Research Square

Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

Does the Inequality Measure Matter for Economic Growth? Evidence from the Palma Ratio

Pedro Clavijo-Cortes
New Mexico Taxation and Revenue Department
Jacobo Campo-Robledo
jacampo@ucatolica.edu.co

Catholic University of Colombia
Nancy Gordillo-Ramirez
Universidad Nacional Abierta y a Distanciaprograma Finanzas y Comercio InternacionaP
Henry Mendoza- Tolosa
Departamento Administrativo Nacional de Estadística

Research Article

Keywords: Palma Ratio, dynamic panels, inequality, economic growth.

Posted Date: November 19th, 2026

DOI: https://doi.org/10.21203/rs.3.rs-11333294/v1

License: This work is licensed under a Creative Commons Attribution 4.0 International License.
Read Full License

Additional Declarations: No competing interests reported.

Does the Inequality Measure Matter for Economic Growth? Evidence from the Palma Ratio

Pedro Clavijo Cortes[♣] Jacobo Campo Robledo[♠]

Nancy Gordillo Ramirez[♦] Henry Mendoza Tolosa[*]

Abstract

This article evaluates the effect of income inequality on economic growth. The empirical literature on this question is extensive, but its findings remain inconclusive. Depending on the sample, the period, and the estimation technique, inequality has been found to hinder, foster, or bear no significant relation to growth. We argue that part of this disagreement may stem from the way inequality is measured. Most previous studies rely on the Gini index, which is most sensitive to changes in the middle of the distribution—precisely the segment that has proven most stable across countries and over time—and therefore tends to understate income disparities driven by the tails. We reexamine the inequality–growth relationship using the Palma Ratio, a measure that focuses on the income shares of the top 10 percent and the bottom 40 percent, where distributional change actually occurs. Using a panel of 98 countries over the period 1980–2010 and system GMM estimators for dynamic panels, we find that higher inequality is associated with significantly slower economic growth. As a robustness exercise, we re-estimate the model using a grouped-decile Gini coefficient and the income share of the richest 10 percent, both constructed from the same underlying distributional data. The negative relationship is preserved across measures, although its standardized magnitude is largest when inequality is measured by the Palma Ratio. These results suggest that the choice of inequality indicator does not merely affect how inequality is described, but also the estimated economic magnitude of its association with growth.

Keywords*: Palma Ratio, dynamic panels, inequality, economic growth.*
JEL Classification*: C23, D63, E25, O11, O47.*

[♣] Senior Economist, New Mexico Taxation and Revenue Department, https://orcid.org/0000-0002-1021-6206, pedro.clavijo@tax.nm.gov

[♠] **Corresponding autor**. Facultad de Ciencias Económicas y Administrativas, Universidad Católica de Colombia, https://orcid.org/0000-0003-3057-6206 , jacampo@ucatolica.edu.co

[♦] Líder Nacional del programa Finanzas y Comercio Internacional, Universidad Nacional Abierta y a Distancia, https://orcid.org/0000-0001-5913-2620, nancy.gordillo@unad.edu.co

[*] Departamento Administrativo Nacional de Estadística (DANE), https://orcid.org/0000-0002-3429-0662, hamendozat@dane.gov.co

1 Introduction

Miguel de Cervantes writes in his legendary work, *The Ingenious Nobleman Sir Quixote of La Mancha*, that there are only two kinds of people: haves and have-nots.[1] Four centuries later, the observation still resonates. In the United States, the three wealthiest individuals possess more wealth than the entire bottom 50 percent of the population combined—some 160 million people (Institute for Policy Studies 2017). Figures of this kind naturally lead one to ask whether such a concentration of income and wealth harms a country's economic performance.

In the aftermath of the 2008 financial crisis, a considerable body of literature emerged on the effects of inequality on growth. The editorial success of books such as Piketty's *Capital in the Twenty-First Century* (2014) and Atkinson's *Inequality: What Can Be Done?* (2015) illustrates the growing prominence of distributional issues in public debate, and the concentration of income and wealth has secured a central position in the research agenda. There is reason to believe that the current concentration of income may have contributed to the period of stagnation experienced by the global economy (Cynamon & Fazzari 2016). Goda, Onaran, and Stockhammer (2017), for instance, place income and wealth inequality at the center of the recent crisis, arguing that rising wealth concentration led low- and middle-income households to accumulate more debt. Stiglitz (2015) questions the 'trickle-down' hypothesis—according to which redistribution toward the more affluent classes enhances growth—and points out that the extraordinary rise of top incomes has instead coincided with an economic slowdown. Jayadev (2013) likewise notes the strong correlation between the income share of the top 10 percent and the instability of economic activity in 2007.

Despite this renewed interest, the empirical literature has not reached a consensus on the sign, size, or robustness of the effect of inequality on growth. Early cross-country studies reported a negative relationship (Alesina & Rodrik 1994; Persson & Tabellini 1994), later panel-data studies found a positive one (Forbes, 2000; Li & Zou, 1998), and subsequent work has documented effects that are nonlinear or conditional on the level of development, financial deepening, or social mobility (Barro 2000; Voitchovsky 2005; Brueckner & Lederman 2018; Braun, Parro & Valenzuela 2019; Aiyar & Ebeke 2020). Recent surveys conclude that the evidence remains mixed (Ferreira, Gisselquist & Tarp 2022). Section 2 reviews this literature in detail.

Recent research suggests that the inequality–growth debate is far from settled, but it has become increasingly clear that both the location of inequality within the income distribution and the empirical setting matter. Using top-income shares for a large international sample, Tuominen (2024) shows that the relationship between top-end inequality and subsequent growth varies with both the level of economic development and the time horizon considered. Recent subnational evidence also points to substantial heterogeneity. Artal-Tur, Osorio-Caballero and

[1] *Dos linajes solos hay en el mundo, como decía una abuela mía, que son el tener y el no tener.*

Nuñez (2025), using alternative distributional measures including the Palma Ratio, report evidence of a positive association between inequality and growth across Mexican states, while Nguyen, Kaizoji and Inoue (2025), using alternative inequality measures and system GMM for Vietnamese provinces, likewise find a positive relationship between inequality and economic development. Taken together, these findings reinforce a central but often overlooked point. The choice of inequality measure is not an innocuous empirical decision. If different segments of the income distribution are associated with different growth mechanisms, an aggregate indicator may conceal precisely the distributive variation that is economically relevant. More generally, recent evidence shows that empirical conclusions about inequality can be sensitive to both the definition of the relevant income groups and the inequality measure employed (Krolage, Peichl & Waldenström 2022; Filauro, Parolin & Valetto 2025).

This article starts from the premise that part of the disagreement may be rooted in measurement. Regardless of whether the estimated relationship is positive or negative, the existing empirical literature relies almost exclusively on the Gini index as the measure of inequality. Yet income distributions around the world display a striking regularity. Palma (2011, 2019) documents that the middle and upper-middle classes (deciles 5–9) capture a remarkably stable share, about half, of national income, irrespective of country and time, so that virtually all distributional change is driven by movements in the shares of the richest 10 percent and the poorest 40 percent. With a new and expanded data set, Cobham, Schlögl, and Sumner (2016) confirm this proposition and find that it has grown stronger over time.

This distributional pattern has serious consequences for the measurement of inequality, because the Gini index is, by construction, most responsive to changes in the middle of the distribution; the very segment where changes are least likely to occur. As Palma (2011: 105) puts it, the Gini index says little about *where* in the distribution inequality arises, and its overall geometry is therefore likely to underestimate income disparities across countries. The Palma Ratio (the income share of the richest decile divided by that of the poorest 40 percent) concentrates on the two tails of the distribution, where distributional change actually occurs (Palma 2011; Cobham *et al.* 2016).

