

Inequality is Bad for Growth of the Poor (but Not for That of the Rich)

Roy van der Weide and Branko Milanovic

Abstract

The paper investigates the relationship between income inequality and future income growth rates of households at different points of the income distribution. The analysis uses micro-census data from U.S. states covering the period from 1960 to 2010, and controls for exposure to imports from China and share of routine jobs, among other variables. It finds evidence that high levels of inequality reduce the income growth of the poor but, if anything, help the growth of the rich.

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1. Introduction

Does high inequality today bode well for future rates of income growth? This question has recently acquired added relevance because of the slowdown of growth in rich countries and simultaneously rising inequality. The relationship between inequality and growth was extensively researched empirically in the 1980s and 1990s with interest declining afterwards.¹ Unfortunately, the results ultimately proved to be inconclusive, as the relationship was found weak and inequality at times seemed positively and at times negatively related to growth (see, e.g., Partridge 1997; Panizza 2002).

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 a negative association (see, for instance, Persson

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1 For reviews of the inequality-growth literature, see, e.g., Aghion, Caroli, and Garcia-Peñalosa (1999); and Bénabou (1996a).

and Tabellini [1994]; Alesina and Rodrik [1994]; and Perotti [1996]).² In Barro (2000) and Banerjee and Duflo (2003), the baseline results were largely inconclusive.

Recently, Voitchovsky (2005) and Marrero and Rodriguez (2012, 2013) have had some success by showing that total inequality is built up of 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 (estimated to be inequality due to “inherited” characteristics such as gender, race, or parental background) and treat the residual inequality as a measure of inequality of efforts. In two separate applications, one to the EU and one to the United States, 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, for instance, Ferreira et al. (2018).

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 to be only interested in how it might affect growth of the average income, not in how it might affect growth rates at various parts of the distribution. One would think that we would be specifically interested in how individuals at different steps of the socioeconomic ladder would fare in societies with different levels of inequality.

Indeed, the logical next step is to disaggregate growth and to verify whether income growths of the poor and the rich are affected differently by inequality. 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 against growth at a wide range of percentiles of the income distribution.

We find that high inequality appears to hurt only the income growth of the poor. When inequality is 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. As such, our study may offer a new perspective on the persistent rise in inequality in the United States in recent decades. 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.

The literature on wage inequality attributes the rise in inequality in recent decades in part to skill-biased technological change and international trade (or offshoring) which have put pressure on the wages of lower-skilled workers and have increased the relative demand for higher-skilled workers (and hence their wages) (see, for instance, Autor, Katz, and Kearney [2008]; Kierzenkowski and Koske [2012]; Autor and Dorn [2013]; and Autor, Dorn, and Hansen [2013, 2015]). We control for both exposure to trade from China and the share of routine jobs that are vulnerable to automation, and we can confirm that (1) competition from China, like inequality, is bad for growth prospects of the poor but not for that of the rich; (2) the share of routine jobs is positively associated with future growth, except for the poor; and (3) controlling for both of these variables (in addition to other controls) does not weaken the effect of inequality on future growth incidence.

Our results are consistent with the recent literature in political science (e.g., Bartels 2010; Gilens and Page 2014) that empirically documents overwhelming control of the political process by the rich. To see this, note that the implication of our results is not just that inequality is good for the rich in the usual

2 More recently, Benjamin, Brandt, and Giles (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.

sense, namely that given the size of the “pie,” greater inequality means higher incomes for the rich, but also implies that higher inequality today disproportionately helps subsequent income growth of the rich. Our hypothesis is that the way it does this is through a political channel that allows the rich to lobby and to have implemented the policies that are in their economic interest. Proving this particular mechanism is beyond the scope of this paper; it could be addressed in future work.

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” the inequality-growth relationship. Section 4 offers a first look at the data. The empirical results, and a discussion of their significance, are presented in section 5. Section 6 provides robustness checks, and section 7 concludes. In this last section, we also present an inductively derived tentative hypothesis linking inequality and growth.

2. Candidate Channels Put Forward in the Inequality-Growth 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 \(1998\)](#).³ The findings of [Forbes \(2000\)](#), 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.⁴ A similar observation is made in [Halter, Oechlin, and Zweimuller \(2014\)](#).

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 \(1994\)](#), [Alesina and Rodrik \(1994\)](#), and [Perotti \(1996\)](#).⁵ 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.⁶ 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.⁷ [Li, Squire, and Zou \(1998\)](#) and [Oded Galor and co-authors \(see Galor and Zeira 1993; Galor and Moav 2004; and Galor 2009\)](#) put the emphasis on credit-market imperfections, namely the inability of the poor

3 The authors were criticized for exclusion of many developing countries and the small number of observations (a problem particularly acute in a dynamic panel setting), econometric procedures, and inadequate inequality statistics (see, e.g., [Aghion, Caroli, 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.

4 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 \(1998\)](#).

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

6 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 at that time.

7 [Ostry, Berg, and Tsangarides \(2014\)](#), in a recent study on redistribution, inequality, and growth, also note that equality-enhancing interventions need not necessarily be bad for growth.

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.

Barro (2000) found the relationship between inequality and growth to be inconclusive. When he split his sample into a low-income sample and a high-income one, 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. The debate on the relationship between inequality and growth became more quiescent after this inconclusiveness.⁸

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.

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 member countries of the European Union and one to the states of the United States, they find strong evidence that levels of inequality of opportunity are negatively correlated with growth while the residual (“good inequality”) helps growth.

Voitchovsky (2005) evaluates inequality among the poor (the 50/10 ratio) and inequality among the rich (the 90/50 ratio) as two separate inequalities.⁹ 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.¹⁰ It might also lead to greater crime and social instability. In contrast, 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. 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 looking at different parts of the income distribution.

The evolution of data has played an important role in shaping the empirical literature on inequality growth. A lack of conclusive results may in part be attributed to the limitations of the data that were available at the time. At best, after the much-used Deininger and Squire (1996) dataset, the new datasets (e.g., UN WIDER’s World Income Inequality Dataset [WIID]) 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.¹¹

- 8 A useful metastudy of the inequality and growth literature is by de Dominicis, de Groot, and Florax (2006).
- 9 Voitchovsky (2005) uses standardized micro data from 81 surveys covering 21 rich countries, in a dynamic panel setting with 5-year intervals coinciding broadly with survey data availability.
- 10 See also the recent study by Ravallion (2012), who directly compares the effects of initial poverty and inequality levels on future growth.
- 11 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]). For a recent review of cross-country income inequality databases, including the WIID, see Jenkins (2015).

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.

3. The Data and Regression Framework

We compute state-level inequality and income growth rates using individual-level data from the Integrated Public Use Microdata Survey (IPUMS) for the United States. We use six surveys made over a period of 50 years at regular decennial intervals: in 1960, 1970, 1980, 1990, 2000, and 2010. The IPUMS is a large micro-census that provides a 1 percent or 5 percent samples from every U.S. state (1 percent for the years 1960, 1970, and 2010; 5 percent for the years 1980 to 2000) (see [Ruggles et al. 2010](#)). The obvious advantage of working with such large data sets is that it reduces sampling errors to a minimum.

Total income over the past 12 months (which is our key variable) is obtained by aggregating incomes from eight 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-year-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).¹² We aggregate income data over all members of a household and then divide it by the household size to obtain household gross (that is, before-tax) per capita income.

The IPUMS is also used to construct selected control variables, namely variables on demographics and education. Additional controls are obtained from [Marrero and Rodriguez \(2013\)](#) and [Autor, Dorn, and Hansen \(2015\)](#). From [Marrero and Rodriguez \(2013\)](#) we borrow state-level data on sectors of employment and public welfare expenditure. From [Autor, Dorn, and Hansen \(2015\)](#) we borrow data on the share of routine jobs and exposure to imports from China. These latter two variables are derived at the commuting zone level (roughly 740 clusters of counties that exhibit strong commuting ties). We aggregate this data to the state level using population weights provided by the authors. The share of routine jobs is available for 1950 and the decades from 1970 through 2000. Data for 1960 are obtained by means of interpolation (after which data for 1950 are omitted from our analysis). The measure that captures exposure to imports from China is available for 1990 and 2000. We extrapolate this data to obtain values for the earlier decades. The extrapolated data suggest that exposure to imports from China was small in 1980 and smaller still in 1960–1970, which is consistent with aggregate data on U.S. imports from China. For further details on the original data and definitions of the variables, we refer the reader to [Autor and Dorn \(2013\)](#) and [Autor, Dorn, and Hansen \(2013, 2015\)](#).

