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Top-end inequality and growth: empirical exploration of nonlinearities and the time dimension

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Abstract
Using the series of the top 1% income shares in 137 countries, I examine the relationship between top-end inequality and subsequent economic growth from the 1920s to the 2010s. These data enable a versatile exploration of various time horizons. To address concerns regarding chosen functional forms, I employ penalized spline methods to accommodate potential nonlinearities. Empirical findings suggest that the relationship between top-end inequality and subsequent growth is complex, contingent upon both the investigated time horizon and the level of economic development. I find some evidence for a positive link at medium levels of economic development, with this positive link being more pronounced in short- to medium-term associations. I also find that the positive medium-run association weakens as economic development advances. In advanced economies, a negative (or nonpositive) medium- to long-term relationship emerges between the top 1% income share and growth in many settings. Furthermore, I conclude that longer-run associations need to be investigated further.

Keywords Inequality · Top incomes · Growth · Nonlinearity · Longitudinal data

JEL Classification O11 · O15

1 Introduction

Theoretical literature has suggested numerous competing channels from income distribution to growth, and empirical studies have provided mixed evidence on the inequality–growth association. The available data on inequality and the tradition of using linear specifications have been challenged, and thus the current study applies flexible methods to new inequality data. This study discusses the association between the top 1% income shares and subsequent growth. Although top income shares describe the upper part of the distribution, Leigh (2007); Roine and Waldenström (2015) provide evidence that these series also reflect changes in many other inequality measures over time. Therefore, these data bring new insights into the inequality–growth literature.

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In this study, I exploit the top 1% income shares (*top*1) to describe top-end inequality in 137 countries from the 1920s to the 2010s, and I explore the data with various time frequencies, thus investigating short-, medium-, and somewhat longer-run associations. My focus is on studying annual data and data averaged over 5- and 10-year periods.[1] The role of top incomes in explaining growth was previously studied by Andrews et al. (2011), who exploit an adjusted data set from Leigh (2007) using the top 10% and top 1% income shares of 12 wealthy countries and relying primarily on standard linear estimation techniques. They find that after 1960, higher inequality may foster growth if measured by the top 10% income share. This result was challenged by Herzer and Vollmer (2013), who argue that the long-run effect of the top 10% share is negative. Moreover, in Andrews et al., many results for the top 1% share are not statistically significant. More recently, Madsen et al. (2018) studied 21 OECD countries over 100 years and utilized both Ginis and top 10% income shares. They report that before achieving a specific level of financial development, inequality hinders growth. Herwartz and Walle (2020) also studied 12 OECD countries and report that high top 1% income shares have had a positive long-run effect on economic development, particularly during the post-1980 period. However, the small number of countries in their samples and the possibility of nonlinearities motivate the current study to investigate the top 1% further.[2]

I apply penalized regression spline methods within the additive model context. Allowing all continuous covariates to enter the estimation equation flexibly surpasses existing approaches in the inequality–growth literature, to the best of my knowledge. I also allow a complex interaction between top-end inequality and the level of economic development, and I utilize an established fitting routine for (generalized) additive models with penalized splines in the statistical program R.[3]

This paper finds that the relation between top-end inequality and subsequent growth varies across different types of countries and also depends on the time horizon. I observe a positive short- to medium-term association between top 1% income shares and subsequent growth at medium development levels, but this association is likely to weaken in the course of economic development. The results also indicate a negative or zero medium- to long-run relationship between *top*1 and growth at high development levels when using data averaged over 5- and 10-year periods. For example, in a subsample of 24 OECD countries, a nonpositive link is observed in 5-year average data. Finally, I conclude that the (very) long-term perspective requires further investigation in future studies. However, my preliminary findings suggest that the relationship in the (very) long run may differ from the previously described medium- to long-term associations.

The remainder of the paper is organized as follows. Section 2 introduces inequality–growth literature (see, e.g., Aghion et al. 1999; Voitchovsky 2009; Neves et al. 2016, for more comprehensive overviews). Section 3 describes the data and methods. Section 4 provides the empirical results. Finally, Section 5 presents the conclusions.

[1] I also provide a sensitivity check with data averaged over 15-year periods.

[2] Moreover, Roine et al. (2009) study top incomes and growth, but they discuss determinants of top-end inequality.

[3] Empirical economics literature has applied penalized splines within the (generalized) additive model framework. Examples include Greiner and Kauermann (2008); Ordás Criado et al. (2011); Bose et al. (2012); Schoder et al. (2013); Berlemann et al. (2015).

2 Literature review

Theoretical models suggest that inequality can both promote and hamper growth. One of the most common arguments that inequality enhances growth is based on the classical approach: inequality channels resources toward wealthier individuals, who are assumed to have a higher propensity to save; in effect, increased inequality may increase investments and thus growth (e.g., Kaldor 1957). Another widely mentioned mechanism is incentives: inequality encourages skilled individuals to increase their effort, which invigorates economic performance.

However, productive investments can be lost if some individuals are unable to utilize their skills due to limited funds. The credit market imperfection approach suggests that credit constraints in the lower parts of the distribution can hinder growth. In countries with sufficient wealth, inequality reduces investment in human capital when credit constraints are binding. In contrast, in sufficiently poor economies, only the affluent might have access to education, potentially resulting in a positive link between inequality and investment in human capital. Consequently, the implications of inequality vary depending on the income level of the country (e.g., Galor and Zeira 1993; Galor and Moav 2004).

Furthermore, Galor and Moav (2004) describe a unified theory that combines two contradictory approaches at different stages of the development process. First, they suggest that the classical channel dominates in the early stages of development, at which time physical capital accumulation is the primary engine of growth. However, the credit market imperfection mechanism begins to dominate in the next stages of the process, at which time human capital is the main source of growth. Finally, they suggest that both mechanisms dim with development.

There are also other arguments that associate higher inequality with lower future growth. For example, inequality may reflect polarization of power. The wealthy may have incentives to lobby against redistribution, thus preventing efficient policies (Bénabou 2000).[4] Further, Galor et al. (2009) suggest that inequality may bring out incentives for the wealthy to impede institutional policies and changes that facilitate human capital formation and economic growth. In a more general perspective, Bénabou (1996) argues that high overall inequality may give rise to sociopolitical instability, which in turn reduces growth.

Early empirical inequality–growth studies relied on cross-sectional data, but the focus has since shifted to panel studies as new data have become available. In addition, most empirical results are based on data on Gini coefficients. In the 1990s, many studies found a negative link between inequality and growth (e.g., Alesina and Rodrik 1994; Persson and Tabellini 1994; Bénabou 1996; Perotti 1996). However, many of the early empirical results have been called into question. It has also been suggested that the positive effects of inequality may materialize in the short term, whereas the negative effects may set in more slowly. Many of the negative effects operate via political processes, institutional changes, and human capital formation, all of which take time to materialize. Some panel estimations, such as Li and Zou (1998); Forbes (2000), have found a positive short- or medium-run association between inequality and subsequent growth. Halter et al. (2014) investigated the time dimension and suggest that the long-run (or total) association between inequality and growth is negative. Meanwhile, Lee and Son (2016) also find a negative link between inequality and growth using Ginis. Further, Berg et al. (2018) used Solt's (2009, 2016) Standardized World Income Inequality Database (SWIID) and report that lower net inequality correlates with faster medium-term growth that also is more durable.

[4] Moreover, Aghion and Bolton (1997) suggest that redistribution creates greater equality of opportunity and enhances the trickle-down process, which is assumed to stimulate growth.

