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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 concentration at the top of the distribution and economic growth. A one standard deviation increase in wealth inequality within countries is associated with a 0.4 percentage points (17%) 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 little evidence to suggest a heterogeneous relationship.

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

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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 makes unethical behaviours more justifiable (Martinangeli & Windsteiger 2024). Where institutions are weak, inequality also hinders public good provision (Kammas, Litina & Palivos 2023). More broadly, inequality shapes a wide range of normatively desirable societal outcomes, like life expectancy (Martin & Baten 2022), or the ability to make policy (Fierro et al 2023).

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 (Attanasio & Binelli, 2003) if the rich have higher marginal propensities to save. On the other hand, economic and political channels have been identified through which inequality is harmful to growth, such as through redistributive taxation that would be favoured by the median voter (Barro, 2000).

Owing to a paucity of data, the literature has largely focused on *income* inequality, rather than *wealth* inequality. Wealth inequality is arguably much more important (Ravallion 2012): income is a flow concept, but wealth is a stock. Thus, studying income inequality is necessarily limiting: if one is interested in how inequality (broadly defined) affects economic outcomes, then focusing on income disparities will be less informative than examining wealth disparities. Wealth inequality can tell us about long-term inequality and paints a more comprehensive picture of how inequality affects economic growth. For Piketty (2014), as wealth accumulates over time and passes on between generations, the effects of wealth inequality on growth are more prominent than income inequality. Moreover, the accumulation of wealth is important in providing opportunity and security. This is especially the case in developing countries, where institutional voids may lead to lower social safety nets, and where access to credit remains a challenge (Davies, Sandström, Shorrocks, & Wolff, 2008). This is then likely to affect long-term economic growth. In addition, the capital shares of national income have increased in many countries, from approximately 15-25% in the 1970s to 25-35% in 2010 (Piketty & Zucman, 2014). Thus, capital income has become relatively more important than in the past, which shows that wealth accumulation increasingly matters.

Our contribution, therefore, is to study the nexus between wealth inequality and economic growth, drawing on new data for 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 a more direct measure of wealth inequality (top wealth shares). Third, we are able to have a more comprehensive time coverage, using annual data over the 1995 – 2019 period. Bagchi & Svejnar's (2015) data only consist of, on average, 6 points in time for each of their 26 countries (N_{Total} = 160); Islam & McGillivray (2020) use 12 time points per country for 45 countries (N_{Total} = 540). In contrast, our data cover 24 time points per country for 165 countries (N_{Total} = 3,959), such that we can estimate dynamic models with greater consistency.

Overall, we find a negative and statistically significant relationship between wealth inequality and economic growth. For identification, we rely on a system generalized method of moments (GMM) approach, which we complement with an extensive battery of robustness checks. Our approach is robust to several important control variables, which may confound the relationship, and to all permutations of controls. In the most demanding specification, we find that a 1 standard deviation (S.D.) increase in wealth inequality is associated with a 0.4 percentage point (p.p.) decline in growth rates. Remarkably, the stylized relationship in the data shown in Figure 1, using all of the available variation, is nearly identical (0.39 p.p. declines in growth rates with 1 S.D. increases in wealth inequality). We also examine whether the relationship 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 methodology and data. Afterward, Section 4 presents the empirical results of the main analyses, followed by sensitivity analyses. Section 5 examines potential heterogeneities; Section 6 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, Sandström, Shorrocks, & Wolff, 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., 2008). 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). 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.

The theoretical ambiguity can thus only be resolved empirically, but the appropriate data to do so have been unavailable until recently. 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. (2008) 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), and later also Deininger & Olinto (2000), 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.

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. (2008, 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 Empirical Approach

3.1 Data: Wealth Inequality

The most novel and complete database on wealth inequality measures, which we use in this paper, comes from the World Inequality Database (WID). WID reports data on wealth inequality indicators concerning the top 1% and 10% shares of net personal wealth. It combines multiple sources of information, such as fiscal data and data from household surveys, for more than 170 countries during the period 1995-2020. Wealth inequality is measured as the concentration of wealth at the top of the distribution. Data on both the 1% wealth concentration share and 10% wealth concentration share are collected from the recently updated database. In contrast to different databases, which often use income inequality as a proxy for wealth, WID (2022) uses various sources to capture net personal wealth, providing a better reflection of total wealth concentration. WID (2022) defines net personal wealth as the total value of non-financial and financial assets (composed of bonds, equities, housing, deposits, lands, etc.) held by households, minus debts. Thus, wealth inequality at the top one percent measures how much of the total wealth in a given country-year is owned by the wealthiest 1% of the population. It is unlikely that a single inequality measure will be sufficient to capture the effects of inequality on growth for the entire distribution. Thus, the results of this research should be interpreted as reflecting the concentration of wealth at the top quantiles, rather than taking into account the complete distribution, which is in line with research by Davies et al. (2008) and Piketty & Saez (2003).

