A Reassessment of the Relation between Economic Growth and Maldistribution of Income

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Abstract

This article aims to evaluate the effect of the maldistribution of income on economic growth. From the empirical point of view, the literature on the matter is considerable. However, previous studies have employed the Gini index as a measure of inequality which tends to underestimate income disparities across countries. Because the complexity of inequality has changed over time and due to the Gini index is incapable of capturing the changing nature of distribution, we employ the Palma Ratio instead of the Gini index. The main advantage of employing the Palma Ratio is that it captures the dynamics of inequality and allows us to analyze the roots of this maldistribution. The relationship is estimated employing the methodology of Arellano-Bond for dynamic panels, and the results suggest that maldistribution of income generates a sluggish economic growth. In fact, our results suggest that inequality could be associated with a substantial reduction in growth.

Resumen

El objetivo de este artículo es evaluar el efecto de la mala distribución del ingreso sobre el crecimiento económico. Desde un punto de vista empírico, la literatura especializada es bastante. Sin embargo, los estudios previos han empleado el índice de Gini como la medida de desigualdad la cual tiende a subestimar las disparidades de ingreso entre países. Puesto que la complejidad de la desigualdad ha cambiado a lo largo del tiempo y el índice de Gini es incapaz de capturar esta naturaleza cambiante de la distribución, se decidió utilizar el cociente de Palma en lugar del índice de Gini. La principal ventaja de emplear el cociente es que este captura la dinámica de la desigualdad y permite analizar las raíces de esa desigualdad. La relación es estimada usando la metodología de Arellano-Bond para páneles dinámicos y los resultados sugieren que la mala distribución del ingreso genera un bajo crecimiento económico.

Keywords: *Palma Ratio, dynamic panels, inequality, economic growth.*
Palabras clave: *cociente de Palma, panel dinámico, desigualdad, crecimiento económico.*
JEL Classification: *C23, D63, E25, O11, O47.*

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1 Introduction

Miguel de Cervantes writes in his legendary *The Ingenious Nobleman Sir Quixote of La Mancha* that in this world there are only two kinds of people: haves and have-nots. In the case of the United States, Silva and Yakovenko (2005) show that the US society has a clear two-class structure. Most of the population (97–99%) belong to the lower class and has a very stable distribution of income over time. The upper class (1–3% of the population) has a distribution which changes in time with the stock market rhythm. Concerning the distribution of wealth (which remains more concentrated than income), the three wealthiest people in the United States own more wealth than the entire bottom 50% of the American population combined, a total of 160 million people (Institute for Policy Studies, 2017). These numbers lead one to wonder whether this maldistribution of income and wealth has harmful effects on the economic performance of the countries.

Recently, in fact mostly in the aftermath of the financial crisis, a considerable literature has grown up around the theme of the effects of inequality on growth. The editorial success of books such as Piketty's *Capital in the XXI Century* and Atkinson's *Inequality. What can be done?* marks the increased awareness of inequality topics in the public debate. Likewise, the alarming concentration of income and wealth and their effects on growth have carved out a prominent position in the research agenda. As a matter of fact, there are grounds for believing that the present distorting concentration of income might be behind the current stagnation period experienced by the global economy (see, e.g., Cynamon & Fazzari, 2016).

For example, Goda, Onaran, and Stockhammer (2017) put both income and wealth inequality at the epicenter of the recent crisis and found that rising wealth concentration contributed to the crisis because the increasing asset demand from the rich lied to low and middle-income households to accumulate increasing amounts of debt. Stiglitz (2015), for his part, questions the ‘trickle down hypothesis’ in which a redistribution that favors the more affluent classes will end up increasing economic growth. Stiglitz, on the contrary, points out that the extraordinary growth in top incomes has coincided with an economic slowdown. Jayadev (2013) also notes the strong correlation between the rise of the income held by the top 10 percent and the instability of economic activity as occurred in 2007. Thus, we are witnessing a renewed interest in the effects of income and wealth distribution on economic growth. However, the attention is placed on how the concentration of income and wealth in the top of the distributive chain might slow down the economic performance.

Theoretical accounts of the relationship between inequality and growth have been subject to considerable discussion. From the more classic point of view on economics, inequality was thought of as a requirement for higher rates of growth (Kaldor, 1957). The reason is that a distribution pattern in favor of capital was considered a necessary condition to allow for faster capital accumulation and thus a higher degree of development. However, as the development process consolidates, it is expected to experience a reduction of inequality, and thus the relationship between inequality and growth exhibits an inverted U shape over time in the lines suggested by Kuznets (Barro, 2008).