Despite the evident notion of heterogeneity in theoretical models, most empirical studies do not allow for heterogeneity in the estimated inequality–growth relationship. Some studies, however, report that the link depends on the level of economic development. For example, Barro (2000) finds that high income inequality can hinder growth in poor countries, whereas it can promote growth in rich countries. Recently, Brueckner and Lederman (2018); Hailemariam and Dzhumashev (2020) incorporated a simple interaction term between income inequality—as measured by the Gini—and the level of GDP per capita in their empirical investigations utilizing SWIID data. Brueckner and Lederman find that inequality is beneficial for transitional growth in low-income countries but harmful for growth in high-income countries. In addition to the interaction term, Hailemariam and Dzhumashev included a quadratic term for inequality, and they report an inverse U-shaped inequality–growth link. Hailemariam and Dzhumashev also find that the sign changes from positive to negative at a lower level of inequality in developed economies compared to developing ones.[5]

The empirical literature has also suffered from the limited availability of high-quality inequality data. Since its release, the panel data set constructed by Deininger and Squire (1996) has been widely used despite its limitations.[6] In addition, the Luxembourg Income Study Database (LIS)[7] provides high-quality data for cross-country comparisons; unfortunately, using LIS data results in a fairly small sample size (as discussed by, e.g., Leigh 2007). Voitchovsky (2005) utilized the panel features of the LIS data primarily for wealthy countries and finds that inequality is positively associated with growth in the upper part of the distribution, whereas inequality is negatively related to growth in the lower part of the distribution.[8]

Studies by Banerjee and Duflo (2003); Chambers and Krause (2010) challenge, for example, Forbes (2000), who suggested a positive relationship between inequality and growth. Banerjee and Duflo studied various specifications, including kernel regression, with the "high quality" subset of the Deininger–Squire data and find that changes in the Gini coefficient, in any direction, relate to lower subsequent growth. They also find some evidence of a negative relationship between growth rates and inequality lagged one period. Banerjee and Duflo argue that nonlinearity may explain why the reported estimates vary greatly in the literature. Furthermore, Chambers and Krause used semiparametric methods in their study with Gini coefficients from the World Income Inequality Database (UNU-WIDER 2008). They find that higher inequality generally reduces growth in the next 5-year period, and they provide some empirical support for the unified theory of Galor and Moav (2004).

Growth regressions without inequality variables have been studied in non- or semiparametric frameworks (e.g., Liu and Stengos 1999; Maasoumi et al. 2007; Henderson et al. 2012), and these studies highlight that important data features are likely lost if linearity is forced into models. Further, Banerjee and Duflo (2003); Chambers and Krause (2010) show that linearity assumptions may be too restrictive in modeling the inequality–growth association. It seems the contradictory evidence in the literature may be a consequence of misspecified models and low-quality inequality data.

[5] In addition, other recent examples that illustrate how the relationship can vary based on the characteristics of the economy are Scholl and Klasen (2019), who consider the role of transition (post-Soviet) countries, and Aiyar and Ebeke (2020), who suggest that income inequality affects growth negatively if intergenerational mobility is low. Woo (2020) allows for interaction between the level of inequality and size of redistribution in his growth estimations, whereas Juuti (2022) explores the role of financial development.

[6] Atkinson and Brandolini (2001) demonstrate these shortcomings.

[7] More information about LIS data: https://www.lisdatacenter.org/our-data/lis-database/.

[8] However, the inequality measures used by Voitchovsky (2005) do not emphasize the very top of the distribution.

3 Data and methods

3.1 Data

Using tax and population statistics, researchers have been able to compose long and fairly consistent series of top income shares. Kuznets (1953) was the first to use this kind of data to produce top income share estimates, and Piketty (2001, 2003) generalized Kuznets's approach. Following Piketty, many researchers have constructed top income share series using the same principles of calculation. Atkinson et al. (2011) provide a thorough overview of the earlier top income literature.[9] The updated data are used in the current study, available from the World Inequality Database (henceforth, WID 2021). This study focuses on the top 1% income share series (note that this is pre-tax income). The top income shares are of interest due to the potential to study extensive time spans, the observed upsurge in top incomes over the past decades in many countries, and the greater sensitivity of the Gini coefficient to asymmetries in the central part of the distribution compared to changes in the top.

The data provide a global perspective on top 1% income shares, as the total sample of 137 countries includes high-, middle- and low-income countries. I have used information from the World Bank (2021) to classify the studied countries into two groups: high- and upper-middle-income (HUM) countries and low- and lower-middle-income (LLM) countries. I study the years from 1920 onward, but it should be stressed that the data set is unbalanced, as the top 1% series begin later for many countries. Table A.1 in the Online Material provides a list of the studied countries and their categorizations.

My main goal is to explore possible nonlinearities and the overall association without focusing on a specific channel from the top of the distribution to growth. For this and data availability reasons, I adopt two different approaches to the empirical analysis. First, I study extensive time series from the 1920s onward in parsimonious specifications that include only GDP per capita as a control variable to account for the level of economic development. This is due to the non-availability of control variable data for a wide range of countries, whereas inequality and GDP data are available. Second, I exploit series from the 1950s onward using specifications first applied in the parsimonious form, and I then include a set of additional covariates (henceforth, "expanded" specifications). Clearly, the interpretation differs in these approaches because the influence of inequality may be channeled (at least to some extent) through some of the control variables; therefore, presenting results with and without control variables is of interest. In addition, I study short-, medium-, and somewhat longer-run associations in all above-mentioned cases.

The parsimonious and expanded models utilize information from the exceptionally long top-end inequality series (WID 2021) and use GDP per capita data for 1920–2018 from the Maddison Project Database (Bolt and van Zanden 2020). In the expanded specifications, most of the additional control-variable data are from the Penn World Table (PWT) version 10.0 (see, Feenstra et al. 2015, for more information), and these variables are commonly used in growth regressions: investment, price level of investment, index for human capital, government consumption, trade openness, and population growth.[10] Although the wider growth literature may find these expanded specifications fairly limited, specifications in the

[9] In addition, see, for example, Atkinson (2007) for the methodology. Piketty and Saez (2006); Leigh (2007); Roine and Waldenström (2015) discuss the advantages and limitations of these series. Two volumes edited by Atkinson and Piketty (2007, 2010) describe the top income data.

[10] Price level of investment is a commonly used proxy for market distortions. Openness measure is defined as the ratio of imports plus exports to GDP. Moreover, population growth can also be used as a proxy for demographic transition.

existing inequality–growth literature tend to be even more parsimonious. Tables A.2 and A.3 in the Online Material provide more detailed information on the variables used and summary statistics.