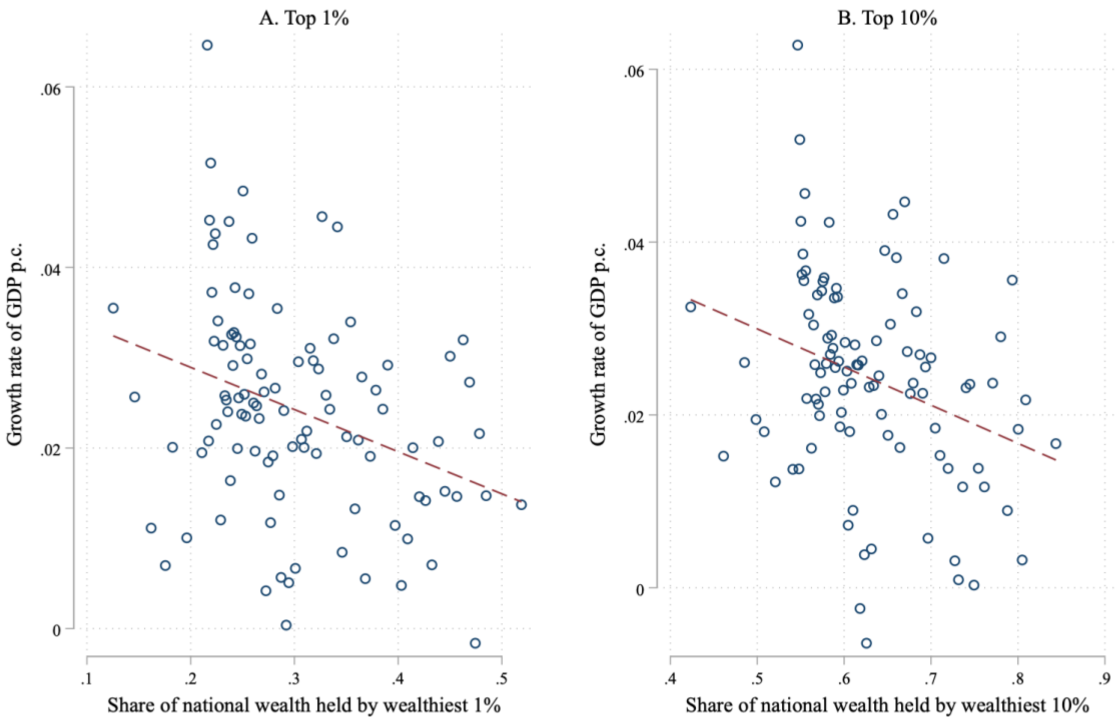

Figure 1. Top wealth shares and economic growth.

Notes: Binned scatterplots with 100 bins.

Figure 1 provides a graphical overview of the relationship we study in this paper. It is apparent that wealth inequality is negatively correlated with economic growth; this is true both for the top 1% share (Panel A) and the top 10% share (Panel B). A one S.D.

increase in the top 1% share is associated with a 0.39 percentage point reduction in growth rates. Considering that average growth across the entire sample is 2.42 percent per year, the observed effect size is, *prima facie*, far from trivial.

3.3 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 regression 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 lower investment rates (Cingano, 2014). 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 Heritage Foundation (2021). *Sixth,* to rule out that differences in economic development can explain away our results, we also control for the natural logarithm of GDP per capita (see Barro & Sala-i-Martin 2007).

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.

Variable	**N**	**Mean**	**SD**	**Min**	**Max**
Year	4,125	2007	7.21	1995	2019
Growth	4,125	0.02	0.05	-0.46	0.65
ln (GDP p.c.)	4,125	9.11	1.25	5.67	11.70
Top 1% Share	4,125	0.30	0.08	0.12	0.58
Top 10% Share	4,125	0.63	0.08	0.37	0.91
Inflation rate	3,802	0.03	0.27	-1.19	7.09
Trade openness	3,805	0.13	0.37	-1.07	3.48
Investment rate	3,750	0.03	0.10	-0.24	0.67
Schooling years	3,876	1.10	2.73	-4.58	14.20
Economic Freedom	3,756	0.09	0.21	-0.23	0.86

3.2 Empirical Approach

To investigate the relationship between wealth inequality and economic growth, panel data on 165 countries for the time period 1995-2019 is used. We estimate dynamic panel data models of the form:

$$g_{it} = \beta_0 + \mu_i + \gamma_t + \beta_1 g_{i,t-1} + \beta_2 \, Top\ Wealth\ Share_{i,t-1} + \mathrm{X}_{\mathrm{i,t-1}} \Omega + \epsilon_{it} \qquad (1)$$

where g_{it} is the per capita GDP growth rate of country *i* in period *t*; μ_i is a vector of country fixed effects; γ_t is a vector of year fixed effects; *Top Wealth Share* is either the top 1% or top 10% wealth share; X is a vector of control variables which may correlate with both inequality and growth; and ϵ is the error term. Note that while, in our main analysis, we lag all control variables by one year, we relax this assumption in the appendix and use contemporaneous values instead, which does not affect the results. We cluster standard errors over countries throughout our analysis.

Addressing the critical challenge of endogeneity and reverse causality—whereby economic growth may influence wealth inequality as much as inequality affects growth—we rely on a system Generalized Method of Moments (GMM) estimator (Blundell & Bond 1988). This approach is particularly useful in our context due to the simultaneous nature of the relationship between wealth inequality and economic growth, and the difficulty in finding suitable external instruments that meet both the exclusion restriction and validity criteria. System GMM is based on the use of 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. However, differencing can introduce serial correlation; the level equation helps to mitigate these issues, as lagged differences serve as instruments for the level equation. The use of a system GMM estimator to investigate the inequality-growth nexus is in line with previous research (Marrero & Rodríguez, 2013; Islam & McGillivray 2020; Ostry, Berg, & Tsangarides, 2014). Moreover, according to Baum, Schaffer, & Stillman (2003), in the presence of heteroscedasticity, which is the case in this panel dataset, the system GMM is more efficient than a simple instrumental variable estimator. The reliability of the system GMM estimator depends on the validity of instruments, which will be checked by the Hansen *J* test on over-identifying restrictions. When too many instruments are entered into the GMM regression, this can lead to instrument proliferation, which causes biased estimates of the endogenous variables, and can weaken the test for over-identifying restrictions. To reduce the number of instruments and thus avoid proliferation, we employ Roodman's (2009) approach, which uses principal components analysis to reduce the dimensionality of the instrument set. Lastly, a Windmeijer (2005) finite-sample correction will be applied to enhance the efficiency of the two-step system GMM estimator.

