Inequality Is Bad for Growth of the Poor

(But Not for That of the Rich)

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ABSTRACT

The paper assesses the impact of overall inequality, as well as inequality among the poor and among the rich, on the growth rates along various percentiles of the income distribution. The analysis uses micro-census data from U.S. states covering the period from 1960 to 2010. The paper finds evidence that high levels of inequality reduce the income growth of the poor and, if anything, help the growth of the rich. When inequality is deconstructed into bottom and top inequality, the analysis finds that it is mostly top inequality that is holding back growth at the bottom.

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1. Introduction

The relationship between inequality and growth, where inequality today may have an effect on future growth, is probably one of the most important in economics. It has recently acquired added relevance because of the slowdown of growth in rich countries and simultaneously rising inequality. The relationship however has been extensively researched empirically in the 1980s and 1990s with interest declining afterwards.[2] Unfortunately, the results ultimately proved to be inconclusive as the relationship was found weak and of uncertain sign.

Forbes (2000), using a panel of mostly rich countries, found that higher inequality was positively associated with growth; so did Li and Zou (1998). Forbes (2000) however found that the relationship was weakened (or could turn negative) when the time-length of the growth spells was increased. Other studies before her in fact had predominantly reported on a negative association, see e.g. Persson and Tabellini (1991), Alesina and Rodrik (1994), and Perotti (1996).[3] In Barro (2000) and Banerjee and Duflo (2003) the baseline results were largely inconclusive. Although both studies ultimately did establish a more intricate relationship when delving deeper; Barro (2000) reported a negative correlation for a subsample of low income countries, while Banerjee and Duflo (2003) found evidence of a non-linear relationship.

Recently, Voitchovsky (2005) and Marrero and Rodriguez (2012, 2013) have had some success by acknowledging that total inequality is built up of

[2] For reviews of the inequality-growth literature, see e.g. Aghion *et al.* (1999) and Bénabou (1996a).

[3] More recently, Benjamin *et al.* (2011) found empirical evidence of a negative relationship between inequality and subsequent growth at the village level in rural China. However, they report that the effect disappears when regressing growth on more recent observations of inequality.

different components that may each have their own relationship to growth. Voitchovsky (2005) separately evaluates inequality among the poor and among the rich, and concludes that bottom inequality (that is, inequality among the poor) is bad for growth while top inequality is good. Marrero and Rodriguez (2012, 2013) measure how much may be attributed to inequality of opportunity and treat the residual inequality as a measure of inequality of efforts. In two separate applications, one to the EU and one to the US, they find that inequality of opportunity is detrimental to growth while inequality of efforts tends to help growth. Despite the intuitive appeal, other studies have since failed to reproduce these results when applied to data for other countries; see e.g. Ferreira *et al.* (2014).

Remarkably, all of the above mentioned studies focus exclusively on growth of average incomes or GDP per capita. This seems rather paradoxical. Measures of inequality summarize at any given point in time how incomes are distributed across the population. Yet when we investigate inequality's relationship to income growth we appear only interested in how it might affect growth of the average income, not how it might affect growth rates at various parts of the distribution. One would think that we would specifically be interested in how individuals at different steps of the socio-economic ladder would fare in societies with different levels of inequality.

Indeed, the logical next step is to also disaggregate growth, and to verify whether income growths of the poor and the rich are affected differently by inequality; whether good (bad) inequality is good (bad) for both the poor and the rich. We explore this empirical question using data for the United States covering the period 1960 to 2010 (at 10 year intervals). Specifically, we regress total inequality as well as bottom and top inequality against growth at a wide range of percentiles of the income distribution. Our results are both conclusive and robust.

We find that high overall inequality only appears to hurt income growth of the poor. While inequality is also found to have a positive effect on growth, this positive effect is exclusively reserved for the top end of the income distribution. This means that the type of growth that inequality stimulates is the type that further advances inequality. It also offers an alternative explanation for why the relationship between average income growth and inequality is so fragile, as the negative and the positive effects from the different ends of the income distribution may cancel each other out.

When we distinguish between bottom and top inequality, by regressing disaggregated inequality on disaggregated growth, we find that it is mostly top inequality that is holding back growth at the bottom. One possible explanation for this observation is that high levels of top inequality serve as a proxy for "social separatism" where the rich lobby for policies that benefit themselves but ultimately limit the growth opportunities of the poor.

The rest of the paper is organized as follows. A brief overview of the literature is provided in Section 2. In Section 3 we discuss the source of data we use and explain how we "disaggregate" both inequality and growth. Section 4 offers a first look at the data. The empirical results, and a discussion of their significance, are presented in Section 5. In the same section we also present an inductively-derived tentative hypothesis linking inequality and growth. Section 6 provides some robustness checks, and Section 7 concludes.

2. Brief discussion of the existing literature

Early thinking was that inequality would be positively associated with growth. The theoretical arguments originally put forward by Kaldor (1956) for example viewed income inequality as necessary in order to provide for savings (only the rich would save), and thus key for capital accumulation and economic growth. Another possible argument for a positive association is that more unequal societies provide stronger incentives which ultimately motivate individuals to work harder in order to succeed. These arguments found support in the empirical studies by Forbes (2000) and Li and Zou (1998).[4] Forbes (2000) findings, however, were rather nuanced as she found that, in short-time spans of about 5 years, inequality appears positively related to growth, but over longer horizons (10 years or more) negatively.[5]

Other schools of thought have since argued for a negative relationship between initial inequality and subsequent growth. One strand of this literature appeals to the Meltzer-Richard's (1981, 1983) median voter hypothesis. Studies believed to have uncovered empirical support for this hypothesis include Persson and Tabellini (1991), Alesina and Rodrik (1994), and Perotti (1996).[6] It is argued that high inequality leads a relatively poor median voter to vote for high tax rates, which in turn reduce incentives for investment and cause low growth.[7] However, one could argue that a poor median voter might also vote for redistributive policies that are not necessarily bad for growth, as for example, investments in public education.[8]

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[4] The authors were criticized for exclusion of many developing countries and small number of observations (a problem particularly acute in a dynamic panel setting), econometric procedures, and inadequate inequality statistics (see e.g. Aghion, Carolli and Garcia-Peñalosa 1999; Malinen, 2007). The latter is something, of course, the authors could not help: it simply reflected the existing statistical basis at the time.

[5] This ambivalence in the results ("sign-switching") was common to most of the literature. Generally speaking, a positive relationship was more commonly found in country fixed-effects formulations (rather than cross-sectional OLS) which were indeed the specifications run by both Forbes (2000) and Li and Zou (1998).

[6] Other authors (Keefer and Knack, 2002) looked at a link between inequality and political instability which would depress investments and economic growth.

[7] These results too raised a number of questions. For example, the studies do not adequately distinguish between inequality of market income which determines the median voter's position in the distribution and thus her desired tax rate, and inequality of disposable income which is the end product of the tax-and-transfer redistribution (for a critique see Milanovic 2000). It should be noted however that the micro household data, needed to get the distribution of market income, were seldom available.

[8] Ostry et al. (2014), in a recent study on redistribution, inequality and growth, also note that equality-enhancing interventions need not necessarily be bad for growth.

Li, Squire and Zou (1998) and Oded Galor in a number of papers, some of which were co-authored by Omer Moav (see Galor, 2009; Galor and Moav 2004) put the emphasis on credit market imperfections, namely the inability of the poor to get loans to finance their education. Therefore, absent a deep financial market, inequality would lead to lower growth. This view was, in the case of Galor and Moav, integrated with their overall argument that, in modern societies, the key to fast growth is not capital accumulation but improvements in human capital. This explained, in their view, why the relationship between inequality and growth historically switched from being positive to being negative.

Barro (2000) found the relationship between inequality and growth to be inconclusive. When he split his sample into a low income- and a high-income sample, the results revealed a negative relationship for low income countries and a borderline positive, if any, relationship between inequality and growth for high income countries. (One might argue that inefficiencies such as credit market imperfections are more likely to play a role in developing countries than in high income countries.) Banerjee and Duflo (2003) also failed to obtain conclusive results from their linear specifications, which prompted them to explore non-linear alternatives. They concluded that all departures from the existing inequality towards either more or less inequality were associated with lower growth, and the greater the change in inequality, the greater the negative effect on growth. This result is perhaps somewhat surprising as it seems to imply that each country is, at least in the short-run, at optimal inequality.[9] Perhaps not surprisingly the debate on the relationship between inequality and growth became more quiescent after such inconclusiveness. [10]

[9] The Banerjee-Duflo model is of a median voter hypothesis type.

[10] A useful meta-study of the inequality and growth literature is by de Dominicis, de Groot and Florax (2006).

Recently there have been some successes in getting a better handle on the relationship between inequality and growth. Voitchovsky (2005) and Marrero and Rodriguez (2012, 2013) argue that inequality ultimately consists of different components, some of which may be bad for growth, and others good. Once this is acknowledged, the earlier inconclusive results with "sign-switching" become more intelligible. Since different components may have opposite effects on growth and we fail to measure which one is more important at a given time and place, it should come as no surprise that the effect of "total inequality" on growth can vary. This approach gets away from looking at how a single inequality measure is associated with a single growth measure ("one-on-one" approach) to a "two (inequality measures) – on—one (growth measure)" approach, and can ultimately lead to an *n*—on—*n* approach.

Voitchovsky (2005) evaluates inequality among the poor (the 50/10 ratio) and inequality among the rich (the 90/50 ratio) as two separate drivers of total inequality.[11] She concludes that bottom inequality is bad for growth while top inequality is good. It is hypothesized that bottom inequality is bad for growth because it implies higher levels of poverty which, in the presence of credit constraints, make it difficult for the poor to acquire education.[12] It might also lead to greater crime and social instability. On the other hand, a positive impact of top inequality on growth is regarded as supporting a classic theoretical argument that links higher inequality to higher savings which finance growth-enhancing investments. It seems reasonable that this argument applies mostly to top income inequality, as opposed to total- or

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[11] Voitchovsky (2005) uses standardized micro data from 81 surveys covering 21 rich countries, in a dynamic panel setting with five-year intervals coinciding broadly with survey data availability.

[12] See also the recent study by Ravallion (2012) who directly compares the effects of initial poverty and inequality levels on future growth.

bottom inequality, as a large share of aggregate savings are made by the rich. In this way, Voitchovsky basically reconciled three very common theories that linked inequality and growth and were often presented as alternatives: credit-constraints, political instability, and marginal propensity to save by the rich. According to Voitchovsky, they may be all true, but are best captured by different parts of the income distribution.