3.2 Methods

In my preferred specifications, I allow all continuous covariates to enter flexibly so that possible incorrect functional forms would not bias the results. This approach provides an opportunity for a richer understanding of the *top*1–growth relationship. My estimation approach is based on penalized cubic regression splines, although I acknowledge that there are numerous alternative approaches to flexible modeling, such as kernel estimation.[11] I assume an additive instead of a fully nonparametric structure. Although the additive structure represents a special case of a more general, multidimensional smooth function, additive models can be considered an extension to previous inequality–growth estimations that have predominantly relied on linear specifications. In addition, the results are easier to interpret when the specifications are additive rather than fully flexible. Further, the chosen method is accessible in that there is a connection to traditional parametric models—traditional linear models are a special case. Moreover, there exist ready-made statistical packages that can be utilized in the analysis. To estimate additive models, I use the established R software package “mgcv” (v1.8-38).[12]

Additive models provide a flexible framework for investigating the relationship of top-end inequality to subsequent economic growth. Additive models are a special case of generalized additive models (GAMs) that were introduced by Hastie and Tibshirani (1986, 1990). They present a GAM as a generalized linear model with a linear predictor that involves a sum of smooth functions of covariates. This study uses an identity link and assumes normality in errors, which leads to additive models. I follow the approach presented in Wood (2006, 2017). The basic idea is that the model consists of a sum of linear and smooth functions of covariates:

$$y_i = \boldsymbol{X}_i^* \boldsymbol{\theta} + f_1(x_{1i}) + f_2(x_{2i}) + f_3(x_{3i}, x_{4i}) + \ldots + \epsilon_i .$$

In the above presentation, y_i is the response variable (here: growth); $\boldsymbol{X}_i^*$ is a row of the model matrix for any strictly parametric model components; $\boldsymbol{\theta}$ is the corresponding parameter vector; the $f_\bullet$ are smooth functions of the covariates, $x_\bullet$; and ϵ_i is the error term. In the above example, function f_3 allows a complex interaction between two variables.

The flexibility of these models comes at the cost of two problems. First, one needs to represent the smooth functions $f_\bullet$ in some manner. One way to represent these functions is to use cubic regression splines, which is the approach adopted in this study.[13] Second, the amount of smoothness of the $f_\bullet$ needs to be chosen. Overfitting is to be avoided and, thus, departure from smoothness is penalized. The appropriate degree of smoothness of $f_\bullet$ can be estimated from the data by, for example, maximum likelihood, which is the approach chosen in this study for its robustness. Smooths of several variables can also be constructed.

[11] Li and Racine (2007) describe nonparametric methods extensively, with a focus on kernels, whereas Ahamada and Flachaire (2010) provide a concise overview of nonparametric methods.

[12] For more information, visit the R project’s web pages https://www.r-project.org/ and https://cran.r-project.org/web/packages/mgcv/.

[13] A cubic regression spline is a curve constructed from sections of cubic polynomials that are joined together so that the resulting curve is continuous up to the second derivative. The points at which sections are joined (and the end points) are the knots of the spline, and these locations must be chosen. The spline can be represented in terms of its values at the knots.

In this study, tensor product smooths are used in cases of smooths of two variables—in some specifications, I allow a complex interaction between top-end inequality and the level of economic development.

The package "mgcv" has an automatic choice in the amount of smoothing and wide functionality, and the relationship between the covariates and the response can be described graphically. Confidence bands for the model terms can be derived using Bayesian methods, and approximate p-values for model terms can be calculated. Models can be compared using information criteria, such as the Akaike information criterion (AIC). See the Online Material (Section F) for more information.

4 Results

4.1 Specifications

The new top income share series enable the study of the overall relationship between top-end inequality and growth in various ways. First, I report the short-term associations using annual data. Second, I provide results based on medium-run associations, where I study consecutive 5-year periods. Finally, I report findings based on medium- to long-run associations using 10-year periods, and I complement these findings with results for 15-year periods. I report models both with and without a set of control variables to demonstrate how this affects the results.

The first expanded specifications are of the form:

$$\begin{aligned} growth_{i,t+1} &= \theta_0 + f_1(top1_{it}) + f_2(\ln(GDP\,p.c.)_{it}) + f_3(government\ consumption_{it}) \\ &+ f_4(investment_{it}) + f_5(price\ of\ investment_{it}) + f_6(human\ capital_{it}) \\ &+ f_7(openness_{it}) + f_8(population\ growth_{it}) + \delta_t + u_i + \epsilon_{it}, \end{aligned} \tag{1}$$

and in alternative specifications I allow for a complex interaction between top-end inequality and GDP per capita with a bivariate smooth:

$$\begin{aligned} growth_{i,t+1} &= \theta_0 + f_{12}(top1_{it}, \ln(GDP\,p.c.)_{it}) + f_3(government\ consumption_{it}) \\ &+ f_4(investment_{it}) + f_5(price\ of\ investment_{it}) + f_6(human\ capital_{it}) \\ &+ f_7(openness_{it}) + f_8(population\ growth_{it}) + \delta_t + u_i + \epsilon_{it}, \end{aligned} \tag{2}$$

where i refers to a country and t to a time period, θ_0 is a constant, functions $f_\bullet$ refer to smooth functions, $\epsilon_{it} \sim \mathrm{N}(0, \sigma^2)$ is the traditional error term, and δ_t and u_i refer to time and country fixed effects, respectively. The country dummies should account for unobserved factors that remain constant over time within each country, and the time dummies should account for factors that affect all countries similarly.

The additive specifications Eqs. (1) and (2) describe the most flexible of the specifications studied in this paper, and all reported models are special cases of them. In the empirical inequality–growth literature, the traditional—or, the most common—approach has been to assume all functions f are linear, but the studied additive models accommodate smooth functions f with no prespecified functional form. However, the additive models may also have some linear terms if the data suggest a linear structure. Linear terms are reported for the additive models if linearity was suggested in the initial stage of model fitting. In reporting my results, graphical illustrations are used for nonlinear smooth terms. In comparison, the interpretation of linear terms is straightforward, and these terms are not plotted. I also study parsimonious specifications without the above-described set of controls (f_3, ..., f_8) to demonstrate how this affects the relationship between top-end inequality and growth.

Moreover, I present the results for three country groups, gradually moving towards advanced economies where the data quality is expected to be higher. First, I study the whole sample of countries for which the control variables are available. Second, I investigate high- and upper-middle-income (HUM) countries.[14] Finally, I pick an even more restricted sub-sample that only includes 24 "old" OECD countries.

4.2 Short-run association

Table 1 reports $top1$–growth results with annual data, wherein $t = \{1920, 1921, ..., 2017\}$, and future growth corresponds to the difference of $\ln(GDP\ p.c.)$ values at $t+1$ and t multiplied by 100. Parts A–B in Table 1 include only the level of economic development as a control variable; Part C includes all controls. In almost all cases (8 out of 9), the model with a bivariate smooth—that is, a model with a complex interaction between $top1$ and $\ln(GDP\ p.c.)$—was preferred to the model with univariate smooths; see the AIC values for each model pair. However, I first briefly describe the results of the models that assume univariate smooths.

The odd-numbered models [1], [3], ..., and [17] in Table 1 have univariate smooth functions, as in specification Eq. (1). Initially, I incorporated the top 1% share in flexible form, but a linear term was suggested in most models, and in these cases, I only report the corresponding coefficient for the linear $top1$ term. These models suggest a positive short-run link between top-end inequality and growth. The only case in which a bivariate-smooth model is not preferred to one with univariate smooths only is the OECD-country model [17]: it suggests an inverse U-shaped $top1$–growth association, with a statistically significant positive-slope part in the region with the most observations (see Fig. 2(c) at $top1 < 15$).[15]

Meanwhile, the even-numbered models [2], [4], ..., and [18] in Table 1 report models with a bivariate smooth, as in specification Eq. (2). The bivariate smooths are visualized in Fig. 1, where the slopes are of interest; further, the discovered $top1$–growth association can most easily be observed by envisioning taking slices vertically at different levels of $\ln(GDP\ p.c.)$. To obtain an overview of the associations, separate perspective plots are presented from the same angle in all studied cases. Furthermore, the plots illustrate the smooths only in regions not too far from the true data points. I also provide additional illustrations of these smooths in Fig. E.1 in the Online Material. I next describe findings related to the $top1$–growth association in the preferred models with a bivariate smooth $f(top1, \ln(GDP\ p.c.))$.