4.Empirical Results

4.1 Main Results

Table 2 reports our main results. We standardize our independent variables, for ease of interpretation. In our baseline specification, which only conditions on the first lag of the dependent variable, in Column (1), a one standard deviation increase in the share of national wealth held by the wealthiest 1% of the population is associated with a 0.3 percentage point decline in economic growth rates. This is in line with the stylized facts presented in Figure 1, with a very similar effect size. The low AR(1) p-value indicates that, as expected, there is first-order serial correlation. The AR(2) p-value, however, is large (p = 0.35), such that we cannot reject the null hypothesis of no second-order autocorrelation. In practical terms, this means that the time series properties of the data are properly accounted for, and we do not need to include a second lag of the dependent variable to account for autocorrelation of the second order. Hansen's *J* test cannot reject the null hypothesis of instrument validity. Moreover, in an efficient GMM estimation, the number of instruments should be below the number of cross-sectional units (Roodman, 2009). As can be seen at the bottom of Table 2, the system GMM estimator generates fewer instruments than the number of countries included, hence there are no signs of instrument proliferation.

Table 2. Main results. Dependent variable: GDP growth rates.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 1% Wealth Share $_{i,t-1}$	-0.003***	-0.004***	-0.004***	-0.003***	-0.003**	-0.003**	-0.003***	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Growth$_{i,t-1}$	0.306***	0.297***	0.262***	0.266***	0.276***	0.245***	0.375***	0.300***
	(0.043)	(0.043)	(0.051)	(0.046)	(0.050)	(0.051)	(0.052)	(0.088)
ln(GDP p.c.) $_{i,t-1}$		-0.005***						-0.005***
		(0.001)						(0.001)
Investment rate $_{i,t-1}$			0.002					0.004
			(0.003)					(0.006)
Years of schooling $_{i,t-1}$				-0.002				0.018
				(0.003)				(0.013)
Trade openness $_{i,t-1}$					0.002			0.015
					(0.003)			(0.010)
Inflation $_{i,t-1}$						-0.004		0.003
						(0.007)		(0.006)
Economic freedom $_{i,t-1}$							-0.000	-0.019*
							(0.002)	(0.009)
N	3795	3795	3442	3552	3493	3488	3428	2941
Countries	165	165	157	161	159	160	162	151
N. Instruments	95	95	95	94	93	90	83	81
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.353	0.362	0.883	0.841	0.930	0.672	0.343	0.390
Hansen p-value	0.104	0.115	0.176	0.069	0.141	0.109	0.051	0.085

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.

In Columns (2) – (7), we introduce each control variable separately; in Column (8), we estimate a model with all control variables. The baseline results are robust to each of these variations. While the Hansen *p*-value in the full model is somewhat small (p = 0.085), the instruments remain jointly valid at the 5% significance level.

A salient feature of Table 2 is that the size of the coefficient of *Top 1% Wealth Share* remains virtually unchanged as control variables are introduced. This is consistent with a world in which the exclusion restriction holds: the results do not depend on which controls are included. In robustness checks, we show that the results are robust to all possible permutations of control variables.

4.2 Alternate Measure of Inequality: Top 10% Share

A potential pitfall of Table 2 is that we are considering only one proxy for wealth inequality, namely the top 1% wealth share. Arguably, the top 1% of the wealth distribution could be considered something of an outlier, whose economic fortunes may not necessarily impinge on the economy at large. In this sub-section, we therefore examine the sensitivity of our results to a different formulation of wealth inequality, namely the top 10% wealth share. In Table 3, we replicate our analysis from Table 2 while substituting the latter proxy for the former.

Table 3. Alternate results with top 10% wealth share as key regressor of interest. Dependent variable: GDP growth rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Top 10% Wealth Share $_{i,t-1}$	-0.003**	-0.004***	-0.004**	-0.003**	-0.003**	-0.003**	-0.003**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Growth$_{i,t-1}$	0.306***	0.298***	0.262***	0.267***	0.276***	0.245***	0.376***	0.301***
	(0.043)	(0.043)	(0.052)	(0.046)	(0.050)	(0.051)	(0.052)	(0.088)
ln(GDP p.c.) $_{i,t-1}$		-0.005***						-0.005***
		(0.001)						(0.001)
Investment rate $_{i,t-1}$			0.002					0.004
			(0.003)					(0.006)
Years of schooling $_{i,t-1}$				-0.002				0.018
				(0.003)				(0.013)
Trade openness $_{i,t-1}$					0.002			0.014
					(0.003)			(0.010)
Inflation $_{i,t-1}$						-0.004		0.003
						(0.007)		(0.006)
Economic freedom $_{i,t-1}$							-0.001	-0.019*
							(0.002)	(0.009)
N	3795	3795	3442	3552	3493	3488	3428	2941
Countries	165	165	157	161	159	160	162	151
N. Instruments	95	95	95	94	93	90	83	81
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.352	0.361	0.885	0.837	0.930	0.671	0.344	0.391
Hansen p-value	0.104	0.115	0.172	0.069	0.142	0.107	0.054	0.090

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.

The results are nearly identical. If anything, the full model from Column (8) indicates that the effect of the 10% wealth share is somewhat larger than its top 1% analogue (Column (8) from Table 2), although the difference is not statistically significant. Across the board, a 1 S.D. increase in the top 10% wealth share results in 0.3 – 0.4 p.p. smaller growth rates. This is true even after we condition for differences in income, education, trade openness, economic institutions, macroeconomic volatility, and the speed of capital accumulation (as proxied by the investment rate).