The contribution of this article is therefore twofold. First, it provides a systematic cross-country reassessment of the inequality–growth relationship using the Palma Ratio as the main measure of inequality. The suitability of conventional inequality measures for this purpose has long been questioned (Atkinson 1970), and recent work continues to show that standard measures such as the Gini may understate distributional changes concentrated among high-income groups (Cowell & Flachaire 2024). Much of the recent debate has consequently focused on changes at the top of the income distribution (Stiglitz 2015; Duménil & Lévy 2018). Second, by testing whether the negative association between inequality and growth survives when inequality is measured at the tails of the distribution, the article speaks directly to one possible explanation for the mixed findings in the previous literature. Conventional inequality measures may not

capture equally well the distributive variation that is relevant for growth. To some extent, the article also contributes to the broader literature on growth determinants.

Viewed in this way, our empirical exercise is not simply a replication of conventional growth regressions with a different inequality indicator. It constitutes a measurement-based reassessment of the inequality–growth nexus. By retaining a dynamic-panel framework comparable to influential contributions in the literature while changing the lens through which inequality is observed, we ask whether part of the instability of previous estimates reflects not only differences in samples, specifications, or estimation methods, but also the distributive margin captured by the inequality indicator itself. This distinction gives the empirical exercise a direct economic interpretation because the Palma Ratio identifies changes in the balance between the income shares of the top 10 percent and the bottom 40 percent.

We complement this baseline exercise with a direct comparison of alternative inequality measures. Using the same underlying GCIP decile-income profiles, we construct a grouped-decile Gini coefficient and the income share of the richest 10 percent and re-estimate the growth model on the same country-period sample. This design holds constant the data source, income concept, sample composition, and econometric framework, allowing us to isolate more cleanly whether the measurement of inequality itself affects the estimated inequality–growth relationship.

The remainder of the article is organized as follows. Section 2 reviews the theoretical channels through which inequality may affect growth and the empirical evidence accumulated to date and develops the case for the Palma Ratio. Section 3 presents the econometric strategy—system GMM estimation of a dynamic panel—together with the data, the choice of control variables, and descriptive statistics, including the evolution of the Palma Ratio across regions. Section 4 presents the baseline estimates, compares the results across alternative inequality measures, and discusses their statistical and economic significance in light of the recent literature. Section 5 concludes.

2 The income distribution–growth connection

The relationship between income inequality and economic growth has long been debated among economists, policymakers, and social scientists. This section first reviews the main theoretical channels through which inequality may affect growth. We distinguish supply-side channels, demand-side channels, political-economy and institutional channels, and the role assigned to inequality in theories of economic crisis, and then turn to the empirical evidence, emphasizing how methodological choices and, in particular, the choice of the inequality measure may account for the mixed findings.

2.1 Theoretical channels

Traditional neoclassical growth theory treated income distribution as largely irrelevant to the long-run growth rate. In the Solow–Swan model (Solow 1956), growth is driven by capital accumulation, labor-force growth, and technological progress, none of which depends directly on the distribution of income. Classical and early post-Keynesian thinking, by contrast, assigned inequality a positive role. Since richer households save a larger fraction of their income, concentrating income in their hands should—in a capital-scarce economy—raise aggregate saving, accelerate capital formation, and enhance growth (Kaldor 1957). Kuznets (1955) famously added a temporal dimension. As economies industrialize, inequality first rises, as the shift out of agriculture benefits a small segment of the population, and later falls, as education, social mobility, and redistributive policies spread the gains; the inverted-U 'Kuznets Curve' (see also Barro 2008). Recent cross-country evidence provides some empirical support for this channel. For example, Koo and Song (2016) find that aggregate saving increases with income inequality, particularly in richer and more financially developed economies. In the same spirit, Galor and Moav (2004) argue that inequality is beneficial in early stages of development, when physical capital is the main engine of growth, and harmful in later stages, when human capital becomes the binding constraint.

The endogenous growth literature of the late 1980s and 1990s provided microeconomic foundations for a negative effect of inequality on growth operating through the supply side. In the seminal model of Galor and Zeira (1993), credit-market imperfections prevent poor households from borrowing to finance education; when initial endowments are highly unequal, inequality therefore translates into persistent underinvestment in human capital, lowering average productivity and growth. Aghion, Caroli, and García-Peñalosa (1999) extend the argument to a Schumpeterian setting in which growth is driven by innovation and skill accumulation. In this framework, high inequality reduces social mobility, weakens incentives for skill formation among the disadvantaged, and, by shrinking the mass market for new goods, can also dampen incentives to innovate. Against this, some models note that wealth concentration provides the capital needed to undertake risky, high-return entrepreneurial investments, so that the net supply-side effect is theoretically ambiguous and likely to depend on the depth of financial markets (Braun *et al.* 2019) and on the degree of intergenerational mobility (Aiyar & Ebeke 2020).

A distinct family of arguments, rooted in the Keynesian and structuralist traditions, operates through aggregate demand. Because the propensity to consume falls with income, a redistribution toward the top depresses consumption demand; unless it is offset by higher investment or net exports, the result is underconsumption and slower growth. In the decades preceding the 2008 crisis, the shortfall in demand was masked by household borrowing, as middle- and low-income households sustained their consumption standards by accumulating debt, a process that proved unsustainable (Cynamon & Fazzari 2016; Goda *et al.* 2017). On this

reading, rising inequality is not merely a distributive concern but a macroeconomic one, weakening the growth engine on the demand side.

A further strand argues that inequality undermines growth through politics and institutions. In the median-voter models of Alesina and Rodrik (1994) and Persson and Tabellini (1994), high inequality generates pressure for distortionary taxation and redistribution, which reduces incentives to invest and innovate; inequality may also fuel political instability and social unrest, deterring domestic and foreign investment. Li and Zou (1998) show, however, that this conclusion is not general. In an extension of the Alesina–Rodrik model in which government revenue finances public consumption, a more equal distribution can lead to higher taxation and lower growth. From a Latin American structuralist perspective, inequality and underdevelopment were rooted in the center–periphery structure and in domestic structural heterogeneity, which tended to reproduce income concentration and unequal access to the gains from development (Prebisch 1981; Furtado 1966). Acemoglu and Robinson (2006) formalize a related idea in which extractive institutions concentrate power and wealth in elites, and high inequality is both cause and consequence of such institutions, leading to rent-seeking, weak state capacity, and stagnation. More recent behavioral work adds that high inequality erodes trust, social cohesion, and cooperation, reducing the efficiency of markets and governance.

Finally, several authors assign income concentration a central role in theories of financial crisis. Jayadev (2013) reviews the linkages between distribution and crisis and documents the correlation between top income shares and macroeconomic instability on the eve of the Great Recession; Stiglitz (2015) argues that the growth of top incomes weakened aggregate demand and encouraged financial fragility; and Goda *et al.* (2017) show that the rising demand for financial assets by the wealthy was mirrored by rising indebtedness among low- and middle-income households, feeding the credit boom that preceded the crisis. These accounts reinforce the presumption that what matters for macroeconomic performance is precisely the polarization between the top and the bottom of the distribution; the segment of the distribution that the Palma Ratio is designed to capture.

2.2 Empirical evidence

The empirical literature is as divided as the theoretical one. A first generation of studies estimated cross-country growth regressions à la Barro and generally found that initial inequality was negatively associated with subsequent growth (Alesina and Rodrik 1994; Persson and Tabellini 1994). This approach, however, cannot control for unobserved country-specific factors, and its results proved fragile.

A second generation exploited the time dimension of the data. Using panel methods that control for country fixed effects, Li and Zou (1998) and Forbes (2000) found, in sharp contrast to the cross-sectional studies, a *positive* short- to medium-run association between inequality and growth. Barro (2000, 2003) reported a nonlinear pattern in which inequality retards growth in poor countries and encourages it in rich ones, while Panizza (2002), using data on US states,

found that the relationship is not robust to changes in specification, and Ciccone and Jarocinski (2010) underscored more generally how sensitive growth regressions are to specification and data choices. More recently, Balcilar, Gupta, Ma and Makena (2021) re-examine the inequality–growth relationship for a sample of 63 countries over 1991–2017 and find evidence of a nonlinear, inverted-U relationship. Using the Gini coefficient, they show that inequality is positively associated with growth below a threshold and negatively associated with growth beyond it. Their findings provide further evidence that the estimated inequality–growth relationship is sensitive to both the empirical specification and the way distributive differences are represented. Voitchovsky (2005) showed that the profile of inequality matters. Inequality at the top of the distribution appears positively associated with growth, whereas inequality at the bottom is negatively associated with it. Herzer and Vollmer (2012), using panel cointegration techniques, found a negative long-run effect of inequality on income. Ravallion (2001) cautioned more generally against averaging over heterogeneous country experiences.