The preferred whole-sample models [2], [8], and [14] in plots (a), (d), and (g) in Fig. 1 show a U-shaped $top1$–growth association or almost zero slope at low development levels (approximately $\ln(GDP\ p.c.) < 8$), and a positive $top1$–growth link is discovered at medium or high development levels (approximately $\ln(GDP\ p.c.) > 9$). After restricting the sample to 61 HUM countries, the preferred models [4], [10], and [16] confirmed the positive but nonconstant $top1$–growth relationship at medium to high development levels (see plots (b), (e), and (h) in Fig. 1).[16] For the 24 OECD countries, the bivariate-smooth specifications

[14] Data availability is more limited in the group of low- or lower-middle-income (LLM) countries, which gives an additional reason to refrain from studying the LLM country group separately.

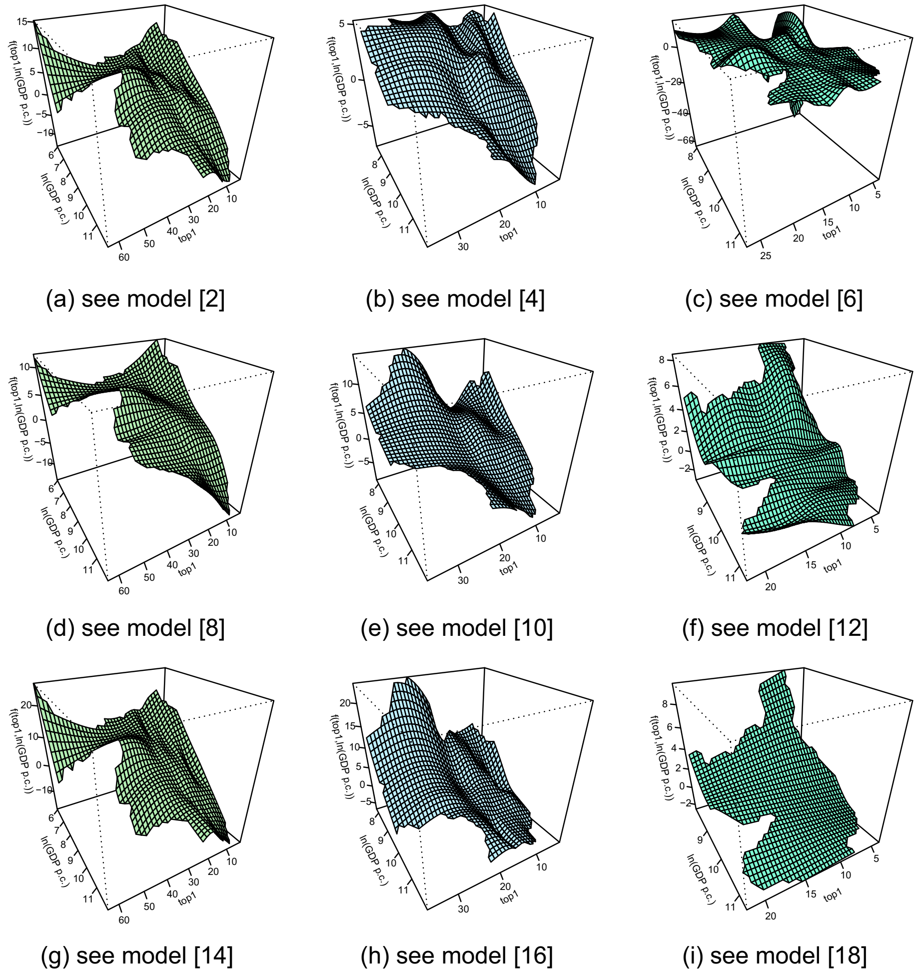
[15] Comparison of plots (b) and (c) in Fig. 2 nicely illustrates how the restriction from 61 HUM countries to the 24 OECD countries also narrows the range of observed top 1% share values; inverse U-shape presented in plot (c) also shows as a "hump" in plot (b).

[16] Moreover, Fig. B.1 in the Online Material provides a graphical illustration of the smooth functions of the control variables from model [16].

Table 1 Annual models for 137 countries: smooth functions $f(top1_t)$ and $f(top1_t, \ln(GDP\ p.c.)_t)$ for the nonlinear terms, and the coefficients (and standard errors) for the linear $top1_t$ terms. The dependent variable is the annual log growth rate. Preferred specification of the two alternatives is **in bold**. See Fig. 1 for illustrations of the bivariate smooths $f(top1_t, \ln(GDP\ p.c.)_t)$ and Fig. 2 for illustrations of the univariate nonlinear terms $f(top1_t)$. Abbreviation "HUM" refers to high- and upper-middle-income countries; see list of countries in Table A.1 in the Online Material

PART A. Data from	All 137 countries (N=6116)		61 HUM countries (N=3154)		24 OECD countries (N=1597)	
the 1920s onward	[1]	**[2]**	[3]	**[4]**	[5]	**[6]**
$f(top1_t)$	0.04230* (0.02288)		0.08121** (0.03683)		0.03967 (0.04344)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 1(a)***		Fig. 1(b)***		Fig. 1(c)***
AIC	38016	37986	19020	19005	8533	8268
controls?	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no
PART B. Data from	All 137 countries (N=5715)		61 HUM countries (N=2795)		24 OECD countries (N=1299)	
the 1950s onward	[7]	**[8]**	[9]	**[10]**	[11]	**[12]**
$f(top1_t)$	0.04940** (0.02354)		0.10094** (0.03944)		Fig. 2(a)**	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 1(d)***		Fig. 1(e)***		Fig. 1(f)***
AIC	35328	35305	16505	16471	5679	5666
controls?	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no
PART C. Data from	All 137 countries (N=5522)		61 HUM countries (N=2671)		24 OECD countries (N=1299)	
the 1950s onward	[13]	**[14]**	[15]	**[16]**	**[17]**	[18]
$f(top1_t)$	0.07873*** (0.02490)		Fig. 2(b)***		Fig. 2(c)**	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 1(g)***		Fig. 1(h)***		Fig. 1(i)***
AIC	33699	33641	15136	15072	5629	5631
controls?	all controls, as in Eq. (1)	all controls, as in Eq. (2)	all controls, as in Eq. (1)	all controls, as in Eq. (2); for illustration, see Online Material: Fig. B.1	all controls, as in Eq. (1)	all controls, as in Eq. (2)

***, **, *, ' denote significance at the 1, 5, 10, and 15% levels, respectively. The smooth terms' significance levels are based on approximate F-tests
All specifications include time and country fixed effects (dummies, not reported)



(a) see model [2] (b) see model [4] (c) see model [6]

(d) see model [8] (e) see model [10] (f) see model [12]

(g) see model [14] (h) see model [16] (i) see model [18]

Fig. 1 Visualization of the bivariate smooths $f(top1_t, \ln(GDP\ p.c.)_t)$ from Table 1 (annual data). The horizontal axes have the top 1% income share and ln(GDP per capita); the vertical axis has the smooth function f. In all plots, plot grid nodes that are too far from the true data points of the top 1% share and ln(GDP per capita) are excluded: the grid has been scaled into the unit square along with $top1$ and ln(GDP per capita) variables; grid nodes more than 0.1 from the predictor variables are excluded

are preferred in parsimonious models [6] and [12]; they suggest a positive or inverse U-shaped link at lower-medium development levels, but an almost zero slope at medium or high development levels (see plots (c) and (f) in Fig. 1). However, with all controls included, univariate-smooth model [17] is preferred for the OECD sample, as mentioned earlier.

