Wealth Inequality and Economic Growth: Evidence from the World Inequality Database

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Abstract

Although it is often argued that wealth inequality matters more for economic growth than income inequality, this relationship has rarely been studied empirically, with a few exceptions covering a very restricted country sample or short timeframe. Leveraging hitherto unexploited wealth inequality data from the World Inequality Database, covering a panel of 165 countries between 1995 and 2019, we document a negative and statistically significant relationship between wealth inequality and economic growth. A one standard deviation increase in the wealth Gini coefficient within countries is associated with a 0.34 percentage points decline in growth rates. Instrumental variables support a causal interpretation of the results. The results survive a large battery of robustness checks, and we find no evidence to suggest a heterogeneous relationship.

Keywords: Inequality; Wealth Inequality; Economic Growth; Economic Development.
JEL: D31; D63; O10; O47

1. Introduction

In *End Times*, Turchin (2023) argues that wealth inequality is one of the two main harbingers of societal collapse (the other being elite overproduction). Scheidel (2017), while not suggesting that inequality necessarily leads to violence, takes stock of the history of inequality dating back to the Bronze Age, and finds that mass violence is the primary *Great Leveler* of riches, i.e. the redistribution mechanism which is most 'effective', for lack of a better word. While the consequences of inequality need not necessarily be deadly, there is mounting evidence that excessive inequality hampers social cohesion. Inequality can result in authoritarian drift (Timoneda 2023), crime (Manea et al 2024), lower public good provision (Bharathi et al 2024), anti-migrant attitudes (Peters & Shin 2023), and can also make unethical behaviours appear more justifiable (Martinangeli & Windsteiger 2024). Excessive inequality also affects economic development in tangible ways: inequality is negatively associated with the Human Development Index (Castells-Quintana, Royuela & Thiel 2023), hampers access to clean cooking fuels (Murshed 2024), and further fuels social stratification, resulting in widening health gaps (Stoebenau et al 2021; Castro Torres, Batyra, & Myrskylä 2022; Rao & Finnoff 2015).[1]

Against this backdrop, we re-visit the question of how inequality affects arguably the most important economic outcome: economic growth, which in turn shapes many other outcomes. A central question in the literature has been whether economic inequality helps or hurts growth, with arguments in both directions. On the one hand, greater initial inequality may foster economic growth if the rich have higher marginal propensities to save, potentially increasing aggregate investment (Barro 2000). On the other hand, economic and political channels have been identified through which inequality is harmful to growth. For example imperfections in credit and capital markets may constrain investment in education and entrepreneurship (Galor & Zeira 1993), while political economy mechanisms suggest that inequality fuels redistributive pressures or instability that can undermine growth (Alesina & Rodrik 1994). More recent evidence further shows that rising inequality is linked to reduced social mobility and inequality of opportunity, which can depress long-run growth (Piketty 2014)

Owing to data limitations, the literature has traditionally focused on income inequality, rather than wealth inequality. Yet wealth inequality may be more relevant for understanding economic dynamics (Ravallion 2012). Income is a flow, while wealth is a stock; as such, wealth better captures persistent disparities in opportunity, resilience, and influence. Studying income inequality alone risks missing these enduring dimensions. Wealth inequality also reflects intergenerational accumulation and transmission (Piketty 2014), and is arguably more tightly linked to capital ownership, which is an increasingly important driver of income. For example, the capital share of

[1] For an overview of the broad trends in global inequality, see Gradin (2024) and Milanovic (2024).

national income rose from 15–25% in the 1970s to 25–35% by 2010 in many countries (Piketty & Zucman 2014). In developing countries, where credit constraints and weak social safety nets are common (Davies et al. 2011), the role of wealth in shaping opportunity is especially pronounced. While we do not take a strong stance on mechanisms, which remain an open question in the literature, we argue that wealth inequality more fully captures the structural inequality relevant to growth outcomes.

Our contribution, therefore, is to study the nexus between wealth inequality and economic growth, drawing on new data for the wealth Gini coefficient and top wealth shares from the World Inequality Database, covering 165 countries over the 1995 – 2019 period. While the literature on income inequality and economic growth is well-established (e.g. Alesina & Perotti 1996), only two recent studies, to the best of our knowledge, attempt to study the relationship between wealth inequality and growth: Bagchi & Svejnar (2015) and Islam & McGillivray (2020). We improve upon these papers in three main ways. First, both studies, owing to data limitations, are only able to study relatively small numbers of countries (26 and 45, respectively), many of which are on the upper end of the development spectrum. In contrast, our data cover a much more globally representative set of 165 countries, at all levels of development. Second, both studies use lists of billionaires (compiled by Forbes and Credit Suisse, respectively) as their proxies for wealth inequality. While a great deal can be learned from billionaire wealth, we rely on more direct measure of wealth inequality (Gini coefficients and top wealth shares). Third, we are able to have a more comprehensive time coverage, using data over the 1995 – 2019 period, allowing us to examine how inequality relates to growth over a longer period of time.

Overall, we find a negative and statistically significant relationship between wealth inequality and economic growth. Our approach is robust to several important control variables, which may confound the relationship, and to various sensitivity checks. We find that a 1 standard deviation (S.D.) increase in wealth inequality is associated with a 0.34 percentage point (p.p.) decline in annual growth rates. We also examine whether the relationship between inequality and growth presents any meaningful heterogeneity; we find that it does not.

The remainder of this paper is structured as follows. Firstly, Section 2 briefly discusses some related literature. Section 3 introduces the data and main results. Afterward, Section 4 presents the results of sensitivity and heterogeneity analyses; Section 5 offers some concluding remarks.

2. Related Literature

2.1 Background

In this section, we discuss some important conceptual issues and stylized facts in the relationship between inequality and growth. According to Stiglitz (2016), wealth can be defined as the stock of economic resources that one has accumulated from either own savings or received inheritances, which typically come from one's parents. Over the past 50 years, wealth inequality within and between countries has steadily increased, and the concentration of wealth is much more dispersed than income. For instance, the top 1 percent of families possessed around 42 percent of the wealth in the United States in 2012, compared to around 17 percent of income (Saez & Zucman, 2016; Islam & McGillivray, 2020). There are significant differences in the level and distribution of household wealth between countries, as shown by the higher Gini coefficient for wealth than for income (Davies et al, 2011). For 2000, the Gini coefficient for global wealth was 0.80, while the corresponding Gini coefficient for disposable income was approximately 0.65 (Davies et al., 2011; Milanovíc, 2005). However, although inter-country wealth differences are substantially greater than income, even larger disparities can be found in the degree of intra-country inequality. Consequently, one of the principal reasons for high global wealth inequality is the high inequality of wealth within countries (Davies et al., 2011). This makes it interesting to take a closer look at differences in wealth concentration and inequality, and potential effects on economic growth.

Models of wealth inequality are much more complicated conceptually than models of income inequality, given that wealth accumulates gradually over time (Jones, 2015). Moreover, the accumulation of wealth is shown to be extremely important in providing opportunity and security. According to Stiglitz (2016: 137): "Probably the most invidious aspect of inequality is that of opportunities". The creation of opportunity matters even more for poorer countries, where institutional voids may lead to lower social safety nets, and where no adequate facilities are provided for lending and borrowing (Davies et al., 2011). Thus, the unequal distribution of wealth could severely impact the growth prospects of developing nations. This further reflects the importance of studying the relationship between wealth inequality and economic growth for many countries characterized by different development trajectories. Thus, this paper contributes to the small and emerging strand of literature that looks at the nexus between wealth inequality and economic growth.