Our analysis is conducted at the level of U.S. states.¹³ Growth is measured in anonymous terms because the surveys are not longitudinal and we do not have information about household per capita income for

- 12 All incomes are adjusted using the same rate of inflation. It is, of course, possible that poor households and rich ones have been subjected to different rates of price inflation over the years (see, e.g., [Hobijn and Lagakos 2005](#)) as households from different ends of the income spectrum arguably consume distinctively different baskets of goods.
- 13 One advantage of working with a single country (the United States in this case), with data from a single source, is that the data are comparable between units of observation. Cross-country income inequality and growth data that lack the same degree of comparability, as different countries measure incomes (as well as other variables used in the regressions) differently, which introduces measurement error (see [Knowles 2005](#); [Jenkins 2015](#)). 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 same persons over several periods. Empirically, we ask in effect the following question: How does the overall Gini at time $t - 1$ affect the growth rate at different percentiles of the income distribution between times $t - 1$ and t ? (The times $t - 1$ and t are, as indicated, always 10 years apart.)

The reduced form growth regression is written as in (1).

$$r_{s,t}^{(p)} = \alpha^{(p)} \ln y_{s,t-1}^{(p)} + \beta^{(p)} G_{s,t-1} + \sum_b \gamma_b^{(p)} X_{b,s,t-1} + \delta_s^{(p)} D_s + \tau_{t-1}^{(p)} d_{t-1} + u_{s,t}^{(p)}. \quad (1)$$

$r_{s,t}^{(p)}$ 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 . In regression (1) $G_{s,t-1}$ denotes the Gini index in state s at time $t - 1$, $X_{b,s,t-1}$ are state-level controls evaluated at time $t - 1$, D_s is a state-level dummy or a broader regional dummy variable (see table A1), d_{t-1} is a time dummy variable, and $u_{s,t}^{(p)}$ is the error term with the conventional properties.

The state-level controls include¹⁴ “age015” and “age65” (the percentage of the population aged 15 or younger and aged 65 or older); “edu_grad”¹⁵ (percentage with a graduate degree among individuals between 21 and 39 years of age); “emp_cons,” “emp_fina,” “emp_gove” (share of employment in construction, finance (and insurance and real estate), and the public sector, respectively); “emp_grow” (the percentage change in nonagricultural employment over the preceding decade); “welf_exp” (state public welfare expenditure divided by state personal income); “sh_routine” (share of routine jobs); “trade_us_ch” (exposure to imports from China); and region or state dummies.¹⁶

We limit the number of controls that are highly persistent over time because these introduce a high degree of co-linearity with the state fixed-effects. This motivates our decision to evaluate the share of the population with a graduate degree for individuals between the ages of 21 and 39. This variable exhibits more variation over time when compared to higher-education attainment among the entire population, and hence carries more information up and above the state fixed-effects. For the same reason, we omitted the share of the population residing in metropolitan areas and employment in farming, manufacturing, mining, and transportation, and, as mentioned before, racial composition.¹⁷ All of these variables are highly persistent.

Two different methods of estimation are considered: (1) System GMM regression allowing for state fixed-effects, and (2) pooled OLS regression with regional dummies (East, Mid-West, South, and West) shown as part of our robustness analysis.

14 The values for “age015,” “age65,” and “edu_grad” are derived from the IPUMS USA micro-data, “emp_*” and “welf_exp” are obtained from [Marrero and Rodriguez \(2013\)](#), and “sh_routine” and “trade_us_ch” are obtained from [Autor, Dorn, and Hansen \(2015\)](#).

15 Data on education are available for all individuals. Each respondent’s education attainment is assigned to 1 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.

16 We have also considered state racial composition as a control variable. However, racial composition is highly persistent and thus highly co-linear with the state fixed-effects. We acknowledge that our list of controls is not exhaustive; other candidate controls include state-level investment in physical capital.

17 While the regression results obtained with pooled OLS are largely robust to including these additional controls, we find that the System GMM regressions become more sensitive to the choice of instruments.

4. An Overview of Income Distribution Changes in the United States

Table 1 shows a variant of the Growth Incidence Curve (GIC) for each 10-year period. The values give the average annual per capita growth rates, calculated across states, at each percentile of state income distribution.¹⁸ 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 growth at the median over time. It almost monotonically declined in every decade: It was 2.9 percent per capita in the 1960s, then 1.5 percent and 1.6 percent in the two next 10-year periods, 1.1 percent 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).

A striking illustration of the change in levels and shape of growth rates is provided in [fig. 1](#) which displays the patterns of growth in the 1960s and in the 1990s.¹⁹ 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 percent of the population). In the 1990s, by contrast, growth rates are lower than in the 1960s everywhere except at the top, and the line is upward sloping.

Table S1.1 (in the supplementary online appendix) shows annualized real per capita growth of the median income in 50 U.S. states and the District of Columbia over the period 1960–2010 and Gini coefficients at 10-year intervals. The column labeled “1960” for the growth of median income gives the real growth rate for the subsequent 10-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.

As for inequality, in only eight states was it 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: in 1960 many of the high inequality states were in the south, but today they are in the west and northeast. It is striking to note that the northeast, 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

Table 1. Average Growth at Different Percentiles of State Income Distribution

Year	Growth (annualized) at percentile							
	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

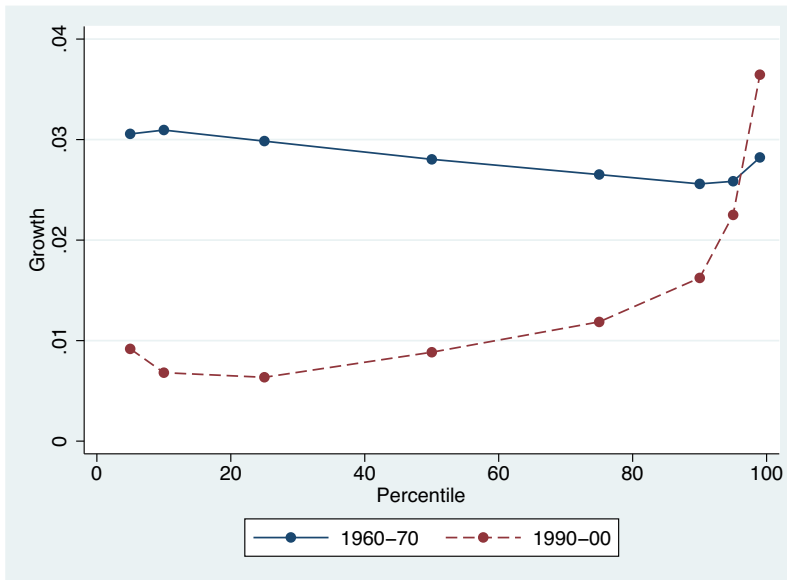
Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

Note: Growth rates are expressed in fractions; thus 0.05 means a 5 percent growth rate.

18 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 indistinguishable. 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.

19 The recent financial crisis has flattened the GIC for 2000–2010, which is why we omit it from the figure.

Figure 1. United States: The Average Population-Weighted State-Level Growth Rates of Real Income at Different Points of Income Distribution (Decennial Averages)



Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

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).