Barro (1999) argues that high levels of inequality reduce growth in relatively developing countries but encourage growth in developed ones. Galor and Moav (1999), on the other hand, claim that inequality is beneficial for growth in early stages of development when physical capital is the prime engine of growth and harmful in more advanced stages when human capital is the prime engine of growth. Alesina and Rodrik (1994) proposed a model of endogenous growth with distributive conflict among agents with varying capital/labor shares. Their theoretical result suggests a definitive negative relationship between growth and inequality of income and wealth: the greater the inequality of wealth and income, the higher the rate of taxation, and the lower growth. Persson and Tabellini (1994) found similar results and they suggest that inequality is harmful to growth in democracies. Nevertheless, Li and Zou (1998) challenge the results found by Alesina and Rodrik, and Persson and Tabellini arguing that income inequality is not harmful to growth. They propose an extension of the theoretical model of Alesina and Rodrik which leads to the result that more equal income distribution can lead to higher income taxation and lower economic growth.

Now, from the empirical perspective, the results are also contradictory. There is a considerable body of empirical literature that recognizes the existence of a relationship between the distribution of income and economic growth (see, e.g. Barro, 2000; 2003;

Ciccone & Jarocinski, 2010; Forbes, 2000; Herzer & Vollmer, 2012; Li & Zou, 1998; Panizza, 2002; Ravallion, 2001, and Voitchovsky, 2005 among others). However, regardless whether the relation found is positive or negative, in overall the whole previous empirical literature is based mainly upon the Gini index as a measure of inequality. This is precisely our objection to the empirical literature on the matter. Let us explain why.

Income distribution has followed an unusual path in which the middle and upper-middle classes (deciles 5-9) steadily maintain their respective national incomes irrespective of country and time. In the words of Silva and Yakovenko (2005), they are in statistical equilibrium. On the other hand, poor and rich people experience the significant volatility of their incomes or, in other words, they are in statistical disequilibrium. This empirical regularity was found by Palma (2011) who revealed that changes in income distribution are exclusively due to changes in the share of the wealthiest 10 percent and poorest 40 percent because the income the middle group seizes is relatively stable at 50 percent of the national income. Cobham, Schlogl, and Sumner (2016), with a new and expanded data set, ratified Palma's proposition and found that it is getting stronger over time.

This pattern of distribution has drastic consequences for measuring inequality since the typical indexes like Gini are oversensitive to changes in the middle of the distribution, which is precisely the most stable fraction of the distributive chain. As Palma (2011:105) has pointed out, the Gini index is unable to measure the true magnitude of the inequality because it says nothing about where that inequality occurs. The discontent with Gini index can be summarized in Palma's words:

> "[...] This raises serious questions regarding how useful the Gini index is as an indicator of overall income inequality, especially because (from a statistical point of view) the Gini is supposed to be more responsive to changes in the middle of the distribution. That is, the most commonly used statistic for inequality is one that is best at reflecting distributional changes where changes are least likely to occur! As a result, the overall geometry of inequality as shown by the Gini is likely to underestimate income disparities across countries."

The Palma Ratio, on the other hand, provides an accurate depiction of the distributional changes since it is a measure of the capture of total income or consumption of the wealthiest decile over the capture of the poorest 40 percent (Palma, 2011; Cobham et al., 2016).

In this sense, the reassessment we propose in this article is a new analysis of the relationship between economic growth and distribution but this time employing the Palma ratio as the measurement of inequality. To our knowledge, no other articles have assessed this relation employing the Palma ratio. This is surprising since the ability of the Gini index to provide an accurate measurement of inequality long has been questioned (Atkinson, 1970). Moreover, it is surprising that the Gini index remains the dominant measure of inequality in times in which there is considerable interest in tracking top incomes like those of the top ten percent (Duménil & Lévy, 2018; Stiglitz, 2015 among others). In this sense, by employing the Palma Ratio as the measure of inequality, this article will generate fresh insight into the relationship between economic growth and income distribution. To some extent, the article also contributes to the literature on the determinants of growth.

The next section discusses the econometric technique of dynamic panels we employed to estimate the relationship between income distribution and economic growth. Section 3 describes the data as well as the treatment we gave it in order to compute our variables. Also, we discuss the evolution of the Palma Ratio over time across different regions. Further, in section 4, we present the results of our estimation and discuss the statistical as well as the economic relevance of the findings. The fifth section concludes highlighting the main result of this document and some general recommendations.