Marrero and Rodriguez (2012, 2013) decompose total inequality into inequality due to inequality of opportunity, that is, to the circumstances outside one's control such as parental education, race, being foreign-born, and the residual, assumed to be due to effort and luck. In two separate applications, one to the European Union member countries and one to the states of the US, they find strong evidence that levels of inequality of opportunity are negatively correlated with growth while the residual ("good inequality") helps growth.

The evolution of data has played an important role in shaping the empirical inequality-growth literature. A lack of conclusive results may in part be attributed to the limitations of the data that was available at the time. At best, after the much-used Deininger Squire (1996) dataset, the new datasets (e.g. UN WIDER's World Income Inequality Dataset) still consisted of Ginis and in some cases of quintiles of disposable or gross income, available for many countries only at long and uneven intervals.[13] The dramatic improvements in data quality and availability, both through household surveys and fiscal data on top incomes, have made it possible to deconstruct inequality and its relationship to growth.

[13] There were many other, technical, problems that were insufficiently appreciated at the time: Ginis calculated across households for household income do differ from Ginis calculated across individuals' household per capita incomes (see Atkinson and Brandolini, 2001). This aspect was either badly documented in Deininger-Squire and World Income Inequality Dataset (WIID), or more commonly, ignored by researchers. The adjustment for consumption or income Gini was done very roughly using a dummy variable (most famously by Li, Squire and Zou, 1998).

3. The data and regression framework

We use individual level data from the Integrated Public Use Microdata Survey (IPUMS) which is a large micro-census conducted once per decade (see Ruggles *et al.*, 2010). We use six surveys made over the period of 50 years at regular decennial intervals: in 1960, 1970, 1980, 1990, 2000 and 2010. The IPUMS data provide a 1 percent or 5 percent samples from every state (1 percent for the years 1960, 1970 and 2010; 5 percent for the years 1980 to 2000), which effectively makes it a micro-census. The obvious advantage of working with such large data sets is that it reduces sampling error to a minimum.

Total income over the past 12 months (which is our key variable) is obtained by aggregating incomes from 8 different sources of income (which are collected via individual questions): (a) wages, salary, commissions, bonuses or tips, (b) self-employment income, (c) interest, dividends, net rental income, or income from estate/trusts, (d) social security or railroad retirement, (e) supplemental security income, (f) public assistance or welfare payments, (g) retirement, survivor or disability pensions, and (h) other regular sources of income, such as veterans payments, unemployment compensation, child support or alimony. Income data are collected for all individuals in the sample aged 15 or older (with the exception of 1960 and 1970, where 14 years olds were also included). The data are representative at the state level and income is made comparable over time by adjusting for inflation (all income data are expressed in 2010 prices). We aggregate income data over all members of a household and then divide it by the household size to obtain household per capita income.

Data on education are available for all individuals. Each respondent's education attainment is assigned to one of the following 11 categories: no schooling; nursery to grade 4; grade 5 to 8; grade 9; grade 10; grade 11; grade 12; 1 year of college; 2 years of college; 4 years of college; and 5 or more years of college. These categories were chosen by IPUMS so as to maximize comparability over time. We construct the following education variables from these: "edushort1518" which measures the average "education shortfall" for individuals between the age of 15 and 18; and "edums_age2139" which measures the percentage of individuals between the age of 21 and 39 with 4 years of college or more. Education shortfall is defined as the difference between the expected grade given the respondents' age and the actual realized grade of the individual. The "expected grades" are set to: grade 9 for age 15; grade 10 for age 16; grade 11 for age 17; and grade 12 for age 18. The variable is then calculated at the state level by calculating the average "shortfall" among all individuals between the ages of 15 and 18. As shown in Table 2, the US average shows a steady decline: from 0.8 years in 1960 to about 0.4 years in 2010.

The IPUMS also provides data on the general employment status which indicates whether the respondent is: (a) employed, (b) unemployed (seeking work), or (c) not in the labor force. This data is derived from a series of different questions, and is deemed comparable over time for adults aged 16 or older. For our analysis, we constructed employment variables for individuals between the age of 25 and 65.

The analysis is conducted at the level of US states.[14] We define as poor all individuals who belong to the bottom 40% of state population ranked by disposable household per capita income and as rich all those belonging to

[14] One advantage of working with a single country, with data from a single source, is that the data is comparable between units of observation. On the other hand, a single country may not offer the same degree of heterogeneity as a cross-country database does, which means that by lowering the "noise" we may also be lowering the "signal". This does not appear to be an issue in the United States. We observe a large degree of variation in both inequality levels and growth patterns between the different states.

the top 40%. As discussed below, these are sufficiently wide partitions to include a large portion of total inequality and also to have arguably a meaningful impact on growth. Growth will be measured in anonymous terms because the surveys are not longitudinal and we do not have information about household per capita income for the same persons over several periods. Empirically, we ask in effect, two related questions. First, in a *one-on-n* formulation, how does the overall Gini at time *t-1* affect the rate growth at different percentiles of income distribution between times *t-1* and *t*? (The times *t-1* and *t* are, as indicated, always ten years apart.) And second, in a more flexible formulation, *two-on-n*, how do inequalities among the poor and the rich at time *t-1* affect the growth rate at different percentiles between times *t-1* and *t*?

The regression for a given income distribution partition *i* (where *i* refers here to the poor π or the rich *ρ* but can obviously be made more general) is written as in (1).

$$r_{s,t}^{(p)} = \alpha^{(p)} ln y_{s,t-1}^{(p)} + \sum_{i=\pi,\rho} \beta_i^{(p)} G_{i,s,t-1} + \sum_h \gamma_h^{(p)} X_{h,s,t-1} + \delta_s^{(p)} D_s \qquad (1)$$
$$+ \tau_{t-1}^{(p)} d_{t-1} + u_{s,t}^{(p)}.$$

$r_{s,t}^{(p)}$ is the growth rate at a given percentile *p* in state *s* between time *t-1* or *t*, that is:

$$r_{s,t}^{(p)} = ln y_{s,t}^{(p)} - ln y_{s,t-1}^{(p)}$$

where $y_{s,t}^{(p)}$ is income at the *p*-th percentile in state *s* at time *t*. Income is always expressed in real terms. In regression (1) $G_{i,s,t-1}$ is Gini of the poor π (or the rich ρ) in state *s* at time *t-1*, $X_{h,s,t-1}$ are state-level controls evaluated at time *t-1*, D_s is a state-level dummy or a broader regional dummy variable, d_{t-1}

is a time dummy variable, and $u_{s,t}^{(p)}$ is the error term with the conventional properties. In a simpler formulation, *one-on-n*, the Gini variable is $G_{s,t-1}$, that is overall state Gini. But in a more complex formulation, *two-on-n*, the regression is estimated across percentile growth rates for both Ginis (that is, for the Gini for the poor and for the rich). We run three formulations of (1): pooled regression with four US regional dummies (East, Mid-West, South, West), (2) generalized method of moments, or system GMM shown as part of our robustness checks, and (3) fixed-effects across individual states.

Note that we could in principle push this all the way to an *n-on-n* approach, where one could look at how inequality at each percentile of income distribution affects growth at every percentile of the income distribution. But pushing disaggregation too far has its costs: we would leave out the between-percentile inequality which is, when the partitions are fine, by far the most important part of total inequality. Empirically, inequality within each percentile (except for the very bottom and the very top)[15] is very small, and it could be hard to argue that it may affect growth at its own percentile or, for that matter, any other.

Therefore the disaggregation level has to be reasonably wide to include enough inequality and also to provide a credible causal narrative whereby inequality around one part of the distribution may affect growth at that or another part of the distribution. We do this by separating total inequality into inequality among the bottom of the income distribution (bottom 40%) and inequality among the top 40% of the population and then allowing bottom and top inequality to have different effects along different points of the income distribution.

[15] Based on some dozen household surveys from various parts of the world, we find that the values of percentile-level Ginis are less than 0.02. It is only among the bottom and top 1% or top 2% that Ginis are higher.

4. An overview of income distribution changes in the US

Tables 1 (and WA1-WA2 in Annex) show some key summary statistics. Table 1 shows a variant of the Growth Incidence Curve (GIC) for each ten-year period. The values give the average annual per capita growth rates, calculated across states, at each percentile of state income distribution.[16] Two conclusions are easily made: there was a marked slowing down of growth, and the growth incidence curves have switched from being pro-poor to being pro-rich. The first conclusion appears if we look at the median growth over time. It almost monotonically declined in every decade: it was 2.9 percent per capita in the 1960s, then 1.5% and 1.6% in the two next ten-year periods, 1.1% in the 1990s, and practically zero in the noughts. The switch to pro-rich growth can be observed from a simple comparison of growth rates at the top and bottom percentiles (i.e. by comparing the 5th to the 95th percentile, say).

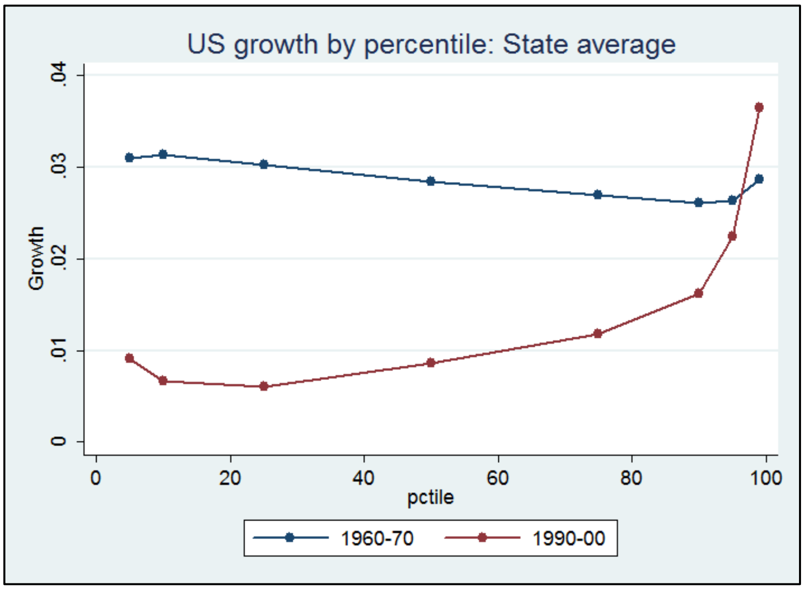
Table 1. Average growth at different percentiles of state income distribution

	Growth (annualized) at percentile							
year	5	10	25	50	75	90	95	99
1960-70	0.031	0.031	0.030	0.028	0.027	0.026	0.026	0.029
1970-80	0.001	0.006	0.010	0.012	0.011	0.009	0.008	0.003
1980-90	0.007	0.010	0.013	0.016	0.020	0.023	0.025	0.033
1990-00	0.009	0.007	0.006	0.009	0.012	0.016	0.022	0.036
2000-10	-0.015	-0.013	-0.007	-0.002	0.000	0.000	-0.003	-0.010
1960-10	0.007	0.008	0.010	0.013	0.014	0.015	0.016	0.018

[16] They are population weighted state averages and thus in principle different from a growth incidence curve which would be obtained for the United States as a single unit. However, empirically the two are practically undistinguishable. We do not show national-level data here because our analysis is conducted in terms of states; national-level results are available from the authors on request.