Table 2 shows how demographics, education, employment by sector, public welfare expenditure, share of routine jobs, and exposure to imports from China have evolved over the last 50 years. Some of the time-trends that stand out are the dramatic increase in education (the percentage of the population between 21 and 39 years of age with a master's degree or higher has more than tripled) and the aging of the population

Table 2. Summary Statistics of Independent Variables by Year

	1960	1970	1980	1990	2000	2010
Gini	0.411	0.403	0.393	0.415	0.446	0.449
age015	0.340	0.315	0.253	0.242	0.229	0.211
age65	0.088	0.099	0.111	0.125	0.129	0.137
edu_grad	0.093	0.134	0.195	0.212	0.236	0.281
emp_cons	0.059	0.052	0.051	0.047	0.050	
emp_fina	0.044	0.046	0.052	0.056	0.055	
emp_gove	0.176	0.200	0.192	0.180	0.167	
emp_grow	0.248	0.348	0.382	0.211	0.233	
welf_exp	0.012	0.015	0.018	0.021	0.029	
trade_us_ch	0.070	0.083	0.160	1.135	2.578	
sh_routine	0.254	0.295	0.313	0.311	0.311	

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA) (for Gini, age015, age65, and edu_grad), from Marrero and Rodriguez (2013) (for emp_* and welf_exp), and Autor, Dorn, and Hansen (2015) (for trade_us_ch and sh_routine).

Note: age015, age65: share of population of ages respectively 0 to 15, and above 65; edu_grad: share of people with a graduate degree among individuals between 25 and 39 years of age; emp_cons, emp_fina, emp_gov: share of employment in respectively construction, finance (and insurance and real estate), and the public sector; emp_grow: growth in nonagricultural employment over the preceding decade; welf_exp: state-level public welfare expenditures divided by state personal income; trade_us_ch: exposure to imports from China; sh_routine: share of routine jobs in total employment. Sources used for emp_*, welf_exp, trade_us_ch and sh_routine do not include data for 2010.

with a steady decline in the share of children combined with a gradual rise in the share of elderly. We also see a gradual increase in welfare expenditures and the size of the financial sector. The share of routine jobs increased until 1980 but has been stable ever since. Exposure to imports from China was negligible up to 1980 but increased rapidly in the following decades. All of these factors will be included as control variables in our growth regressions.

5. Results

Table 3 presents the main regression results obtained using System GMM estimation allowing for state fixed-effects (see [Blundell and Bond 1998](#)). All explanatory variables (lagged income, lagged inequality, and all controls) are treated as endogenous variables. We use the second and third lags of these variables as instruments in the differenced equation, and the first and second lagged differences in the levels equation. To guard against the proliferation of instruments, we collapse the instrument matrix, which is a standard approach when the number of endogenous regressors is large (see, e.g., [Roodman 2009, 2012](#)).

Table 3. System GMM Estimation

	pc(5)	pc(10)	pc(25)	pc(50)	pc(75)	pc(90)	pc(95)	pc(99)
lag income	-0.0661*** (-4.23)	-0.0916*** (-4.34)	-0.125*** (-7.10)	-0.149*** (-7.54)	-0.124*** (-6.15)	-0.0983*** (-5.70)	-0.0872*** (-6.51)	-0.101*** (-5.58)
Gini	-0.105 (-0.48)	-0.359 (-1.64)	-0.455*** (-3.63)	-0.238*** (-3.58)	-0.0608 (-0.81)	0.0391 (0.53)	0.0832 (1.25)	0.186** (2.50)
age015	-0.337*** (-2.72)	-0.373*** (-3.90)	-0.408*** (-4.57)	-0.518*** (-5.87)	-0.466*** (-4.19)	-0.377*** (-3.47)	-0.343*** (-3.26)	-0.379*** (-2.86)
age65	-0.258 (-1.24)	-0.197 (-1.12)	-0.232* (-1.78)	-0.368*** (-3.44)	-0.318*** (-2.95)	-0.231** (-2.66)	-0.227** (-2.25)	-0.192 (-1.44)
edu_grad	0.124* (1.75)	0.147* (1.94)	0.171*** (2.69)	0.225*** (4.27)	0.190*** (3.65)	0.154*** (2.72)	0.140*** (2.83)	0.135** (2.34)
emp_cons	-0.508 (-1.32)	-0.201 (-0.89)	0.0226 (0.19)	0.0696 (0.46)	0.0496 (0.28)	0.0982 (0.72)	0.148 (1.19)	0.105 (0.56)
emp_fina	-0.0734 (-0.20)	0.0537 (0.15)	0.339 (1.67)	0.360** (2.43)	0.255 (1.48)	0.246 (1.34)	0.283 (1.31)	0.364 (1.21)
emp_gove	0.212*** (2.76)	0.162** (2.52)	0.121** (2.42)	0.109* (1.85)	0.101 (1.58)	0.0822 (1.57)	0.0627 (1.18)	0.102* (1.96)
emp_grow	-0.0111 (-0.50)	-0.0146 (-0.85)	-0.0224** (-2.16)	-0.0226* (-1.90)	-0.0169 (-1.30)	-0.0155* (-1.85)	-0.0198** (-2.41)	-0.0168* (-1.69)
welf_exp	-0.252 (-0.65)	-0.394 (-0.95)	-0.582** (-2.05)	-0.650** (-2.47)	-0.574** (-2.21)	-0.466** (-2.22)	-0.430* (-2.01)	-0.691*** (-2.95)
trade_us_ch	-0.00405** (-2.50)	-0.00379** (-2.34)	-0.00219* (-1.91)	-0.00237** (-2.41)	-0.00168 (-1.46)	-0.00110 (-1.19)	-0.000917 (-0.99)	-0.000900 (-0.72)
sh_routine	0.161 (1.19)	0.152 (1.50)	0.216*** (3.30)	0.238*** (3.66)	0.202*** (3.31)	0.186*** (3.43)	0.178*** (3.20)	0.266*** (3.06)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	240	240	240	240	240	240	240	240
Hansen p	0.475	0.482	0.592	0.543	0.207	0.253	0.203	0.334
ar1 p	0.000450	0.00115	0.000407	0.00228	0.00152	0.00126	0.00121	0.00778
ar2 p	0.569	0.778	0.664	0.469	0.414	0.409	0.315	0.746
instruments	53	53	53	53	53	53	53	53

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA) (for income growth, lagged income, Gini, age015, age65, and edu_grad), from [Marrero and Rodriguez \(2013\)](#) (for emp_* and welf_exp), and [Autor, Dorn, and Hansen \(2015\)](#) (for trade_us_ch and sh_routine).

Note: Dependent variable = per capita income growth at given percentile of state income distribution; 1960–2010. All right-hand side variables are estimated at time $t - 1$. Income is household per capita. Gini calculated across individuals. t -statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The standard errors are derived from the robust estimator of the covariance matrix. The reported Hansen test accepts the hypothesis of orthogonality of the instruments.

Overall, initial inequality is negatively associated (at the conventional level of statistical significance) with subsequent real growth for the population located below the median, and positively with growth for the population belonging to the top percentile. The size and significance 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 (but not beyond the bottom decile). In other words, total inequality seems to be negatively associated with growth among the poor and those around the median and positively among the top 1 percent. Initial income, as usual in the convergence literature, enters with a statistically significant negative sign in all regressions.

Let us also inspect the effects associated with our controls. Since the results on these controls do not vary much between this and other formulations, we shall discuss them only here. 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. Having a graduate degree is, as expected, positively correlated with income growth at all percentiles. (The omitted variable is all schooling below the graduate degree.) Higher levels of welfare expenditure are associated with lower growth rates, also across all percentiles. [Marrero and Rodriguez \(2013\)](#) similarly find a negative association between public welfare expenditures and growth in GDP per capita (although the effect is not significant in their case). In theory, the effect of higher public welfare expenditures on future growth could be positive (by lifting credit constraints of disadvantaged individuals, thereby promoting investments in human capital) as well as negative (due to distortions associated with redistributive policies). The negative effect obtained in our regression analysis suggests that the latter may dominate the former in the United States.

The size of the financial sector (in terms of employment) appears to be uncorrelated with income growth, except at the median, where its effect is found to be positive. This is in contrast with estimates obtained using pooled OLS with region fixed-effects presented in section 6 (as part of the robustness analysis), where we find a negative effect for low percentiles and a positive effect for top percentiles. The size of the public sector is found to have a positive association with future growth, while the effect of employment in the construction sector is insignificant (relative to employment in the omitted sectors, which include the services sector).