In the whole sample and HUM subsample cases, the observed $top1$–growth association shows similarities with or without the set of control variables (see Fig. 1: compare plot (d) vs. plot (g), and plot (e) vs. plot (h)). In the case of the OECD subsample, the interaction between $top1$ and economic development becomes unnecessary when controls are included in the model. However, this is unsurprising as this subsample consists of advanced economies with relatively high levels of $\ln(GDP\ p.c.)$. In summary—regardless of whether controls

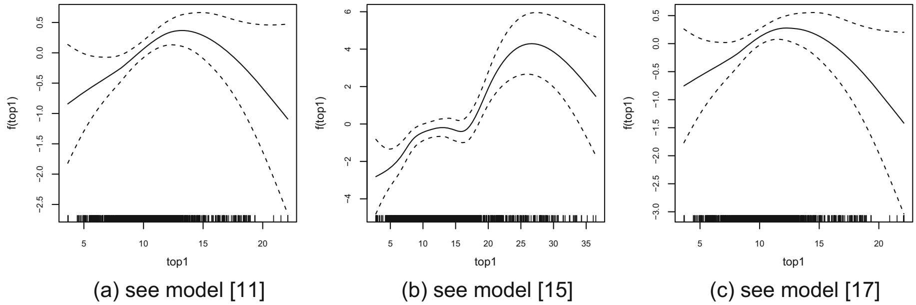


Fig. 2 Visualization of the univariate nonlinear smooths $f(top1_t)$ provided in Table 1 (annual data). Each plot presents the smooth function as a solid line. The plots also show the 95% confidence bands as the dashed lines and the covariate values as a rug plot along the horizontal axis

are included—I find some support for a positive (or at least nonnegative) short-run association between top-end inequality and subsequent growth at medium or high development levels.

For comparison, I also estimated the traditional linear counterparts of the reported models, but the flexible models in Table 1 were preferred. Examples of traditional models for the 61 HUM countries are provided in Table D.1 in the Online Material. Traditional models with linear and simple interaction terms cannot capture the complex links that the flexible models describe.[17]

4.3 Medium-term relationship

I then investigate the relationship using 5-year average data, which is the most often used time horizon in the inequality–growth literature. I partition the studied time span into consecutive periods and measure each period with its average value. The averaged data should mitigate potential problems related to short-run disturbances. Moreover, the data are constructed such that the data points of the dependent and explanatory variables do not overlap in the estimation equation. This should rule out direct reverse causation and reduce the endogeneity problem related to using a (lagged) GDP variable as a regressor. In the 5-year average data, the time periods t are 1920–1924, 1925–1929, ..., 2010–2014, and the model specifications are as described in Eqs. (1) and (2), but now applied to 5-year average data instead of annual data.[18] Again, I report linear terms of the models when I find linearity in the initial stage of the estimation.

Table 2 reports the findings with respect to $top1$: Parts A–B include only the level of economic development as a control variable; Part C includes all controls. Pairwise comparison of the AIC values again reveals that in most cases, the models with $f_{12}(top1, \ln(GDP\ p.c.))$

[17] In the case of annual data for the 61 HUM countries, I have also studied expanded specifications Eqs. (1) and (2) in an alternative form, where country fixed effects are replaced with random effects. Differences in the shapes of the obtained smooths are minor.

[18] Each future growth estimate is the average of the subsequent five annual log growth rates (multiplied by 100). For example, average growth rates calculated using $\ln(GDP\ p.c.)$ values in 1925–1930 are regressed on the averages of the covariates in 1920–1924, and so on. The only exception is future growth for the last 5-year period 2010–2014, where future growth is calculated using $\ln(GDP\ p.c.)$ values in 2015–2018 (i.e., in this case, average growth is based on three—not five—growth rates due to data unavailability in the used version of the Maddison Project Database).

Table 2 5-year-average models for 137 countries: smooth functions $f(top1_t)$ and $f(top1_t, \ln(GDP\ p.c.)_t)$ for the nonlinear terms and the coefficients (and standard errors) for the linear $top1_t$ terms. The dependent variable is the average of five annual log growth rates in the subsequent period. Preferred specification of the two alternatives is **in bold**. See Fig. 3 for illustrations of the bivariate smooths $f(top1_t, \ln(GDP\ p.c.)_t)$ and Fig. 4 for illustrations of the univariate nonlinear terms $f(top1_t)$. Abbreviation "HUM" refers to high- and upper-middle-income countries; see list of countries in Table A.1 in the Online Material

PART A. Data from	All 137 countries (N=1184)		61 HUM countries (N=635)		24 OECD countries (N=332)	
the 1920s onward	[19]	**[20]**	[21]	**[22]**	[23]	**[24]**
$f(top1_t)$	0.04264 (0.03083)		Fig. 4(a)'		−0.07155 (0.05785)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 3(a)***		Fig. 3(b)***		Fig. 3(c)***
AIC	6082	6079	3124	3122	1438	1435
controls?	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no
PART B. Data from	All 137 countries (N=1083)		61 HUM countries (N=544)		24 OECD countries (N=258)	
the 1950s onward	[25]	**[26]**	[27]	**[28]**	**[29]**	[30]
$f(top1_t)$	0.06896** (0.03180)		Fig. 4(b)*		−0.05326 (0.04521)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 3(d)***		Fig. 3(e)***		Fig. 3(f)***
AIC	5504	5495	2578	2570	812	812
controls?	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no
PART C. Data from	All 137 countries (N=1043)		61 HUM countries (N=517)		24 OECD countries (N=258)	
the 1950s onward	**[31]**	[32]	[33]	**[34]**	**[35]**	[36]
$f(top1_t)$	0.05203* (0.03044)		0.08759' (0.05604)		−0.09058* (0.05370)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 3(g)***^{,a}		Fig. 3(h)***		Fig. 3(i)***^{,b}
AIC	5020	5021	2322	2301	799	801
controls?	all controls, as in Eq. (1)	all controls, as in Eq. (2)	all controls, as in Eq. (1)	all controls, as in Eq. (2); for illustration, see Online Material: Fig. B.2	all controls, as in Eq. (1)	all controls, as in Eq. (2)

***, **, *, ' denote significance at the 1, 5, 10, and 15% levels, respectively. The smooth terms' significance levels are based on approximate F-tests

All specifications include time and country fixed effects (dummies, not reported)

[a] In this special case, the bivariate smooth is simple: $f(top1_t, \ln(GDP\ p.c.)_t) = \theta_1 top1_t + \theta_2 \ln(GDP\ p.c.)_t + \theta_3 top1_t \ln(GDP\ p.c.)_t$. We now get: $\hat{\theta}_1 = 0.2174$, $\hat{\theta}_2 = -5.4393$, and $\hat{\theta}_3 = -0.0214$, but only $\hat{\theta}_2$ is statistically significantly different from zero (p-value < 0.01)

[b] In this special case, the bivariate smooth is simple: $f(top1_t, \ln(GDP\ p.c.)_t) = \theta_1 top1_t + \theta_2 \ln(GDP\ p.c.)_t + \theta_3 top1_t \ln(GDP\ p.c.)_t$. We now get: $\hat{\theta}_1 = -0.0537$, $\hat{\theta}_2 = -3.1559$, and $\hat{\theta}_3 = -0.0036$, but only $\hat{\theta}_2$ is statistically significantly different from zero (p-value < 0.01).

are preferred to models with $f_1(top1) + f_2(\ln(GDP\ p.c.))$. Below, I focus on describing the results of the preferred specifications.