A similar pattern is reported by Fawaz, Rahnama and Valcarcel (2014), who use system GMM and international data for 1960–2010 and find a negative inequality–growth relationship among low-income developing countries but a positive relationship among higher-income developing economies. Their results provide further evidence that the sign of the estimated relationship may depend on country characteristics and empirical specification.

Recent evidence also reinforces the heterogeneous nature of the inequality–growth relationship. Acheampong *et al.* (2023), using quantile-on-quantile techniques for the BRICS economies, find that both the sign and magnitude of the relationship vary across countries and across different parts of the growth distribution. Their results provide additional evidence that conclusions about the inequality–growth nexus can be sensitive to the empirical framework and to the distributional margin under consideration.

More recent contributions, typically based on panel data and system GMM or instrumental-variable estimators, have refined rather than settled the debate. Berg, Ostry, Tsangarides, and Yakhshilikov (2018) find that inequality is robustly negatively related to both the pace and the duration of growth spells, whereas redistribution is generally benign. Brueckner and Lederman (2018) show that the effect of inequality depends on the initial income level, with a positive effect in poor countries and a significantly negative effect in high-income countries. Braun *et al.* (2019) find that the negative effect of inequality on growth weakens as financial markets deepen, consistent with the credit-constraint channel of Galor and Zeira (1993). Aiyar and Ebeke (2020) show that the growth cost of income inequality is concentrated in societies with low intergenerational mobility, where unequal outcomes translate into unequal opportunities. Surveying this body of work, Ferreira *et al.* (2022) conclude that the evidence on the inequality–growth nexus remains mixed and call for further empirical work that pays closer attention to data quality and measurement.

Measurement is precisely where this article seeks to contribute. Much of this literature, regardless of the sign of the estimated relationship, has relied on the Gini index as the main measure of inequality, occasionally supplemented by income shares. Yet the empirical regularity documented by Palma (2011, 2019) and Cobham *et al.* (2016) implies that the Gini is poorly matched to the phenomenon it is meant to track because it is most sensitive to the middle of the distribution, which is the stable part, and comparatively insensitive to the tails, which is where distributional change is concentrated. Palma's discontent with the index is worth quoting:

> "[…] 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 shown by the Gini is likely to underestimate income disparities across countries." (Palma, 2011: 105)

If the theoretically relevant dimension of inequality is the polarization between top and bottom incomes—as both the demand-side and the crisis literatures suggest, and as Voitchovsky's (2005) findings on the profile of inequality intimate—then an index that targets the tails directly is a more appropriate measuring rod. The Palma Ratio, defined as the income share of the richest 10 percent divided by that of the poorest 40 percent, does exactly this. The following sections reexamine the inequality–growth relationship on this basis.

3 Empirical Framework

We estimate the relationship between economic growth and income distribution using panel data. Although the early empirical literature explored this relationship with cross-sectional regressions à la Barro, cross-country growth estimates are likely to be biased by unobserved country-specific effects; most recent studies therefore rely on panel methods (e.g., Forbes 2000; Berg *et al*. 2018; Brueckner and Lederman 2018; Aiyar and Ebeke 2020), and we follow this practice. We adopt a dynamic specification for a country's growth rate in which the right-hand side includes the variables that have received the most attention in the theoretical and empirical literature (see, e.g., Barro 2000, 2003; Forbes 2000):

$$g_{i,t} = \delta_t + \mu_i + \beta_1 g_{i,t-1} + \beta_2 PR_{i,t} + X_{i,t}\Psi + \varepsilon_{i,t} \quad (1)$$

where g is the rate of economic growth measured as real GDP growth; PR is the Palma Ratio; X is a matrix of covariates; μ_i is an unobserved country-specific effect; δ_t captures time-specific effects; and $\varepsilon_{i,t}$ is the error term. The coefficients β_j $(j = 1,2)$ and the matrix Ψ are the parameters to be estimated.

Equation (1) poses two well-known estimation problems. First, following standard practice in the growth literature, we work with non-overlapping five-year averages, which shrink the time dimension (T) of the panel; fixed-effects estimation of a dynamic model with small T is biased.

Second, the typical explanatory variables, including inequality itself, are likely to be jointly endogenous with growth, so that estimates may suffer from simultaneity and reverse causation. The Generalized Method of Moments (GMM) estimators for dynamic panels developed by Arellano and Bond (1991), Arellano and Bover (1995), and Blundell and Bond (1998) are designed precisely for panels with small T and large N, and they address endogeneity by using appropriately lagged observations of the variables as instruments. The approach also keeps our results comparable with the closest antecedents in the literature that applied the same technique but reached the opposite conclusion (Forbes 2000).

Within the GMM family, the first-difference estimator (Arellano and Bond 1991) removes the country-specific effects by differencing and instruments the differenced variables with their lagged levels. Its weakness is that, for variables with little within-country variation over time, lagged levels are weak instruments for subsequent differences, which biases the coefficients in small samples. Because the Palma Ratio is likely to display exactly this kind of persistence, we use the *system* GMM estimator of Arellano and Bover (1995) and Blundell and Bond (1998), which combines the equations in differences with equations in levels, instrumenting the latter with lagged differences of the variables.

The validity of the estimator rests on the instruments' exogeneity and the absence of higher-order serial correlation in the errors. We report the Hansen J-test and the Sargan test of overidentifying restrictions, whose null hypothesis is the joint validity of the instruments, and the Arellano–Bond tests for first- and second-order serial correlation of the differenced residuals; first-order correlation is expected by construction, while second-order correlation would invalidate the instruments. Following Roodman (2009), we also guard against instrument proliferation, which can overfit the endogenous variables and weaken the Hansen test, by keeping the instrument count below the number of countries and by collapsing the instrument matrix. Finally, we report both the two-step estimator, with the Windmeijer (2005) finite-sample correction to the standard errors, and, as a robustness check, the one-step estimator with robust standard errors, since the asymptotic approximations for the two-step estimator can be unreliable in small samples (Bond 2002).

3.1 Data and Descriptive Statistics

The panel comprises 98 countries, both developed and developing, and covers the period 1980–2010. The complete list of countries included in the estimation sample is reported in Appendix A (Table A1).[2] We compute the growth rate over non-overlapping five-year periods. This is a

[2] The estimation period is dictated by the coverage of the Global Consumption and Income Project data used to construct the Palma Ratio. Restricting the analysis to 1980–2010 allows us to maintain a consistent source and construction of the inequality measure across countries and periods. More recent Palma Ratios, including five-year averages reported in the Human Development Reports, provide an important opportunity for extending the analysis. Such an extension would require assessing the comparability of the inequality series across data sources and is therefore left for future research.

standard practice in panel growth empirics to smooth business-cycle fluctuations and mitigate unit-root problems. The latter point matters for our estimation strategy. As Bound, Jaeger, and Baker (1995) show, when the individual series are near unit roots, the instruments available for the equations in first differences are weak, and instrumental-variable estimators can suffer severe finite-sample biases. After computing growth rates, we can exploit a maximum of six non-overlapping observations per country.