A striking illustration of the change in levels and shape of growth rates is provided in Figure 1 which displays the patterns of growth in the 1960 and in the 1990s.[17] In the 1960s, GIC was mostly downward sloping indicating that growth rates were higher at lower parts of the income distribution (in effect, the highest growth rate was registered for the bottom 5% of the population). In 1990s, by contrast, growth rates are lower than in the 1960s everywhere except at the top, and the line is upward sloping. Figure 2 shows the same GIC but disaggregated by region: North-East, Mid-West, South, and the West (see Table A1 in the Annex for a definition of these regions). This tells us that while all regions are showing an upward sloping GIC in recent years, not all regions experienced pro-poor growth in the early years. In the North-East and the West, growth increased with income in both periods.

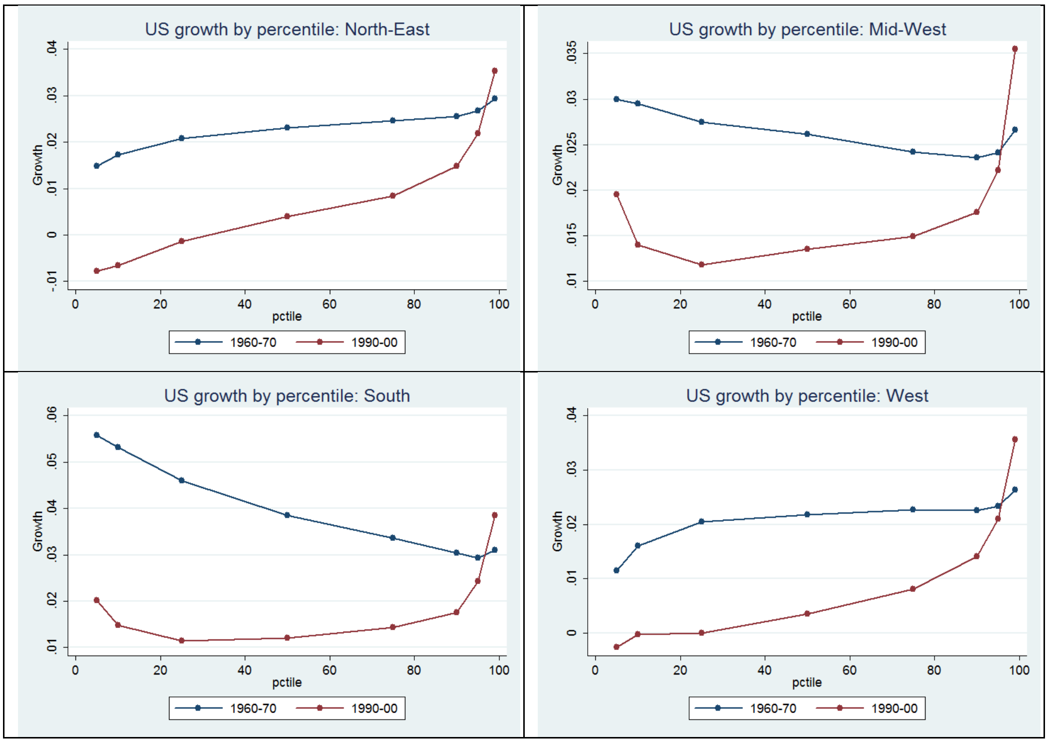
Figure 1. US: The average population-weighted state-level growth rates of real income at different points of income distribution (decennial averages)



[17] The recent financial crisis has flattened the GIC for 2000-10, which is why we omit it from the figure.

Table WA1 (in the Annex) shows annualized real per capita growth of the median income in 50 US states and the District of Columbia over the period 1960-2010 and Gini coefficients at ten-year intervals. The column labeled "1960" for the growth of median income gives the real growth rate for the subsequent ten-year period, starting with 1960-1970. The column labeled "1960" for the Ginis gives Gini values in that year. Here again we observe the two developments mentioned above: median growth rates have declined over the entire period of half a century and inequality has increased. There are only two states (New Mexico and Wyoming) that in the 1990s had a greater rate of growth at their median than in the 1960; and in the 2000s, there was none except the District of Columbia.

Figure 2. By region: The average state-level growth rates of real income at different points of income distribution (decennial averages)



As for inequality, in only 8 states, it was lower in 2010 than in 1960. The average (population-weighted) state-level Gini increased from about 0.41 in 1960 to 0.48 in 2010. The geography of inequality changed too: while in 1960, many of the high inequality states were in the South, today they are in the West and North-East (see also Figure 3). It is striking to note that the North-East which in 1970 had relatively low Ginis, now displays relatively high inequality. New York is emblematic of this development. Its Gini in 1960 was 0.387, below the mean for all states; in every decade its Gini increased, reaching almost 0.5 in 2010, a value exceeding the national average (which in turn has gone up).

Figure 3. Population-weighted average State Ginis by region, 1960-2010

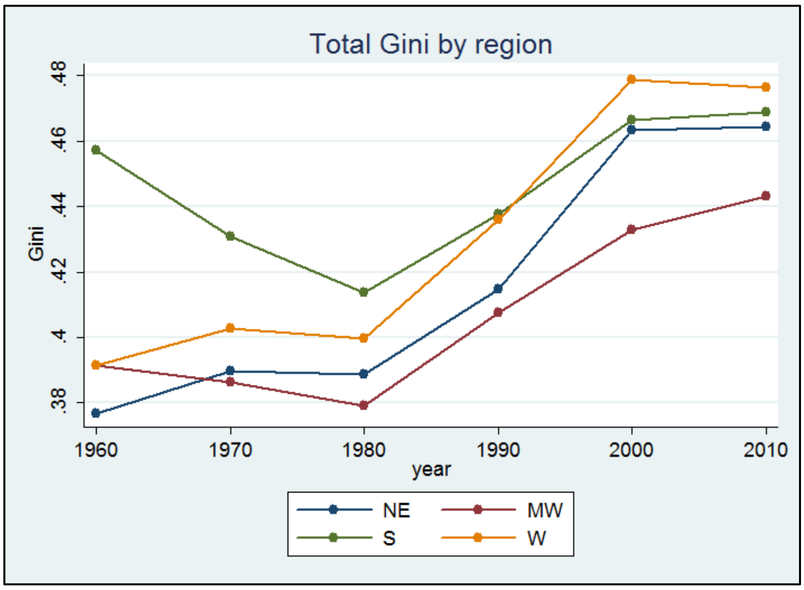
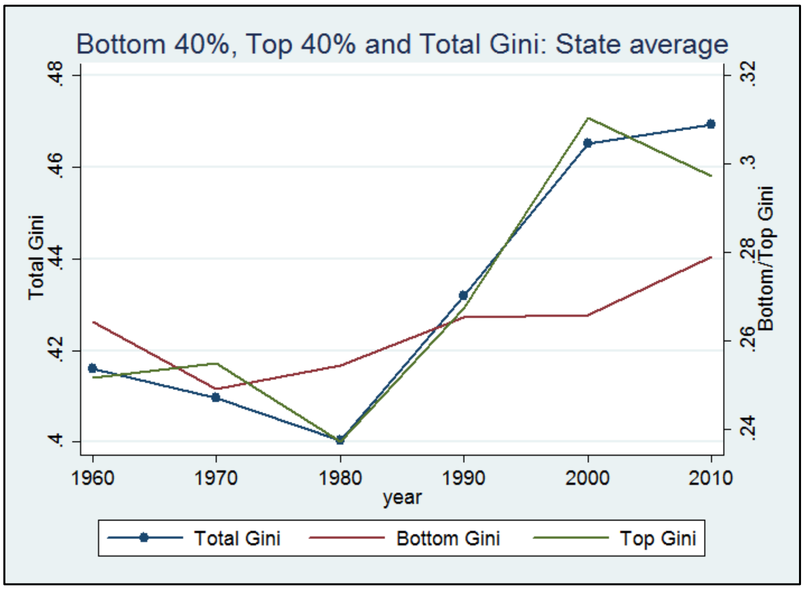


Table WA2 shows the Gini coefficients for the bottom 40% and top 40% of the population over the same half-a-century and across 50 states and the District of Columbia. The general trend is that top inequality has been rising faster than bottom inequality. We can notice the effect of the recent financial crisis which has reduced heterogeneity (inequality) among top earners more than among the bottom: inequality among the top 40% suddenly drops between 2000 and 2010 in most states. The average (population-weighted) top Gini thus peaked at 0.3 in 2000 before dropping to 0.28 ten years later (Figure 4). The average (populaton-weighted) state-level bottom Gini however shows a steady increase from 1970 to 2010, catching up in the last year with the top Gini. However over the whole period, with the exception of the last decade, it appears that changes in total inequality were essentially driven by the changes in top Gini.[18] This can also be seen in Figure 4, where the movements of total Gini (shown on a different axis; thick line) are practically the same as the movements of the top Gini.

Figure 4. Aaverage top, bottom and total State Ginis, 1960-2010



Note: Ginis are the means of corresponding population-weighted state Ginis.

[18] The trend in inequality is consistent with the trend obtained by Piketty and Saez (2003).