For the whole sample of 137 countries, models [20], [26], and [31] are preferred. Let us investigate the bivariate smooths from models [20] and [26] first with the help of Fig. 3 (additional illustrations of these smooths can also be of help and are found in Fig. E.2 in the Online Material). In plots (a) and (d) of Fig. 3, the slopes with respect to $top1$ are not steep. The bivariate smooth from model [20] shows very mild curvature that illustrates a very mild positive slope at lower-medium levels of $\ln(GDP\ p.c.)$, and there is a very mild negative (almost zero) slope at the highest levels of $\ln(GDP\ p.c.)$. The bivariate smooth from model [26] shows some curvature as well: a positive $top1$–growth relationship at lower-medium levels of $\ln(GDP\ p.c.)$, but this association fades at higher development levels. In model [31], $top1$ enters in linear form and obtains a positive coefficient. For the 61 HUM countries, preferred models [22], [28], and [34] reveal an inverse U-shaped or positive $top1$–growth association at medium development levels (around $\ln(GDP\ p.c.) \approx 9$), but at higher development levels, the relation is negative: see plots (b), (e), and (h) in Fig. 3.[19] For the 24 OECD countries, I find a mild negative $top1$–growth association (see Fig. 3(c) and coefficients in models [29] and [35] of Table 2).

Thus, it appears the medium-term link also varies at different development levels. There are signs of a positive medium-run association at lower-medium or medium development levels, but this association turns negative in advanced economies. The inclusion of control variables affects the relationship between $top1$ and subsequent growth minimally (compare the parsimonious models in Part B of Table 2 to the expanded models in Part C).

Again, I found that the flexible specifications are preferred to their linear model counterparts. I report some examples of traditional linear models for HUM countries in Table D.1 in the Online Material for comparison; in this case, the traditional linear models yield information regarding the $top1$–growth link quite similar to that of the models presented in Table 2.[20]

4.4 Medium- to long-run association

In this subsection, I focus on 10-year averages consecutively from 1920–1929 to 2000–2009 to grasp the somewhat longer-run association between top-end inequality and growth.[21] Because the concept of the "long run" is challenging to define, I prefer to use the term "medium to long run" when referring to the 10-year average data. At the end of this subsection, I also provide a sensitivity check, where I investigate 15-year periods.

Table 3 provides results concerning the $top1$–growth association with the 10-year average data, and the table is again divided into three parts: Parts A–B give results without the set of controls and Part C includes controls. Almost all the preferred specifications (7 out of 9)

[19] Note that although models [21] and [27] are dispreferred, in these cases, smooth functions $f(top1_t)$ also show a positive association or inverse U-shape (see Fig. 4). In addition, Fig. B.2 in the Online Material provides a graphical illustration of the smooth functions of the control variables from model [34].

[20] In the case of 5-year average data for 61 HUM countries, I have also studied expanded specifications Eqs. (1) and (2), where I replaced the country fixed effects with random effects. The shapes of the smooths did not change significantly.

[21] Each future growth estimate is the average of the subsequent ten annual log growth rates (multiplied by 100). The only exception to the rule is the future growth for the last 10-year period 2000–2009, where future growth is calculated using $\ln(GDP\ p.c.)$ values in 2010–2018 (i.e., average growth is an average of eight—not ten—annual growth rates due to data unavailability in the used version of the Maddison Project Database).

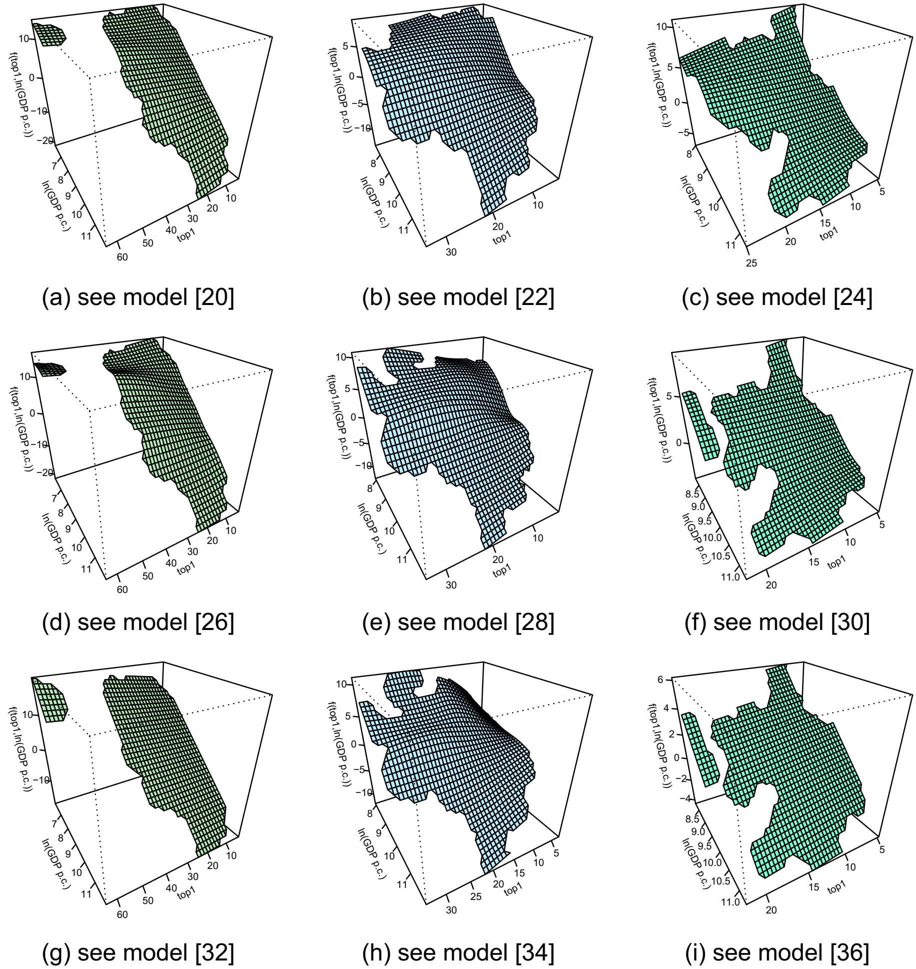


Fig. 3 Visualization of the bivariate smooths $f(top1_t, \ln(GDP\ p.c.)_t)$ from Table 2 (5-year average data). The horizontal axes have the top 1% income share and ln(GDP per capita); the vertical axis has the smooth function f. In all plots, plot grid nodes that are too far from the true data points of the top 1% share and ln(GDP per capita) are excluded: the grid has been scaled into the unit square along with $top1$ and ln(GDP per capita) variables; grid nodes more than 0.1 from the predictor variables are excluded

include a complex interaction between the top 1% share and GDP per capita. The bivariate smooths are illustrated in Fig. 6, and corresponding additional plots are provided in Fig. E.3 in the Online Material.

