coefficient and thus, the system GMM estimator additionally instruments levels with previous changes in the variables, making the instruments more relevant as compared to the difference GMM.

The system GMM[25] estimator merges first-differenced equations with a supplementary set of equations in levels. Thus, it also allows for including time-invariant variables in the level equation. Hence, one must assume that first differences and country fixed effects are not correlated. Blundell-Bond (1998) suggests that in growth regressions it is necessary to assume that the divergence of lagged values from their steady states is not correlated with the country-specific fixed effects.

The system generalized method of moments (*Sys*-GMM) estimator, apart from using the variables lagged two and further periods as instruments in the first-difference equation, it also uses the evidence provided by lagged differences to instrument an equation in levels.

Thus, the use of this estimator will provide efficient and consistent estimations for the persistent inequality measures and like this confirm if the small positive impact of income

[25] used by Ostry et al. (2014) and Halter et al. (2014) to estimate the impact of inequalities on economic performance.

inequalities on economic growth with the first differences GMM estimators is robust to the used of the system GMM.

In the Table 8 in the *Appendix,* it is visible that the gini coefficient calculated with the gross income is significant, while the one that makes use of the net income is not significant.

The coefficient of interest in columns 1 to 3 is very close to zero and it is not significant. Looking to the gross inequalities in columns 4 to 6 the coefficient on gross inequalities ranges from 0,004 to 0,006 and is highly significant (1% level of significance).

In column 9, the impact of redistribution on growth can be evaluated. Its coefficient positive and highly significant. Thus, according to these estimates redistribution policies promote economic growth, contrarily to the previous results, which goes in accordance with the fact that the magnitude of coefficient of gross inequalities is larger than the one of net inequalities.

In general, human capital, schooling, institutions' quality and redistribution are positive for growth and investment and labor force participation negative. However, only human capital, years of schooling and control of corruption are significant.

In a nutshell, system GMM estimation again highlights the almost inexistent but positive (when human capital is used instead of years of schooling) impact of income inequalities on *per capita* economic growth.

Section 6.3 Country Heterogeneity

Another robustness check is performed to analyze if the positive, but weak relationship between inequalities and growth is due to the heterogeneity between countries. In specific, this Section analyses if the results apply to countries with different institutions quality levels.

Forbes (2000) states that the results in previous works are many times driven by external factors (exogenous variables) that are not accounted for, like institutions quality.

In fact, depending on its political stability and control of corruption, each country's income inequalities may differently impact economic growth.

Data on these two indicators is obtained from the WGI in the World Bank database. These estimates range from approximately -2.5 (weak) to 2.5 (strong) governance performance.

Table 9 on the *Appendix* shows that using the fixed effects method (with cluster robust standard errors) and accounting only for those observations in which political stability is greater than zero (proxy to observations with greater stability levels) the coefficient on net inequalities is 0,004 (significant at 1% level) and when looking to column 2, which account for those lower levels of political stability (below zero) the coefficient is 0,017, which is much greater, however it is not statistically significant. This suggests that the more political instability a country faces the greater (more positive) will be the impact of income inequalities on growth. Yet, the impact of inequalities on the most stable countries is more evident, suggesting that in political instable countries there are other factors that play a much greater role than Income Inequalities in determining growth. However, the result is not clear because of the non-significancy of the second coefficient.

Performing the same test now using the difference GMM the opposite happens being the magnitude of the coefficient greater in those countries with greater political stability (0,005 *versus* 0,003). Because of this, one cannot conclude if being more or less political stable increases or decreases the impact of inequalities on growth, however since the magnitude of the coefficient is still very low and it is not significant, it is unlikely that this is the external factor that drives the almost null impact of inequalities on growth.

Now the impact of corruption is analyzed, and the results are shown in Table 10 in the *Appendix*. In order to this robustness check offer reliable results, one must assume that corruption is an exogenous variable i.e., it should be perceived as an external factor to the economy like Forbes (2000) proposes.

Using fixed effects (with cluster robust standard errors), the causal effect of inequalities on economic growth is greater for those countries with more corruption. The coefficient is 0,005 (highly significant) for the group in which the control of corruption index is above zero *versus* 0,016 (not significant) to those below zero. With the GMM estimation the idea is the same and the countries with less control over corruption seem to experience a greater positive impact of inequalities on growth, but in the countries with greater control over corruption the predictive power of Income Inequalities in determining growth is greater.