The dependent variable is the average annual rate of real GDP growth over each non-overlapping five-year period, computed as $\frac{1}{5}(\log GDP_t - \log GDP_{t-5})$. Our main explanatory variable is the Palma Ratio (PR), defined as the income share received by the richest 10 percent of the population relative to that received by the poorest 40 percent. Let d_j denote the mean income of decile j. Because each decile contains the same population share, the Palma Ratio can be written as

$$PR_{it} = \frac{d_{10,it}}{d_{1,it} + d_{2,it} + d_{3,it} + d_{4,it}} \tag{2}$$

The decile-income profiles are obtained from the Global Consumption and Income Project (GCIP). To examine whether the results depend on the inequality indicator, we construct two additional measures from exactly the same decile-income profiles. The first is the income share of the richest 10 percent,

$$Top10_{it} = 100\left(\frac{d_{10,it}}{\sum_{j=1}^{10} d_{j,it}}\right) \tag{3}$$

and the second is a grouped-decile Gini coefficient,

$$Gini_{it} = 100\left[\frac{2\sum_{j=1}^{10} d_{j,it}}{10\sum_{j=1}^{10} d_{j,it}} - \frac{11}{10}\right] \tag{4}$$

The latter should be interpreted as a grouped-data approximation to the Gini coefficient, since it is constructed from mean incomes for ten equal-sized population groups and therefore does not capture inequality within deciles. This limitation is particularly relevant for the richest decile. Its advantage for the present exercise, however, is comparability: the *Palma Ratio*, *grouped-decile Gini*, and *top-10* income share are derived from the same source, income concept, country-year observations, and underlying distributional information. All remaining variables are obtained from Penn World Table 9.0 (Feenstra, Inklaar and Timmer 2015).

To keep our work consistent and comparable with the existing empirical literature, the covariates (all in logs) are those most commonly used in previous growth studies:

1) The real GDP level in period t (*GDP*), at constant 2011 national prices (in mil. 2011US$), captures transitional dynamics. In mainstream growth models, the conditional convergence hypothesis states that, other things constant, lagging economies

should grow faster than rich ones because of diminishing returns to factors of production (Solow 1956; Barro 2000, 2003). Although nothing in the more radical Keynesian approach generates a tendency toward convergence, we follow the standard practice in the literature and include the log of initial GDP (see also Forbes 2000).

2) The share of government consumption (*Ggdp*), at current PPPs, proxies for the government burden. Growth models argue that governments burden the economy when they impose high taxes, run inefficient programs, and distort market signals, although public investment in health, education, and security is also acknowledged to promote growth. The ratio of government current expenditure to GDP is a commonly used proxy in the literature (Barro 2000, 2003).

3) The stock of capital (*K*), at current PPPs (in mil. 2011US$), and a human capital index (*H*), based on years of schooling and returns to education, account for a fuller theory of capital accumulation in which physical and human capital complement each other (Rebelo 1991; Mankiw, Romer and Weil 1992). Classical development theory also viewed capital accumulation as the engine of growth, particularly for developing countries (Lewis 1954; Gerschenkron 1962).

4) The terms of trade (*TOT*), computed as the price level of exports over that of imports, and period-specific dummies capture external factors (Barro 2000; Levine and Renelt 1992). The terms of trade reflect country-specific external influences—changes in foreign demand, relative production costs, and external financial inflows—whereas the period dummies capture conditions common to all countries in a given period, such as booms and recessions, waves of technological change, and economic reforms.

5) Region dummies, equal to one if the country belongs 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), account for norms, institutions, culture, geography, and natural-resource endowments that tend to cluster regionally and can affect growth (Barro 2003). We classified our sample by region according to the World Bank's grouping.

The GMM methodology allows variables to be treated as endogenous, predetermined, or exogenous. Only the region and period dummies were treated as exogenous. The terms of trade were treated as predetermined. Their degree of endogeneity depends on whether the country is large or small in world markets. All remaining variables, including the inequality indicator used in each specification—the Palma Ratio, grouped-decile Gini, or top-10 income share—were treated as endogenous, since income distribution and the other covariates may themselves be affected by economic growth.

Before presenting the regression results, we briefly examine descriptive statistics, focusing on the evolution of the Palma Ratio. Table 1 summarizes the main variables used in the empirical

analysis and reports the pairwise correlations between economic growth and the alternative inequality indicators. As shown in Table 1, the Palma Ratio averages 3.91, implying that, in the average country-period, the richest 10 percent receive almost four times the income received by the poorest 40 percent. The grouped-decile Gini averages 47.3, while the richest decile receives, on average, approximately 39 percent of total income. Table 1 also shows that the three inequality measures are strongly, but not perfectly, correlated. The Palma Ratio correlates 0.920 with the grouped-decile Gini and 0.932 with the top-10 income share, whereas the correlation between the Gini and the top-10 share reaches 0.986. These correlations indicate that the indicators capture a substantial common component of inequality, while the Palma Ratio retains distinct variation associated with the relative position of the bottom 40 percent.

Table 1. Descriptive Statistics and Correlations.

Panel A. Descriptive Statistics

Variable	Mean	Std. Dev.	Min	Max
g	0.033	0.028	-0.107	0.128
PR	3.908	2.446	0.731	14.433
Grouped-decile Gini	47.321	11.653	21.955	70.361
Top 10 income share (%)	39.036	10.678	18.593	66.136
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

Panel B. Pairwise correlations between growth and alternative inequality measures

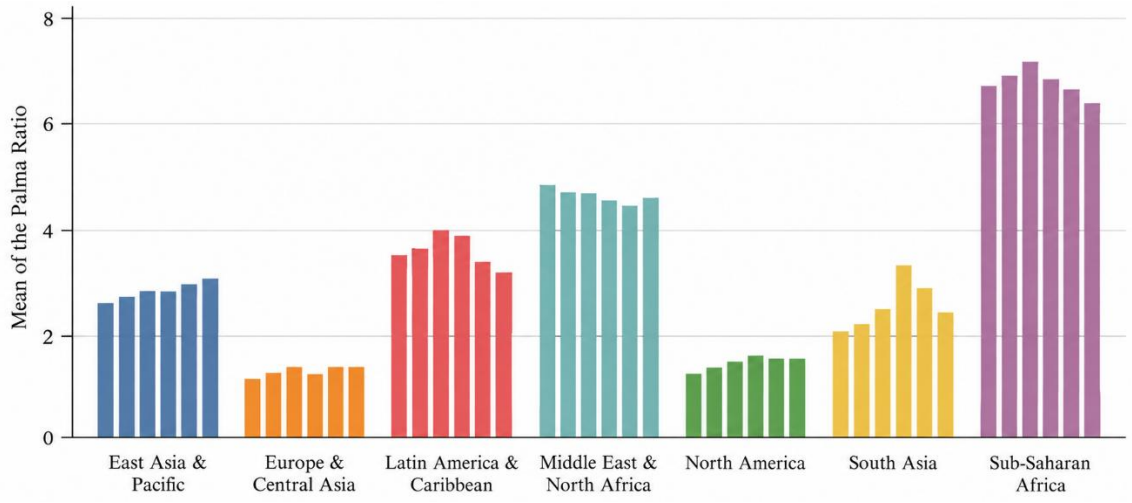
	Growth	Palma Ratio	Grouped-decile Gini	Top 10 income share
Growth	**1**			
Palma Ratio	0.038	**1**		
Grouped-decile Gini	0.111	0.920	**1**	
Top 10 income share	0.103	0.932	0.986	**1**

Source: Authors' calculations based on the Global Consumption and Income Project (GCIP) and Penn World Table 9.0

To assess the trajectory of inequality across countries, we plotted the mean Palma Ratio per region over the five-year periods considered. Figure 1 shows the results.

Figure 1 reveals substantial and persistent regional heterogeneity in the Palma Ratio. Sub-Saharan Africa records the highest average values throughout the sample, peaking above 7 in the mid-1990s before declining toward the end of the period. The Middle East and North Africa also exhibits persistently high Palma Ratios, around 4.5–4.8. Latin America and the Caribbean displays an increase through the mid-1990s followed by a marked decline, from approximately 4.1 in 1995 to 3.35 in 2010. By contrast, Europe and Central Asia and North America exhibit substantially lower ratios throughout the sample. These patterns show that top-to-bottom income concentration differs considerably across regions and that its evolution is not uniform over time.

Figure 1. Evolution of the Palma Ratio by region, 1985-2010.



Notes: Within each region, bars correspond to 1985, 1990, 1995, 2000, 2005, and 2010, respectively, from left to right. Higher values indicate a larger income share of the richest 10 percent relative to the poorest 40 percent.

Source: Authors' calculations based on GCIP.