For the whole sample, the preferred models are [38], [44], and [50]: I observe a mild positive association at lower levels of $\ln(GDP\ p.c.)$, but this association turns negative at the highest levels of $\ln(GDP\ p.c.)$ (see plots (a), (d), and (g) in Fig. 6 and also in Fig. E.3 in the Online Material). Preferred models for the subsample of 61 HUM countries are [40], [46], and [52]: plots (b), (e), and (h) in Fig. 6 show an inverse U-shaped association at medium development levels (around $\ln(GDP\ p.c.) \approx 9$), but a clear negative association at the highest levels of economic development (approximately $\ln(GDP\ p.c.) > 10$). For the whole sample and for the HUM subsample, the results remain considerably the same with or without the

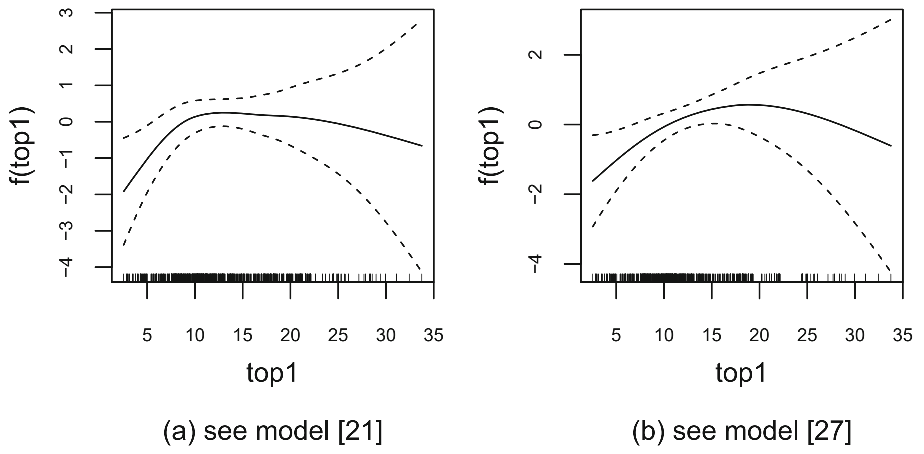


Fig. 4 Visualization of the univariate nonlinear smooths $f(top1_t)$ provided in Table 2 (5-year average data). Each plot presents the smooth function as a solid line. The plots also show the 95% confidence bands as the dashed lines and the covariate values as a rug plot along the horizontal axis

set of control variables.[22] Finally, I study the subsample of 24 OECD countries, and the preferred models are [42], [47], and [53]: the number of observations is small, and I find no support for a statistically significant association between top-end inequality and growth in the data starting from the 1950s (note that for these 24 OECD countries, Parts B–C of Table 3 only have $N = 118$).

In general, there is some evidence of a negative (or nonpositive) medium- to long-term association at high levels of economic development. However, the data size still limits the exploration of nonlinearities in "old" OECD countries. I also provide examples of traditional linear 10-year-average models for HUM countries in Table D.1 in the Online Material for comparison. However, the flexible specifications presented in Table 3 are preferred over these.[23]

As a sensitivity check, I analyzed longer-run links with 15-year averages consecutively from 1925–1939 to 1985–1999 (see Table C.1 and Figs. C.1–C.2 in the Online Material).[24] However, the data limit the investigation in this case: the number of studied countries decreases by 16 (from 137 to 121) because I only investigate countries that have a minimum of two observations,[25] and the number of observations becomes small in the HUM and OECD subsets. The whole-sample models with the 15-year average data indicate a positive (but nonconstant) connection between *top*1 and subsequent growth. Results for the HUM countries suggest a more complex relationship: there are signs of an inverse U-shaped association at least at medium development levels, and possibly a positive association at high development levels. The group of 24 OECD countries shows a positive *top*1–growth link

[22] In addition, Fig. B.3 in the Online Material provides a graphical illustration of the smooth functions of the control variables from model [52].

[23] In the case of the 10-year average data for 61 HUM countries, I also studied expanded specifications Eqs. (1) and (2), where I replace the country fixed effects with random effects. The main findings hold.

[24] Each future growth estimate is the average of the subsequent 15 annual log growth rates (multiplied by 100). For example, the last period is 1985–1999, where future growth is calculated using ln(*GDP p.c.*) values in 2000–2015. In models from the 1950s onward, I consider periods t as the following: 1955–1969, 1970–1984, and 1985–1999; thus, the number of observations per country is 2–3 in this case.

[25] The main results with the 10-year average data are not sensitive to excluding these 16 countries.

Table 3 10-year-average models for 137 countries: smooth functions $f(top1_t)$ and $f(top1_t, \ln(GDP\ p.c.)_t)$ for the nonlinear terms and the coefficients (and standard errors) for the linear $top1_t$ terms. The dependent variable is the average of ten annual log growth rates in the subsequent period. Preferred specification of the two alternatives is **in bold**. See Fig. 5 for illustrations of the univariate nonlinear terms $f(top1_t)$ and Fig. 6 for illustrations of the bivariate smooths $f(top1_t, \ln(GDP\ p.c.)_t)$. Abbreviation "HUM" refers to high- and upper-middle-income countries; see list of countries in Table A.1 in the Online Material

PART A. Data from	All 137 countries (N=534)		61 HUM countries (N=297)		24 OECD countries (N=160)	
the 1920s onward	[37]	**[38]**	[39]	**[40]**	[41]	**[42]**
$f(top1_t)$	Fig. 5(a)'		Fig. 5(b)***		−0.11533** (0.05753)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 6(a)***		Fig. 6(b)***		Fig. 6(c)***
AIC	2383	2381	1216	1187	576	564
controls?	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)^{***,a}$	no
PART B. Data from	All 137 countries (N=477)		61 HUM countries (N=245)		24 OECD countries (N=118)	
the 1950s onward	[43]	**[44]**	[45]	**[46]**	**[47]**	[48]
$f(top1_t)$	0.07807** (0.03558)		Fig. 5(c)**		−0.03183 (0.05298)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 6(d)***		Fig. 6(e)***		Fig. 6(f)***
AIC	2078	2075	944	928	312	313
controls?	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no	$f(\ln(GDP\ p.c.)_t)$***	no
PART C. Data from	All 137 countries (N=457)		61 HUM countries (N=231)		24 OECD countries (N=118)	
the 1950s onward	[49]	**[50]**	[51]	**[52]**	**[53]**	[54]
$f(top1_t)$	0.05204' (0.03509)		−0.00227 (0.06717)		0.04594 (0.06133)	
$f(top1_t, \ln(GDP\ p.c.)_t)$		Fig. 6(g)***		Fig. 6(h)***		Fig. 6(i)^{***,b}
AIC	1892	1887	839	811	314	316
controls?	all controls, as in Eq. (1)	all controls, as in Eq. (2)	all controls, as in Eq. (1)	all controls, as in Eq. (2); for illustration, see Online Material: Fig. B.3	all controls, as in Eq. (1)[c]	all controls, as in Eq. (2)[c]

***, **, *, ' denote significance at the 1, 5, 10, and 15% levels, respectively. The smooth terms' significance levels are based on approximate F-tests

All specifications include time and country fixed effects (dummies, not reported)

[a] The univariate smooth $f(\ln(GDP\ p.c.)_t)$ is linear in this case; so the resulting model corresponds to the traditional model, where continuous variables have linear terms

[b] In this special case, the bivariate smooth is simple: $f(top1_t, \ln(GDP\ p.c.)_t) = \theta_1 top1_t + \theta_2 \ln(GDP\ p.c.)_t + \theta_3 top1_t \ln(GDP\ p.c.)_t$. We now get: $\hat{\theta}_1 = -0.1444$, $\hat{\theta}_2 = -3.7839$, and $\hat{\theta}_3 = 0.0196$, but only $\hat{\theta}_2$ is statistically significantly different from zero (p-value < 0.01)