From a theoretical perspective, the effect of inequality on growth is ambiguous. On the one hand, Meltzer & Richard (1981) argue that higher levels of inequality cause the median voter to favour more redistribution as one shifts away from a mean income level. As a result, inequality will increase redistributive taxation, inducing large distortions of economic activity, and thus reducing economic growth. Moreover, according to Madsen, Islam, and Doucouliagos (2018), wealth inequality will adversely affect research and development (R&D), as individuals with little wealth will find it more difficult to finance innovative projects through credit. In turn, lower levels of R&D will hamper economic growth (Aghion, Caroli, & García-Peñalosa, 1999). A related line of reasoning comes from Lee (2023), who finds that rising inequality generates large welfare losses, through declining returns to R&D. In addition, if upwards social mobility prospects are low, as is usually the case in highly unequal societies, individuals are less likely to invest in human capital acquisition, which further dampens macro-level growth prospects. On the other hand, inequality could benefit economic growth (García-Peñalosa 2010) if wealthy individuals have higher savings propensities than workers. In this framework, inequality favours growth by increasing the stock of physical capital, as greater savings allow greater investments in productive capital.[2] Inequality may also be growth-enhancing if it creates segmented labour markets that help reduce production costs (Ghosh 2019).

Another important source of ambiguity in the relationship between inequality and growth stems from the fact that the cause of inequality is not always known. Unfair inequality (Marrero and Rodriguez 2013, 2023), i.e. an inequality of outcomes which reflects inequality of opportunity, is deleterious to growth; however, inequality which reflects from unequal effort is growth-enhancing (Marrero and Rodriguez 2013; see also Chavez Juarez 2015, who shows that most existing measures of inequality of opportunity are downward biased).

In a cross-country setting, the appropriate data to resolve these ambiguities have been unavailable until recently. Cross-country inequality studies hinge on consistent measurement. Ferreira et al. (2016) underscore how international poverty lines and survey methodologies impact global assessments, influencing empirical work on inequality and growth. In the next section, we briefly review the empirical literature on the wealth inequality – growth nexus, and explain how the data used in this article allow us to surmount the difficulties that affect the existing literature.

2.2 Empirical Literature

The literature has shown that, as far as disparities in income are concerned, inequality is negatively related to economic growth (Alesina & Perotti, 1996; Easterly, 2007). As mentioned earlier, the lack of data regarding the distribution and concentration of wealth is a recurring problem in empirical research on the effects of wealth inequality. According to Aghion et al. (1999), in the absence of data on wealth distribution for multiple countries, many researchers are forced to use alternative measures, and data on income inequality is regularly used as a proxy for wealth inequality. However, Davies et al.

[2] Savings and wealth inequality are notably influenced by the intergenerational transmission of human capital, entrepreneurship, and medical expenses (De Nardi and Fella 2017). Relatedly, Lusardi et al (2017) show that financial literacy accounts for 30-40% of wealth inequality. These papers help shed light on why wealth inequality may be self-reinforcing.

(2011) show that proxies composed of income inequality measures cannot sufficiently represent wealth discrepancies, as these authors showed that wealth distributions were much more unequal than income distributions in all countries for which they had the required data. Thus, one should be cautious in believing that income inequality adequately captures the impact that wealth concentration has on economic growth. This makes the link between wealth inequality and economic growth novel and interesting to explore thoroughly.

To counter the data availability issue, Alesina & Rodrik (1994) have used land inequality as a proxy for wealth inequality, and both find that inequality in land distribution is negatively and significantly associated with subsequent economic growth. Yet, while land inequality may be an appropriate proxy for wealth in poorer countries due to higher levels of agriculture, it is not an adequate measure for wealth inequality in more developed nations (Bagchi & Svejnar, 2015). Moreover, these two papers have a cross-sectional focus, which is more likely to be confounded by unobserved country-specific, time-invariant heterogeneity. Davies et al. (2011) support that land equality cannot be seen as a suitable measure for wealth inequality, as real property consisting of farm assets and land matter more in developing countries, while financial assets are more important in developed countries. Moreover, Castelló & Doménech (2002) argue that both land inequality and income inequality are insufficient measures of wealth inequality, as there are other variables, such as human capital, that are also relevant in determining the direction and scope of economic growth and development. Thus, while land inequality is important in its own right and can even affect food security (Urbina, Garza & Viana 2024), its usefulness as a proxy for wealth inequality should not be overstated.

According to Davies et al. (2011), wealth inequality statistics measured at the country level are suitable to use as regressors in studies of economic growth. Therefore, in this research, emphasis will be placed on the concentration of wealth at the top of the pyramid, and will thus use the share of wealth concentration at the top 1% and 10% of the population to estimate the association between wealth inequality and economic growth. Two arguments can be given for this emphasis. Firstly, due to increasing returns on capital accumulation, wealth-holders at the top may experience faster wealth growth than those at the bottom. Thus, the effects of wealth on the economy are the greatest for accumulation at the top of the distribution, as a snowballing effect may arise. These types of effects are stronger for wealth inequality than for income inequality (Scheve & Stasavage, 2017). Second, wealth concentration at the top decile or percentile correlates well with Gini coefficients in both wealth and income, hence it is an adequate measure of wealth inequality (Islam & McGillivray, 2020). Yet, as data on wealth Gini coefficients continue to be scarce, data on wealth concentration at the top are used in this paper.

Large differences can be found between existing datasets on wealth concentration variables, taking into account time dimensions, indicators used as proxy for wealth inequality, or the extent of global coverage. For example, while Piketty (2014) and Roine & Waldenström (2015) provide data on wealth inequality over a long period, these datasets are limited to a few high-income OECD countries, which makes the analysis less representative from a global development perspective. Davies et al. (2011) provide a dataset on the household distribution of wealth, which contains data on a wider range of countries, including emerging, non-OECD countries (such as China, Indonesia, and India). However, this cross-sectional dataset is limited to the year 2000, and therefore does not allow studying the relationship between wealth inequality and growth over time. Lastly, in their recent paper investigating the link between wealth inequality and economic growth, Islam & McGillivray (2020) have opted for data from Credit Suisse (2014) for 45 sample countries over the period 2000-2012. Yet, they acknowledge that direct observations on wealth distribution across households or individuals were only available for 31 countries, and for the remainder of the countries, proxies based on income were used. Thus, the extent to which Islam & McGillivray (2020) truly capture wealth, rather than income inequality, is unclear.

3. Data and Main Results

3.1 Data: Wealth Inequality

The most novel and comprehensive database on wealth inequality, which we use in this paper, is the World Inequality Database (WID). It reports several indicators of wealth inequality, including the Gini coefficient and the shares of net personal wealth held by the top 1% and top 10%. The WID combines fiscal data, household surveys, and other sources for over 170 countries between 1995 and 2020,[3] and defines net personal wealth as the total value of financial and non-financial assets (such as equities, bonds, housing, and land) held by households, minus debts. In this paper, we focus on the wealth Gini coefficient as our main measure, as it captures inequality across the entire distribution. We use the top 1% wealth share as a robustness check to specifically assess concentration at the very top. While no single indicator fully captures the complexity of wealth inequality, this combination allows us to explore both broad and top-heavy dimensions, in line with prior work such as Piketty and Saez (2003).

While the World Inequality Database represents a significant advance in the measurement of inequality, its estimates are not without limitations. In countries with high-quality administrative tax data, inequality estimates are relatively robust. However, in many low-income countries, data limitations are more severe. There, the WID relies

[3] We only consider data starting from 1995 because of data availability issues. Prior to 1995, wealth variables are severely limited, covering only ten countries over the entire pre-1995 period and, at most, seven countries in any given year. These countries, which are primarily high-income economies, are a narrow subset of the global distribution, making meaningful comparisons difficult. For reference, the pre-1995 coverage includes Switzerland (2 obs.), Germany (1), Denmark (15), Spain (11), France (96), India (4), The Netherlands (81), Poland (1), United States (33), and South Africa (2).

more heavily on imputations or extrapolations from national accounts, which introduces potential measurement error. Galbraith (2018) discusses such examples from the 2018 instalment of the WID: for instance, Yemen has a single true data point for the top 1% wealth share in 2006, from which subsequent data points are extrapolated. Galbraith (2018, p. 337) also describes some assumptions as "heroic." From an empirical perspective, we partially address this concern by controlling for the level of development in our main regressions. To the extent that data quality correlates with income level, this helps mitigate potential bias stemming from measurement error.