On the econometric side, the diagnostics again support a causal interpretation of the results, with jointly valid instruments and no signs of instrument proliferation.

4.3 Alternate Panel Structure

In this sub-section, we examine whether the particular dynamic structure we impose on our data may be driving our results. To do so, we replace lagged independent variables with their contemporary values. We replicate Tables 2 and 3 from the main text, which respectively take the top 1% and 10% as inequality proxies, with the modified structure in Appendix Tables A3 and A4. The results are unchanged, suggesting that the particular structure from our main estimates does not play a role in determining our results.

4.4 A Systematic Approach to Robustness

So far, we have shown that our results are robust to alternate specifications, including several control variables, two different proxies for inequality, and replacing the lagged independent variables with their contemporaneous values.

We recognize, however, that the choice of control variables, in any empirical study, is potentially idiosyncratic. We therefore re-run our estimates using every possible permutation of control variables, each inequality proxy, and each lag structure. More specifically:

(i) There are 2 inequality proxies (top 1% share; top 10% share)

(ii) There are 2 'lag structures' (lagged explanatory variables; contemporaneous explanatory variables)

(iii) There are 64 different ways of combining our 6 control variables, as $C_6^0 + C_6^1 + C_6^2 + C_6^3 + C_6^4 + C_6^5 + C_6^6$ = 64.

This approach results in estimating 2 * 2 * 64 = 256 regressions. Figure 2 displays the results from doing so. The blue spikes represent 95% confidence intervals, and the coefficients are ordered from smallest to largest, in absolute value. In all cases, the effect of wealth inequality is negative and statistically significant.

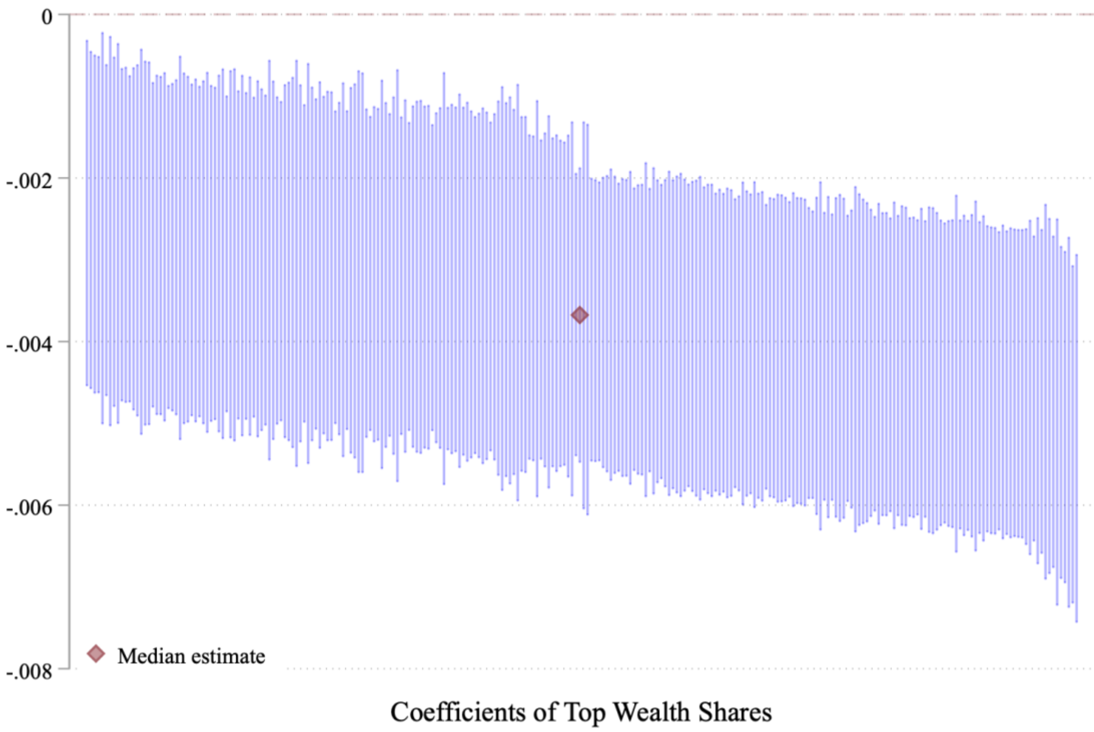

Figure 2. 95% confidence intervals of the effect of top wealth shares on economic growth rates across 256 specifications (see main text).

5. Heterogeneity Analysis

So far, we have shown that our results, in terms of average effects, are very robust. However, mean effects can obscure substantial heterogeneities. Ignoring such heterogeneities can result in drawing broad-brush, one-size-fits-all lessons from the data, which can be misleading. In this section, we thus systematically examine whether heterogeneous effects exist alongside the distribution of covariates, across variously defined country sub-groups, or both. We find that they do not.

5.1 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 *Top 1% Wealth Share* 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 *Top 1% Wealth Share* by quintile of ln(GDP p.c.) should then reveal an upward pattern.

In Figure 3, we report these interactions, with the *Top 1% Wealth Share * Quintile 1* as the reference category. 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.