Given the substantial regional differences documented in Figure 1, Appendix B examines whether the association between the Palma Ratio and economic growth also varies systematically across regions. Figure B1 reports the corresponding region-specific estimates from a supplementary dynamic fixed-effects specification.

4 Results and Discussion

Table 2 reports the baseline estimates of equation (1) using the system-GMM estimator. Column (1) presents the two-step estimates, while Column (2) reports the one-step specification. As shown in Table 2, the lagged growth rate is positive and statistically significant in both specifications, indicating persistence in economic growth and supporting the dynamic

specification. Table 2 also reports satisfactory specification diagnostics. The Hansen and Sargan tests do not reject the null hypothesis of instrument validity, while the number of instruments remains below the number of countries, reducing concerns about instrument proliferation and an uninformative Hansen test (Roodman 2009). The Arellano–Bond tests behave as expected. First-order serial correlation is present in the differenced residuals, whereas the null of no second-order serial correlation is not rejected, which is required for the validity of the lagged instruments (Arellano and Bond 1991). Taken together, the diagnostic statistics reported in Table 2 support the baseline specification.

Turning to the remaining covariates, Table 2 provides little evidence of conditional convergence, since the coefficient on the level of GDP is positive but statistically insignificant in both specifications. The coefficient on the human capital index is negative and statistically insignificant; although this does not support the conventional human-capital prediction, similar results have been reported in growth models estimated with dynamic-panel methods (Forbes 2000). The coefficient on physical capital is positive and marginally significant in the two-step specification, although it is not statistically significant in the one-step model. Government consumption enters positively but is statistically insignificant in both specifications. The terms of trade are positive and statistically significant in both columns. Among the regional indicators, Latin America and the Caribbean, East Asia and Pacific, the Middle East and North Africa, and Sub-Saharan Africa have positive and statistically significant coefficients, while South Asia and North America are not statistically significant.

The central result in Table 2 concerns the coefficient on the Palma Ratio. As shown in both columns of Table 2, the coefficient is negative and statistically significant, with an estimate of −0.0114 in the two-step specification and −0.00806 in the one-step specification. These coefficients imply that a one-point increase in the Palma Ratio, holding the remaining growth determinants constant, is associated with approximately 1.14 percentage points lower average annual growth under the two-step estimator and 0.81 percentage points lower growth under the one-step estimator. Table 2 therefore provides consistent evidence across the two estimation procedures that greater top-to-bottom income concentration is associated with slower subsequent economic growth. This result contrasts with Forbes (2000), who, using the Gini coefficient and a dynamic-panel framework, reported a positive short- to medium-run association between inequality and growth.

The magnitude of the estimates reported in Table 2 is also economically meaningful. Given a sample standard deviation of approximately 2.45 for the Palma Ratio, the two-step coefficient implies that a one-standard-deviation increase in the Palma Ratio is associated with roughly 2.8 percentage points lower annual growth. The corresponding effect under the one-step estimate is approximately 2.0 percentage points. Thus, Table 2 indicates that the estimated inequality effect is not only statistically significant but also substantial in economic terms.

Table 2. Regression Results, system GMM.

Variables	(1) Two-steps	(2) One-steps
g_{t-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	-0.111
	(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

Source: Authors' calculations.

4.1 Does the inequality measure matter?

The baseline results in Table 2 establish a negative and statistically significant relationship between the Palma Ratio and economic growth. To determine whether this result depends on the way inequality is measured, Table 3 re-estimates the growth model using the Palma Ratio, the grouped-decile Gini coefficient, and the income share of the richest 10 percent. All three measures are constructed from the same GCIP decile-income profiles, and the specifications reported in Table 3 use the same country-period sample, controls, dynamic structure, and restricted system-GMM instrument strategy. Consequently, differences across the columns of Table 3 can be interpreted primarily as differences associated with the inequality indicator rather than with the underlying data or sample composition.

To ensure that the comparison across inequality indicators is not driven by differences in instrument choice, Table 3 re-estimates the model using a common and more parsimonious instrument set for all three measures. Specifically, the instrument matrix is restricted to the second available lag and collapsed, which reduces the number of instruments from 47 in the baseline specification reported in Table 2 to 22 in each specification reported in Table 3. The Palma Ratio is therefore re-estimated under the restricted instrument structure rather than mechanically reproducing the baseline estimate.

Table 3. Alternative Inequality Measures and Economic Growth: Restricted System-GMM Estimates

	(1) Palma Ratio	(2) Grouped-decile Gini	(3) Top 10 share
Inequality measure	−0.0126***	−0.00174***	−0.00194***
Robust SE	(0.00457)	(0.00056)	(0.00070)
Effect of +1 SD, pp	−3.08	−2.02	−2.07
Countries	98	98	98
Instruments	22	22	22
Hansen p-value	0.629	0.401	0.450
AR(2) p-value	0.818	0.678	0.670

*Notes: All specifications use the same country-period sample, control variables, and restricted system-GMM instrument structure. To ensure comparability across inequality measures and limit instrument proliferation, the GMM-style instrument matrix is collapsed and restricted to the second available lag. Consequently, the Palma Ratio estimate in Column (1) differs slightly from the baseline estimate reported in Table 2, which uses a broader instrument set. Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1*

Source: Authors' calculations.

Importantly, the Palma Ratio estimate reported in Table 3 is very close to the baseline estimate in Table 2. The coefficient changes only from −0.0114 to −0.0126 when the instrument set is reduced from 47 to 22 instruments, while remaining negative and statistically significant. This stability indicates that the baseline Palma result is not driven by the larger instrument set.

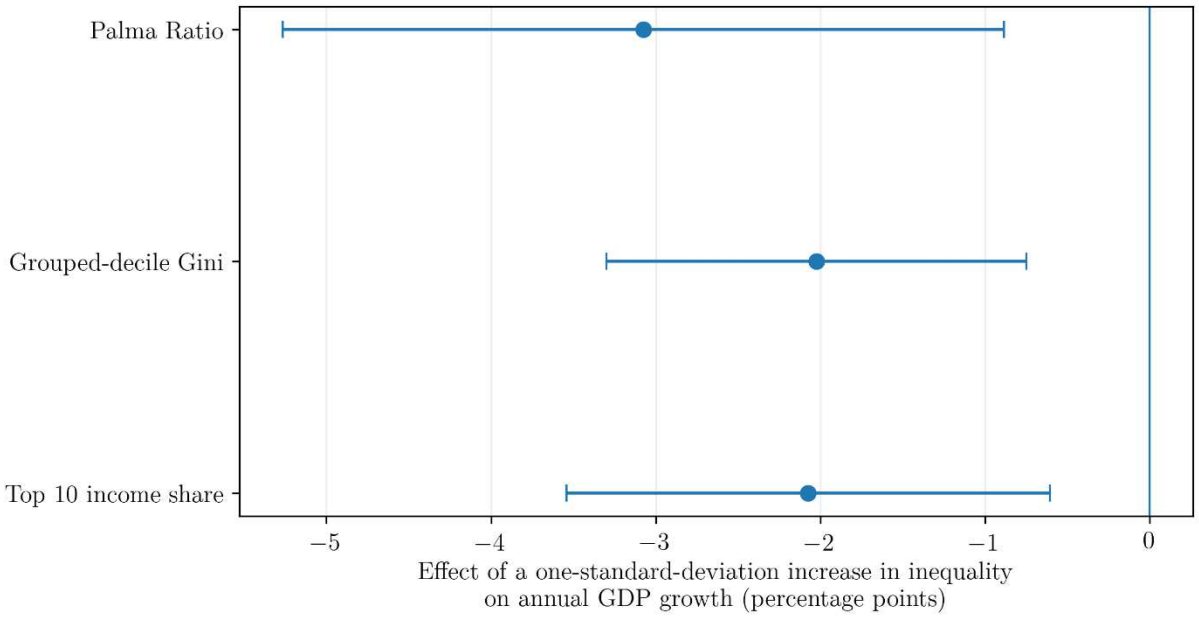
Table 3 shows that the negative inequality–growth relationship is not unique to the Palma Ratio. The coefficient on each of the three inequality measures is negative and statistically significant. The Palma coefficient is −0.0126, the grouped-decile Gini coefficient is −0.00174, and the coefficient on the top-10 income share is −0.00194. The specification diagnostics reported in Table 3 also support the restricted system-GMM models. The Hansen p-values are 0.629 for the Palma specification, 0.401 for the grouped-decile Gini, and 0.450 for the top-10 income share, while the instrument count remains well below the number of countries. Thus, Table 3 indicates that the negative association between inequality and subsequent growth is robust to alternative ways of summarizing the income distribution.