Table 2. Summary statistics of independent variables by year

	1960	1970	1980	1990	2000	2010
Gini	0.408	0.404	0.397	0.425	0.461	0.464
	[0.038]	[0.025]	[0.020]	[0.024]	[0.028]	[0.023]
gini_b40	0.242	0.239	0.251	0.260	0.262	0.279
	[0.036]	[0.023]	[0.017]	[0.020]	[0.015]	[0.010]
gini_t40	0.250	0.252	0.235	0.265	0.308	0.288
	[0.019]	[0.013]	[0.012]	[0.014]	[0.019]	[0.019]
age015	0.329	0.308	0.247	0.237	0.231	0.213
	[0.024]	[0.016]	[0.017]	[0.019]	[0.015]	[0.017]
age65	0.089	0.100	0.112	0.124	0.126	0.133
	[0.013]	[0.016]	[0.019]	[0.021]	[0.020]	[0.019]
Hhsize	4.246	4.081	3.566	3.477	3.398	3.328
	[0.282]	[0.172]	[0.133]	[0.195]	[0.254]	[0.235]
inschool5	0.457	0.549	0.764	0.681	0.849	0.866
	[0.194]	[0.146]	[0.079]	[0.063]	[0.046]	[0.048]
edushort1518	0.805	0.697	0.705	0.560	0.593	0.431
	[0.206]	[0.129]	[0.089]	[0.065]	[0.065]	[0.076]
edu_hs	0.157	0.194	0.229	0.206	0.237	0.216
	[0.024]	[0.024]	[0.024]	[0.027]	[0.025]	[0.024]
edu_ba	0.057	0.077	0.114	0.173	0.140	0.160
	[0.013]	[0.017]	[0.021]	[0.023]	[0.013]	[0.013]
edu_ms	0.043	0.059	0.094	0.125	0.145	0.170
	[0.009]	[0.011]	[0.018]	[0.025]	[0.026]	[0.030]
edu_ms_age2139	0.098	0.138	0.198	0.220	0.244	0.289
	[0.019]	[0.024]	[0.032]	[0.041]	[0.046]	[0.057]
olf_female	0.600	0.525	0.414	0.304	0.303	0.271
	[0.035]	[0.031]	[0.035]	[0.033]	[0.037]	[0.032]
olf_male	0.076	0.090	0.116	0.111	0.176	0.163
	[0.017]	[0.021]	[0.022]	[0.019]	[0.027]	[0.026]
race_white	0.854	0.835	0.796	0.758	0.702	0.654
	[0.104]	[0.098]	[0.109]	[0.126]	[0.141]	[0.150]
race_hisp	0.031	0.042	0.062	0.085	0.119	0.153
	[0.049]	[0.055]	[0.073]	[0.093]	[0.112]	[0.125]
race_black	0.105	0.111	0.118	0.118	0.128	0.131
	[0.092]	[0.083]	[0.082]	[0.080]	[0.082]	[0.080]
race_asian	0.005	0.008	0.017	0.029	0.041	0.052
	[0.030]	[0.036]	[0.043]	[0.049]	[0.056]	[0.058]

Table 2 below shows how demographics, education levels, labor force participation, and ethnic composition have evolved over the last 50 years. Some of the time-trends that stand out are a dramatic increase in education (the percentage with a master's degree or higher has quadrupled over the years; and we see a significant decline in education shortfall among adults aged 15-18); and an equally dramatic shift in labor force participation rates. In 1960 well over 90 percent of men participated in the labor force compared to only 40 percent of the women. (Note that the variable in Table 2 is defined as percentage of the male/female population *outside* the labor force.) Fifty years later we see a remarkable convergence; this gender gap has almost disappeared. We also see evidence of aging in the population with a steady decline in the share of children combined with a gradual rise in the share of elderly. All of these factors help explain income growth, and will be included as candidate control variables in our growth regressions.

5. Results and a hypothesis

We move next to the results. The first set of results (Table 3) is for the *one-on-n* formulation, namely a formulation where we look at the effect of overall Gini on growth along many points of income distribution for all US states (we drop however Alaska and DC which are both identified as outliers).[19] We run regional fixed-effects (FE) regressions where we control for unobservable characteristics using four geographical regions: Mid-West, South, West and (omitted in the regression) East.[20]

[19] We identified DC and Alaska as outliers using standard regression diagnostics.

[20] One argument in favour of working with region- as opposed to state fixed effects (FE) is that inequality tends to be a slow-moving process, which makes it highly correlated with FE at the state level. Hence, by adopting state FE estimators one risks throwing the baby out with the bathwater. An advantage of working with state level FE of course is that it is more

Table 3. State-level growth vs. total Gini (dependent variable = per capita income growth at given percentile of state income distribution; 1960-2010; 10-year periods)

	dlny5	dlny10	dlny25	dlny50	dlny75	dlny90	dlny95	dlny99
Gini	-0.245***	-0.242***	-0.127***	-0.0280	0.0319*	0.0525***	0.0645***	0.0728***
	(-3.17)	(-3.51)	(-2.97)	(-1.09)	(1.69)	(3.05)	(3.68)	(3.42)
edu_ms_age2139	0.0626**	0.0847***	0.0935***	0.0934***	0.0849***	0.0830***	0.0741***	0.0792***
	(2.34)	(3.52)	(4.70)	(5.48)	(5.40)	(5.57)	(4.89)	(3.81)
edushort1518	-0.0372***	-0.0286***	-0.0128**	-0.00963*	-0.0107**	-0.010***	-0.0081**	-0.00426
	(-3.46)	(-3.40)	(-1.99)	(-1.91)	(-2.56)	(-2.64)	(-2.12)	(-0.81)
age015	-0.127**	-0.187***	-0.172***	-0.178***	-0.158***	-0.159***	-0.146***	-0.152***
	(-2.05)	(-3.36)	(-3.54)	(-4.13)	(-4.25)	(-5.01)	(-4.82)	(-3.98)
age65	-0.0640	-0.106**	-0.107***	-0.121***	-0.111***	-0.111***	-0.098***	-0.0680*
	(-1.00)	(-2.01)	(-2.62)	(-3.47)	(-3.63)	(-3.98)	(-3.05)	(-1.73)
olf_female	-0.0957***	-0.0794***	-0.0515***	-0.0446***	-0.035***	-0.028***	-0.027***	-0.0195
	(-3.69)	(-4.15)	(-3.51)	(-3.62)	(-3.31)	(-2.62)	(-2.65)	(-1.29)
Mid-West	0.000151	0.000903	0.00118	0.000610	-0.000247	-0.000793	-0.00165	-0.00216
	(0.06)	(0.42)	(0.72)	(0.44)	(-0.19)	(-0.67)	(-1.45)	(-1.51)
South	0.000778	0.000539	0.000406	0.000119	0.0000001	-0.000039	-0.000814	-0.000795
	(0.24)	(0.21)	(0.21)	(0.07)	(0.00)	(-0.03)	(-0.55)	(-0.47)
West	0.00285	0.00118	-0.000520	-0.000872	-0.000452	-0.000147	-0.000996	-0.000899
	(0.90)	(0.45)	(-0.26)	(-0.53)	(-0.30)	(-0.10)	(-0.69)	(-0.53)
log income	-0.0677***	-0.0725***	-0.0631***	-0.0567***	-0.048***	-0.042***	-0.035***	-0.037***
	(-9.85)	(-10.20)	(-9.64)	(-9.91)	(-9.44)	(-9.63)	(-7.95)	(-6.59)
constant	0.783***	0.852***	0.728***	0.657***	0.559***	0.511***	0.432***	0.464***
	(8.13)	(8.73)	(8.60)	(9.18)	(9.18)	(9.82)	(8.54)	(7.32)
N	245	245	245	245	245	245	245	245
adj. R-sq	0.731	0.776	0.795	0.770	0.742	0.758	0.812	0.883

Note: All right-hand side variables estimated at time *t-1*. Income is household per capita. Gini calculated across individuals ranked by their household per capita income. *t*-statistics in parentheses.
* p<0.1, ** p<0.05, *** p<0.01. Time-period dummies are included but not reported.

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ambitious in controlling for omitted variables. We will present the System GMM estimates in Section 6, while the standard state FE estimates can be found in the Annex.

Overall, initial inequality is negatively associated (at the conventional level of statistical significance) with subsequent real growth for the population located below the 25th percentile, and positively with growth for the population belonging to the top decile. The size of the (positive) coefficient increases as we move toward the richer parts of the top decile, and likewise, the absolute size of the negative coefficient increases as we move toward the poorest parts of the distribution. In other words, total inequality seems to be negatively associated with growth among the poorest people and positively among the top decile while there is no statistically significant effect on the growth among the middle of income distribution.

We use several state-level controls: demographic (age, gender), education, labor force participation, and geographical (the four regions), and it is instructive to look at their effects.[21] Since the results on these controls do not vary much between this and other formulations, we shall discuss them here in some detail. Predictably, the increase in the share of household members who are either too young (*age015*) or too old (*age65*) to work has a negative effect on income growth for all income percentiles, and in most cases, the effect is statistically significant. The share of women who are outside the labor force (variable *olf_female*) is similarly strongly negatively correlated with growth except at the top 1% level (99th percentile). (This effect is stronger for households with lower incomes who are also expected to gain the most from an increase in female labor force participation.)

Having master's and higher degrees (expressed as percentage of state population with such degrees; variable *edu_ms_age2139*) is, as expected, positively correlated with income growth at all percentiles except the top 1%.

[21] We have also considered state racial composition as control variables since they are significant in pooled OLS regressions. However, these variables are highly persistent and thus highly co-linear with the state fixed effects. For this reason we did not include them into the final specification.

(The omitted variable is all schooling below the master's degree.) In order to have a somewhat richer picture of how education might affect income growth, we constructed, as explained before, a new variable *edushort1518* which is the expected school year shortfall. The shortfall affects real growth negatively along the entire income distribution. It hurts growth at the bottom more than it does at the top though.

Geographical regional dummies are not statistically significant, indicating that variation in growth rates across the regions can largely be explained by variation in the independent variables. Finally, initial income, as usual in the convergence literature, enters with a statistically significant negative sign in all regressions.

It could be thought that regressions based on anonymous growth rates along different percentiles of the income distribution may introduce an inequality effect whereby growth rates among the poor are spuriously reduced (and those among the rich spuriously increased). We considered this possibility, and in a separate note (available to the reader on request) found that any such spurious effect would lead to exactly the opposite result, that is, it would predict that high initial inequality would help growth for lower incomes while hurting growth for top incomes.[22] This therefore strengthens our findings.