2 Empirical Framework

We seek to explain the relationship between economic growth and income distribution by employing Panel Data analysis. Most of the literature have researched this relationship employing using a cross-sectional approach *à la* Barro. Cross-country growth estimates, however, are likely biased because of potential country-specific effects not captured by this approach. By employing panel data, we control by those country-specific effects avoiding spurious results. We follow a dynamic specification of the equation for a country's growth rate where the right-hand side variables are some of the usual suspects as potential determinants. We selected some of the variables that have received the most attention in both empirical and theoretical literature. In particular, the growth regression we seek to estimate is formulated as follows (see, e.g., Tam, 2011):

$$g_{i,t} = \delta_t + \mu_i + \beta_1 g_{i,t-1} + \beta_2 PR + X_{i,t}\Psi + \varepsilon_{i,t} \tag{1}$$

Where g stands for the rate of economic growth measure as the real GDP rate of growth; PR represents the Palma Ratio; X is a matrix of covariates; μ represents unobserved country-specific effect; δ captures time-specific effects, and ε is the error term. On the other hand, $\beta_j\ (j = 1,2)$ and the matrix Ψ stand for parameters to estimate which expected sign can be either positive or negative.

In order to estimate the equation (1) we follow Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998), and use the Generalized Method of Moments (GMM) to estimate the parameters of the model. We selected GMM methodology since we also follow the typical procedure in the empirical literature on economic growth of using averages of 5-year periods. The procedure shrinks the number of observations over time (T) which poses some difficulties to the method of fixed effects because it requires a relatively large T. However, the methodology of Arellano-Bond dynamic panel estimators is designed for situations where T is relatively small and n (individual units) relatively large. Additionally, the typic explanatory variables are likely to be jointly endogenous with economic growth, and, therefore, estimates might be biased as a result from simultaneous or reverse causation.

The Arellano-Bond methodology has been employed widely to assess the relationship between variables under a dynamic context. As stated by Bond (2002:142):

> *"Dynamic models are of interest in a wide range of economic applications, including Euler equations for household consumption, adjustment cost models for*

> *firm's factor demands, and empirical models of economic growth. Even when coefficients on lagged dependent variable are not of direct interest, allowing for dynamics in the underlying process may be crucial for recovering consistent estimator of other parameters."*

In this sense, the methodology suggested here seems to cope accurately with the dynamic nature of the relationship we seek to estimate and the availability of information. Additionally, the Arellano-Bond methodology keeps the document tractable and comparable with similar literature which have applied the same technique but have found opposite results (see, Forbes, 2000).

The Arellano-Bond dynamic panel estimators are based on differencing regressions and instruments to control for unobserved country-specific effects. Also, instruments are required to cope with the likely endogeneity of the explanatory variables, as well as with the fact that after differentiating, the resulting error term is correlated with the lagged dependent variable. These instruments come from previous observations of dependent and explanatory variables.

There are two types of GMM estimation techniques: first-difference GMM and the system GMM. The GMM difference method represents a significant improvement concerning the standard fixed-effects and first difference estimators. The first-difference GMM estimator (Arellano & Bond, 1991) seeks to eliminate country-specific effects and uses lagged observations of the explanatory variables as instruments. However, the first-difference GMM method has a disadvantage in dealing with variables that tend to have a low degree of variability over time within a country because it eliminates most of the variation in the variable(s) by taking the first difference. In this context, lagged observations of the explanatory variables tend to be weak instruments for the variables in difference, thus yielding also weak estimators. Instrument weakness influences the asymptotic and small-sample performance of the difference estimator. Also, experiments carried out in small samples show that the weakness of the instruments can produce biased coefficients.

Since the Palma Ratio possibly exhibiting a lower degree of variability in some countries, we use the system GMM technique by Arellano and Bover (1995), and

Blundell and Bond (1998) to avoid the problem mentioned above. This GMM technique creates a system of regressions in differences and level. The instruments of the regressions in first differences remain the same as in the GMM difference. The instruments used in the regressions in level are the lagged differences of the explanatory variables and they will be appropriate if there is no correlation between the differences of these variables and the country-specific effect even though the levels of the explanatory variables can still be correlated with the country-specific effects.