The comparison of standardized effects in Table 3 nevertheless shows that the choice of inequality measure matters for the estimated economic magnitude of the relationship. Because the three indicators are expressed in different units, Table 3 reports the effect associated with a one-standard-deviation increase in each measure. A one-standard-deviation increase in the Palma Ratio is associated with approximately 3.08 percentage points lower annual growth, compared with about 2.02 percentage points for the grouped-decile Gini and 2.07 percentage points for the top-10 income share. As shown in Table 3, the standardized Palma effect is therefore approximately 50 percent larger than the effects obtained from either alternative indicator. The measurement choice does not reverse the sign of the inequality–growth relationship, but it materially affects its estimated economic strength.

To facilitate the comparison of economic magnitudes across inequality indicators, Figure 2 plots the standardized effects reported in Table 3 together with their 95 percent confidence intervals.

Figure 2 provides a visual representation of the differences in economic magnitude reported in Table 3. As shown in the figure, a one-standard-deviation increase in each inequality indicator is associated with lower economic growth, but the Palma Ratio produces the largest point estimate in absolute value. The standardized Palma point estimate is approximately 50 percent larger in absolute magnitude than those obtained with either alternative indicator. At the same time, the overlapping confidence intervals shown in Figure 2 caution against interpreting these differences as evidence that the Palma coefficient is statistically larger than the coefficients obtained with the alternative measures. Rather, Figure 2 reinforces the more limited conclusion that the estimated economic magnitude of the inequality–growth relationship varies with the indicator used.

Figure 2. Standardized Effects of Alternative Inequality Measures on Economic Growth



Notes: Dots report the estimated change in average annual GDP growth associated with a one-standard-deviation increase in each inequality indicator, expressed in percentage points. Horizontal lines represent 95 percent confidence intervals. Estimates correspond to the restricted system-GMM specifications reported in Table 3.

Source: Authors' calculations.

As an additional robustness check, Appendix C re-estimates the inequality–growth relationship using an alternative dynamic instrumental-variable approach. Table C1 reports the corresponding Anderson–Hsiao-type estimates. The Palma Ratio coefficient remains negative and statistically significant under this alternative estimator, providing further evidence that the baseline Palma result reported in Tables 2 and 3 is not specific to the system-GMM implementation.

The results reported in Tables 2 and 3 are broadly consistent with the recent evidence of Berg *et al.* (2018), Brueckner and Lederman (2018), and Aiyar and Ebeke (2020), all of whom document adverse growth effects associated with inequality under different panel-data settings. At the same time, the negative coefficients across all three measures in Table 3 contrast with earlier panel studies reporting a positive inequality–growth relationship, including Forbes (2000) and Li and Zou (1998), and with the nonlinear pattern documented by Balcilar *et al*. (2021). Together with the heterogeneous findings of Fawaz *et al*. (2014), Tuominen (2024), Artal-Tur *et al*. (2025), and Nguyen *et al*. (2025), the estimates in Tables 2 and 3 reinforce the view that the inequality–growth relationship remains sensitive to the empirical setting, specification, and measurement strategy.

More specifically, Table 3 contributes to this literature by holding the underlying distributional information and econometric framework constant while changing the inequality indicator. The fact that all three coefficients remain negative suggests that the sign of the relationship in our sample is not an artifact of using the Palma Ratio. However, the differences in standardized magnitudes reported in Table 3 support Voitchovsky's (2005) broader argument that the location of inequality within the distribution matters for growth. In this sense, the measurement question concerns not only whether inequality affects growth, but also how strongly that relationship is detected when different parts of the income distribution receive different weights.

Overall, the evidence reported in Tables 2 and 3 points to a robust negative association between income inequality and economic growth in our sample. Table 3 further shows that this conclusion is preserved across the three inequality indicators, while the estimated magnitude varies with the measure employed. From a policy perspective, this distinction highlights the value of looking beyond a single summary measure of inequality. The diagnostic advantage of the Palma Ratio is not that it is the only indicator capable of identifying an inequality–growth relationship, but that it explicitly identifies the relative income position of the top 10 percent and the bottom 40 percent, thereby providing a more transparent interpretation of the distributional imbalance underlying the aggregate measure.

5 Conclusion

The purpose of this article was to examine whether income inequality is associated with economic growth and whether the estimated relationship depends on how inequality is measured. The Palma Ratio is used as the main inequality indicator because it focuses explicitly on the income shares of the richest 10 percent and the poorest 40 percent—the segments of the distribution where, as Palma (2011) and Cobham *et al*. (2016) document, much of the distributional variation is concentrated. The relationship is estimated for a panel of 98 countries over 1980–2010 using system-GMM methods for dynamic panels, and the baseline Palma estimates are complemented with alternative measures constructed from the same underlying GCIP decile-income profiles.

The baseline estimates reported in Table 2 show that greater inequality, measured by the Palma Ratio, is associated with significantly slower economic growth. A one-point increase in the Palma Ratio is associated with approximately 0.8–1.1 percentage points lower average annual growth, depending on the system-GMM estimator employed. The alternative-measure estimates reported in Table 3 show that this negative relationship is not exclusive to the Palma Ratio. The grouped-decile Gini coefficient and the top-10 income share also produce negative and statistically significant coefficients when estimated on the same sample and with the same restricted system-GMM framework.

What differs more substantially across the specifications in Table 3 is the economic magnitude of the estimated effect. In standardized terms, a one-standard-deviation increase in the Palma Ratio is associated with approximately 3.1 percentage points lower annual growth, compared with approximately 2.0 percentage points for the grouped-decile Gini and 2.1 percentage points for the top-10 income share. The evidence in Table 3 therefore suggests that the inequality measure matters primarily for the estimated strength of the relationship rather than for its sign.

Taken together, Tables 2 and 3 sharpen the article's measurement contribution. The results do not imply that conventional inequality indicators are uninformative; instead, they demonstrate that alternative measures emphasizing different parts of the income distribution are not empirically interchangeable. In particular, the larger standardized point estimate associated with the Palma Ratio is consistent with the possibility that explicitly incorporating the relative position of the bottom 40 percent captures growth-relevant distributional information that is not fully reflected either in a grouped-decile Gini coefficient or in the income share of the richest decile alone.

From a policy perspective, the results in Tables 2 and 3 also suggest that monitoring inequality exclusively through a single aggregate indicator may provide an incomplete picture of the distributional imbalances associated with economic performance. The Palma Ratio has a useful diagnostic advantage in this respect because it identifies explicitly the relative position of the top 10 percent and the bottom 40 percent. This does not imply that policy should target the Palma Ratio itself, but rather that distributional analysis should pay attention to which parts of the income distribution are driving changes in aggregate inequality.

Further research might extend the analysis in three directions. First, the relationship between growth and the distribution of wealth—which remains more concentrated than income—deserves further attention. Second, the sample could be extended beyond 2010 using more recent distributional information, provided that the comparability of the underlying inequality series across sources and over time is carefully assessed. Third, the differences across the inequality indicators documented in Table 3 could be investigated further using richer percentile or microdata-based measures that separately identify changes at the very top and the bottom of the income distribution. Such evidence would help determine whether the stronger Palma effect is driven primarily by top-income concentration, deterioration in the relative position of the bottom 40 percent, or the interaction of both tails.

Ultimately, understanding whether inequality constrains growth may require knowing not only how unequal an economy is, but also where that inequality is located.