[22] An intuitive explanation for such a spurious inequality effect is as follows: Any divergence between the anonymous and the non-anonymous growth rate will be driven by the extent to which the ranking of households in terms of their incomes has changed over time (if the income ranking has remained constant, then anonymous growth will coincide with non-anonymous growth). When initial inequality is low, the income gaps between households will be small. This makes it more likely for households to switch positions on the income ladder. If a new household now occupies a lower percentile in the income distribution, then it is more likely that this household is a previously higher-ranked household which experienced low growth than a previously lower-ranked household which experienced high growth (in the bottom half there are more households ranked immediately above than below you). So at lower percentiles, low (high) inequality will be associated with low (high) anonymous growth rates, resulting in a spurious positive correlation between growth and initial inequality. The opposite holds true for higher percentiles.

But how big is the effect of inequality on growth; is it economically meaningful? One standard deviation of state-level Gini is 0.038 (population weighted and excluding DC and Alaska; the average Gini across all states and years is 0.426). Thus, one standard deviation decrease in Gini would be, on average, associated with a 0.9 percentage point increase in the average growth rate of the 5th or 10th income percentile (0.038*0.245 or 0.038*0.242). Since their average growth over the 50-year period was 0.8 percent per capita (see Table 1), the decline in state-level Gini would, on average, double the growth rate. Both the absolute and relative effect of lower inequality on real growth of the rich is less: one-standard deviation decrease in Gini is associated with a 0.3 percentage point *decline* in the growth rate of the rich which given that their average annual growth over the entire period was almost 2 percent is just about 1/7th of the growth rate. Finally, the effects of overall Gini on the middle of states' income distributions is, whether positive or negative, small and statistically insignificant. Throughout, the adjusted R^2 is relatively high, ranging from 0.73 to 0.88, and increasing for higher income percentiles. In conclusion, we find that overall inequality, measured by Gini, has a different impact on income growth of the rich and the poor.

The results for a more complex *two-on-n* (here: *two-on-8*) formulation are shown in Table 4. We replace the overall state Gini by two Ginis: one for the bottom 40% of the population ("the bottom Gini"), and the other for the top 40% of the population ("the top Gini"). The bottom Gini has a negative impact on income growth among the poorest (bottom 10%), and a positive impact on growth among the top 10%. In effect, its coefficient almost monotonically increases, starting with a high negative and statistically significant value (for the poorest income group) and ending with a strongly positively significant and big coefficient at the very top of income distribution. Consider now the top Gini. It is negatively associated with the growth between the 10th percentile and the median, and is statistically insignificant in the upper half of the distribution.

Table 4. State growth vs. bottom and top Gini (dependent var. = per capita income growth at given percentile of state income distribution; 1960-2010; 10-year periods)

	dlny5	dlny10	dlny25	dlny50	dlny75	dlny90	dlny95	dlny99
gini_b40	-0.379***	-0.183**	-0.0309	0.0248	0.0488*	0.0601**	0.0745***	0.0651**
	(-2.91)	(-2.34)	(-0.68)	(0.74)	(1.75)	(2.43)	(3.06)	(2.00)
gini_t40	-0.118	-0.163**	-0.143**	-0.0823*	-0.0123	0.00320	-0.000675	0.0187
	(-1.25)	(-2.04)	(-2.35)	(-1.73)	(-0.31)	(0.09)	(-0.02)	(0.34)
edu_ms_age2139	0.0936***	0.0840***	0.0821***	0.0888***	0.0818***	0.0791***	0.0680***	0.0760***
	(3.09)	(3.37)	(4.21)	(5.27)	(5.08)	(5.17)	(4.35)	(3.34)
edushort1518	-0.0349***	-0.0272***	-0.0137**	-0.0115**	-0.0121***	-0.0115***	-0.00932**	-0.00453
	(-3.19)	(-3.15)	(-2.04)	(-2.21)	(-2.74)	(-2.84)	(-2.38)	(-0.85)
age015	-0.240***	-0.207***	-0.145***	-0.159***	-0.143***	-0.141***	-0.121***	-0.132***
	(-2.73)	(-3.10)	(-2.80)	(-3.47)	(-3.60)	(-4.09)	(-3.63)	(-3.01)
age65	-0.159*	-0.119**	-0.0776*	-0.0988**	-0.0954***	-0.0941***	-0.0745**	-0.0515
	(-1.96)	(-2.04)	(-1.77)	(-2.54)	(-2.77)	(-2.98)	(-2.08)	(-1.11)
olf_female	-0.0798***	-0.0724***	-0.0538***	-0.0471***	-0.0380***	-0.0311***	-0.0315***	-0.0219
	(-3.19)	(-3.72)	(-3.52)	(-3.74)	(-3.36)	(-2.76)	(-2.87)	(-1.35)
Mid-West	0.00258	0.00177	0.000862	0.000218	-0.000640	-0.00125	-0.00224*	-0.00259*
	(0.92)	(0.76)	(0.49)	(0.15)	(-0.48)	(-1.00)	(-1.88)	(-1.78)
South	0.00118	0.000494	0.000158	-0.00000181	-0.0000911	-0.0000836	-0.000875	-0.000708
	(0.36)	(0.19)	(0.08)	(-0.00)	(-0.06)	(-0.06)	(-0.59)	(-0.41)
West	0.00267	0.000383	-0.000848	-0.000733	-0.000249	0.0000733	-0.000744	-0.000629
	(0.83)	(0.15)	(-0.43)	(-0.46)	(-0.17)	(0.05)	(-0.52)	(-0.37)
log income	-0.0828***	-0.0728***	-0.0586***	-0.0552***	-0.0464***	-0.0404***	-0.0319***	-0.0348***
	(-7.65)	(-9.03)	(-9.47)	(-9.61)	(-8.91)	(-8.88)	(-6.99)	(-5.38)
constant	0.951***	0.844***	0.673***	0.641***	0.549***	0.495***	0.408***	0.446***
	(6.84)	(8.07)	(8.59)	(9.03)	(8.80)	(9.22)	(7.73)	(6.17)
N	245	245	245	245	245	245	245	245
adj. R-sq	0.733	0.773	0.793	0.770	0.743	0.758	0.813	0.882

Note: All right-hand side variables estimated at time *t-1*. Income is household per capita. Gini calculated across individuals ranked by their household per capita income. *t*-statistics in parentheses.
* p<0.1, ** p<0.05, *** p<0.01. Time-period dummies are included but not reported.

How sizeable are these effects? At the level of the 10^{th} percentile, one standard deviation increase in top Gini (from the average value of 0.266 to 0.296), reduces annual per capita growth rate by almost 0.5 percentage points. This is a sizeable effect since the average annual growth over 50 years at that point of income distribution was less than 1 percent (Table 1). But inequality among the poor affects positively growth rate of the rich. The standard deviation of Gini bottom is 0.025 and its increase would raise the growth rate of the rich by about 0.2 percentage point per annum, which is about $1/10^{th}$ of the average growth rate of the rich over the 50-year period. The adjusted R^2 is, as before, between 0.73 and 0.88 and greater for higher income percentiles.

What are the channels whereby inequality among the rich may affect negatively the growth rate of the poor, and inequality among the poor positively the growth rate of the rich? We cannot test them, so we are reduced to simply discussing some hypotheses. Consider first the role of high inequality among the rich. A possibility which seems to us most compelling is that inequality in general, and among the rich in particular (where a given Gini coefficient implies much larger absolute gaps in income) is an indicator of societal fragmentation. We view it similarly to the ethnolinguistic fragmentation that was interpreted as a cause of conflicts and in many cases was found to correlate with civil strife (see the review in Hegre and Sambanis, 2006). Alike ethnic fragmentation that creates "horizontal" cleavages between the groups, income fragmentation creates "vertical" cleavages between the poor, middle class and the rich. These cleavages particularly strongly, and negatively, affect the poor. This might promote "social separatism" whereby the rich prefer to opt out of publicly-funded and publicly-provided education, health, urban infrastructure and other services because their private equivalents may be of better quality and signal the wealth and power of those who can afford them. One example of this is the vastly different preferences of the rich (top 1%) and the rest of the population when it comes to the cuts in Medicare, education and infrastructure spending as a way to reduce federal deficit; according to the survey data reported by Page, Bartels and Seawright (2011; quoted in West, p. 10, forthcoming); 58% of the rich are in favor of such cuts versus only 21% among the rest of the population.[23] "Social separatism" in turn means that the poor, especially the bottom decile, may find it harder to escape poverty because with rich's lack of interest in public health and education, the quality of the services deteriorates. It is a model of society sketched by Bénabou (2000) where high inequality, combined with credit constraint and influence of the rich on the political process, results in a steady-state of low government spending and persistent high inequality.[24]

Note that it does not mean that none of the economic benefits trickles down to lower incomes. An inspection of the unconditional growth incidence curves in Section 4 shows that the lower incomes have also participated in growth, albeit not as much as the top incomes. Rather our findings suggest that the "trickle-down effect" is larger in states or times that

[23] Using cross-country data from the Americas, Sokoloff and Zolt (2005) find empirically that higher levels of inequality are associated with more regressive taxes and consequently less funding for public investments and services. In a study of the US federal tax system, Piketty and Saez (2007) provide evidence that over the last 40 to 50 years, since the 1960s, the federal tax system has evolved from being progressive toward being regressive. It is reported that the marginal tax rate on the highest incomes, for example, has declined from 91 percent around 1960 to 35 percent in 2003. This remarkable decline has been accompanied by an equally remarkable upward trend in income inequality. Alvaredo et al. (2013) puts the co-evolution of top income shares and top tax rates into a more global perspective. For further empirical evidence that inequality also acts as a barrier to the provision of public goods, see e.g. Araujo et al. (2008) and Easterly (2007).

[24] See also the studies by e.g. Bénabou (1996b), Alesina and La Ferrara (2000), and Lloyd-Ellis (2000).

can be characterized by lower levels of inequality. This is also implied by the recent results by Chetty et al. (2014, p. 38), that show that locations in the U.S. with lower income inequality display more inter-generational mobility.