Concluding, there is little evidence that those countries with worst institutions are those where the role of income inequalities on growth is more evident. But the net almost null impact of inequalities on growth found before is not yet explained with countries heterogeneity, since in both countries with good and less good institutions the impact of seems to be positive.

Section 7. Conclusion

This paper has studied one of the most debated theories in economics: the impact of income inequalities on economic growth. It exploits a fixed-effects linear estimation that controls for time-invariant omitted variables and a difference generalized method of moments technique developed by Arellano and Bond to estimate the causal effect of interest. It represents a great contribution for the existing literature by using an improved and expanded database of 170 countries from 1971 until 2019.

Results suggest that inequalities do not necessarily impact growth, however since all the coefficients of interest are positive, an increase in the country's degree of income inequality is likely to have a positive impact on subsequent economic growth. The main conclusion points that that a one-point increase in income inequalities is expected to cause a 1% increase in the growth of GDP *per capita* when exploiting fixed effects and even though GMM does not offer a significant coefficient, the direction of the relationship is positive as well: a one-point increase in the gini Index (calculated with net income) would lead to around 0,3% increase in the GDP *per capita* growth rate.

The findings described in this paper challenge the most common belief within previous literature that income inequality harms economic growth. However, the baseline results are not significant and robust to all the specifications and model estimations, thus no absolute conclusions can be drawn, yet there is some evidence on the positive direction of the relationship of interest since all the coefficients take a statistically significant positive value and when exploiting fixed effects or controlling for the country heterogeneity concerning countries with better *versus* worst institutions. In specific, those countries with lower control of corruption seem to be the ones where the inequalities degree has a greater and more significant impact on economic growth.

Nonetheless, the positive relationship between inequality and growth found might have negative implications to countries' welfare, since the economies may face a trade-off between reducing inequality and improving growth performance. Still, it is not possible to draw any definitive policy conclusions, since endogeneity and serial correlation could still influence estimates. Measurement error is also a concern, even though the database is notably improved, and although panel estimation accounts for time-invariant omitted variables, it does not control for omitted variables that vary across time. Therefore, the estimates of the current work should be perceived as a hint for the possibility of a positive causal effect of inequalities on economic growth *per capita*, but this economic question is far from determined. Further careful reassessment of the sign, direction and strength of the association between these two variables is needed and thus, further theoretical and empirical work on this matter should be developed.

Section 8. Appendix

List 1. Countries on the database (170)

Albania, Algeria, Angola, Antigua and Barbuda, Argentina, Armenia, Australia, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cabo Verde, Cambodia, Cameroon, Canada, Central African Republic, Chad, Chile, China, Colombia, Comoros, D.R. of the Congo, Congo, Costa Rica, Côte d'Ivoire, Croatia, Cyprus, Czech Republic, Denmark, Djibouti, Dominica, Dominican Republic, Ecuador, Egypt, El Salvador, Equatorial Guinea, Estonia, Ethiopia, Fiji, Finland, France, Gabon, Gambia, Georgia, Germany, Ghana, Greece, Grenada, Guatemala, Guinea, Guinea-Bissau, Guyana, Haiti, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Kuwait, Kyrgyzstan, Laos, Latvia, Lebanon, Lesotho, Liberia, Lithuania, Luxembourg, Madagascar, Malawi, Malaysia, Maldives, Mali, Malta, Mauritania, Mauritius, Mexico, Republic of Moldova, Mongolia, Montenegro, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, North Macedonia, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russia, Rwanda, São Tome and Principe, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Singapore, Sint Maarten, Slovakia, Slovenia, South Africa, Spain, Sri Lanka, Saint Kitts and Nevis, Saint Lucia, St. Vincent and Grenadines, Sudan, Suriname, Sweden, Switzerland, Syria, Tajikistan, Tanzania, Thailand, Togo, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Turks and Caicos Islands, Uganda, Ukraine, United Arab Emirates, United Kingdom, United States, Uruguay, Uzbekistan, Venezuela, Vietnam, Yemen, Zambia and Zimbabwe.