3.2 Data: Other Variables

The dependent variable in this study, economic growth, comes from version 10 of the Penn World Tables (Feenstra, Inklaar & Timmer 2015). It is calculated as the annual percentage change in real GDP per capita. It is important to construct a per-capita value, as a changing population is an important confounder in inequality research (Piketty, 2014). This measure is often used as a dependent variable in (cross-country) growth regressions (Feenstra, Inklaar, & Timmer, 2015).

We also account for a set of control variables which may impinge on both inequality and economic growth, thereby potentially confounding our estimates. First, a measure of educational attainment is included, as a larger human capital stock increases a country's ability to develop technological innovations, as well as to resort to existing knowledge. According to Benhabib & Spiegel (1994), educational attainment is one of the preconditions for growth and is therefore included in this analysis. Moreover, as a positive relationship exists between the level of education and wealth (Hartog & Oosterbeek, 1998), the average years of schooling within a country is likely to influence wealth inequality. Data are collected from the United Nations Development Programme (2021), and educational attainment is measured by the average number of years of education received by people aged 25 and older.

Second, Levine & Renelt (1992) found the investment rate to be the most robust determinant of growth when considering many variables, and we therefore include it in our regression. Moreover, higher inequality is associated with investment (Lee & Roemer 1998). The investment rate is calculated as the average annual growth rate of gross fixed capital formation based on constant local currency, and data is collected from the World Development Indicators (World Bank 2022a). Third, trade openness has been shown to be important for economic growth and development, as exports increase a country's GDP (Radelet, Sachs, & Lee, 2001), and a positive relationship can be found between trade openness and economic inequality (Dorn, Fuest, & Potrafke, 2021). Trade openness is defined as the sum of exports and imports of goods and services measured as a share of GDP, and data is collected from the World Development Indicators by the World Bank (2022a).

Fourth, to capture the effects of macroeconomic volatility, we control for the inflation rate (Fisher, 1993). Inflation is related to wealth inequality, as it leads to precautionary savings and thereby contributes to the accumulation of wealth (Colciago, Samarina, & de Haan, 2019). Inflation is measured by the consumer price index, and data is collected from the World Development Indicators by the World Bank (2022a). Fifth, institutional quality, more specifically the quality of economic institutions, should also be accounted for, as better economic institutions are likely to both foster economic growth and affect inequality. In this paper, we measure the quality of economic institutions with the Economic Freedom Index, which is a composite index for various measures, developed by the Fraser Institute (Gwartney et al 2021).

A list of sample countries and detailed information on variables and data sources can be found in Appendix Tables A1 and A2 respectively. Summary statistics are reported in Table 1.

Table 1. Summary statistics.

	Mean	SD	Min	Max	N
ln(GDP p.c.)	9.136	1.221	5.455	11.671	1020
Wealth Gini	0.775	0.063	0.539	1.040	1042
Trade (% of GDP)	82.572	48.190	0.021	420.431	950
Inflation	13.806	95.133	-3.846	2666.451	995
Schooling Years	7.817	3.315	0.650	14.167	1027
Economic Freedom	6.705	1.054	2.770	8.832	858
Investment	22.373	7.561	1.097	78.001	911
Top 1% wealth share	0.304	0.083	0.121	0.572	1042
Income Gini	0.522	0.122	0.128	0.745	1043

3.3 Cross-Sectional Results

We begin with a graphical overview of the relationship between wealth inequality and growth over the 1995 – 2019 period, à la Acemoglu et al (2015). Panel A of Figure 1 plots the initial wealth Gini (measured in 1995) against $\ln(\text{GDP p.c.})_{2019} - \ln(\text{GDP p.c.})_{1995}$, which is the "long-difference" growth. Panel B replaces the wealth Gini with the top 1% wealth share. In either case, it is apparent that higher initial equality translates into lower economic growth over the 1995 – 2019 period.

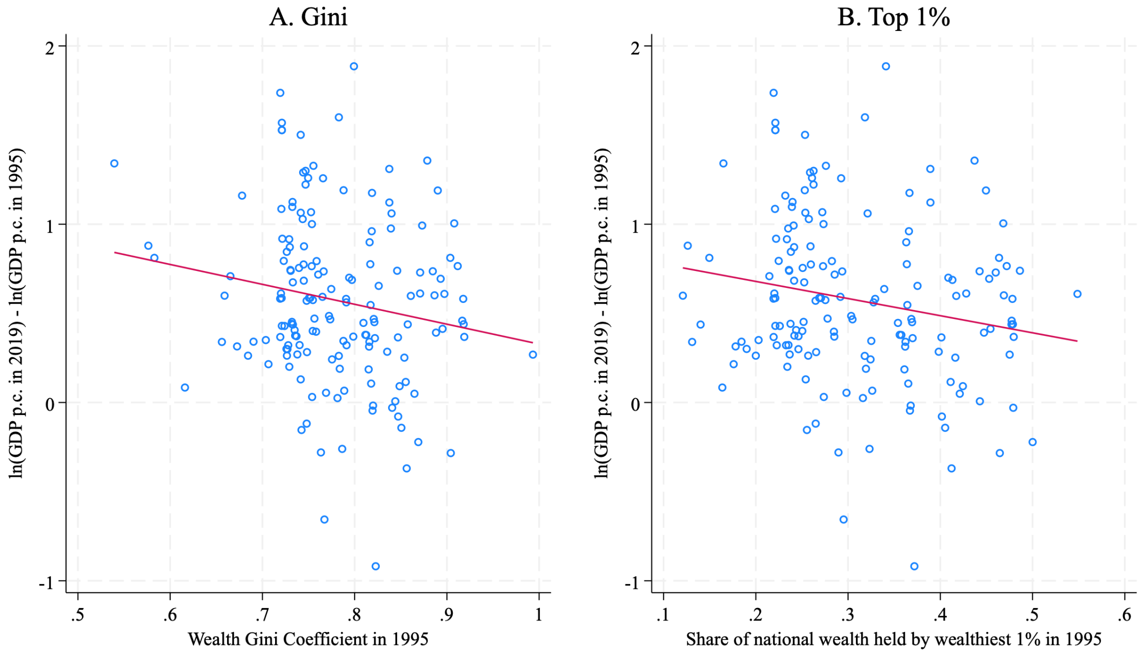

Figure 1. Initial wealth inequality and economic growth over 1995 – 2019.

How large is the association between wealth inequality and long-difference growth, and what should we compare it to? To ascertain whether wealth inequality is just income inequality by another name, we estimate:

$$ln(GDPp.c.)_{i,2019} - ln(GDPp.c.)_{i,1995} = \alpha_0 + Gini_{i,1995} + \epsilon_i \quad (1)$$

Equation (1), estimated in the cross-sectional domain, relates the growth over 1995 – 2019 to the initial Gini coefficient. In Table 2, we present results for the wealth Gini as well as for the income Gini. Both Gini variables are standardized.

Table 2. Long Difference Growth and Initial Inequality

	(1)	(2)
Wealth Gini	-0.0726***	
	(0.0278)	
Income Gini		-0.0373
		(0.0287)
Observations	165	164
R-squared	0.03	0.01

Heteroskedasticity-robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

A one standard deviation increase in initial wealth inequality is associated with a 0.073 percentage point reduction in cumulative growth over 1995–2019 ($p = 0.010$, heteroskedasticity-robust standard errors), equivalent to roughly 0.30 percentage points lower annual growth. By contrast, repeating the analysis using income inequality yields a coefficient of –0.037 ($p = 0.195$), or about 0.16 percentage points per year. Even ignoring statistical significance, the estimated correlation between wealth inequality on growth is nearly twice as large as that of income inequality.