Exposure to imports from China is bad for growth rates of the poor but not for that of the rich, which is consistent with the argument that competition from China particularly affects lower-skilled workers. Interestingly, higher shares of routine jobs are positively associated with growth, particularly at the higher percentiles. It is conceivable that higher shares of routine jobs raise the productivity, scarcity, and compensation of skilled workers. Our findings are also broadly consistent with the empirical results obtained by [Autor, Dorn, and Hansen \(2015\)](#). They find that import competition from China lowers employment, particularly of lower-skilled workers. While routine jobs are found to have a polarizing effect, they are not associated with a decline in employment.

How big is the effect of inequality on growth; is it economically meaningful? One standard deviation of state-level Gini is 0.038. Thus, one standard deviation decrease in Gini would be associated with an increase in the average annual growth rate of the 25th income percentile through the median that ranges between a 1.7 and 0.9 percentage points (0.038×0.455 or 0.038×0.238). Since their average growth over the 50-year period was little over 1 percent per capita annually (see [table 1](#)), the decline in state-level Gini would, on average, double or more than double their growth rates. Both the absolute and relative effect of lower inequality on real growth of the rich is less: a one-standard-deviation decrease in Gini is associated with 0.7 percentage point *decline* in the growth rate of the top 1 percent, which, given that their average annual growth over the entire period was almost 2 percent, is a more modest fraction of their growth rate.

The regressions as run here are controlling for a number of state characteristics, which is important to distinguish between conditional and unconditional divergence in Gini among the states. It could be thought, for example, that in more unequal states there would be higher growth rates among the rich, which in turn will further increase inequality, and then again push up the growth rate of the rich and so on. There would thus be a vicious cycle of permanently rising inequality in some states, and the opposite in the others. We would then expect to find divergence in Gini levels between the states. This, however, is not the case in the United States. And it is also not implied by our results, where the positive relation between inequality and subsequent top income growth is conditional upon a number of controls. The regression thus allows us to interpret our results in terms of conditional, but not unconditional, inequality divergence.

6. Robustness Checks

This section provides robustness checks of our results.

Weak Instrument Tests

The instruments used in the GMM estimation of inequality and growth regressions are known to exhibit a weak correlation with the endogenous explanatory variables (notably lagged log income and inequality). When instruments are weak, the finite sample distribution of the instrumental variable estimator may not be well approximated by its asymptotic normal distribution, such that conventional inference based on the asymptotic distribution can be misleading. To address this concern, we adopt the procedures advocated by [Bazzi and Clemens \(2013\)](#) and [Kraay \(2015\)](#), which diagnose instrument strength and construct alternative confidence sets that remain valid even when instruments are weak. These confidence sets are obtained by “inverting” test statistics that are functions of the parameters of interest and whose asymptotic distribution is independent of instrument strength. Popular examples of such statistics include the AR statistic ([Anderson and Rubin 1949](#)), the CLR statistic ([Moreira 2003](#)), and the KJ statistic ([Kleibergen 2005](#)). For further details, we refer the reader to [Kraay \(2015\)](#) and the references therein.

To facilitate the presentation of weak instrument-consistent confidence sets, we focus on the case where initial income and initial inequality are the only explanatory variables. Following [Bazzi and Clemens \(2013\)](#) and [Kraay \(2015\)](#), we evaluate the estimators based on the differenced and levels equations separately in addition to the System GMM estimator, which combines the two. As mentioned before, the second and third lags of endogenous variables serve as instruments in the differenced equation, while the first and second lagged differences serve as instruments in the levels equation. To contain the number of instruments, we collapse the instruments in the differenced equation, but will work with the complete set of instruments in the levels equation.²⁰ To diagnose instrument strength, we inspect the [Kleibergen and Paap \(2006\)](#) rk-LM statistic, which tests the null hypothesis that the matrix of coefficients from the first-stage regression is not of full rank. As failing to reject this null hypothesis would suggest a complete failure of identification, it would be a strong indicator of weak instruments. By the same token, a rejection by itself would not make a compelling case for strong instruments. To this end, we also report the Cragg-Donald statistic. [Stock and Yogo \(2005\)](#) derive critical values for this statistic corresponding to a maximal bias threshold of the 2SLS estimates relative to OLS estimates that is set by the user.

[Tables 4](#) and [5](#) report the results. This confirms the negative inequality effect for lower percentiles (which now extends to the upper middle class), but does not confirm the positive and statistically significant association between inequality and future growth of the top percentile. The Kleibergen-Paap rk-LM test of underidentification is comfortably rejected in the levels equation but not in the differenced equation.

20 It follows that the inequality effect is in large part identified by the levels equation. A similar observation is made in [Kraay \(2015\)](#).

Table 4. System GMM Estimation

	pc(5)	pc(10)	pc(25)	pc(50)	pc(75)	pc(90)	pc(95)	pc(99)
lag income	-0.0358*** (-4.07)	-0.0427*** (-4.73)	-0.0437*** (-5.04)	-0.0336*** (-3.53)	-0.0228*** (-2.98)	-0.0217*** (-3.03)	-0.0133** (-2.20)	-0.0175 (-1.48)
Gini	-0.118 (-0.79)	-0.161 (-1.63)	-0.152** (-2.11)	-0.0734 (-1.13)	-0.00394 (-0.11)	-0.0395 (-1.04)	0.00471 (0.11)	0.0210 (0.50)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	245	245	245	245	245	245	245	245
Hansen p	0.0560	0.0478	0.0628	0.0109	0.0152	0.0146	0.00561	0.115
ar1 p	0.00000711	0.0000226	0.0000565	0.0000335	0.0000359	0.0000343	0.0000952	0.000144
ar2 p	0.00423	0.00292	0.00891	0.00185	0.00601	0.0200	0.591	0.166
instruments	19	19	19	19	19	19	19	19

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

Note: Dependent variable = per capita income growth at given percentile of state income distribution; 1960–2010. All right-hand side variables are estimated at time $t - 1$. Income is household per capita. Gini calculated across individuals. t -statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. GMM Estimation: (a) Differenced Equation (top panel), and (b) Levels Equation (bottom panel)

	pc(5)	pc(10)	pc(25)	pc(50)	pc(75)	pc(90)	pc(95)	pc(99)
Differenced equation, 2SLS								
lag income	-0.245*** (-4.08)	-0.240*** (-5.38)	-0.327*** (-4.03)	-0.253*** (-4.52)	-0.262*** (-3.46)	-0.180*** (-4.76)	-0.163*** (-5.35)	-0.172*** (-4.69)
Gini	-1.807** (-2.45)	-1.563*** (-3.36)	-1.822*** (-2.82)	-0.749*** (-2.83)	-0.490** (-2.06)	-0.191* (-1.85)	-0.0702 (-0.79)	0.0166 (0.14)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	196	196	196	196	196	196	196	196
Hansen p	0.0000951	0.00167	0.948	0.153	0.253	0.276	0.186	0.164
Kleibergen-Paap p	0.0574	0.0113	0.129	0.141	0.235	0.0465	0.0103	0.0787
Cragg-Donald stat	2.349	3.417	1.865	2.069	1.343	2.617	3.746	2.255
Levels equation, 2SLS								
lag income	-0.0325*** (-3.82)	-0.0359*** (-4.31)	-0.0304*** (-4.15)	-0.0228*** (-3.60)	-0.0155*** (-2.92)	-0.0165*** (-3.67)	-0.00923** (-2.21)	-0.0121 (-1.52)
Gini	-0.113 (-0.94)	-0.139 (-1.37)	-0.0877 (-1.25)	-0.0629 (-1.15)	-0.0201 (-0.50)	-0.0757** (-2.18)	-0.0610* (-1.74)	-0.0550 (-0.99)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	245	245	245	245	245	245	245	245
Hansen p	0.0977	0.0956	0.0896	0.00808	0.0140	0.0767	0.0643	0.352
Kleibergen-Paap p	0.0000857	0.00000458	0.0000523	0.000275	0.000107	0.000124	0.0000408	0.000266
Cragg-Donald stat	3.234	3.389	3.427	3.180	3.266	3.424	3.483	3.051

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

Note: Dependent variable = per capita income growth at given percentile of state income distribution; 1960–2010. All right-hand side variables are estimated at time $t - 1$. Income is household per capita. Gini calculated across individuals. t -statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The critical value for the Cragg-Donald statistic that allows for a 30 percent maximal bias is 4.66. While neither the differenced equation nor the levels equation reports statistics that exceed this threshold, the failure is largest for the former. In sum, this confirms that the instruments used in the System GMM regressions are weak, as is often the case in inequality and growth regressions (see, e.g., Kraay 2015). This motivates the computation of weak instrument-consistent confidence sets for the parameters of interest.