References

Acheampong, A.O., Adebayo, T.S., Dzator, J., Koomson, I.: Income inequality and economic growth in BRICS: insights from non-parametric techniques. *J. Econ. Inequal*. 21, 619–640 (2023). https://doi.org/10.1007/s10888-023-09567-9

Acemoglu, D., Robinson, J.: *Economic Origins of Dictatorship and Democracy*. Cambridge University Press, Cambridge (2006)

Aghion, P., Caroli, E., García-Peñalosa, C.: Inequality and economic growth: the perspective of the new growth theories. *J. Econ. Lit*. 37(4), 1615–1660 (1999)

Aiyar, S., Ebeke, C.: Inequality of opportunity, inequality of income and economic growth. *World Dev*. 136, 105115 (2020)

Alesina, A., Rodrik, D.: Distributive politics and economic growth. *Q. J. Econ*. 109(2), 465–490 (1994)

Anderson, T.W., Hsiao, C.: Formulation and estimation of dynamic models using panel data. *J. Econom*. 18(1), 47–82 (1982)

Arellano, M., Bond, S.: Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *Rev. Econ. Stud*. 58(2), 277–297 (1991)

Arellano, M., Bover, O.: Another look at the instrumental-variable estimation of error-components models. *J. Econom*. 68(1), 29–52 (1995)

Artal-Tur, A., Osorio-Caballero, M.I., Nuñez, R.: Growth and inequality linkages of the Mexican states in the new century: a panel data approach with spatially lagged variables. *Economies* 13(2), 54 (2025)

Atkinson, A.B.: On the measurement of inequality. *J. Econ. Theory* 2, 244–263 (1970)

Atkinson, A.B.: Inequality: *What Can Be Done?* Harvard University Press, Cambridge (2015)

Balcilar, M., Gupta, R., Ma, W., Makena, P.: Income inequality and economic growth: a re-examination of theory and evidence. *Rev. Dev. Econ*. 25(2), 737–757 (2021)

Barro, R.J.: Inequality and growth in a panel of countries. J. Econ. Growth 5(1), 5–32 (2000)

Barro, R.J.: Determinants of economic growth in a panel of countries. *Ann. Econ. Financ*. 4, 231–274 (2003)

Barro, R.J.: Inequality and growth revisited. ADB Working Paper Series on Regional Economic Integration, No. 11. *Asian Development Bank*, Manila (2008)

Berg, A., Ostry, J.D., Tsangarides, C.G., Yakhshilikov, Y.: Redistribution, inequality, and growth: new evidence. *J. Econ. Growth* 23(3), 259–305 (2018)

Blundell, R., Bond, S.: Initial conditions and moment restrictions in dynamic panel data models. *J. Econom*. 87, 115–143 (1998)

Bond, S.R.: Dynamic panel data models: a guide to micro data methods and practice. *Port. Econ. J.* 1(2), 141–162 (2002)

Bound, J., Jaeger, D.A., Baker, R.M.: Problems with instrumental variables estimation when the correlation between the instruments and the endogenous explanatory variable is weak. *J. Am. Stat. Assoc*. 90, 443–450 (1995)

Braun, M., Parro, F., Valenzuela, P.: Does finance alter the relation between inequality and growth? *Econ. Inq.* 57(1), 410–427 (2019)

Brueckner, M., Lederman, D.: Inequality and economic growth: the role of initial income. *J. Econ. Growth* 23(3), 341–366 (2018)

Ciccone, A., Jarocinski, M.: Determinants of economic growth: will data tell? *Am. Econ. J. Macroecon*. 2(4), 222–246 (2010)

Cobham, A., Schlögl, L., Sumner, A.: Inequality and the tails: the Palma proposition and ratio. *Glob. Policy* 7(1), 25–36 (2016)

Cowell, F.A., Flachaire, E.: Inequality measurement and the rich: why inequality increased more than we thought. *Rev. Income Wealth* 70, 254–277 (2024). https://doi.org/10.1111/roiw.12638

Cynamon, B.Z., Fazzari, S.M.: Inequality, the Great Recession and slow recovery. *Camb. J. Econ*. 40, 373–399 (2016)

Duménil, G., Lévy, D.: *Managerial Capitalism: Ownership, Management and the Coming New Mode of Production*. Pluto Press, London (2018)

Fawaz, F., Rahnama, M., Valcarcel, V.J.: A refinement of the relationship between economic growth and income inequality. *Appl. Econ*. 46(27), 3351–3361 (2014)

Feenstra, R.C., Inklaar, R., Timmer, M.P.: The next generation of the Penn World Table. *Am. Econ. Rev*. 105(10), 3150–3182 (2015)

Ferreira, I.A., Gisselquist, R.M., Tarp, F.: On the impact of inequality on growth, human development, and governance. *Int. Stud. Rev*. 24(1), viab058 (2022)

Filauro, S., Parolin, Z., Valetto, P.: What explains recent trends in income inequality in the European Union? *J. Econ. Inequal*. 23, 483–505 (2025). https://doi.org/10.1007/s10888-024-09651-8

Forbes, K.J.: A reassessment of the relationship between inequality and growth. *Am. Econ. Rev*. 90(4), 869–887 (2000)

Furtado, C.: *Subdesenvolvimento e estagnação na América Latina*. Civilização Brasileira, Rio de Janeiro (1966)

Galor, O., Moav, O.: From physical to human capital accumulation: inequality and the process of development. *Rev. Econ. Stud.* 71(4), 1001–1026 (2004)

Galor, O., Zeira, J.: Income distribution and macroeconomics. *Rev. Econ. Stud*. 60(1), 35–52 (1993)

Gerschenkron, A.: *Economic Backwardness in Historical Perspective*. Harvard University Press, Cambridge (1962)

Goda, T., Onaran, Ö., Stockhammer, E.: Income inequality and wealth concentration in the recent crisis. *Dev. Change* 48, 3–27 (2017)

Herzer, D., Vollmer, S.: Inequality and growth: evidence from panel cointegration. *J. Econ. Inequal*. 10, 489–503 (2012)

Institute for Policy Studies: Billionaire Bonanza: The Forbes 400 and the Rest of the US. *Institute for Policy Studies*, Washington, DC (2017)

Jayadev, A.: Distribution and crisis: reviewing some of the linkages. In: Epstein, G., Wolfson, M. (eds.) *The Handbook of the Political Economy of Financial Crises*, pp. 95–112. Oxford University Press, Oxford (2013)

Kaldor, N.: A model of economic growth. *Econ. J.* 67, 591–624 (1957)

Koo, J., Song, Y.: The relationship between income inequality and aggregate saving: an empirical analysis using cross-country panel data. *Appl. Econ.* 48(10), 892–901 (2016)

Krolage, C., Peichl, A., Waldenström, D.: Long-run trends in top income shares: the role of income and population growth. *J. Econ. Inequal*. 20, 97–118 (2022). https://doi.org/10.1007/s10888-021-09520-8

Kuznets, S.: Economic growth and income inequality. *Am. Econ. Rev.* 45(1), 1–28 (1955)

Levine, R., Renelt, D.: A sensitivity analysis of cross-country growth regressions. *Am. Econ. Rev*. 82(4), 942–963 (1992)

Lewis, W.A.: Economic development with unlimited supplies of labour. *Manch. Sch*. 22(2), 139–191 (1954)

Li, H., Zou, H.F.: Income inequality is not harmful for growth: theory and evidence. *Rev. Dev. Econ*. 2(3), 318–334 (1998)

Mankiw, N.G., Romer, D., Weil, D.N.: A contribution to the empirics of economic growth. *Q. J. Econ*. 107(2), 407–437 (1992)

Nguyen, L., Kaizoji, T., Inoue, T.: The causal relationship between income inequality and economic growth: evidence from panel data for Vietnam. *Appl. Econ*. 57(19), 2333–2347 (2025)

Palma, J.G.: Homogeneous middles vs. heterogeneous tails, and the end of the "inverted-U": it's all about the share of the rich. *Dev. Change* 42(1), 87–153 (2011)

Palma, J.G.: Behind the seven veils of inequality. What if it's all about the struggle within just one half of the population over just one half of the national income? Dev. *Change* 50, 1133–1213 (2019). https://doi.org/10.1111/dech.12505