The validity of the GMM estimators depends significantly on the exogeneity of the instruments used in the model. The exogeneity of the instruments can be tested by the J statistics of the commonly used Hansen test. The null hypothesis implies the joint validity of the instruments. In other words, a rejection of the null hypothesis indicates that the instruments are not exogenous and hence the GMM estimator is not consistent. Roodman (2009) advises not to take comfort in a Hansen test p-value below 0.1. Additionally, we also employ the Sargan test of over-identifying restrictions suggested by Arellano and Bond (1991) and Arellano and Bover (1995), which tests the overall validity of the instruments by analyzing the sample analog of the moment conditions used in the estimation process. Failure to reject the null hypothesis provides support to the model.

As for the instruments, a large number of instruments is likely to overfit the endogenous variables. The literature is not very specific in determining the maximum number of instruments to be used in each case. Roodman (2009) suggests, as a relatively arbitrary rule of thumb, that instruments should not outnumber individual units in the panel (or countries in this case). Here we tried to keep the number of instrumental variables to a minimum and used the 'collapse' function to limit the proliferation of instruments.

The parameters can be estimated using either one- or two-steps estimators. We employed both. In two-step estimation we performed the Windmeijer (2005) finite-sample correction to the reported standard errors, without which those standard errors tend to be severely downward biased. Nevertheless, Bond (2002:147) mentioned that: "[...]the dependence of the two-step matrix on estimated parameters makes the usual asymptotic distribution approximations less reliable for the two-step estimator." For this reason, we also employed the robust one-step estimator for purposes of robustness.

Let us now move on to describe and analyze the data in the next subsection.

2.1 Data and Descriptive Statistics

The panel is composed of 98 countries (See appendix) including both developed as well as developing countries and the estimation covers the period 1980-2010. However, we consider periods of five years to compute the rate of growth which is a widespread practice in panel data analysis to avoid business cycle fluctuations and effects caused by unit roots. Regarding the latter, Bound, Jaeger, and Baker (1995) stated that when the individual series have near unit root properties, the instruments available for the equations in first difference are likely to be weak and therefore the instrument variable estimator can be subject to severe finite sample biases where the instruments used are weak. Hence, after the calculation of the rate of growth, we can exploit a maximum of 6 non-overlapping observations per country.

As mentioned above, the dependent variable is the rate of economic growth computed as: $\frac{1}{5}(\log GDP_t - \log GDP_{t-5})$. The main explanatory variable will be the Palma Ratio which is calculated as: $\frac{D10}{D1+D2+D3+D4}$ where $D\#$ is the income-share appropriated by decile #.

We include additional covariates to improve the explanatory power of the model. Our covariates (all logged) are the stock of capital (K) at current PPPs (in mil. 2011US$); a human capital index (H) based on years of schooling and returns to education; terms of trade (TOT) computed as the price level of exports over the price level of imports; the real GDP level in period t (GDP) at constant 2011 national prices (in mil. 2011US$); the share of government consumption (Ggdp) at current PPPs; time dummies; and a region dummy variable equal to one if the country belongs either to Latin America and the Caribbean (LA), East Asia and Pacific (EA), Middle East and North Africa (MENA), North America (NA), South Asia (SA), or Sub-Saharan Africa

(SSA). We classified our sample by region according to the grouping made by the World Bank. Except for the Palma Ratio, the source of the variables is PWT9.0 (Feenstra, Inklaar & Timmer, 2015). For the calculation of the Palma Ratio, we used data from Global Consumption and Income Project where all incomes are expressed in 2005 USD PPP.

There are a large number of variables that can be used to explain growth. To maintain our work consistent and comparable with the existing empirical literature, we have decided to consider some of the most commonly used variables in the previous studies:

1) The real GDP level in period t stands for the hypothesis of transitional dynamics. In mainstream growth models, a country's growth rate depends on the initial level of the GDP. The conditional convergence hypothesis states that other things held constant, economies that are lagging should grow faster than the rich countries usually due to the existence of diminishing returns to factors of production. Even though there is nothing in the more radical Keynesian theoretical approach that generates a tendency to convergence, we nonetheless follow the existing literature and include the log of the initial GDP as a potential explanatory variable in our regression.

2) Growth models also use government spending (%GDP) as a proxy for government burden. These models argue that governments can be a heavy burden on the economy when they impose high taxes, promote inefficient programs, do not eliminate unnecessary bureaucracy, and distort market signals. The proxy commonly used to account for the government burden is the ratio of government current expenditures to GDP. However, typically economists also acknowledge the importance of public investments on health, education, and security to promote growth.