Figure 2 shows the two-dimensional confidence sets derived from the AR statistic for the System GMM estimator.²¹ The parameter range of -1.5 to 1.5 for the inequality effect (vertical axis) and -0.5 to 0 for the income convergence effect (horizontal axis) provides a generous range; realistically one would expect the convergence effect parameter to lie somewhere between -0.2 and -0.02 . While a zero inequality effect cannot be ruled out for near-zero values of the convergence effect, the larger part of the confidence sets suggests a negative inequality effect. Overall, larger negative inequality effects are paired with larger income convergence effects. This correspondence is seen to flatten, however, toward higher-income percentiles, which confirms that a non-negative inequality effect on future growth toward the top end of the income distribution cannot be ruled out for a wide range of convergence parameters. To verify this, we will next fix the convergence parameter and compute the weak instrument-consistent confidence sets for the inequality effect (which now denotes one-dimensional intervals).

We set the value of the convergence effect parameter at -0.09 , which corresponds to the mid-range of the System GMM estimates obtained in table 3, and re-estimate the instrumental variable regressions where initial inequality now denotes the only endogenous regressor. The results are reported in table 6. This confirms that the negative inequality effect is supported by the levels equation, while the positive inequality effect at the very top of the income distribution is supported by the differenced equation. The negative effect identified in the levels equation is robust to changing the value of the convergence parameter (results not reported here). The positive inequality effect identified in the differenced equation, however, is seen to gradually expand to lower percentiles when we move the convergence effect parameter closer to zero. When the convergence effect is set sufficiently close to zero, the System GMM estimator that combines the two can no longer reject a zero inequality effect, even at lower percentiles (note that the income process is assumed to approach a unit root process in that case).

Also here, instruments are found to be weak. While the Kleibergen-Paap underidentification test is comfortably rejected in both equations, the Cragg-Donald statistic is close to the Stock-Yogo critical value (corresponding to a 30 percent maximal bias), which equals 5.25 in this case. The weak instrument-consistent confidence sets presented in fig. A1 (in the appendix) confirm that the negative inequality effect among the poor is robust, but that the positive effect for the rich is not.

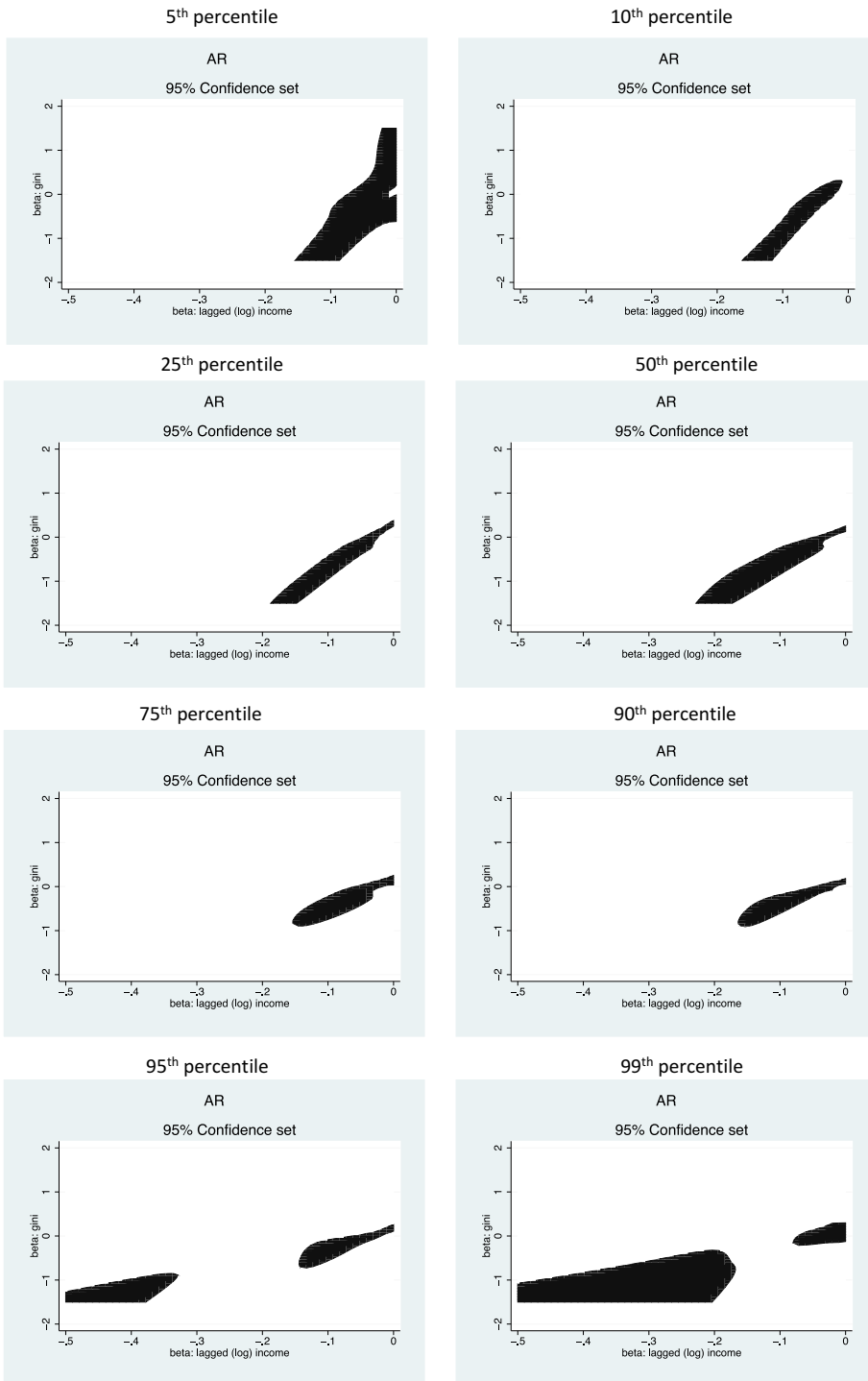
Accounting for Between-State Migration

Another concern is that the relationship between initial inequality and future income growth rates of the poor and the rich may be driven by between-state migration. According to migration data collected by the IPUMS, around 8–10 percent of the population migrates between states over 10-year intervals. Individual decisions to migrate are arguably in part determined by local inequality and economic prospects. A recent study by Chetty, Hendren, and Katz (2016) finds that moving to better neighborhoods when young significantly improves long-term outcomes of adults from disadvantaged families.

The sign of the relationship between initial inequality and future growth incidence resulting from between-state migration is theoretically ambiguous. Suppose that between time t and $t + 1$, higher-productivity workers among the poor migrate from high-inequality to low-inequality states. Keeping all else equal, this migration will mechanically increase the income growth rate at low percentiles between time t and $t + 1$ in high-inequality states (as the workers who stayed behind have higher incomes), which would predict a positive correlation between initial inequality and future income growth of the poor. The

21 Similar results are obtained using the CLR and KJ statistics.

Figure 2. Weak Instrument Consistent Confidence Sets



Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

Note: Figure shows confidence sets for the coefficient on Gini (vertical axis) and lagged log income (horizontal axis). The dark regions correspond to combinations for these two coefficients that jointly are not rejected by the AR test.