It is harder to see why inequality among the poor would have a positive effect on the growth rate of the rich. This is a more speculative part. Segmentation among the poor can ensure that the rich are provided some services and amenities at cheaper rates than they would pay if the poor were more homogeneous. In other words, the poor who have a choice between facing destitution and being willing to work for a very low remuneration may prefer the latter. Segmentation among the poor, some of which may be also due to them being non-documented aliens, creates perhaps what Marx called "the reserve army of the unemployed" which may be conveniently used to improve real incomes of the rich.

6. Robustness checks

In this Section we present briefly several robustness checks of our results. A couple of others are relegated to the Annex. Tables 5 and 6 present the same results as Tables 3 and 4 (that is, for respectively total Gini, and bottom and top Ginis) using system GMM estimation. System GMM is useful in dynamic panels like ours because it addresses simultaneously the omitted variable bias and endogeneity, and exploits the variation of growth rates over time in each state as well as inter-state variation (see Blundell and Bond, 1998). We use Principal Component Analysis to reduce the number of instruments in an effective manner. Using too many instruments relative to the dimension of the panel data is found to reduce the effectiveness of the System GMM estimator (see e.g. Roodman, 2009, 2012).

Table 5. System GMM estimation with total Gini (dependent variable = per capita income growth at given percentile of state income distribution; 1960-2010; five 10-year periods)

	dlny5	dlny10	dlny25	dlny50	dlny75	dlny90	dlny95	dlny99
Gini	-0.306	-0.294*	-0.166*	0.0116	0.118**	0.143***	0.172***	0.204***
	(-1.57)	(-1.75)	(-1.70)	(0.20)	(2.47)	(3.26)	(3.68)	(2.92)
edu_ms_age2139	0.0561	0.0983	0.115*	0.109**	0.0936*	0.0994**	0.0987**	0.106*
	(0.75)	(1.23)	(1.87)	(2.04)	(1.83)	(2.18)	(2.32)	(1.92)
edushort1518	-0.131***	-0.0956***	-0.0526***	-0.0362***	-0.0410***	-0.0343***	-0.0254**	-0.0242
	(-4.27)	(-4.86)	(-4.05)	(-3.23)	(-3.56)	(-3.05)	(-2.34)	(-1.41)
age015	0.000659	-0.105	-0.202*	-0.214**	-0.209**	-0.228***	-0.239***	-0.225**
	(0.00)	(-0.88)	(-2.00)	(-2.29)	(-2.44)	(-3.28)	(-3.35)	(-2.61)
age65	-0.0609	-0.00419	0.00420	-0.0186	-0.0467	-0.0597	-0.0466	-0.00804
	(-0.34)	(-0.03)	(0.05)	(-0.23)	(-0.58)	(-0.87)	(-0.77)	(-0.12)
olf_female	-0.183***	-0.150***	-0.106***	-0.0982***	-0.0915***	-0.0686**	-0.0592**	-0.0506
	(-2.82)	(-2.84)	(-2.97)	(-3.02)	(-2.94)	(-2.68)	(-2.18)	(-0.94)
log income	-0.0987***	-0.103***	-0.0938***	-0.0810***	-0.0712***	-0.0649***	-0.0537***	-0.0573***
	(-4.47)	(-4.63)	(-5.19)	(-4.88)	(-4.43)	(-4.70)	(-4.40)	(-3.75)
constant	1.133***	1.181***	1.074***	0.919***	0.822***	0.766***	0.644***	0.685***
	(4.58)	(4.89)	(5.42)	(5.10)	(4.65)	(5.15)	(4.95)	(3.99)
N	245	245	245	245	245	245	245	245
Hansenp	0.590	0.461	0.110	0.202	0.227	0.109	0.191	0.114
ar1p	0.000744	0.0000457	0.0000362	0.00000606	0.0000219	0.0000261	0.00000819	0.000127
ar2p	0.817	0.172	0.0726	0.0162	0.0643	0.235	0.957	0.318
instruments	33	33	33	33	33	33	33	33

Note: All right-hand side variables estimated at time *t-1*. Income is household per capita. Gini calculated across individuals ranked by their household per capita income. *t*-statistics in parentheses.
* p<0.1, ** p<0.05, *** p<0.01. Time-period dummies are included but not reported.

Table 6. System GMM estimation with bottom and top Ginis
(dependent variable = per capita income growth at given percentile of state income distribution; 1960-2010; five 10-year periods)

	dlny5	dlny10	dlny25	dlny50	dlny75	dlny90	dlny95	dlny99
gini_b40	-0.643	-0.0167	0.201	0.267**	0.258***	0.227**	0.188**	0.323**
	(-1.60)	(-0.08)	(1.65)	(2.63)	(2.69)	(2.60)	(2.26)	(2.63)
gini_t40	-0.447*	-0.414*	-0.309*	-0.281**	-0.126	-0.0423	0.0831	-0.0440
	(-1.70)	(-1.71)	(-1.83)	(-2.03)	(-0.99)	(-0.35)	(0.70)	(-0.22)
edu_ms_age2139	0.172*	0.0645	0.0327	0.0608	0.0531	0.0695	0.0978**	0.0274
	(1.68)	(0.82)	(0.56)	(1.02)	(0.89)	(1.36)	(2.43)	(0.48)
edushort1518	-0.111***	-0.0920***	-0.0628***	-0.0588***	-0.0602***	-0.0530***	-0.0437**	-0.0581**
	(-3.35)	(-3.32)	(-2.93)	(-2.96)	(-3.12)	(-2.84)	(-2.43)	(-2.50)
age015	-0.231	-0.0448	-0.0163	-0.00462	-0.0370	-0.102	-0.167*	0.00797
	(-0.90)	(-0.23)	(-0.11)	(-0.04)	(-0.33)	(-1.15)	(-1.92)	(0.05)
age65	-0.119	0.0547	0.0808	0.0799	0.0298	-0.0151	-0.0473	0.0663
	(-0.59)	(0.42)	(0.90)	(0.94)	(0.36)	(-0.21)	(-0.63)	(0.70)
olf_female	-0.115*	-0.148**	-0.140***	-0.117**	-0.108**	-0.0909**	-0.0727**	-0.119**
	(-1.69)	(-2.35)	(-2.83)	(-2.61)	(-2.40)	(-2.36)	(-2.35)	(-2.36)
log income	-0.141***	-0.0922***	-0.0621***	-0.0612***	-0.0552***	-0.0558***	-0.0543***	-0.0346**
	(-4.37)	(-4.06)	(-3.62)	(-3.40)	(-3.05)	(-3.80)	(-4.75)	(-2.04)
constant	1.618***	1.055***	0.729***	0.703***	0.649***	0.674***	0.654***	0.446**
	(4.33)	(4.07)	(3.82)	(3.67)	(3.37)	(4.35)	(5.21)	(2.34)
N	245	245	245	245	245	245	245	245
hansenp	0.355	0.302	0.127	0.137	0.190	0.104	0.303	0.338
ar1p	0.000299	0.0000480	0.0000644	0.00000838	0.0000141	0.0000575	0.0000126	0.000384
ar2p	0.867	0.108	0.0842	0.0488	0.0779	0.421	0.621	0.420
instruments	34	34	34	34	34	34	34	34

Note: All right-hand side variables estimated at time *t-1*. Income is household per capita. Gini calculated across individuals ranked by their household per capita income. *t*-statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Time-period dummies are included but not reported.

We discuss here only the role of inequality, because the effects of the control variables are very similar to what we found in the pooled regressions. As before, the overall Gini (Table 5) displays a statistically significant and positive effect for the growth of the rich (the top 40%) and the reverse for the growth at 10th and 25th percentile (although the statistical significance of the latter two is less). Also here, the coefficient increases monotonically as we move from the poor percentiles toward the rich. The Hansen test accepts the hypothesis of orthogonality of the instruments although not with equal strength across the distribution.

When we use separately inequality among the bottom and inequality among the top (Table 6), the results change slightly compared to the initial formulation. Now, inequality among the bottom 40% does not have a discernable negative effect on their growth rate, but remains positive correlated with the growth rate of the rich. Inequality among the rich still remains bad for the growth of the poor and its effect now extends to the entire lower half of the income distribution. Above that point, inequality among the rich is neutral.

7. Conclusions

The objective of this paper is to "unpack" both inequality and growth and estimate how different types of inequality may impact subsequent growth at different points of the income distribution. We do this using US micro-census data covering between 1 and 5 percent of the population, at ten-year intervals, over the period 1960-2010. The paper was motivated by two principal concerns: failure to find anything resembling a systematic relationship between inequality and growth in formulations where both inequality and growth were used as single, "homogeneous" variables, and a gradual realization that both variables are much more complex. The very fact that the earlier literature often found that the sign of the effect switched between positive and negative may be interpreted as implying the existence of heterogeneity in the variables, with for example one type of inequality being dominant at one time (or place) and producing one type of effect, and another type of inequality, with the opposite effect, being more important at a different time or place. Thus, breaking both inequality and growth into inequality/growth among the rich and among the poor provides, we believe, a much more nuanced and realistic picture of the possible relationship.

In the first part of the paper, we keep total inequality as a single variable and look at its effects along US states' income distributions. We find that inequality is negatively associated with subsequent growth rates among the poorer income percentiles, and positively among the higher percentiles. In the main part of the paper, we decompose total inequality into inequality among the poor (bottom 40%) and the rich (top 40 %). We find that both top and bottom inequalities are negatively associated with real income growth of the poor, but that the bottom inequality is in addition positively associated with the growth of the rich. As the summary in Table 7 shows, these effects are present in all six formulations even if at times their statistical significance varies and the exact ranges of the top and bottom income distributions for which a given type of inequality is bad or good slightly differ.

We cannot test for the channels whereby inequality has such effects, and are reduced to simply proposing some plausible hypotheses. Following other authors (Bénabou, 1996b, 2000; Lloyd-Ellis, 2000), we believe that the "social separatism" implied by high inequality among the rich results in their lack of interest in financing many public goods that are crucial for the sustained income growth of the poor. We think that this may be a mechanism explaining why inequality among the rich may have a negative impact on income growth of the poor. More tentatively, we argue that segmentation among the poor (implied by high inequality among them) might provide the rich with opportunities to "exploit" them as a very cheap and pliant labor force unable to command sufficient market wage due perhaps to its insecurity of economic and social status. However, both points are, at this stage, conjectures and their acceptance or rejection clearly requires more empirical and theoretical work.