3.4 Panel Results

We now turn to our panel estimates, which regress economic growth on lagged wealth inequality and lagged controls. To address short-term volatility and long-term persistence in the data, we aggregate observations into five-year intervals: $t \in \{1995, 2000, 2005, 2010, 2015, 2019\}$. This approach reduces noise from year-to-year fluctuations while allowing enough time for gradual shifts in persistent variables like wealth inequality to be captured meaningfully. The empirical specification takes the form:

$$\ln(\mathrm{GDP}p.c.)_{i,t} - \ln(\mathrm{GDP}p.c.)_{i,t-5} = \gamma_0 + \mathrm{WealthGini}_{i,t-5} + \mathbf{X}_{i,t-5}\beta + u_{it} \qquad (2)$$

where the dependent variable, ln (GDP p.c.)$_i$ - ln (GDP p.c.)$_{i,t-1}$, is the growth rate of per capita GDP between a given point in time and the previous time point, i.e. 5 years earlier. All explanatory variables are lagged one period (5 years). Table 3 presents the results of our main analysis.

Table 3. Wealth inequality and economic growth, 1995 – 2019.

	(1)	(2)	(3)	(4)	(5)
Wealth Gini	-0.319*	-0.244*	-0.401***	-0.275***	-0.300**
	(0.189)	(0.147)	(0.092)	(0.087)	(0.128)
Annualized coef.	-0.064	-0.045	-0.080	-0.055	-0.060
ln(GDP p.c.)			-0.030***	-0.068***	-0.068***
			(0.008)	(0.012)	(0.012)
Trade (% of GDP)		0.001		0.000***	0.000***
		(0.000)		(0.000)	(0.000)
Inflation		-0.001***		-0.001***	-0.001***
		(0.000)		(0.000)	(0.000)
Schooling Years		-0.031**		0.015***	0.015***
		(0.014)		(0.005)	(0.005)
Economic Freedom		-0.010		0.011	0.011
		(0.014)		(0.009)	(0.009)
Investment		-0.002		0.001	0.001
		(0.002)		(0.002)	(0.002)
Mean Wealth Gini					0.038
					(0.181)
N	800	590	800	590	590
Countries	162	141	162	141	141
R^2 (within)	0.051	0.108	0.089	0.110	0.110
R^2 (overall)	0.047	0.001	0.071	0.158	0.158
Country FE	Yes	Yes	No	No	No

Standard errors in parentheses are clustered over countries. All specifications include a set of year fixed effects. All explanatory variables are lagged 5 years; growth rates are calculated over a 5-year interval (see Equation 2).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Column (1) includes country fixed effects, while Column (2) adds control variables. The coefficient on the wealth Gini is negative and statistically significant at the 10% level in both cases. Notably, the fixed effects alone account for 79% of the variation in the wealth Gini, severely limiting usable within-country variation. This likely explains why the coefficient is only marginally significant, despite having the expected negative sign and a sizable magnitude.

In Columns (3) through (5), we drop fixed effects in favour of including the natural logarithm of lagged income per capita. Lagged GDP per capita conditions on previous income and essentially acts as a lagged dependent variable, since ln(GDP p.c.) is, by construction, also included in the dependent variable. Temple (1999) argues that fixed effects and lagged dependent models can be viewed as bounding the true effect when T is small. On the other hand, including both fixed effects and a lagged dependent variable is not advisable due to the Nickell (1981) bias, which is particularly severe in panels with few time periods, as is the case here (max T = 5). Reassuringly, the estimated coefficients on the wealth Gini remain negative and statistically significant, and their magnitudes are very similar across specifications. Column (4), which includes controls, suggests that a one standard deviation increase in wealth inequality is associated with a 0.34 percentage point decline in annual growth, which is virtually identical to the long-difference result derived from the estimates in Table 1.

The main limitation of Columns (3) and (4) is that the coefficient on wealth inequality reflects a mix of within- and between-country variation, since the specifications do not control for country fixed effects. To isolate the within-country component more clearly, Column (5) adopts a Mundlak correction by including the country-level mean of the wealth Gini. The coefficient is about 10% larger than that of Column (4), although the difference is no statistically significant This suggests that our findings are unlikely to be not driven by cross-country differences in wealth inequality.

3.5 Benchmarking against Income Inequality

A natural question is whether the observed relationship is simply capturing the effect of income inequality rather than wealth inequality. To address this, Appendix Table A3 replicates the analysis using income inequality measures. Specifically, we retain the Mundlak-style specification from Column (5) of Table 2, but replace both the time-varying and country-mean wealth Gini with their income inequality counterparts. The results are striking: the coefficient on income inequality is close to zero and statistically insignificant ($p = 0.88$). In Column (2), we go further and run a horserace comparison by including both the wealth and income Gini measures (each in its Mundlak form) in the same model. Wealth inequality remains statistically significant and economically meaningful, while income inequality continues to have no discernible effect.

This asymmetry highlights that wealth inequality and income inequality do not operate as interchangeable proxies. One plausible interpretation is that wealth inequality better captures the more persistent and distortionary aspects of inequality emphasized in the literature, such as intergenerational persistence, unequal access to credit, or political influence concentrated among the wealthy. By contrast, the income Gini likely reflects more transitory variation in earnings and may fail to pick up these deeper structural channels. While our data do not allow us to pinpoint the exact mechanisms, the consistent negative association between wealth inequality and subsequent growth suggests that it is these structural, long-lived dimensions of inequality that matter most. Further research is needed to disentangle the specific pathways through which wealth inequality constrains economic performance.

3.6 GMM Estimates

So far, our results do not address the critical challenge of endogeneity, namely, that economic growth may influence wealth inequality just as much as inequality affects growth. To tackle this, we employ a system Generalized Method of Moments (GMM) estimator (Blundell & Bond, 1998). This approach is particularly well-suited to our context, where simultaneity and the absence of credible external instruments make traditional identification strategies difficult.

System GMM exploits instruments internal to the model by estimating a system of equations in both first differences and levels. The first-difference equation removes unobserved country-specific fixed effects, improving upon the specifications from Table 3. However, differencing can induce serial correlation; the level equation, in which lagged differences serve as instruments, helps mitigate this issue. The use of system GMM in the inequality–growth literature is well established (e.g., Marrero & Rodríguez, 2013; Berg et al., 2018; Islam & McGillivray, 2020).

In addition, Baum, Schaffer, and Stillman (2003) note that system GMM is more efficient than standard instrumental variable estimators in the presence of heteroskedasticity, an important consideration given the characteristics of our panel dataset. The reliability of the system GMM estimator hinges on the validity of the instruments, which we assess using the Hansen J test for overidentifying restrictions. To guard against instrument proliferation, a common concern in GMM estimation that can bias coefficient estimates and weaken tests, we limit the number of lags used as instruments and collapse the instrument set. Collapsing reduces the dimensionality of the instrument matrix by creating one instrument per variable and lag, rather than one for each available time period. This helps avoid overfitting, and improves the reliability of inference. Finally, we implement the Windmeijer (2005) finite-sample correction to improve the efficiency of the two-step GMM estimator.

Table 4 presents the GMM results. In Columns (1) and (2), we collapse the instrument matrix and respectively limit the number of lags to one and two. The results show a clear negative effect of wealth inequality on economic growth, which is significant at the 5% level. In Column (1), the Lagrange Multiplier K test for instrument strength has a p-value of 0.007, indicating no issues with weak instruments. In Column (2), however, the K test returns a large p-value; we therefore rely on the Anderson-Rubin weak instrument robust test to guide our inference. The Anderson-Rubin test supports a causal interpretation of the effect of wealth Gini in Column (2).