Table 6. GMM Estimation: (a) Differenced Equation (top panel), and (b) Levels Equation (bottom panel)

	pc(5)	pc(10)	pc(25)	pc(50)	pc(75)	pc(90)	pc(95)	pc(99)
Differenced equation, 2SLS								
Gini	0.0305 (0.08)	0.104 (0.34)	0.151 (0.67)	0.276 (1.35)	0.229 (1.22)	0.226 (1.27)	0.277 (1.60)	0.328* (1.84)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	196	196	196	196	196	196	196	196
Hansen p	0.0000142	0.0000518	0.000525	0.00337	0.00380	0.0202	0.0591	0.0738
Kleibergen-Paap p	0.00422	0.00422	0.00422	0.00422	0.00422	0.00422	0.00422	0.00422
Cragg-Donald stat	6.693	6.693	6.693	6.693	6.693	6.693	6.693	6.693
Levels equation, 2SLS								
Gini	-0.936*** (-7.44)	-0.851*** (-8.01)	-0.711*** (-7.90)	-0.575*** (-6.47)	-0.473*** (-4.95)	-0.439*** (-4.18)	-0.403*** (-3.57)	-0.321*** (-2.86)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	245	245	245	245	245	245	245	245
Hansen p	0.0631	0.0836	0.179	0.247	0.192	0.148	0.0869	0.191
Kleibergen-Paap p	0.0000433	0.0000433	0.0000433	0.0000433	0.0000433	0.0000433	0.0000433	0.0000433
Cragg-Donald stat	5.136	5.136	5.136	5.136	5.136	5.136	5.136	5.136

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

Note: Dependent variable = per capita income growth at given percentile of state income distribution; 1960–2010. All right-hand side variables are estimated at time $t - 1$. Income is household per capita. Gini calculated across individuals. t -statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

low-inequality states, who are at the receiving end of the migration, may see an increase in income growth rates at lower percentiles when the poor migrants become more productive in the states they moved to. This would imply a negative correlation between initial inequality and future growth of the poor that is consistent with our empirical findings.

We will account for migration by recomputing all the inequality and income growth variables for the subset of the population that excludes all migrants. The IPUMS-USA includes a variable that records in what state (or country) the individual was residing five years earlier (with the exception of the 2000/10 round where a one-year recall is adopted). All respondents that are defined as migrants on the basis of this variable are dropped (for this robustness check only).

Table 7 reports the regression results obtained using this modified version of the U.S. population where there is no migration (i.e., where income growth and inequality are computed for the nonmigrant population), using the same method of estimation that is adopted for the main specification in section 5. The results are very similar to the original results that were obtained using the entire population (see table 3): inequality is negatively correlated with subsequent income growth at the 25th percentile and the median, and positively (albeit not statistically significantly) among the top decile.

Pooled OLS with Region Fixed-Effects

In a dynamic panel data context with a lagged dependent variable and endogenous regressors least squares (LS) estimators, that is, fixed-effects or random effects estimators, are biased and inconsistent. The LS estimator will be biased even when disturbances are white noise and all regressors are predetermined (conditional on state effects), although in this case it will be consistent as the number of time periods (T) tends to infinity. This bias associated with small T is also referred to as Nickell bias, which does not disappear as the number of cross-sectional observations (N) tends to infinity.

Table 7. System GMM Estimation

	pc(5)	pc(10)	pc(25)	pc(50)	pc(75)	pc(90)	pc(95)	pc(99)
lag income	-0.0560** (-2.18)	-0.0879*** (-4.96)	-0.123*** (-6.64)	-0.149*** (-6.57)	-0.116*** (-5.03)	-0.0956*** (-5.23)	-0.0806*** (-6.26)	-0.108*** (-6.34)
Gini	-0.0208 (-0.06)	-0.340* (-1.72)	-0.463*** (-3.89)	-0.293*** (-3.29)	-0.0734 (-1.06)	0.0123 (0.23)	0.0690 (1.23)	0.0992 (1.02)
age015	-0.354* (-2.00)	-0.317** (-2.41)	-0.366*** (-3.79)	-0.480*** (-4.66)	-0.445*** (-3.78)	-0.382*** (-3.91)	-0.347*** (-3.95)	-0.422** (-2.51)
age65	-0.291 (-1.62)	-0.176 (-0.92)	-0.208 (-1.55)	-0.329*** (-2.84)	-0.321*** (-3.25)	-0.266*** (-2.95)	-0.212** (-2.22)	-0.212 (-1.59)
edu_grad	0.121* (1.89)	0.150* (1.88)	0.192*** (3.52)	0.233*** (3.97)	0.157** (2.57)	0.142** (2.61)	0.133*** (3.20)	0.125* (1.97)
emp_cons	-0.591 (-1.41)	-0.377 (-1.30)	-0.0352 (-0.22)	0.0321 (0.22)	0.0514 (0.30)	0.123 (0.85)	0.130 (0.97)	0.146 (0.62)
emp_fina	-0.131 (-0.35)	0.0455 (0.13)	0.275 (1.33)	0.311 (1.53)	0.343** (2.09)	0.251 (1.28)	0.243 (1.17)	0.409 (1.26)
emp_gove	0.195*** (3.03)	0.146** (2.14)	0.129** (2.28)	0.112 (1.65)	0.111* (1.84)	0.0775 (1.39)	0.0495 (1.11)	0.0785 (1.33)
emp_grow	-0.00839 (-0.36)	-0.00842 (-0.49)	-0.0159 (-1.20)	-0.0153 (-1.17)	-0.0191 (-1.59)	-0.0169 (-1.65)	-0.0163 (-1.66)	-0.0172 (-1.62)
welf_exp	-0.0474 (-0.12)	-0.360 (-0.94)	-0.418 (-1.58)	-0.642** (-2.11)	-0.653*** (-2.91)	-0.518** (-2.56)	-0.414* (-1.91)	-0.804*** (-3.04)
trade_us_ch	-0.00481** (-2.61)	-0.00404*** (-2.70)	-0.00295** (-2.54)	-0.00261** (-2.23)	-0.00154 (-1.26)	-0.00111 (-1.16)	-0.000768 (-0.85)	-0.000783 (-0.65)
sh_routine	0.0696 (0.46)	0.128 (1.06)	0.189*** (3.10)	0.231*** (3.29)	0.195*** (3.14)	0.174*** (3.45)	0.149** (2.67)	0.237*** (2.74)
state FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	240	240	240	240	240	240	240	240
Hansen p	0.567	0.437	0.404	0.381	0.273	0.291	0.233	0.325
ar1 p	0.000499	0.000768	0.000732	0.00201	0.000826	0.000642	0.000760	0.0165
ar2 p	0.393	0.820	0.996	0.471	0.449	0.563	0.789	0.911
instruments	53	53	53	53	53	53	53	53

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA) (for income growth, lagged income, Gini, age015, age65, and edu_grad), from Marrero and Rodriguez (2013) (for emp_* and welf_exp), and Autor, Dorn, and Hansen (2015) (for trade_us_ch and sh_routine).

Note: Dependent variable = per capita income growth at given percentile of state income distribution; 1960–2010. All right-hand side variables are estimated at time $t - 1$. Income is household per capita. Gini calculated across individuals. t -statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

The GMM estimator (both Difference and System GMM) appears to be a natural choice in this context. It addresses endogeneity of regressors by using internal instruments. Furthermore, GMM is designed for small T (but large N); consistency only requires that N tend to infinity (hence no Nickell bias), in which case it provides asymptotically efficient inference based on relatively modest assumptions.

When N is small, however, the GMM estimator is known to behave rather poorly due to weakness of internal instruments and its dependence on crucial nuisance parameters (see, e.g., Binder, Hsiao, and Pesaran 2005; Bun and Kiviet 2006; and Bun and Sarafidis 2015). This is particularly true when the panel data is highly persistent, and applies both to Difference and System GMM. It is conceivable that for small N , as is the case in our application, the LS estimator may denote a competitive alternative (or may even outperform GMM). Firstly, Nickell bias is found to affect the lagged dependent variable more than the added regressors. Secondly, high persistence of panel data affects GMM more than it affects LS. Thirdly, LS estimators are not subject to ambiguity stemming from the choice of instruments.