Table 1: Summary of the Previous Literature on the Impact of Inequalities on Growth

Authors	Data	Methodology	Results
Persson and Tabellini, 1991	9 developed countries (1830-1985); 67 developed and developing countries (1960-85).	Measures of inequality: share of the top quintile; ratio between the income share of the bottom 40% and that of the top 20%. (OLS and 2SLS)	Negative relationship, but it is not statistically significant in non- democratic countries.
Clarke, 1995	Around 70 countries, 1970-88.	Measures of inequality: Gini coefficient, Theil index, income coefficient of variation and ratio between the income share of the bottom 40% and that of the top 20%. (OLS, WLS ans 2SLS)	Negative relationship
Alesina and Rodrik, 1994	70 OCSE countries and developing countries, 1960-85.	Income and land Gini coefficient (OLS and 2SLS)	Negative relationship
Perotti 1996	67 countries, data closest as possible to year 1960.	Income share of the third and of the fourth population quintile.	Negative relationship (not statistically significant in poor countries).
Partridge 1997	USA (48 single states), 1960-90.	Gini coefficient and income share of the third quintile.	Positive relationship
Birdsall and Londono (1997)	43 countries 1960-1992	Gini Coefficient, OLS	Negative relationship
Deininger and Squire 1998	87 countries, among which 27 developing countries, 1960-92.	Income and land Gini coefficient. (OLS)	Negative relationship, which become statistically insignificant with the inclusion of regional dummies.
Li and Zou 1998	46 countries, 1960-90.	Income Gini coefficient (FE,RE)	Positive relationship

Deininger and Olinto 2000	31/60 countries, 1966-1990	Gini Coefficient for income and land, System GMM	Positive when income and land inequality are considered simultaneously; negative for land gini.
Forbes 2000	45-67 countries, for the most part OCSE members; 1970-95.	Income Gini coefficient, GMM	Positive relationship
Mo 2000	20 countries, 1970-85	Income Gini coefficient, FE and RE	Positive Relationship
Panizza 2002	USA (48 single states), 1940-80.	Gini coefficient and income share of the third quintile, FE and GMM	Not statistically significant results.
Balisacan and Fuwa 2003	Philippines, provincial data, 1988-97	Land Gini coefficient, OLS and IV	Positive Relationship
Banerjee and Duflo 2003	45 countries, 1965-90.	Income Gini coefficient, non-parametric methods	Changes in inequality in whatever direction are associated to negative changes in the growth rate.
Chen, 2003	54 countries, 1970-1992	Income Gini coefficient, OLS	Inverted-U relationship
De La Croix and Doepke, 2003	68 countries, 1960-1992	Income Gini Coefficient, Difference GMM	Negative relationship, that becomes non-significant when adding fertility rate.
Gylfason and Zoega, 2003	87 countries, 1965-98	Income Gini Coefficient, SUR	Negative Relationship
Pagano 2004	40 countries, 1950-1990	Income Gini coefficient, GMM	Positive relationship in rich countries, negative relationship in the poor ones.
Iradian 2005	82 countries, 1965-2003	Income Gini coefficient, FE and difference GMM	Positive in the short term and negative in the long term
Knowles 2005	40 countries, 1960-1990	Gini Coefficient (OLS)	Negative for the whole sample; Insignificant for high/mid-income countries and negative for low-income countries; Insignificant for gross-income.
Voitchovsky (2005)	21 developed countries, 1975-2000	Gini coefficient; 90/75 and 50/10 ratios (System GMM)	Insignificant considering aggregate inequality; Positive at the top of inequality distribution; Negative at the bottom of inequality distribution
Easterly 2006	More than 100 countries, 1960-98.	Ratio between the extension of land suitable to grow wheat and that suitable for sugarcane, OLS	Negative relationship
Castelló- Climent 2007	56 countries, 1965-2000	Income and human capital Gini coefficient, first diff GMM and System GMM	Negative relationship
Sukiassyan 2007	26 transition economies, 1988-2002	Income Gini coefficient, OLD and difference GMM	Negative Relationship
Barro 2008	47 to 70 countries, 1965-2003	Income Gini coefficient, OLS	Positive relationship in rich countries, negative relationship in the poor ones.
Noh and Yoo 2008	60 countries, 1995-2003	Income Gini coefficient, FE	Positive Relationship
Lin and Yeh, 2009	83 countries, 1965-2003	Income Gini coefficient, SEM and difference GMM	Negative Relationship
Grijalva 2011	Around 100 countries, 1950-2007	Income Gini coefficient, First diff GMM and System GMM	Inverted "U" relationship the short and medium term (5-10 years). In the long term the results confirm Barro (2008).
Assa 2012	141 countries (100 in the restricted sample), 1998- 2008.	Income Gini coefficient, OLS and 2SLS	Negative relationship in the developing countries, less evident in the advanced economies.
Ravallion 2012	90 countries, 1980-2005	Income Gini coefficient, Difference GMM	Not statistically significant when controlling for initial poverty.