In the interest of robustness, we also estimate models using uncollapsed instrument matrices in Columns (3) and (4). While the wealth Gini remains statistically significant at the 10% level in both cases, Hansen's J test suggests that the instruments may not be jointly valid. Weak instrument diagnostics further indicate that identification is problematic in these specifications. Notably, Columns (3) and (4) contain approximately twice as many instruments as Columns (1) and (2), reflecting the well-known issue of instrument proliferation in system GMM. The resulting overfitting of endogenous variables likely explains the deterioration in diagnostic test performance.

Table 4. GMM estimates.

	(1)	(2)	(3)	(4)
Wealth Gini	-1.165**	-1.098**	-0.873*	-0.677*
	(0.551)	(0.533)	(0.495)	(0.374)
Annualized coef.	-0.233	-0.220	-0.175	-0.135
ln(GDP p.c.)	-0.243***	-0.218***	-0.169***	-0.160***
	(0.056)	(0.046)	(0.045)	(0.039)
Trade (% GDP)	0.001***	0.001***	0.001**	0.001**
	(0.000)	(0.000)	(0.000)	(0.000)
Inflation	-0.001***	-0.001***	-0.001***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Schooling Years	0.051***	0.044***	0.035***	0.034***
	(0.014)	(0.012)	(0.011)	(0.010)
Economic Freedom	0.058***	0.052**	0.027	0.019
	(0.021)	(0.020)	(0.019)	(0.019)
Investment	0.001	0.000	0.002	0.001
	(0.002)	(0.002)	(0.002)	(0.002)
N	590	590	590	590
Countries	141	141	141	141
N Instruments	14	16	26	32
Lag limits	1	2	1	2
Collapse	Yes	Yes	No	No
AR(1) p-value	0.008	0.007	0.005	0.005
AR(2) p-value	0.145	0.137	0.076	0.076
Hansen's J p-value	0.504	0.316	0.004	0.001
LM K test p-value	0.007	0.322	0.192	0.534
Anderson-Rubin p-value	0.000	0.000	0.000	0.000

Standard errors in parentheses are clustered over countries. All specifications include a set of year fixed effects. All explanatory variables are lagged 5 years; growth rates are calculated over a 5-year interval (see Equation 2).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

4. Sensitivity and Heterogeneity

4.1 Alternate Wealth Inequality Measure: Top 1% Share

A potential pitfall of Table 3 is that we are considering only one proxy for wealth inequality, namely the Gini coefficient. In this sub-section, we therefore examine the sensitivity of our results to a different formulation of wealth inequality, namely the top 1% wealth share. In Table 5, we replicate our analysis from Table 3 while substituting the latter proxy for the former. The results are robust to the top 1% share as an alternate proxy.

Table 5. Alternate results with top 1% wealth share as key regressor of interest. Dependent variable: GDP growth rates

	(1)	(2)	(3)	(4)	(5)
Top 1% wealth share	-0.270*	-0.247*	-0.339***	-0.237***	-0.279**
	(0.150)	(0.134)	(0.069)	(0.070)	(0.119)
Annualized coef.	-0.054	-0.049	-0.068	-0.047	-0.056
ln(GDP p.c.)			-0.031***	-0.067***	-0.067***
			(0.008)	(0.012)	(0.012)
Trade (% of GDP)		0.001		0.000***	0.000***
		(0.000)		(0.000)	(0.000)
Inflation		-0.001***		-0.001***	-0.001***
		(0.000)		(0.000)	(0.000)
Schooling Years		-0.031**		0.014***	0.014***
		(0.013)		(0.005)	(0.005)
Economic Freedom		-0.009		0.010	0.011
		(0.014)		(0.009)	(0.009)
Investment		-0.002		0.001	0.001
		(0.002)		(0.002)	(0.002)
Mean Income Gini					0.066
					(0.148)
Observations	800	590	800	590	590
Countries	162	141	162	141	141
R-squared (within)	0.052	0.110	0.090	0.113	0.113
R-squared (overall)	0.050	0.002	0.076	0.159	0.160
Country FE	Yes	Yes	No	No	No

Standard errors in parentheses are clustered over countries. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include a full set of year fixed effects. All explanatory variables are lagged 5 years; growth rates are calculated over a 5-year interval (see Equation 2).

4.2 Covariate Selection: LASSO

We recognize that the choice of control variables in any empirical study may be somewhat arbitrary. To address this, we re-estimate our main specification (Column (4) of Table 3) using the LASSO procedure for control variable selection. In each case, we force the inclusion of the wealth Gini, log GDP per capita, and time fixed effects, and allow LASSO to select from increasingly flexible sets of controls. Specifically, we draw candidate variables from: (i) the baseline set of controls (Column 1), (ii) all pairwise interactions of those variables (Column 2), and (iii) both first- and second-order interactions (Column 3). As shown in Table 6, the estimated coefficient on the wealth Gini remains stable and statistically significant across all three specifications, suggesting that our main result is not sensitive to the specific set of controls included.

Table 6. Main specification, with LASSO-selected controls.

	(1)	(2)	(3)
Wealth Gini	-0.275***	-0.234***	-0.243***
	(0.087)	(0.080)	(0.087)
Annualized coef.	-0.055	-0.047	-0.049
ln(GDP p.c.)	-0.068***	-0.074***	-0.052***
	(0.012)	(0.012)	(0.013)
Trade (% of GDP)	0.000***	0.001**	0.002**
	(0.000)	(0.001)	(0.001)
Inflation	-0.001***	-0.001***	-0.000
	(0.000)	(0.000)	(0.000)
Schooling Years	0.015***	0.036***	0.034***
	(0.005)	(0.010)	(0.009)
Economic Freedom	0.011		
	(0.009)		
Investment	0.001	0.007*	0.005
	(0.002)	(0.004)	(0.004)
Observations	590	590	590
Countries	141	141	141
R-squared (within)	0.110	0.136	0.158
R-squared (overall)	0.158	0.213	0.222
Candidate controls	All independent variables	All independent variables + interactions	All independent variables + interactions + second-order interactions
Country FE	No	No	No

Standard errors in parentheses are clustered over countries. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include a full set of year fixed effects. All explanatory variables are lagged 5 years; growth rates are calculated over a 5-year interval (see Equation 2).

4.3 Covariate Selection: Bayesian Averaging

To further assess the robustness of the association between wealth inequality and economic growth across different model specifications, we use Bayesian Model Averaging (BMA) for covariate selection. As above, we force wealth inequality, log (GDP p.c.), and time fixed effects into all models, and we use the same three sets of candidate controls as we do in Table 6. This framework allows us to evaluate the stability of the effect of wealth inequality across a wide range of control combinations, as reported in Table 7.

The posterior mean of the coefficient ranges between -0.205 and -0.217, which is similar in size to our main results. The posterior standard deviations imply 95% credible interval which do not include zero in all three sets of models. This suggests that the negative association between wealth inequality and growth is consistently present, regardless of which covariates are included, reinforcing the robustness of our main findings.

Table 7. Bayesian Model Averaging (BMA) estimates.

	(1)	(2)	(3)
Wealth Gini			
Posterior Mean	-0.217	-0.205	-0.206
Posterior SD	(0.074)	(0.073)	(0.073)
Credible 95% intervals	[-0.362, -0.072]	[−0.348,−0.063]	[−0.348,−0.063]
Annualized Pos. Mean	-0.043	-0.041	-0.041
N. Models	32	954	554
Candidate controls	All independent variables	All independent variables + interactions	All independent variables + interactions + second-order interactions

4.4 Is the Effect Contingent on Covariate Values?

If our main finding applies only (or primarily) to countries with particular values of certain covariates, then an examination of the interactions between the wealth Gini and the relevant covariate should be informative. For example, suppose the effect of inequality is zero (or even positive) in the poorest countries, but is more negative for richer countries. Plotting the coefficient of the wealth Gini by quintile of ln(GDP p.c.) should then reveal an upward pattern.