Table 8. Pooled OLS Estimation (with region fixed-effects)

	pc(5)	pc(10)	pc(25)	pc(50)	pc(75)	pc(90)	pc(95)	pc(99)
lag income	-0.0598*** (-7.40)	-0.0724*** (-9.51)	-0.0703*** (-9.94)	-0.0663*** (-9.22)	-0.0562*** (-9.41)	-0.0505*** (-9.99)	-0.0434*** (-9.47)	-0.0513*** (-8.71)
Gini	-0.238*** (-2.81)	-0.290*** (-4.07)	-0.190*** (-4.27)	-0.0767*** (-2.84)	-0.00134 (-0.08)	0.0277** (2.07)	0.0459*** (3.13)	0.0705*** (3.87)
age015	-0.192*** (-2.80)	-0.231*** (-4.00)	-0.202*** (-4.25)	-0.215*** (-5.11)	-0.191*** (-5.03)	-0.195*** (-5.85)	-0.175*** (-5.59)	-0.174*** (-5.00)
age65	-0.0636 (-0.89)	-0.0921 (-1.64)	-0.0979** (-2.27)	-0.128*** (-3.40)	-0.111*** (-3.34)	-0.116*** (-3.78)	-0.101*** (-2.97)	-0.0724* (-1.87)
edu_grad	0.117*** (3.52)	0.135*** (4.77)	0.136*** (6.55)	0.129*** (6.86)	0.111*** (6.47)	0.101*** (6.09)	0.0895*** (5.26)	0.0810*** (4.27)
emp_cons	-0.160 (-1.53)	-0.149* (-1.92)	-0.0634 (-1.11)	-0.0458 (-0.91)	-0.0236 (-0.52)	0.00658 (0.16)	0.0221 (0.48)	0.0338 (0.66)
emp_fina	-0.187** (-1.99)	-0.148** (-2.02)	-0.0938* (-1.83)	-0.0503 (-1.04)	-0.0335 (-0.77)	0.00291 (0.07)	0.0266 (0.52)	0.117* (1.69)
emp_gove	0.0373 (0.91)	0.0304 (0.97)	0.00976 (0.42)	0.0111 (0.56)	0.0244 (1.44)	0.0340** (2.14)	0.0314** (2.07)	0.0148 (0.83)
emp_grow	-0.00201 (-0.27)	0.000975 (0.17)	-0.00233 (-0.56)	-0.00153 (-0.40)	-0.00245 (-0.76)	-0.00286 (-0.95)	-0.00202 (-0.66)	-0.00286 (-0.67)
welf_exp	-0.391*** (-2.65)	-0.403*** (-3.43)	-0.211*** (-2.62)	-0.142** (-2.03)	-0.136** (-2.24)	-0.141** (-2.45)	-0.119** (-2.01)	-0.191*** (-2.76)
trade_us_ch	-0.00195 (-1.65)	-0.00230** (-2.32)	-0.00218*** (-3.00)	-0.00175*** (-2.79)	-0.00121** (-2.12)	-0.000688 (-1.31)	-0.000387 (-0.80)	-0.000612 (-0.91)
sh_routine	0.0142 (0.32)	0.0462 (1.30)	0.0567** (2.08)	0.0575** (2.41)	0.0694*** (3.28)	0.0726*** (3.54)	0.0725*** (3.50)	0.0739*** (2.98)
region FE	YES	YES	YES	YES	YES	YES	YES	YES
decade FE	YES	YES	YES	YES	YES	YES	YES	YES
Obs	240	240	240	240	240	240	240	240
adj. R-sq	0.728	0.784	0.816	0.785	0.756	0.769	0.821	0.894

Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA) (for income growth, lagged income, Gini, age015, age65, and edu_grad), from [Marrero and Rodriguez \(2013\)](#) (for emp_* and welf_exp), and [Autor, Dorn, and Hansen \(2015\)](#) (for trade_us_ch and sh_routine).

Note: Dependent variable = per capita income growth at given percentile of state income distribution; 1960–2010. All right-hand side variables are estimated at time $t - 1$. Income is household per capita. Gini calculated across individuals. t -statistics in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Therefore, as a robustness check, we run pooled OLS regressions with region fixed-effects: Midwest, South, West, and (omitted in the regression) East. The results/estimates are reported in [table 8](#).

As before, the overall Gini ([table 3](#)) displays a statistically significant and positive effect for the growth of the rich (top decile) and the reverse for the growth at the median and below. Here too, the coefficient increases monotonically across the distribution as we move from the poor percentiles toward the rich and remains statistically significant throughout.

The adjusted R^2 is relatively high, ranging from 0.73 to 0.89, 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.

7. Conclusions

The objective of this paper is to disaggregate the inequality-growth relationship by estimating how inequality correlates with subsequent growth at different points of the income distribution. We do this using U.S. micro-census data covering between 1 and 5 percent of the population, at 10-year intervals, over the

period 1960–2010. The very fact that the earlier literature often found that the sign of the effect switched between positive and negative may be viewed as a hint of an intricate relationship between inequality and growth, with inequality producing one type of effect for one segment of the population and a very different effect for another segment.

We find that inequality is negatively associated with subsequent growth rates among the poorer income percentiles, and positively among the higher percentiles. The sensitivity analysis suggests that this result is not driven by between-state migration.

What are the channels whereby inequality may affect negatively the growth rate of the poor and positively the growth rate of the rich? We cannot test them, so we are reduced to simply discussing some hypotheses. A possibility that seems to us most compelling is that inequality in general, and among the rich in particular, 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 \[2006\]](#)). Similar to 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. They 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 may 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 percent) and the rest of the population when it comes to the cuts in Medicare, education, and infrastructure spending as a way to reduce the federal deficit. According to the survey data reported by [Page, Bartels, and Seawright \(2011\)](#); quoted in [West 2014](#)), 58 percent of the rich are in favor of such cuts versus only 21 percent among the rest of the population.²² [Gilens and Page \(2014\)](#) confirm that the preferences of the rich are ultimately more likely to determine public policy than the preferences of the majority, at least in the United States: “When the preferences of economic elites and the stands of organized interest groups are controlled for, the preferences of the average American appear to have only a minuscule, near-zero, statistically non-significant impact upon public policy (p. 575).”

“Social separatism” means that the poor, especially the bottom decile, may find it harder to escape poverty because when the rich lack 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.²³

This does not mean that none of the economic benefits trickle 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 can be characterized by lower levels of inequality. This is also implied by the recent results by [Chetty et al. \(2014\)](#), that show that locations in the United States with lower income inequality display more intergenerational mobility.

22 Using cross-country data from North America and Latin America, [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 U.S. 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 gradually become less progressive. 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. \(2013\)](#) put 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 \(2007\)](#).

23 See also the studies by, e.g., [Bénabou \(1996b\)](#); [Alesina and La Ferrara \(2000\)](#); [Lloyd-Ellis \(2000\)](#); [Ferreira \(2001\)](#).

At this stage, however, these arguments are conjectures, and their acceptance or rejection clearly requires more empirical and theoretical work. For example, one could test whether inequality (and inequality among the rich) indeed influences state spending on public goods (and state minimum wages).

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 where the pressure to change would come from.

Appendix A1: US Statistical Regions

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

Source: U.S. census bureau designated regions.