Table 7. The effect of inequality among the poor and the rich on income growth among the poor and the rich: a summary

	Pooled regression (regional FE)		GMM estimation		State fixed effects (see Annex)	
	Bottom growth	Top growth	Bottom growth	Top growth	Bottom growth	Top Growth
Total Gini	Negative ≤25	Positive ≥75	Negative ≤25	Positive ≥75	Negative ≤75	---
Bottom Gini	Negative ≤10	Positive ≥90	---	Positive ≥50	Negative ≤10	---
Top Gini	Negative ≤50	-----	Negative ≤50	---	---	---

Note: number indicates the percentiles to which the effect applies (e.g. ≤10 means that the effect applies to the people whose incomes are equal to, or below, the 10th percentile). "---" indicates no statistically significant effect.

If our key results hold with other datasets and formulations, they may have both optimistic and pessimistic implications. On the positive side, they should make evident the importance of lower inequality for faster growth of the poor or for a more sustained trickle-down. The "trickle-down" effect and high inequality rather than going together would be shown to exclude each other. On the more pessimistic side, if high inequality is positively associated with income growth of the rich, there is no reason for the rich to change such a pattern of growth. And since the recent empirical political literature shows that the rich largely control the political process (Page, Bartels and Seawright, 2011; Gilens and Page, 2014), it is unclear from where the pressure to change would come from.

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Annex

Table A1. Four statistical regions: Northeast, Midwest, South, and West

Region	States
Northeast	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont, New Jersey, New York, Pennsylvania
Midwest	Illinois, Indiana, Michigan, Ohio, Wisconsin, Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South	Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, Washington DC, West Virginia, Alabama, Kentucky, Mississippi, Tennessee, Arkansas, Louisiana, Oklahoma, Texas
West	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming, Alaska, California, Hawaii, Oregon, Washington

For Online Publication

Growth and inequality by State: 1960 – 2010

Table WA1. Growth of median income (per capita, p.a.) and level of Gini coefficient by state

	Growth of median income					Gini					
State	1960	1970	1980	1990	2000	1960	1970	1980	1990	2000	2010
Alabama	0.040	0.021	0.018	0.015	0.000	0.473	0.445	0.422	0.439	0.463	0.466
Alaska	0.029	0.027	0.006	-0.004	0.004	0.451	0.430	0.423	0.411	0.429	0.440
Arizona	0.027	0.014	0.012	0.010	-0.005	0.423	0.422	0.404	0.444	0.472	0.475
Arkansas	0.048	0.021	0.015	0.017	-0.002	0.480	0.439	0.417	0.435	0.457	0.458
California	0.019	0.007	0.014	-0.003	-0.002	0.390	0.407	0.408	0.451	0.505	0.499
Colorado	0.024	0.020	0.012	0.017	-0.004	0.398	0.402	0.388	0.416	0.446	0.456
Connecticut	0.024	0.004	0.036	0.001	-0.002	0.363	0.374	0.376	0.399	0.464	0.468
Delaware	0.020	0.011	0.028	0.006	-0.001	0.393	0.395	0.394	0.390	0.438	0.437
DC	0.015	0.011	0.026	0.001	0.032	0.466	0.495	0.481	0.495	0.570	0.535
Florida	0.033	0.014	0.019	0.007	-0.006	0.435	0.429	0.408	0.430	0.470	0.472
Georgia	0.045	0.016	0.025	0.012	-0.010	0.462	0.434	0.419	0.438	0.468	0.474
Hawaii	0.041	0.004	0.023	-0.001	0.008	0.396	0.378	0.394	0.397	0.432	0.414
Idaho	0.025	0.011	0.009	0.014	-0.007	0.377	0.381	0.387	0.414	0.439	0.443
Illinois	0.021	0.010	0.011	0.010	-0.005	0.384	0.391	0.391	0.425	0.458	0.466
Indiana	0.027	0.010	0.012	0.013	-0.011	0.384	0.375	0.372	0.395	0.420	0.440
Iowa	0.029	0.018	0.008	0.015	0.001	0.402	0.384	0.377	0.394	0.410	0.418
Kansas	0.025	0.019	0.008	0.014	0.001	0.397	0.394	0.383	0.411	0.431	0.440
Kentucky	0.039	0.019	0.013	0.017	-0.002	0.465	0.434	0.409	0.432	0.454	0.450
Louisiana	0.032	0.029	-0.003	0.019	0.010	0.467	0.457	0.432	0.470	0.477	0.465
Maine	0.026	0.011	0.031	0.009	0.004	0.375	0.375	0.369	0.381	0.422	0.418
Maryland	0.032	0.011	0.027	0.005	0.006	0.396	0.395	0.387	0.398	0.434	0.443
Massachusetts	0.024	0.005	0.036	0.006	0.003	0.359	0.377	0.377	0.393	0.448	0.454
Michigan	0.029	0.010	0.012	0.013	-0.013	0.385	0.378	0.379	0.413	0.437	0.444
Minnesota	0.032	0.017	0.016	0.018	-0.002	0.403	0.384	0.371	0.395	0.417	0.435
Mississippi	0.050	0.031	0.012	0.021	-0.003	0.523	0.479	0.441	0.464	0.477	0.469
Missouri	0.029	0.013	0.014	0.013	-0.004	0.420	0.409	0.389	0.416	0.439	0.443
Montana	0.023	0.016	0.004	0.012	0.015	0.389	0.400	0.385	0.410	0.435	0.430
Nebraska	0.028	0.018	0.008	0.017	0.001	0.404	0.397	0.382	0.396	0.420	0.423
Nevada	0.017	0.012	0.008	0.005	-0.008	0.385	0.389	0.382	0.406	0.448	0.459
New Hampshire	0.022	0.014	0.036	0.008	0.005	0.353	0.372	0.359	0.363	0.405	0.414

New Jersey	0.023	0.005	0.032	0.004	0.002	0.367	0.375	0.378	0.401	0.450	0.449
New Mexico	0.007	0.022	0.008	0.013	0.007	0.441	0.455	0.428	0.461	0.480	0.472
New York	0.021	-0.001	0.027	0.000	0.003	0.387	0.411	0.412	0.445	0.499	0.497
North Carolina	0.051	0.015	0.025	0.013	-0.009	0.471	0.415	0.397	0.414	0.449	0.467
North Dakota	0.033	0.022	0.008	0.018	0.015	0.404	0.404	0.388	0.399	0.416	0.412
Ohio	0.023	0.011	0.011	0.014	-0.008	0.383	0.383	0.374	0.407	0.433	0.444
Oklahoma	0.027	0.019	0.006	0.011	0.001	0.431	0.414	0.407	0.438	0.453	0.460
Oregon	0.023	0.013	0.007	0.013	-0.005	0.381	0.386	0.379	0.407	0.440	0.449
Pennsylvania	0.024	0.010	0.018	0.009	0.002	0.378	0.380	0.375	0.406	0.439	0.443
Rhode Island	0.027	0.004	0.028	0.005	0.003	0.364	0.382	0.371	0.391	0.443	0.455
South Carolina	0.049	0.021	0.020	0.015	-0.005	0.486	0.444	0.408	0.423	0.450	0.458
South Dakota	0.032	0.017	0.013	0.021	0.007	0.423	0.415	0.397	0.402	0.425	0.439
Tennessee	0.040	0.019	0.019	0.015	-0.007	0.460	0.426	0.412	0.432	0.458	0.458
Texas	0.032	0.020	0.004	0.012	-0.001	0.455	0.433	0.425	0.467	0.491	0.488
Utah	0.021	0.010	0.006	0.021	-0.006	0.371	0.373	0.380	0.397	0.421	0.435
Vermont	0.034	0.007	0.033	0.008	0.007	0.388	0.375	0.383	0.374	0.421	0.426
Virginia	0.040	0.017	0.025	0.009	0.006	0.453	0.423	0.405	0.418	0.453	0.457
Washington	0.027	0.013	0.012	0.011	0.000	0.376	0.383	0.378	0.403	0.447	0.446
West Virginia	0.027	0.026	0.003	0.014	0.007	0.442	0.412	0.395	0.427	0.456	0.435
Wisconsin	0.025	0.014	0.013	0.017	-0.005	0.388	0.377	0.362	0.386	0.409	0.424
Wyoming	0.013	0.028	-0.007	0.015	0.011	0.389	0.382	0.373	0.404	0.431	0.430

Table WA2. Bottom and top Gini by state and year

	Gini of bottom 40 percent						Gini of top 40 percent					
State	1960	1970	1980	1990	2000	2010	1960	1970	1980	1990	2000	2010
Alabama	0.318	0.283	0.277	0.282	0.274	0.291	0.270	0.265	0.243	0.267	0.307	0.283
Alaska	0.280	0.268	0.291	0.242	0.250	0.252	0.271	0.263	0.226	0.246	0.265	0.269
Arizona	0.261	0.257	0.255	0.281	0.267	0.284	0.258	0.268	0.241	0.269	0.310	0.287
Arkansas	0.291	0.280	0.255	0.267	0.257	0.271	0.290	0.268	0.252	0.276	0.311	0.279
California	0.220	0.240	0.252	0.261	0.271	0.275	0.243	0.255	0.240	0.275	0.332	0.311
Colorado	0.232	0.229	0.241	0.251	0.248	0.275	0.258	0.255	0.229	0.257	0.297	0.277
Connecticut	0.190	0.210	0.231	0.236	0.260	0.280	0.236	0.236	0.227	0.250	0.317	0.303
Delaware	0.225	0.235	0.252	0.236	0.254	0.277	0.251	0.256	0.234	0.237	0.290	0.260
DC	0.247	0.278	0.294	0.301	0.341	0.360	0.286	0.312	0.281	0.306	0.371	0.302
Florida	0.252	0.253	0.249	0.256	0.254	0.270	0.278	0.275	0.251	0.273	0.326	0.309
Georgia	0.292	0.275	0.273	0.273	0.268	0.287	0.271	0.258	0.244	0.271	0.312	0.290
Hawaii	0.196	0.224	0.235	0.233	0.248	0.257	0.250	0.230	0.236	0.248	0.280	0.261
Idaho	0.206	0.208	0.228	0.222	0.230	0.253	0.247	0.240	0.235	0.271	0.303	0.277
Illinois	0.232	0.234	0.262	0.271	0.268	0.281	0.232	0.243	0.225	0.266	0.305	0.293
Indiana	0.226	0.218	0.236	0.244	0.246	0.276	0.238	0.239	0.220	0.246	0.280	0.270