Panizza, U.: Income inequality and economic growth: evidence from American data. *J. Econ. Growth* 7(1), 25–41 (2002)

Persson, T., Tabellini, G.: Is inequality harmful for growth? *Am. Econ. Rev*. 84(3), 600–621 (1994)

Piketty, T.: *Capital in the Twenty-First Century*. Harvard University Press, Cambridge (2014)

Prebisch, R.: *Capitalismo periférico: crisis y transformación*. Fondo de Cultura Económica, Mexico City (1981)

Ravallion, M.: Growth, inequality and poverty: looking beyond averages. *World Dev*. 29(11), 1803–1815 (2001)

Rebelo, S.: Long-run policy analysis and long-run growth. *J. Polit. Econ*. 99(3), 500–521 (1991)

Roodman, D.: How to do xtabond2: an introduction to difference and system GMM in Stata. *Stata J.* 9(1), 86–136 (2009)

Solow, R.M.: A contribution to the theory of economic growth. *Q. J. Econ.* 70(1), 65–94 (1956)

Stiglitz, J.E.: Inequality and economic growth. *Polit. Q*. 86, 134–155 (2015)

Tuominen, E.: Top-end inequality and growth: empirical exploration of nonlinearities and the time dimension. *J. Econ. Inequal*. 22, 311–331 (2024)

United Nations: *Income Inequality Trends in Sub-Saharan Africa: Divergence, Determinants and Consequences*. UNDP, New York (2017)

Voitchovsky, S.: Does the profile of income inequality matter for economic growth? Distinguishing between the effects of inequality in different parts of the income distribution. *J. Econ. Growth* 10(3), 273–296 (2005)

Windmeijer, F.: A finite sample correction for the variance of linear efficient two-step GMM estimators. *J. Econom*. 126, 25–51 (2005)

Appendix A. List of Countries.

Table A1 reports the 98 countries included in the estimation sample used throughout the baseline and alternative-measure specifications. The country composition is held constant across Tables 2 and 3 to ensure that differences across the inequality estimates are not driven by changes in sample composition.

Table A1. Countries Included in the Estimation Sample.

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

Notes: The sample contains 98 countries observed at a maximum of six non-overlapping five-year intervals between 1985 and 2010. The same country sample is used for the Palma Ratio, grouped-decile Gini, and top-10 income-share specifications.

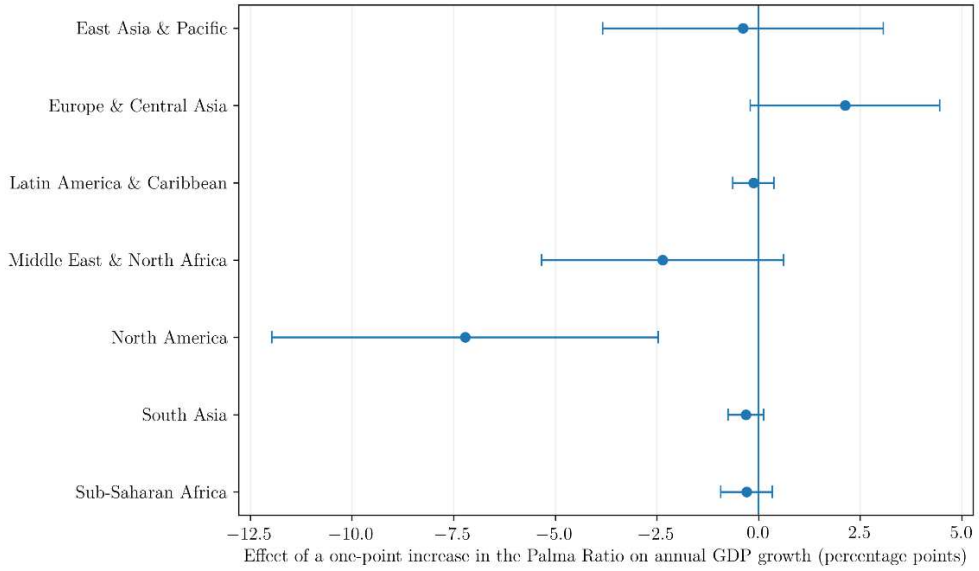
Source: Authors' compilation based on GCIP and Penn World Table 9.0.

Appendix B. Regional Heterogeneity in the Palma Ratio–Growth Relationship.

The substantial regional differences in the level and evolution of the Palma Ratio documented in Figure 1 raise the question of whether its association with growth also differs systematically across regions. Figure B1 examines this possibility using a supplementary dynamic fixed-effects specification in which the Palma Ratio is interacted with regional indicators. The model includes lagged growth, the baseline controls, country fixed effects, and period effects, with standard errors clustered at the country level. Because this exercise is based on a fixed-effects specification rather than the system-GMM estimator used in the main analysis, it is interpreted as a heterogeneity diagnostic rather than as an alternative baseline model.

Figure B1 provides little evidence of robust regional heterogeneity in the Palma Ratio–growth relationship. Most region-specific estimates are statistically imprecise and their 95% confidence intervals include zero. A joint test of the regional interaction terms is only marginally significant (*p=0.061*). Moreover, this result is sensitive to the North American subsample, which contains only two countries. Once North America is excluded, the joint test no longer provides evidence of regional heterogeneity (*p=0.263*). Figure B1 should therefore be interpreted as suggesting limited and fragile regional differences rather than stable region-specific effects. These results support retaining the pooled system-GMM estimates in Tables 2 and 3 as the preferred specifications.

Figure B1. Regional Heterogeneity in the Palma Ratio–Growth Relationship.



Notes: Dots report region-specific estimates of the association between a one-point increase in the Palma Ratio and average annual GDP growth.. Estimates are obtained from a supplementary dynamic fixed-effects specification including lagged growth, the baseline covariates, country fixed effects, and period effects. Standard errors are clustered at the country level. The estimation sample contains 490 observations from 98 countries. North America contains only two countries, and its estimate should therefore be interpreted with particular caution. These estimates are intended as a heterogeneity diagnostic and do not replace the baseline system-GMM specification.

Source: Authors' calculations based on GCIP and Penn World Table 9.0.

Appendix C. Alternative Dynamic-IV Robustness.

As an additional robustness exercise, Table C1 estimates an alternative dynamic instrumental-variable specification in the spirit of Anderson and Hsiao (1982). The model is estimated in first differences, thereby removing time-invariant country effects, and lagged levels are used as instruments for the dynamic specification. The baseline set of controls and period effects is retained, and standard errors are clustered at the country level. Because the Anderson–Hsiao approach generally uses a smaller set of moment conditions and is less efficient than system GMM, these estimates are intended as a robustness check rather than as the preferred specification.

Table C1 shows that the coefficient on the Palma Ratio remains negative and statistically significant under the alternative dynamic-IV estimator. The coefficients on the grouped-decile Gini and the top-10 income share are also negative, although they are estimated less precisely and are not statistically significant at conventional levels. The results in Table C1 therefore provide additional evidence that the negative Palma–growth relationship reported in Tables 2 and 3 is not specific to the system-GMM estimator. At the same time, the lower precision of the alternative-measure coefficients reinforces the use of the system-GMM specifications in Table 3 as the preferred basis for comparing inequality indicators.

Table C1. Alternative Dynamic-IV Estimates.

	(1) ***Palma Ratio***	***(2)*** ***Grouped-decile Gini***	***(3)*** ***Top 10 share***
Inequality measure	−0.01772**	−0.00281	−0.00433
Clustered SE	(0.00820)	(0.00204)	(0.00316)
p-value	0.033	0.171	0.174
Observations	392	392	392
Number of countries	98	98	98
Baseline controls	Yes	Yes	Yes
Period effects	Yes	Yes	Yes
Country effects	*First-differenced*	*First-differenced*	*First-differenced*

*Notes: The dependent variable is average annual real GDP growth. The equations are estimated in first differences using lagged levels as instruments for the dynamic specification. All models include the baseline controls and period effects. Standard errors are clustered at the country level. ** $p<0.05$.*

Source: Authors' calculations.