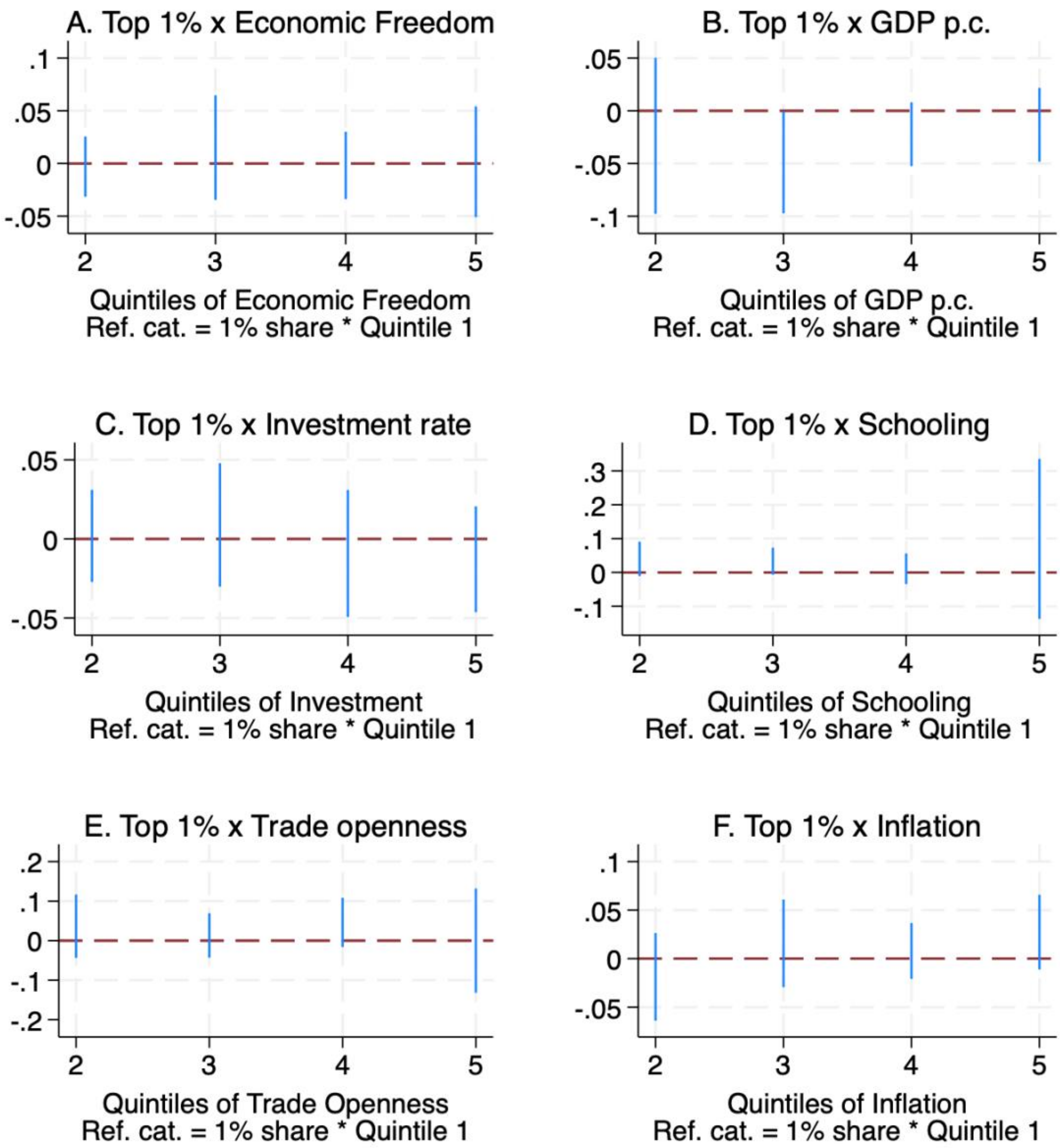

Figure 3. Heterogeneity of *Top 1% Wealth Share* across covariate quintiles.

5.2 Heterogeneity Over Country Groups

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 *Top 1% Wealth Share* coefficients should be multi-peaked when we estimate the relationship across many country sub-sets. 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.

We thus proceed as follows. 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 2 Column (8), which includes all covariates, and store the coefficient of *Top 1% Wealth Share*. 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.

In practice, standard errors could not be computed in 13 instances, but we nevertheless obtain 4,487 coefficients for *Top 1% Wealth Share.* 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 4 shows the distribution of these 4,487 standardized estimates. The solid blue line shows the observed distribution, while the red dashed line is the normal distribution, shown for comparison.