3) The stock of capital and the human capital index account for an ampler theory of capital accumulation (Rebelo, 1991) where both types of capital complement each other. In a broader sense, the accumulation of physical as well as of human capital is considered a primary source of growth. The classical theory of

development (Lewis, 1954; Gerschenkron, 1962) also contemplated the capital accumulation as the engine of growth, particularly for developing countries.

4) The terms of trade and period-specific dummy variables account for external factors that can affect growth. Terms of trade tend to capture the external influence on each country, whereas the period-specific dummies are used to capture external factors affecting all countries simultaneously. For instance, the terms of trade account for changes in foreign demand, relative costs of production, and external financial inflows. Period-specific dummies capture conditions at a given period such as booms and recessions, waves of technological change, economic reforms, among other issues.

5) Some norms and institutions that can either promote or hamper economic growth are usually clustered in groups of countries. Countries belonging to the same region typically share many other factors that can affect growth like those related to culture, geography, or endowments of natural resources. For this reason, we decided to include a region dummy variable to account for those differences across countries in our sample.

The GMM methodology allows giving different treatment to variables involved in the estimation. Variables can be thought of as endogenous, exogenous, or predetermined. The only exogenous variables we considered were region and the period dummies. Terms of trade were treated as predetermined. They cannot be treated either as endogenous or exogenous because typically the terms of trade a country face depend on whether the country is a large or small economy in the global market. If the country is a large economy, the terms of trade are endogenous. The opposite is true in the case where the country is a small economy. The rest of the variables were treated as endogenous, and the reason was given above: the income distribution, as well as the rest of the covariates, can be determined by the rate of economic growth. To control for this possibly endogeneity we treated them as endogenous.

Before presenting the regression results, we spent some lines analyzing some descriptive statistics paying closer attention to the evolution of the Palma Ratio. Table 1 provides an overview of some basic statistics of the variables considered in this study like the mean, standard deviation, minimum, and maximum of the variables. The dependent variable, the rate of growth of GDP, shows considerable dispersion, with a range of almost 30 percentage points during the five-years period. What is interesting about the data in this table is that the Palma Ratio has reached worrying levels. In general, ten percent of the wealthiest people have appropriated, approximately, four times the income of people in the bottom 40 percent on average. The situation is even more dramatic in developing countries.

Table 1. Descriptive Statistics of the Panel.

Variable	Mean	Std. Dev.	Min	Max
g	0.033	0.028	-0.107	0.128
PR	3.908	2.446	0.731	14.433
K	12.187	2.100	7.026	17.705
Ggdp	-1.814	0.431	-3.487	-0.180
H	0.725	0.331	0.038	1.309
GDP	11.539	1.883	7.387	16.542
TOT	-0.003	0.099	-0.391	0.255

To assess the trajectory of inequality across countries, we classified our sample by region according to the grouping made by the World Bank and represented the path of the Palma Ratio over the five-year periods we have considered. Figure 1 shows the results.

Figure 1. Mean of the Palma Ratio per region.