Ostry, Berg and Tsangarides 2014	90 countries, 1966-2005	System GMM, First-diff GMM	First-diff GMM: positive link in whole and in sub-samples by income. System GMM: positive in rich and negative in poor countries.

Source: Author's own elaboration

Table 6: Impact of Income Inequalities on *per capita* GDP Growth – *Fixed Effects estimation not controlling for the convergence hypothesis*

	(1)	*(2)*	*(3)*	*(4)*	*(5)*	*(6)*	*(7)*
Net Inequalities (t-1)	0.013	0.001	0.010*				0.009
	[0.010]	[0.001]	[0.006]				[0.006]
Gross Inequalities (t-1)				0.008	0.000	0.005	
				[0.008]	[0.001]	[0.005]	
GFCF (t-1)	-0.008	-0.014**	-0.009	-0.008	-0.015**	-0.009	-0.009
	[0.009]	[0.006]	[0.013]	[0.009]	[0.006]	[0.014]	[0.013]
Labor Force Participation (t-1)	-0.147	-0.066*	0.015	-0.153	-0.066*	-0.007	0.058
	[0.089]	[0.037]	[0.147]	[0.094]	[0.037]	[0.151]	[0.154]
Human Capital (t-1)	0.027		0.036	0.084		0.058	0.010
	[0.053]		[0.119]	[0.089]		[0.125]	[0.106]
Political Stability and No Violence (t-1)	-0.010	-0.001		-0.009	-0.001		
	[0.009]	[0.004]		[0.009]	[0.004]		
Control Of Corruption (t-1)	-0.024	0.005		-0.020	0.006		
	[0.024]	[0.006]		[0.023]	[0.006]		
Schooling (t-1)		0.024			0.022		
		[0.014]			[0.015]		
Redistribution (t-1)							-0.014**
							[0.006]
Constant	0.357	0.540***	-0.165	0.532**	0.581***	0.080	-0.225
	[0.296]	[0.187]	[0.777]	[0.263]	[0.186]	[0.748]	[0.771]

Note: The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. In this specification the lagged GDP per capita is not included. Cluster adjusted (Country) standard errors are in parentheses**;** ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 7: Robustness Check – Use of Palma ratio instead of the Gini Coefficient

	Fixed Effects		*GMM*	
	(1)	(2)	(3)	(4)
GDP per capita (t-1)	-0.061***	-0.074***	-0.105	-0.137
	[0.017]	[0.019]	[0.072]	[0.114]
Palma Ratio (t-1)	0.001	-0.001	-0.000	-0.002
	[0.001]	[0.001]	[0.002]	[0.004]
GFCF (t-1)	0.006	0.012	-0.002	-0.018
	[0.009]	[0.011]	[0.032]	[0.059]
Labor Force Participation (t-1)	-0.096*	-0.020	-0.002	0.170
	[0.051]	[0.058]	[0.143]	[0.152]
Human Capital (t-1)	0.150***	0.109***	0.313*	0.346
	[0.045]	[0.034]	[0.175]	[0.241]
Political Stability and No Violence		0.004		0.005
		[0.004]		[0.019]
Control Of Corruption (t-1)		0.012		0.013
		[0.008]		[0.044]
Constant	0.719***	0.442	0.769	0.709
	[0.251]	[0.276]	[0.609]	[0.637]