In Figure 2, we report these interactions, with Wealth Gini * Quintile 1 as the reference category, starting from the fully controlled specification (Table 2 Column (4)). We do not detect any significant heterogeneity in any of Panels A-F, which perform this procedure for each covariate. Thus, we find no evidence that covariate values matter for the effect of wealth inequality on economic growth. In particular, income levels (Panel B) do not appear to moderate the relationship, as there are no meaningful differences in the coefficient of wealth inequality across income quintiles.

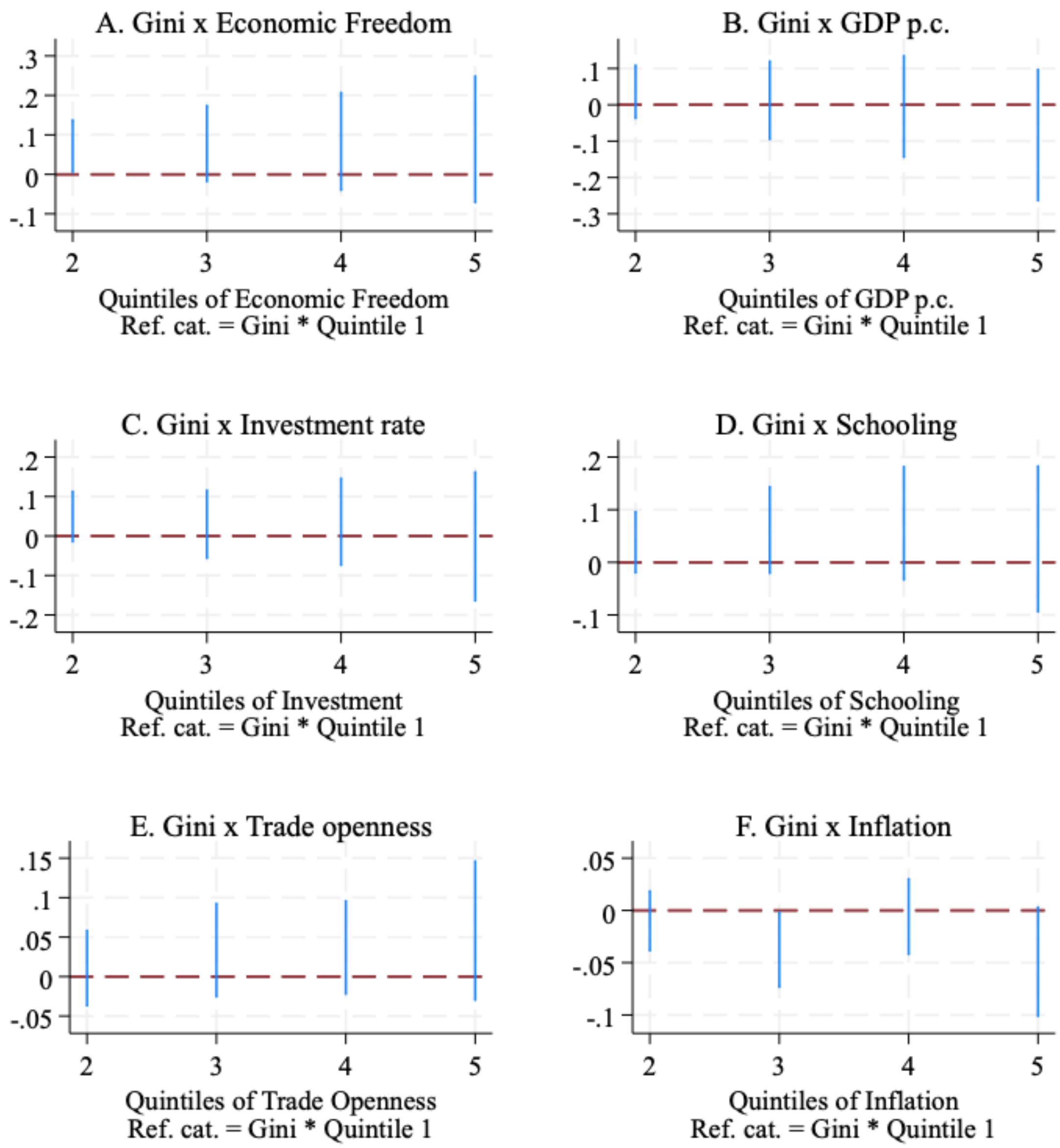

Figure 2. Heterogeneity of the Gini coefficient for wealth, across covariate quintiles.
Note. The blue spikes are 95% confidence intervals.

4.5 Other Heterogeneity Checks

Having shown that the effect is insensitive to where we are in the distribution of individual covariates, we examine whether we can find any meaningful heterogeneity across countries. If the relationship between wealth inequality and growth is starkly different across country groups, then the distribution of the coefficients on the wealth Gini should be multi-peaked when we estimate the relationship across many country subsets. Put differently, if there is substantial heterogeneity in the data, we should observe 'lumpy' distributions, as if arising from a finite-mixture data generating process. Our concern is that there may be a substantial lump of coefficients larger than zero, which would overturn our main findings, as far as particular subsets of countries are concerned. On the other hand, if there is no substantial heterogeneity, then our distributional plots should be smooth. Figure A2 in the Appendix reports on the results of this analysis, which do not suggest any meaningful heterogeneity.

One potential shortcoming of forming random country groups is that the relationship of interest might indeed be heterogeneous across ex ante similar countries. To some extent, we already consider this possibility above, where we study similarity along any one covariate. Similarity along many covariates, however, may also matter, and requires a different approach. We thus examine the wealth inequality – growth nexus across sub-groups of countries selected to be as similar as possible, based on a k-means clustering approach. We report this analysis in Figure A3 in the Appendix and its explanatory notes; here also, we can safely conclude that, even in subgroups of ex ante similar countries, the wealth inequality – economic growth relationship displays no meaningful heterogeneity.

5. Discussion and Conclusion

Many economists have investigated the relationship between economic disparities and growth, and a fundamental question has been the extent to which inequality facilitates or hinders economic growth. However, these studies have, largely, investigated the effect of income inequality as the only source of economic inequality, disregarding the possible effects of wealth inequality, owing to a dearth of data. Although it is argued that wealth inequality has higher explanatory power for economic growth than income inequality, this relationship had rarely been studied empirically.

In this paper, we have shown, using a panel of 165 countries over the time period 1995 to 2019, that wealth inequality exerts a significant negative effect on economic growth. A one standard deviation increase in wealth inequality results in 0.34 p.p. lower growth rates, which is approximately 15% of mean growth over the full sample. Stated differently, these numbers imply that, ceteris paribus, an economy with wealth inequality one standard deviation below the mean (i.e. approximately at the 16th percentile of the wealth inequality distribution) experiences a doubling in living standards in 28 years, while it takes 38 years for such a doubling to occur in an otherwise identical economy at the 84th percentile of wealth inequality (Appendix Figure A1). These effects are far from trivial.

Our findings are consistent with Alesina & Rodrik (1994), who find significant negative effects of unequal distribution of wealth on cross-country income growth. However, these studies consider land inequality as a proxy of wealth inequality, and thus only focus on one component of wealth, which might not be an adequate measure for total wealth inequality. Moreover, the results of this paper align with Bagchi & Svejnar (2015) and Islam & McGillivray (2020), who both find a negative and significant coefficient for their wealth inequality variable, thereby supporting the idea that wealth inequality hinders economic growth. Yet, both papers have used a shorter timeframe and a small sample (26 and 45 countries respectively, compared to the 165 countries in this research), and therefore this study provides novel perspectives that reflect a more global context.

Our results are robust to the inclusion of several control variables which may simultaneously impinge on both inequality and growth, as well as to covariate selection via LASSO and Bayesian averaging methods. In an extensive search for heterogeneities, in which we deploy, inter alia, k-means clustering techniques and a wide enumeration of country subgroups, we do not find any evidence that our results are specific to particular groups of countries. This finding is critical, because point estimates can sometimes obscure substantial heterogeneities, which have different policy implications. Such is not the case here.