Iowa	0.238	0.209	0.229	0.229	0.230	0.265	0.256	0.247	0.228	0.253	0.278	0.258
Kansas	0.227	0.225	0.229	0.237	0.240	0.267	0.247	0.249	0.232	0.263	0.289	0.274
Kentucky	0.302	0.271	0.271	0.283	0.271	0.284	0.279	0.262	0.237	0.261	0.298	0.272
Louisiana	0.289	0.296	0.297	0.318	0.289	0.284	0.286	0.276	0.252	0.285	0.313	0.288
Maine	0.196	0.202	0.220	0.219	0.235	0.257	0.236	0.243	0.222	0.242	0.289	0.258
Maryland	0.236	0.234	0.253	0.247	0.257	0.278	0.241	0.245	0.224	0.241	0.279	0.260
Massachusetts	0.193	0.212	0.233	0.240	0.265	0.289	0.224	0.235	0.223	0.240	0.296	0.284
Michigan	0.221	0.223	0.241	0.267	0.255	0.287	0.235	0.238	0.221	0.255	0.291	0.267
Minnesota	0.242	0.219	0.225	0.230	0.238	0.269	0.256	0.241	0.222	0.256	0.280	0.273
Mississippi	0.318	0.294	0.280	0.301	0.281	0.285	0.301	0.282	0.258	0.283	0.319	0.285
Missouri	0.256	0.242	0.242	0.252	0.253	0.272	0.251	0.258	0.233	0.262	0.297	0.275
Montana	0.224	0.222	0.236	0.255	0.252	0.273	0.246	0.267	0.233	0.258	0.285	0.261
Nebraska	0.232	0.232	0.229	0.224	0.233	0.267	0.251	0.251	0.232	0.259	0.284	0.250
Nevada	0.221	0.207	0.232	0.236	0.244	0.270	0.236	0.246	0.230	0.258	0.308	0.294
N. Hampshire	0.205	0.201	0.216	0.210	0.224	0.248	0.226	0.245	0.216	0.225	0.274	0.264
New Jersey	0.208	0.216	0.246	0.244	0.259	0.276	0.227	0.236	0.221	0.247	0.294	0.274
New Mexico	0.283	0.277	0.269	0.281	0.265	0.274	0.265	0.276	0.252	0.283	0.318	0.289
New York	0.218	0.236	0.261	0.276	0.290	0.295	0.244	0.259	0.248	0.283	0.340	0.325
North Carolina	0.314	0.261	0.251	0.248	0.258	0.287	0.275	0.251	0.234	0.257	0.299	0.286
North Dakota	0.244	0.231	0.237	0.234	0.242	0.272	0.244	0.263	0.233	0.256	0.282	0.249
Ohio	0.224	0.223	0.243	0.264	0.256	0.292	0.235	0.241	0.219	0.253	0.290	0.266
Oklahoma	0.261	0.239	0.242	0.261	0.254	0.275	0.268	0.261	0.249	0.277	0.304	0.294
Oregon	0.210	0.227	0.227	0.236	0.247	0.271	0.242	0.243	0.228	0.259	0.290	0.270
Pennsylvania	0.219	0.217	0.236	0.248	0.257	0.279	0.237	0.241	0.222	0.261	0.296	0.280
Rhode Island	0.206	0.230	0.230	0.235	0.272	0.299	0.230	0.243	0.223	0.243	0.287	0.271
South Carolina	0.329	0.292	0.265	0.267	0.265	0.286	0.278	0.263	0.238	0.256	0.296	0.281
South Dakota	0.276	0.242	0.258	0.255	0.252	0.273	0.261	0.257	0.235	0.251	0.290	0.279
Tennessee	0.295	0.263	0.266	0.270	0.261	0.281	0.270	0.259	0.244	0.273	0.313	0.283
Texas	0.286	0.262	0.273	0.289	0.272	0.282	0.276	0.266	0.248	0.286	0.326	0.300
Utah	0.205	0.204	0.213	0.220	0.225	0.250	0.239	0.240	0.234	0.259	0.290	0.275
Vermont	0.207	0.208	0.224	0.208	0.234	0.262	0.246	0.234	0.232	0.234	0.286	0.265
Virginia	0.289	0.259	0.254	0.251	0.254	0.275	0.269	0.259	0.241	0.257	0.299	0.280
Washington	0.194	0.218	0.234	0.240	0.253	0.282	0.236	0.242	0.222	0.247	0.297	0.264
West Virginia	0.289	0.261	0.254	0.282	0.272	0.272	0.262	0.249	0.235	0.260	0.305	0.266
Wisconsin	0.219	0.216	0.220	0.233	0.237	0.273	0.240	0.236	0.217	0.247	0.274	0.259
Wyoming	0.241	0.222	0.219	0.236	0.240	0.243	0.239	0.234	0.229	0.256	0.291	0.268

State-level Fixed Effects estimation of growth regression model

Table WA3. State-level fixed effect estimation with overall Gini

	dlny5	dlny10	dlny25	dlny50	dlny75	dlny90	dlny95	dlny99
gini	-0.239**	-0.310***	-0.338***	-0.197***	-0.102***	-0.0161	0.0244	-0.0181
	(-2.22)	(-2.86)	(-4.82)	(-4.30)	(-3.15)	(-0.57)	(0.83)	(-0.46)
edu_ms_age2139	0.0112	0.0462	0.121***	0.160***	0.170***	0.164***	0.160***	0.165***
	(0.21)	(1.13)	(3.20)	(4.93)	(5.61)	(5.84)	(5.45)	(6.42)
edushort1518	-0.0644***	-0.0532***	-0.0314***	-0.0227***	-0.0231***	-0.0224***	-0.0198***	-0.00729
	(-5.57)	(-5.31)	(-4.13)	(-3.58)	(-4.15)	(-4.72)	(-3.75)	(-1.04)
age015	-0.215**	-0.192**	-0.148**	-0.169***	-0.173***	-0.169***	-0.150***	-0.121**
	(-2.13)	(-2.51)	(-2.35)	(-3.22)	(-3.57)	(-3.71)	(-3.29)	(-2.12)
age65	-0.0860	-0.0477	-0.0249	-0.0645	-0.0842*	-0.0637	-0.0659	-0.0490
	(-0.81)	(-0.62)	(-0.36)	(-1.18)	(-1.87)	(-1.53)	(-1.23)	(-0.75)
olf_female	-0.0769*	-0.0682*	-0.0455	-0.0488**	-0.0281	-0.0150	-0.00785	0.0289
	(-1.71)	(-1.83)	(-1.59)	(-2.05)	(-1.30)	(-0.74)	(-0.39)	(1.02)
log income	-0.105***	-0.111***	-0.122***	-0.128***	-0.127***	-0.110***	-0.0955***	-0.106***
	(-12.57)	(-10.14)	(-12.42)	(-15.06)	(-13.76)	(-11.50)	(-9.53)	(-9.41)
constant	1.111***	1.209***	1.320***	1.378***	1.381***	1.222***	1.069***	1.205***
	(10.77)	(9.29)	(12.22)	(15.29)	(14.00)	(11.83)	(9.98)	(9.59)
N	245	245	245	245	245	245	245	245
adj. R-sq	0.820	0.847	0.866	0.866	0.856	0.860	0.880	0.926

Note: All right-hand side variables estimated at time *t-1*. Income is household per capita. Gini calculated across individuals ranked by their household per capita income. *t*-statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Time-period dummies are included but not reported.

Table WA4. State-level fixed effect estimation with top and bottom Gini

	dlny5	dlny10	dlny25	dlny50	dlny75	dlny90	dlny95	dlny99
gini_b40	-0.483**	-0.247**	-0.0822	-0.0455	-0.0459	-0.0196	0.00331	-0.00697
	(-2.17)	(-2.43)	(-1.42)	(-1.20)	(-1.53)	(-0.82)	(0.13)	(-0.18)
gini_t40	-0.0217	-0.0230	-0.0195	0.00502	0.0260	0.0669	0.0730	0.0706
	(-0.21)	(-0.29)	(-0.29)	(0.05)	(0.32)	(1.03)	(1.28)	(0.92)
edu_ms_age2139	0.0763	0.0477	0.0624	0.117***	0.151***	0.158***	0.157***	0.152***
	(1.09)	(0.93)	(1.56)	(3.41)	(4.62)	(5.25)	(5.27)	(5.70)
edushort1518	-0.0665***	-0.0467***	-0.0255***	-0.0204***	-0.0194***	-0.0173***	-0.0144**	0.000567
	(-5.57)	(-4.67)	(-3.25)	(-3.14)	(-3.36)	(-3.38)	(-2.60)	(0.07)
age015	-0.365***	-0.315***	-0.190***	-0.206***	-0.217***	-0.215***	-0.191***	-0.195**
	(-3.29)	(-3.50)	(-2.85)	(-3.66)	(-4.15)	(-4.06)	(-3.53)	(-2.66)
age65	-0.169	-0.0562	0.00791	-0.0299	-0.0619	-0.0499	-0.0497	-0.0236
	(-1.43)	(-0.68)	(0.11)	(-0.52)	(-1.27)	(-1.13)	(-0.90)	(-0.35)
olf_female	-0.0809	-0.0736*	-0.0737**	-0.0682***	-0.0366	-0.0164	-0.00498	0.0281
	(-1.67)	(-1.89)	(-2.46)	(-2.73)	(-1.58)	(-0.79)	(-0.25)	(1.01)
log income	-0.128***	-0.108***	-0.0912***	-0.103***	-0.113***	-0.104***	-0.0927***	-0.0964***
	(-7.00)	(-8.75)	(-8.41)	(-9.36)	(-10.01)	(-10.02)	(-10.56)	(-8.88)
constant	1.371***	1.161***	0.968***	1.101***	1.229***	1.150***	1.037***	1.097***
	(6.86)	(8.57)	(8.52)	(9.46)	(10.10)	(10.35)	(11.11)	(9.20)
N	250	250	250	250	250	250	250	250
adj. R-sq	0.824	0.844	0.855	0.850	0.838	0.845	0.864	0.911

Note: All right-hand side variables estimated at time *t-1*. Income is household per capita. Gini calculated across individuals ranked by their household per capita income. *t*-statistics in parentheses. * p<0.1, ** p<0.05, *** p<0.01. Time-period dummies are included but not reported.