Note: The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. Columns (1) and (2) exploit a Fixed Effects Estimation and cluster adjusted (Country) standard errors are in parentheses. Columns (3) and (4) exploit the Generalized Method of Moments and Windmeijer bias-corrected (WC) robust VCE standard errors are in parentheses; ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 8: Robustness Check– Impact of Income Inequalities on *per capita* GDP Growth – System *Generalized Method of Moments estimation*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
GDP per capita (t-1)	-0.062***	-0.063***	-0.056***	-0.074***	-0.068***	-0.069***	-0.092***
	[0.022]	[0.022]	[0.018]	[0.025]	[0.024]	[0.019]	[0.023]
Net Inequalities (t-1)	0.001	0.001	0.001				0.004**
	[0.001]	[0.001]	[0.001]				[0.002]
Gross Inequalities (t-1)				0.006***	0.005***	0.004***	
				[0.002]	[0.002]	[0.001]	
GFCF (t-1)	-0.014	-0.022**	-0.015	-0.009	-0.017	-0.011	-0.005
	[0.010]	[0.010]	[0.010]	[0.011]	[0.011]	[0.011]	[0.012]
Labor Force Participation (t-1)	-0.001	0.022	-0.071	-0.024	0.056	-0.084	-0.124**
	[0.056]	[0.064]	[0.058]	[0.060]	[0.063]	[0.062]	[0.062]
Human Capital (t-1)	0.160***		0.218***	0.180***		0.230***	0.238***
	[0.050]		[0.071]	[0.066]		[0.071]	[0.076]
Political Stability and No Violence	0.005	-0.002		0.008	-0.001		
	[0.006]	[0.006]		[0.006]	[0.006]		
Control Of Corruption (t-1)	0.049***	0.051***		0.035***	0.038***		
	[0.011]	[0.012]		[0.010]	[0.012]		
Schooling (t-1)		0.105***			0.115***		
		[0.030]			[0.038]		
Redistribution (t-1)							0.009***
							[0.003]
Constant	0.738**	0.823**	0.951***	0.542	0.337	0.859**	1.087***
	[0.317]	[0.332]	[0.337]	[0.367]	[0.343]	[0.362]	[0.345]

Note: Arellano-Bover/ Bundell-Bond Estimation. The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. Two- step GMM estimator applied. Robust, 2-step System GMM estimator with Windmeijer-corrected standard errors; ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 9: Robustness Check- Country heterogeneity: Political Stability and No Violence

	Fixed Effects		*GMM*	
	(1)	(2)	(3)	(4)
GDP per capita (t-1)	-0.087***	-0.283	-0.239***	-0.180**
	[0.022]	[0.172]	[0.043]	[0.082]
Net Inequalities (t-1)	0.004***	0.017	0.005	0.003
	[0.001]	[0.012]	[0.004]	[0.005]
GFCF (t-1)	0.009	0.068	-0.005	0.024
	[0.013]	[0.048]	[0.019]	[0.021]
Labor Force Participation (t-1)	-0.115**	-0.153	0.134	0.007
	[0.047]	[0.183]	[0.135]	[0.152]
Human Capital (t-1)	0.218***	0.252	0.544***	0.231
	[0.049]	[0.157]	[0.118]	[0.222]
Constant	0.783***	0.633	1.135*	0.674
	[0.244]	[0.826]	[0.635]	[0.696]

Note: The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. Columns (1) and (2) exploit fixed effects and the cluster adjusted (Country) standard errors are in parentheses. Columns (3) and (4) use a 2-step GMM estimation and Windmeijer bias-corrected standard errors are in parentheses**;** Columns (1) and (3) present the regression when the index is above 0 and columns (2) and (4) when it is below 0. ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Table 10: Robustness Check- Country heterogeneity: Control of Corruption

	Fixed Effects		*GMM*	
	(1)	(2)	(3)	(4)
GDP per capita (t-1)	-0.094***	-0.229***	-0.178***	-0.192***
	[0.011]	[0.019]	[0.005]	[0.008]
Net Inequalities (t-1)	0.005***	0.016***	0.001***	0.003***
	[0.001]	[0.001]	[0.000]	[0.001]
GFCF (t-1)	0.010**	0.050***	-0.016***	0.020***
	[0.005]	[0.009]	[0.001]	[0.002]
Labor Force Participation (t-1)	-0.080**	-0.131*	0.124***	0.011
	[0.033]	[0.067]	[0.040]	[0.017]
Human Capital (t-1)	0.179***	0.290***	0.416***	0.239***
	[0.025]	[0.049]	[0.020]	[0.046]
Constant	0.687***	0.514	1.154***	0.857***
	[0.144]	[0.334]	[0.167]	[0.080]

Note: The dependent variable "Growth *per capita*" refers to the growth in period t and all the independent variables are reported in period t-1. Columns (1) and (2) exploit fixed effects and the cluster adjusted (Country) standard errors are in parentheses. Columns (3) and (4) use a 2-step GMM estimation and Windmeijer bias-corrected standard errors are in parentheses**;** Columns (1) and (3) present the regression when the index is above 0 and columns (2) and (4) when it is below 0. ***Significant at 1% level. **Significant at 5% level. *Significant at 10% level.

Section 9. References

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