The implications from our findings are important. According to Saez (2016), the only way the public favours more progressive taxation is if it is convinced that unequal wealth accumulation is detrimental to economic growth. Our results lend support to this concern and underscore the need to better understand the channels through which wealth inequality affects long-term development. Discussions about sources of economic growth ought to focus more on the (re-)distribution of wealth, rather than on the distribution of income. Considering that capital is often highly concentrated among wealthy individuals and represents a significant fraction of their total income, our evidence highlights the importance of addressing questions regarding the taxation of, for instance, capital income and inheritances in order to facilitate economic growth.

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Appendix - For online publication only

Table A1: List of sample countries by geographic region (165 countries, 5 regions)

Africa: Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cape Verde, Central African Republic, Chad, Comoros, Congo, Cote d'Ivoire, Dem. Rep. Congo, Djibouti, Egypt, Equatorial Guinea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Morocco, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, South Africa, Sudan, Swaziland, Tanzania, Togo, Tunisia, Uganda, Zambia, Zimbabwe
Americas: Argentina, Bahamas, Belize, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Dominican Republic, Ecuador, El Salvador, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Suriname, Trinidad and Tobago, United States, Uruguay, Venezuela
Asia: Armenia, Azerbaijan, Bahrain, Bangladesh, Bhutan, Brunei, Cambodia, China, Cyprus, Georgia, India, Indonesia, Iran, Iraq, Israel, Japan, Jordan, Kazakhstan, Kuwait, Kyrgyz Republic, Laos, Lebanon, Macao, Malaysia, Maldives, Mongolia, Myanmar, Nepal, Oman, Pakistan, Palestine, Philippines, Qatar, Saudi Arabia, Singapore, South Korea, Sri Lanka, Syria, Taiwan, Tajikistan, Thailand, Turkey, Turkmenistan, United Arab Emirates, Uzbekistan, Vietnam, Yemen
Europe: Albania, Austria, Belarus, Belgium, Bosnia and Herzegovina, Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, Ireland, Italy, Latvia, Lithuania, Luxembourg, Macedonia, Malta, Moldova, Montenegro, Netherlands, Norway, Poland, Portugal, Romania, Russia, Slovak Republic, Slovenia, Spain, Sweden, Switzerland, Ukraine, United Kingdom, Yugoslavia
Oceania: Australia, New Zealand

Table A2: Variable descriptions and data sources

Variable	Description	Source
GDP growth rate	Growth rate of real GDP per capita, created by the author by taking the first difference of the natural logarithm of per capita real GDP, using national-accounts growth rates in country i at time t.	Penn World Tables, 10th version (Feenstra, Inklaar, & Timmer, 2015).
ln (GDP p.c.)	Natural logarithm of real GDP per capita using national-accounts growth rates, divided by population in country i at time t.	Penn World Tables, 10th version (Feenstra, Inklaar, & Timmer, 2015).
Wealth inequality top 1%	The share of total value of non-financial and financial assets (housing, deposits, equities, land, bonds, etc.) minus their debts, held by the wealthiest 1% of the population within country i at time t.	World Inequality Database (WID) (2022).
Wealth inequality top 10%	The share of total value of non-financial and financial assets (housing, deposits, equities, land, bonds, etc.) minus their debts, held by the wealthiest 10% of the population within country i at time t.	World Inequality Database (WID) (2022).
Inflation rate	The annual percentage change in the cost to the average consumer of acquiring a basket of goods and services in country I at time t.	World Development Indicators by the World Bank (2022a).
Trade openness	The sum of exports and imports of goods and services measured as the share of GDP in country I at time t.	World Development Indicators by the World Bank (2022a).
Investment rate	The average annual growth rate of gross fixed capital formation in country I at time t, measured in constant local currency.	World Development Indicators by the World Bank (2022a).
Average years of schooling	The average number of years of education received by people aged 25 years or older.	United Nations Development Programme (2021).
Economic Freedom	Composite index based on 21 components in five major areas: size of government, property rights, sound money, trade freedom, credit regulation, and labour and business. Scores range from least (0) to most (10) free.	Gwartney et al (2021).

Table A3. Wealth inequality, income inequality, and growth: Mundlak estimates.

	(1)	(2)
Wealth Gini		-0.384^{***}
		(0.129)
Income Gini	0.025	0.200
	(0.163)	(0.172)
ln(GDP p.c.)	-0.073^{***}	-0.073^{***}
	(0.012)	(0.012)
Trade (% of GDP)	0.000^{***}	0.000^{***}
	(0.000)	(0.000)
Inflation	-0.001^{***}	-0.001^{***}
	(0.000)	(0.000)
Schooling Years	0.012^{**}	0.013^{***}
	(0.005)	(0.005)
Economic Freedom	0.009	0.009
	(0.009)	(0.009)
Investment	0.001	0.001
	(0.002)	(0.002)
Mean Income Gini	-0.241	-0.386^{**}
	(0.173)	(0.194)
Mean Wealth Gini		0.317
		(0.219)
Observations	591	589
Countries	141	141
R-squared (within)	0.114	0.122
R-squared (overall)	0.152	0.158
FE	No	No

Standard errors in parentheses are clustered over countries. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. All regressions include a full set of year fixed effects. All independent variables are lagged one period (5 years).

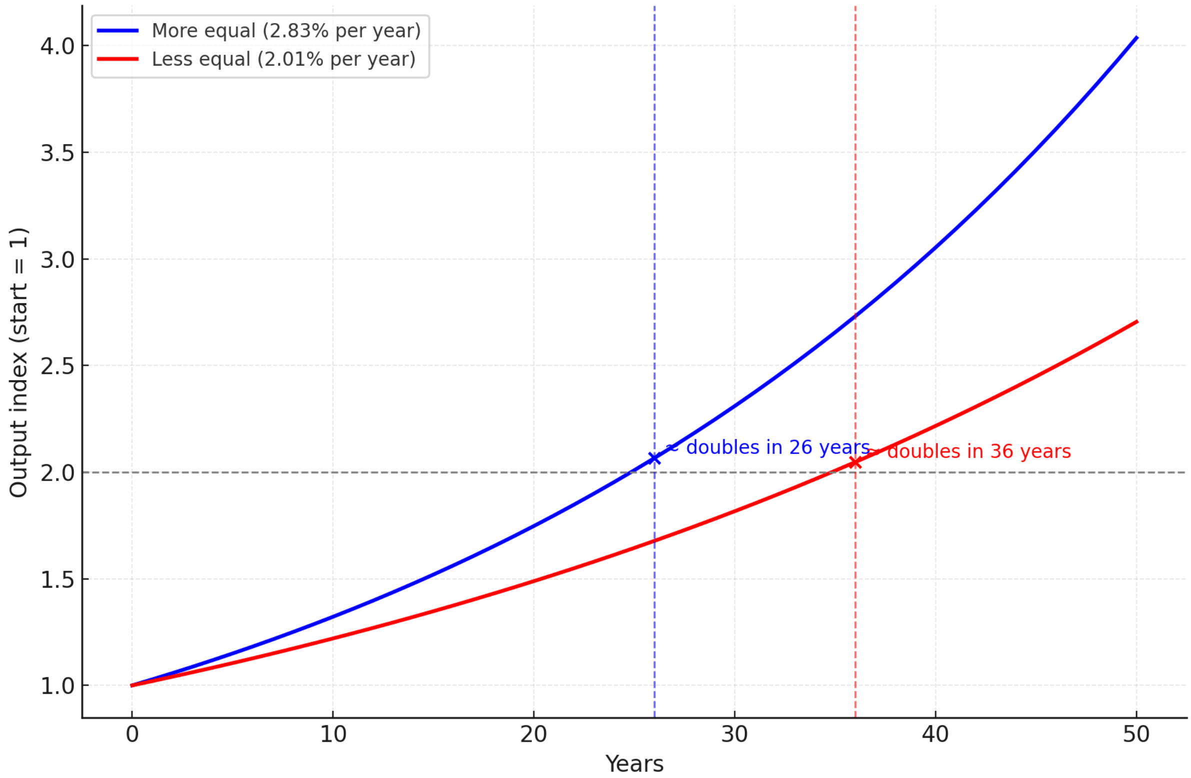

Figure A1. Hypothetical economies at the 16th percentile (blue line; more equal) and 84th percentile (red line; less equal) of the wealth inequality distribution.