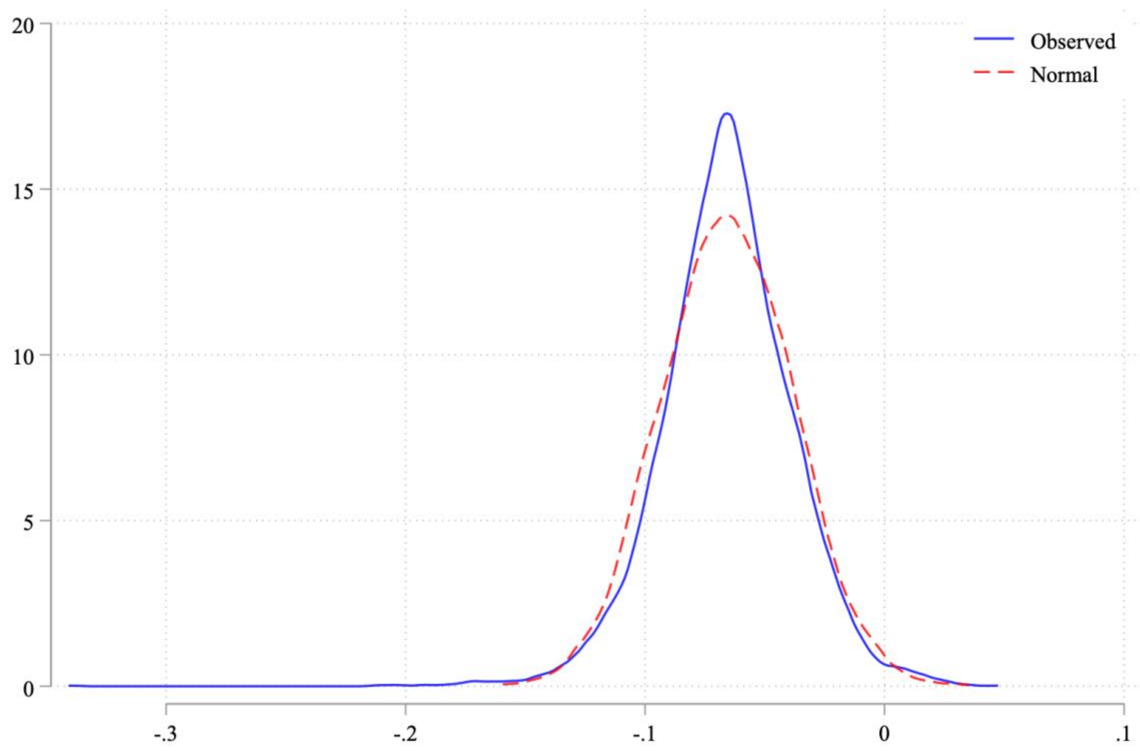

Figure 4. Distribution of 4,487 standardized coefficients of *Top 1% Wealth Share*
Notes. Each coefficient is estimated over a different sub-set of countries.

It is apparent from Figure 4 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 (from -0.066 to -0.064). Thus, we find no heterogeneities over country groups.

5.3 k-means Clustering

One potential shortcoming of forming random country groups, as we do in Section 5.2, is that the relationship of interest might indeed be heterogeneous across ex ante similar countries. To some extent, we already consider this possibility in Section 5.1, where we study similarity along any one covariate. Similarity along many covariates, however, also matters, and requires a different approach. In this section, we push the logic further: we examine the wealth inequality – growth nexus across sub-groups of countries selected to be as similar as possible.

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 51% 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 2 Column (8)) 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 90% 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 5 is that an overwhelming majority of estimates are close together in size and significance. With the exception of two large outliers (one positive and one negative; neither significant), the other 34 estimates show substantial overlap. Thus, we can safely conclude that, even in subgroups of ex ante similar countries, the wealth inequality – economic growth relationship displays no meaningful heterogeneity.

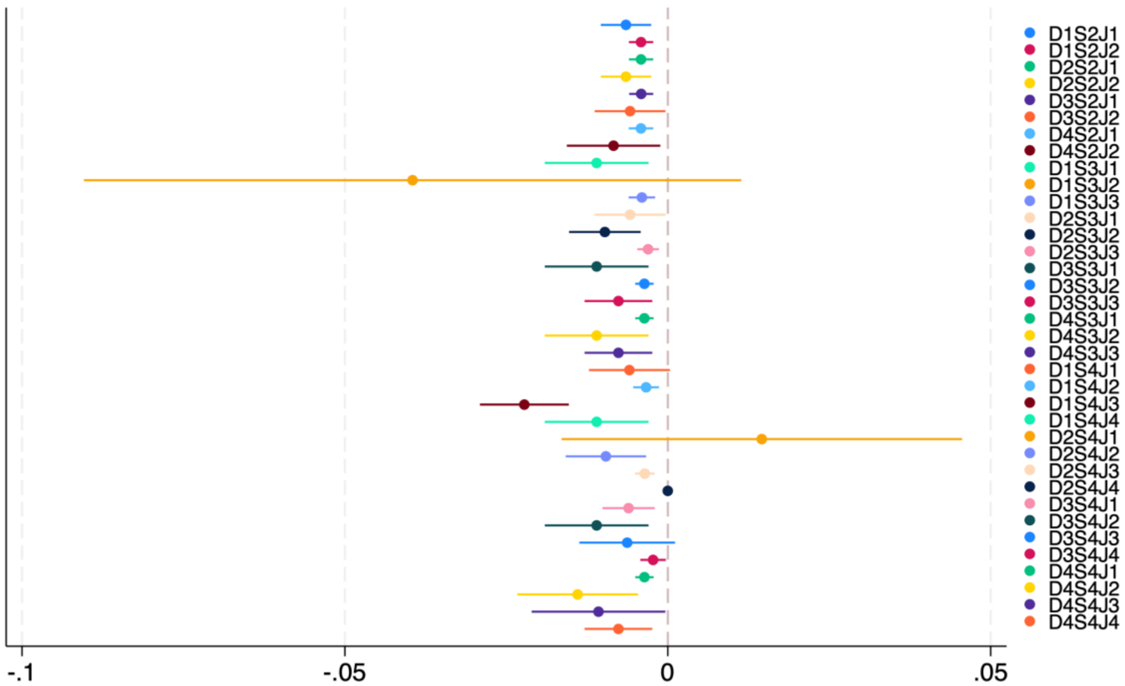

Figure 5. Coefficients of *Top 1% Wealth Shares* across k-means clustered country groups. Legend Key: D = number of dimensions. S = number of clusters. J = cluster identifier.

5.4 Does the Effect Change Over Time?

Finally, if the effect of wealth inequality on growth is driven by particular time periods, then one would expect significant heterogeneity over time. To assess this possibility, we interact the top 1% wealth share with each year dummy and plot the results in Figure 6, where *Top 1% Share * (Year = 1996)* is the reference category. Only 3 of the interaction coefficients are significantly different from the omitted category, with no clear time trend emerging. Thus, the wealth inequality – growth relationship is not contingent on time, at least not in the medium-run period (1995 – 2019) we study in this paper.