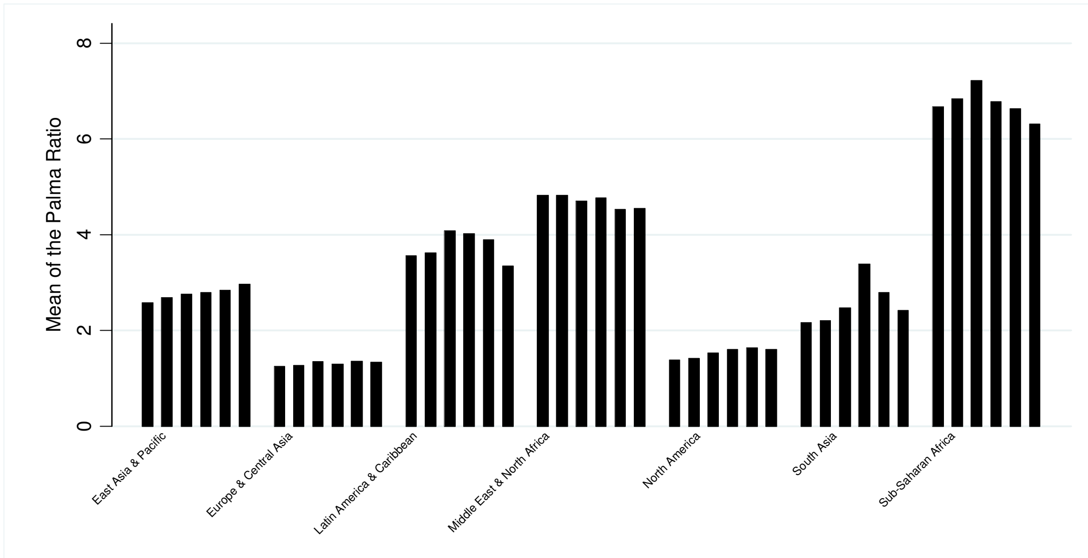

Figure 1 is quite revealing in several ways. First, undoubtedly the level of inequality across the sample of countries exhibits worrisome concentrations regardless of the degree of development. Second, the income distribution gets worse as the degree of development is lower. In relatively developed regions like Europe and Central Asia as well as North America, the upper-level class seizes about two times the income of the entire bottom 40 percent. However, this is significantly lower than the portion of the income that the same class seizes in regions lagged in the race for development like Sub-Saharan Africa. United Nations (2017) points to highly dualistic economic apparatus characterized by a significant oil and mining sector as well as the limited distributive capacity of the state, as determinants of this increasing inequality in Sub-Saharan Africa. Noteworthy is the reduction of inequality in a region like Latin America and the Caribbean, which has been considered one of the most unequal across the world.

3 Results and Discussion

In this section, we present the regression results of equation (1). Table 2 reports estimates of equation (1) using Arellano and Bond's GMM technique. Column 1 exhibits the results employing the two-steps procedure while Column 2 shows the results utilizing one-step.

Table 2. Regression Results, system GMM.

Variables	1 Two-Steps	2 One-Steps
gt-1	0.191**	0.204***
	(-0.0763)	(-0.0722)
PR	-0.0114***	-0.00806**
	(-0.00358)	(-0.0041)
K	0.0259*	0.0188
	(-0.0141)	(-0.0202)
Ggdp	0.0097	0.0056
	(-0.0115)	(-0.0133)
H	-0.239	-0.101
	(-0.162)	(-0.161)
GDP	0.0105	0.00507
	(-0.0095)	(-0.00969)
TOT	0.0997***	0.0930**
	(-0.0353)	(-0.0384)
LA	0.0508***	0.0413**
	(-0.0196)	(-0.0167)
EA	0.0461***	0.0377***
	(-0.0149)	(-0.0134)
MENA	0.0678**	0.0508**
	(-0.0271)	(-0.0205)
NA	-0.0162	-0.0149
	(-0.0182)	(-0.0172)
SA	0.0352	0.0296
	(-0.0228)	(-0.0212)
SSA	0.0955***	0.0739**
	(-0.0361)	(-0.0309)
Constant	-0.103	0
	(-0.0763)	(0.00)
Observations	490	490
Number of countries	98	98
Instruments	47	47

Hansen Test (p-value)	0.243	0.243
Sargan Test (p-value)	0.206	0.206
Arellano-Bond Test for AR(1)	0.001	0.000
Arellano-Bond Test for AR(2)	0.701	0.537

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Results are relatively consistent with each other under both procedures. First, the lagged value of the rate of economic growth is statistically significant, which might be perceived as a validation of our identification strategy. Dynamic panel-data estimates are relevant if the dynamic component is significant, otherwise, a different methodology of estimation might be more appropriate. The reported Hansen test validates the instruments utilized as exogenous, and the p-value is larger than 0.1 as recommended by Roodman. The Sargan test has the same null hypothesis as Hansen and confirms the exogeneity of the instruments as well.

The Arellano-Bond test examines whether the error term is serially correlated. The null hypothesis is no serial autocorrelation among the error term, and the tests support the model specification when the null hypothesis is not rejected. In the system specification, we test whether the differenced error term (that is, the residual of the regression in differences) is second-order serially correlated. First-order serial correlation of the differenced error term is expected even if the original error term (in levels) is uncorrelated unless the latter follows a random walk. Second-order serial correlation of the differenced residual indicates that the original error term is serially correlated and follows a moving average process at least of order one. This would reject the appropriateness of the proposed instruments (and would call for higher-order lags to be used as instruments). Thus, the Arellano-Bond test supports our model specification.