[c] All control variables enter the estimated model in linear form, so the model corresponds to its traditional counterpart. Note the small number of observations

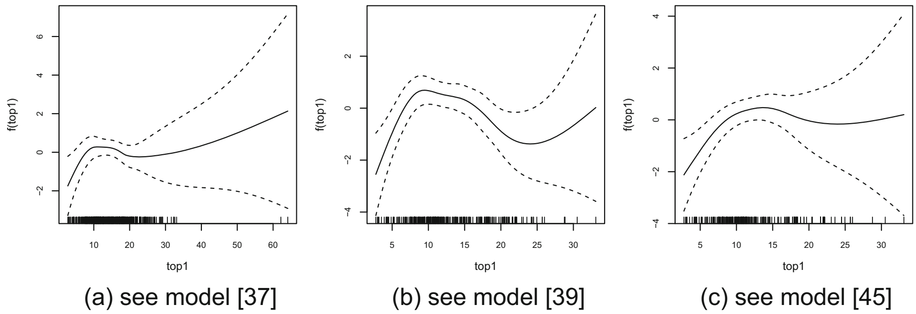


Fig. 5 Visualization of the univariate nonlinear smooths $f(top1_t)$ provided in Table 3 (10-year average data). Each plot presents the smooth function as a solid line. The plots also show the 95% confidence bands as the dashed lines and the covariate values as a rug plot along the horizontal axis

when the set of control variables is included. In comparison, Herwartz and Walle (2020) also report a positive long-run association between the top 1% share and economic development in their study of 12 OECD countries. In sum, the 10-year result of a negative (or nonpositive) relationship between top-end inequality and growth at high levels of $\ln(GDP\ p.c.)$ is not confirmed with the 15-year average data. However, the number of observations is very small in my models, as I utilize period averages—especially when I investigate subsamples. I conclude that the (very) long run should be studied more in the future.

5 Conclusions

Several studies have discussed the relationship between inequality and subsequent growth. However, this study adopted a novel approach by exploiting series of top 1% income shares and focusing on different time-period specifications and possible nonlinearities. I used penalized regression splines to circumvent problems related to prespecified functional forms and allowed a complex interaction between top-end inequality and economic development. Recently, Brueckner and Lederman (2018); Hailemariam and Dzhumashev (2020) reported that the development level matters in inequality–growth estimations, and my results support this view.

The study covers a wide range of economies from all over the world. I find support for a positive *top*1–growth association in annual data at medium to high development levels, but a differing pattern in data averaged over 5- or 10-year periods. The medium- to long-term association between top-end inequality and growth can be positive at lower-medium or medium levels of economic development, but this relationship is likely to weaken and may even turn negative at the highest levels of economic development. The initially positive and then negative medium-term association between inequality and subsequent growth is consistent with the unified theory of Galor and Moav (2004), although the channel from the top of the distribution to growth is unclear.

As discussed in the data section, some controls in the expanded models may work as mediators of the effects of inequality. However, in most cases reported in Tables 1–3, the inclusion of controls had little effect on the observed association between top-end inequality and subsequent growth. This speaks to the notion that top-end inequality is likely to have other channels through which it is linked to growth. However, stating the mechanisms behind

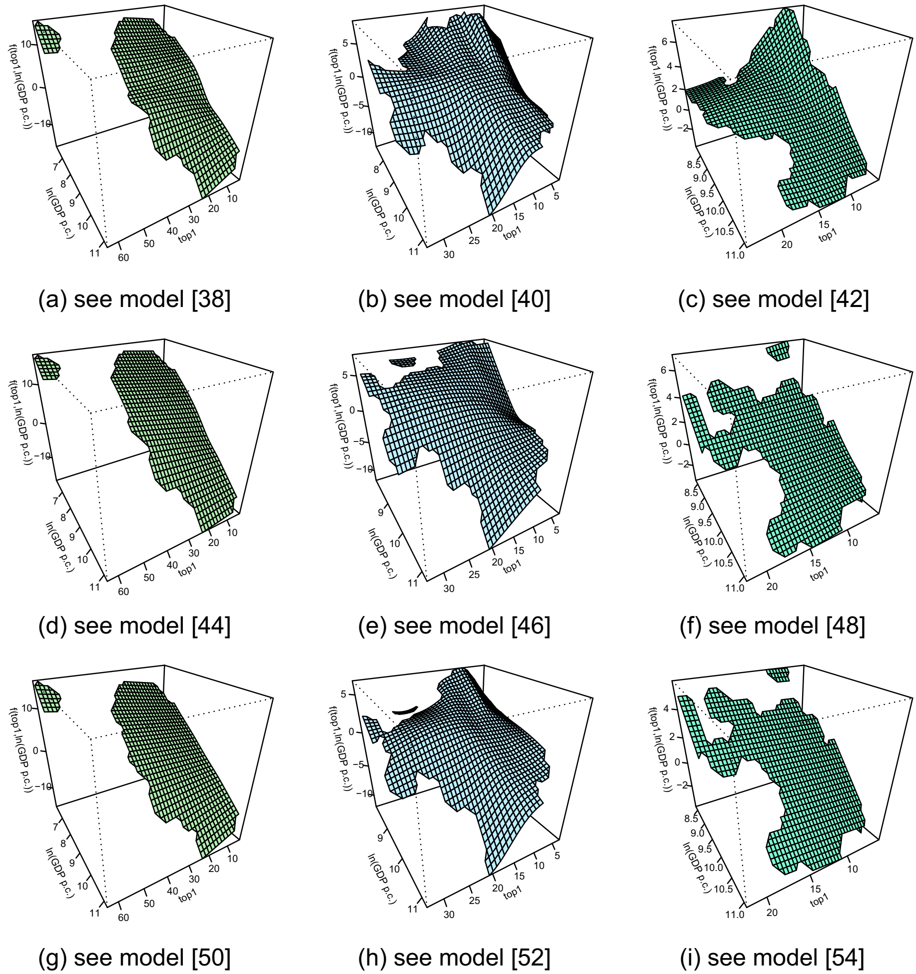


Fig. 6 Visualization of the bivariate smooths $f(top1_t, \ln(GDP\ p.c.)_t)$ from Table 3 (10-year average data). The horizontal axes have the top 1% income share and ln(GDP per capita); the vertical axis has the smooth function f. In all plots, plot grid nodes that are too far from the true data points of the top 1% share and ln(GDP per capita) are excluded: the grid has been scaled into the unit square along with *top*1 and ln(GDP per capita) variables; grid nodes more than 0.1 from the predictor variables are excluded

the discovered associations is more or less guesswork. The concentration of resources in the upper class could be consistent with growth in less-affluent economies, but this situation may change with development. The well-off may also have incentives to impede some policies that would facilitate growth. Although the current study refrains from making causal claims, the findings add to the growing literature that suggests high inequality does not foster growth in the medium (or, medium to long) run in advanced economies. However, very long-run associations may differ from medium- to long-run relationships.

This study investigated nonlinearities and the time dimension in reduced-form models and demonstrated the complexity of the *top*1–growth relationship. Allowing for heterogeneity in the association is possibly a fruitful direction for future research as well. Other potential venues for future research include the exploration of the (very) long-run associations and channels through which top-end inequality and growth are related.

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Data Availability The data that support the findings of this study are available from the author upon request.

Declarations

Competing interests The author declares no competing interests.

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