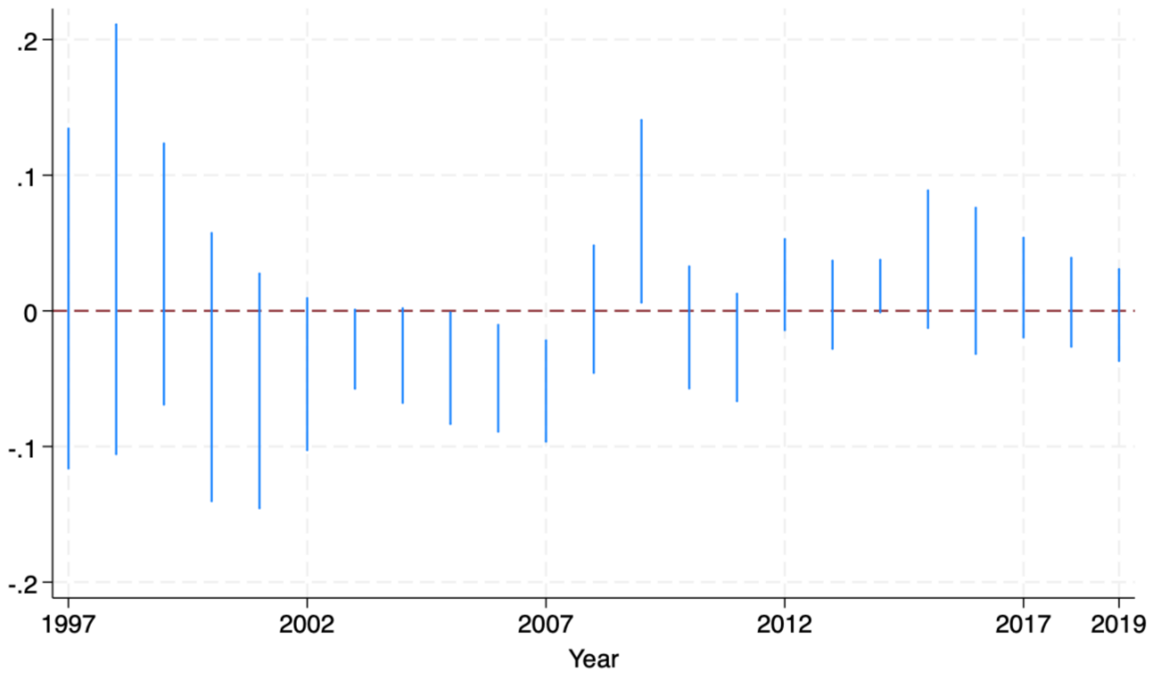

Figure 6. Coefficients of *Top 1% Wealth Share * Year.*
Reference category = *Top 1% Wealth Share * (Year=1996).*

6. 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 0.4 p.p. lower growth rates, which is approximately 17% 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 26 years, while it takes 36 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 Deininger & Olinto (2000) and 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 all potential combinations of those controls. 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, which has now been established in this research. Therefore, the policy debate 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, policymakers should be less reluctant about the taxation of capital income to facilitate further 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	Ethiopia	Niger
Angola	Gabon	Nigeria
Benin	Gambia	Rwanda
Botswana	Ghana	Sao Tome and Principe
Burkina Faso	Guinea	Senegal
Burundi	Guinea-Bissau	Seychelles
Cameroon	Kenya	Sierra Leone
Cape Verde	Lesotho	South Africa
Central African Republic	Liberia	Sudan
Chad	Madagascar	Swaziland
Comoros	Malawi	Tanzania
Congo	Mali	Togo
Cote d'Ivoire	Mauritania	Tunisia
Dem. Rep. Congo	Mauritius	Uganda
Djibouti	Morocco	Zambia
Egypt	Mozambique	Zimbabwe
Equatorial Guinea	Namibia	
Americas		
Argentina	Dominican Republic	Nicaragua
Bahamas	Ecuador	Panama
Belize	El Salvador	Paraguay
Bolivia	Guatemala	Peru
Brazil	Guyana	Suriname
Canada	Haiti	Trinidad and Tobago
Chile	Honduras	United States
Colombia	Jamaica	Uruguay
Costa Rica	Mexico	Venezuela
Asia		
Armenia	Jordan	Qatar
Azerbaijan	Kazakhstan	Saudi Arabia
Bahrain	Kuwait	Singapore
Bangladesh	Kyrgyz Republic	South Korea
Bhutan	Laos	Sri Lanka
Brunei	Lebanon	Syria

Cambodia	Macao	Taiwan
China	Malaysia	Tajikistan
Cyprus	Maldives	Thailand
Georgia	Mongolia	Turkey
India	Myanmar	Turkmenistan
Indonesia	Nepal	United Arab Emirates
Iran	Oman	Uzbekistan
Iraq	Pakistan	Vietnam
Israel	Palestine	Yemen
Japan	Philippines	
Europe		
Albania	Greece	Norway
Austria	Hungary	Poland
Belarus	Iceland	Portugal
Belgium	Ireland	Romania
Bosnia and Herzegovina	Italy	Russia
Bulgaria	Latvia	Slovak Republic
Croatia	Lithuania	Slovenia
Czech Republic	Luxembourg	Spain
Denmark	Macedonia	Sweden
Estonia	Malta	Switzerland
Finland	Moldova	Ukraine
France	Montenegro	United Kingdom
Germany	Netherlands	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 12 quantitative and qualitative factors grouped into Rule of Law, Government Size, Regulatory Efficiency and Open Markets. Average score on 12 indicators is provided on a scale of 0-100 in country i at time t.	The Heritage Foundation (2021).