Now, models implying conditional convergence predict that the coefficient on initial income must be negative and, of course, significant. The coefficient associated with GDP level is negative under the one-step procedure and positive if the two-step is employed. However, both are insignificant. The coefficient on the human capital index

(H) is negative (but not significant). Although this result may not support the traditional human capital theory, these coefficients are similar to those found in other growth models estimated using the same technique (see, Forbes, 2000). The stock of capital (K) has a positive effect on growth as expected and predicted by economic theory although not significant as well as the public spending. Terms of trade, as well as the region dummy, are significant and the coefficients associated are positive except for North America.

The most important result to emerge from the regression is the coefficient of inequality. No matter which estimation procedure is utilized, this coefficient is always negative, as hypothesized in recent work examining the relationship between inequality and growth. This coefficient is also significant although more significant under the two-step procedure.

The coefficient found means that if the inequality in the country, measured by the Palma Ratio, increases in one point, holding constant with other growth determinants, this will be associated with approximately -1.14 percent decrease in average annual growth over the next five years. The decrease in the rate of economic growth, as a result of an increase of inequality, would be lower according to the parameter estimated with the one-step procedure (-0.8 percent). The resulting estimate of a negative coefficient on inequality suggests that countries with lower levels of inequality tend to have higher steady-state levels of income. The magnitude reached by the coefficient seems reasonable in economic terms. In contrast, similar approaches employing the same technique have found disproportionate values of the coefficient associated with inequality (see Forbes, 2000).

Overall, these results confirm the association between economic growth and income distribution and are consistent with current literature which suggests that maldistribution of income may have contributed to the decrease in economic activity across the world. Several reasons can be found in economic theory to explain the sluggish economic growth, but economists generally agree that one reason output has stagnated, mainly in the aftermath of the financial crisis, is due to the distorting distribution of income.

An implication of this study is the possibility to implement policies intended to correct these distortions and therefore improve economic growth. In particular, policies aimed to deviate income from capital to labor could enhance growth. The main advantage of employing the Palma Ratio instead of the Gini index as the measure of inequality, it is that the ratio, unlike the Gini, allows us to analyze the roots of inequality since it points to where the primary process of inequality is happening.

4 Conclusion

The purpose of the current article was to determine, first, whether the income distribution affects economic growth, and, second, the sign of the relation. This study employed a relatively new measurement of inequality as it is the Palma Ratio which can capture the current dynamics of inequality. The correlation between maldistribution of income and the rate of economic growth was tested utilizing Arellano-Bond's GMM methodology. The results of the regression analysis show that maldistribution of income has an adverse effect on economic performance. Because the sample of countries included developed as well as developing countries, this result can be taken as evidence against the hypothesis that posits that 'things have to get worse before they can get better.'

Further studies might explore the relationship between economic growth and maldistribution of wealth. As stated above, wealth remains more concentrated than income and research on the matter is few in numbers even though wealth concentration has carved out a prominent position in the research agenda I topic related to growth. Finally, as a note of caution, the generalizability of these results is subject to certain limitations as any regression analysis. For instance, results can depend on the specific identification strategy that was chosen and the sample of countries.

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Appendix. List of Countries

Albania	Algeria	Angola	Argentina	Australia	Austria	Bangladesh
Belgium	Benin	Bolivia	Botswana	Brazil	Bulgaria	Burundi
Cambodia	Cameroon	Canada	Central Afr. Rep.	China	Colombia	Congo, Dem. Rep.
Congo, Rep.	Costa Rica	Cote d'Ivoire	Denmark	Dominican Rep.	Ecuador	Egypt
El Salvador	Ethiopia	Finland	France	Germany	Ghana	Greece
Guatemala	Haiti	Honduras	Hungary	India	Indonesia	Iran
Ireland	Israel	Italy	Jamaica	Japan	Jordan	Kenya
Lao	Lesotho	Madagascar	Malawi	Malaysia	Mali	Mauritius
Mexico	Mongolia	Morocco	Mozambiq ue	Myanmar	Namibia	Nepal
Netherlands	Nicaragua	Niger	Nigeria	Norway	Pakistan	Panama
Paraguay	Peru	Philippines	Poland	Portugal	Romania	Rwanda
Senegal	Sierra Leone	South Africa	Spain	Sri Lanka	Sudan	Sweden
Switzerland	Syrian Arab Rep.	Taiwan	Tanzania	Thailand	Togo	Trinidad and Tobago
Tunisia	Turkey	United Kingdom	United States	Uruguay	Venezuela	Vietnam