Explanatory notes. The more equal economy has an annual growth rate of 2.83% per year, which is the sum of the sample mean (2.42% per year) plus 0.4 p.p. (our estimate of a 1 SD decline in wealth inequality), and doubles in 26 years. The less equal economy grows at a rate of 2.01% per year, and doubles in 36 years.

Heterogeneity over random country groups. First, we define an arbitrary number of country groups k = {2, 3, 4}. For each k, we randomly draw 165/k countries into each group (where 165 is the number of countries in the sample), Second, we estimate the full model from Table 3 Column (4), which includes all covariates, and store the coefficient of Wealth Gini. Third, we repeat the procedure 500 times. For k = 2, we obtain 500 estimates for each of the two country groups (which contain 82 and 83 countries), resulting in 1000 estimates. Similarly, for k = 3, we obtain 1,500 estimates; while we get 2,000 estimates for k = 4.

We thus obtain 4,500 for Wealth Gini. To account for uncertainty, we divide each coefficient by its standard deviation (which is equal to its standard error multiplied by the square root of N), thus obtaining a set of standardized coefficients. Figure A2 shows the distribution of these 4,500 standardized estimates. The solid blue line shows the observed distribution, while the red dashed line is the normal distribution, shown for comparison.

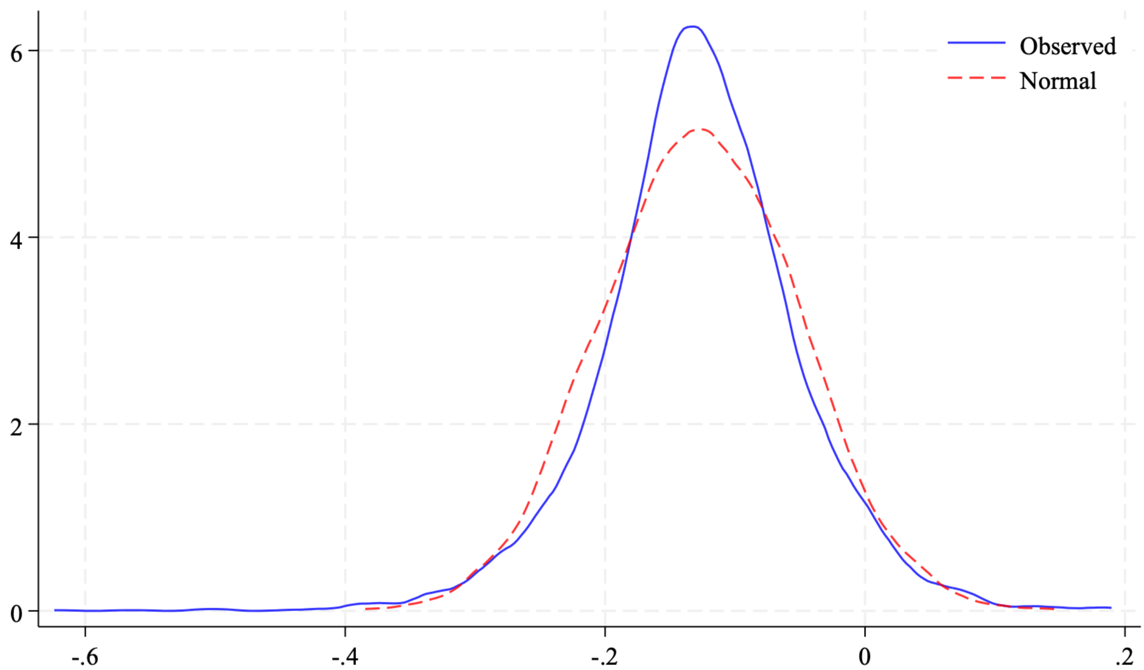

Figure A2. Distribution of 4,500 standardized coefficients of Wealth Gini
Notes. Each coefficient is estimated over a different sub-set of countries.

It is apparent from Figure A2 that the distribution of our estimates, each obtained from a different country sample, is smooth and one-peaked. It is not substantially different from the normal distribution in the positive range: we can thus comfortably rule out any large positive mass, which would imply that inequality affects growth positively for some groups of countries. The distribution is asymmetric, but extreme negative outliers are too few to affect our conclusions: if we (conservatively) drop observations further to the left than two S.D. from the mean, the mean standardized coefficient barely changes at all. Thus, we find no heterogeneities over country groups.

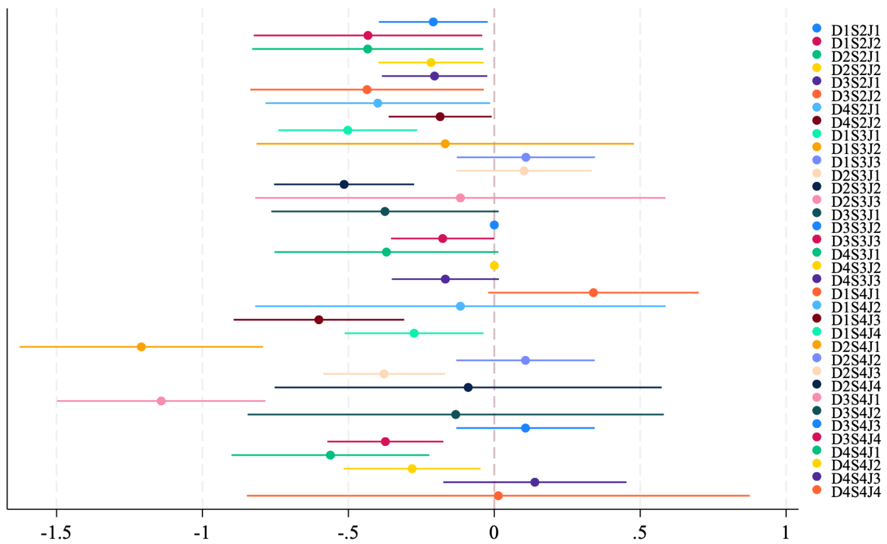

Figure A3. Coefficients of Wealth Gini across k-means clustered country groups. Legend Key: D = number of dimensions. S = number of clusters. J = cluster identifier.

Heterogeneity over similar country groups. First, we use principal components analysis to reduce the dimensionality of the data. In the baseline case, we retain only the first principal component, which alone explains 55% of the cross-sectional variation in our 6 control variables. Second, we group countries together with a k-means clustering approach, where k = {2, 3, 4}. The clustering is determined by countries' similarity along one dimension, namely the first principal component. Specifically, k-means clustering splits the dataset into k distinct subgroups, by minimizing the variance within each group while maximizing the variance between groups. The approach assigns data points to the nearest cluster centroid, then iteratively refines the positions of these centroids. Once we partition the dataset into k subgroups, we estimate the full model (with all controls; see Table 3 Column (4)) separately for each subgroup.

Of course, similarity according to a one-dimensional metric (the first principal component) is far from perfect, so we also repeat our procedure for 2, 3, and 4 dimensions (i.e. the first 2, 3, or 4 principal components). We stop at 4 principal components, since the first 4 components explain 92% of the cross-sectional variation in the covariates. In total, we estimate 36 iterations of the model, each over a different subgroup of countries, which are selected to be ex ante similar.

If there is substantial heterogeneity in the data, the 36 estimates should show relatively little overlap. Instead, what we see in Figure A3 is that a majority of estimates are close together in size. Thus, we can safely conclude that, even in subgroups of ex ante similar countries, the wealth inequality – economic growth relationship displays no meaningful heterogeneity.