Table A3. Replication of Table 2 from the main text, with independent variables at contemporaneous values. Explanatory variable of interest: Top 1% wealth share.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
L.Growth	0.312***	0.309***	0.263***	0.292***	0.266***	0.229***	0.330***	0.252***
	(0.049)	(0.048)	(0.061)	(0.063)	(0.058)	(0.054)	(0.042)	(0.052)
Top 1% Wealth Share	-0.003**	-0.004***	-0.004***	-0.003***	-0.003***	-0.002*	-0.003**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(GDP p.c.)		-0.005***						-0.005***
		(0.001)						(0.001)
Investment Rate			0.001					0.001
			(0.003)					(0.007)
Years of schooling				0.000				0.001
				(0.003)				(0.008)
Trade Openness					0.005*			0.020**
					(0.002)			(0.006)
Inflation						0.001		-0.004
						(0.005)		(0.005)
Economic Freedom							0.000	-0.024*
							(0.002)	(0.010)
N	3960	3960	3592	3711	3645	3639	3587	3081
Countries	165	165	157	161	159	160	162	151
N. instruments	96	96	95	95	93	90	84	82
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.237	0.240	0.815	0.603	0.879	0.592	0.394	0.286
Hansen p-value	0.106	0.122	0.277	0.130	0.343	0.054	0.037	0.078

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.

Table A4. Replication of Table 2 from the main text, with independent variables at contemporaneous values. Explanatory variable of interest: Top 10% wealth share.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
L.Growth	0.312***	0.309***	0.263***	0.292***	0.266***	0.229***	0.330***	0.266***	0.252***
	(0.049)	(0.049)	(0.061)	(0.063)	(0.058)	(0.054)	(0.042)	(0.058)	(0.051)
Top 10% Wealth Share	-0.002**	-0.004***	-0.003**	-0.003**	-0.003**	-0.002*	-0.003**	-0.003**	-0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ln(GDP p.c.)		-0.005***							-0.005***
		(0.001)							(0.001)
Investment Rate			0.001						0.001
			(0.003)						(0.007)
Years of schooling				0.000					0.001
				(0.003)					(0.008)
Trade Openness					0.005*			0.005*	0.020**
					(0.002)			(0.002)	(0.006)
Inflation						0.001			-0.004
						(0.005)			(0.005)
Economic Freedom							0.000		-0.024*
							(0.002)		(0.010)
N	3960	3960	3592	3711	3645	3639	3587	3645	3081
Countries	165	165	157	161	159	160	162	159	151
N. instruments	96	96	95	95	93	90	84	93	82
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.237	0.240	0.816	0.602	0.881	0.593	0.393	0.881	0.283
Hansen p-value	0.110	0.127	0.281	0.136	0.347	0.055	0.039	0.347	0.081

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.

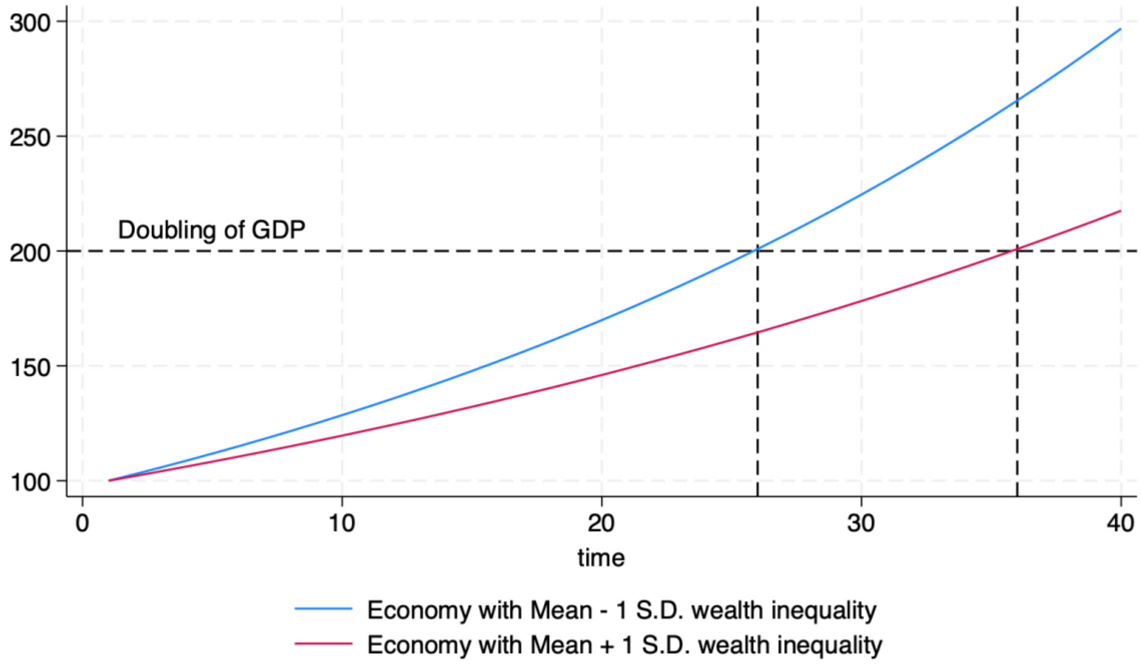

Figure A1. Hypothetical economies at the 16th percentile (blue line; more equal) and 84th percentile (red line; less equal) of the wealth inequality distribution.

Explanatory notes. The more equal economy grows 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.