Figure A1. Weak Instrument Consistent Confidence Sets

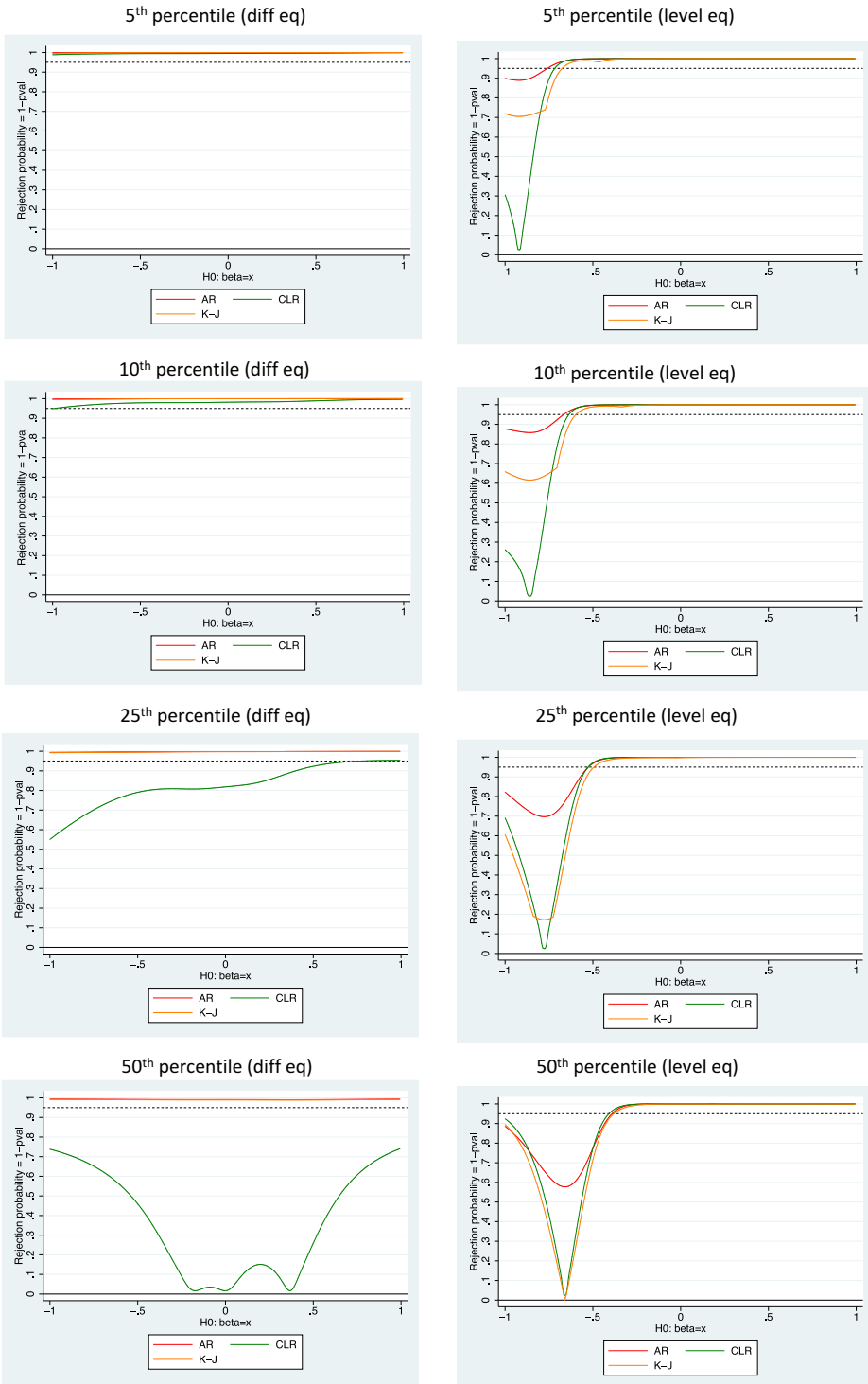
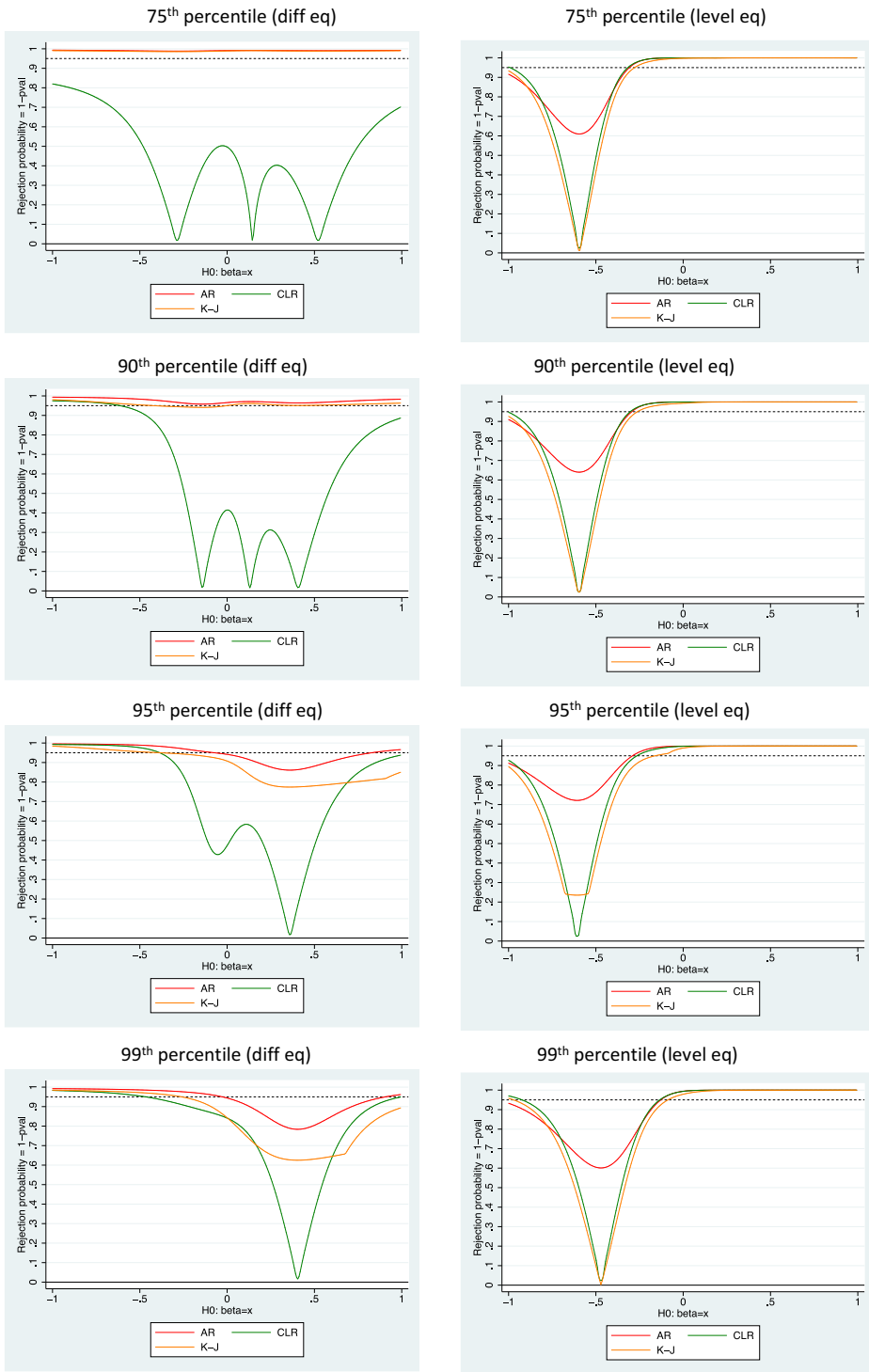


Figure A1. (Continued)



Source: Authors' analysis based on data from the Integrated Public Use Microdata Survey (IPUMS-USA).

Note: Figure shows confidence sets for the coefficient on Gini based on the AR statistic, the KJ statistic, and the CLR statistic.

References

- Aghion, P., E. Caroli, and C. Garcia-Peñalosa. 1999. "Inequality and Economic Growth: The Perspective of New Growth Theories." *Journal of Economic Literature* 37 (4): 1615–60.
- Alesina, A., and E. La Ferrara. 2000. "Participation in Heterogeneous Communities." *Quarterly Journal of Economics* 115 (3): 847–904.
- Alesina, A., and D. Rodrik. 1994. "Distributive Politics and Economic Growth." *Quarterly Journal of Economics* 109 (2): 465–90.
- Alvaredo, F., A. Atkinson, T. Piketty, and E. Saez. 2013. "The Top 1 Percent in International and Historical Perspective." *Journal of Economic Perspective* 27 (3): 3–20.
- Anderson, T. W., and H. Rubin. 1949. "Estimation of the Parameters of a Single Equation in a Complete Set of Stochastic Equations." *Annals of Mathematical Statistics* 20 (1): 46–63.
- Araujo, C., F. Ferreira, P. Lanjouw, and B. Özler. 2008. "Local Inequality and Project Choice: Theory and Evidence from Ecuador." *Journal of Public Economics* 92 (5–6): 1022–46.
- Atkinson, A. B., and A. Brandolini. 2001. "Promise and Pitfalls in the Use of 'Secondary' Data-Sets: Income Inequality in OECD Countries as a Case Study." *Journal of Economic Literature* 39 (3): 771–99.
- Autor, D., and D. Dorn. 2013. "The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market." *American Economic Review* 103 (5): 1553–97.
- Autor, D., D. Dorn, and G. Hansen. 2013. "The China Syndrome: Local Labor Market Effects of Import Competition in the United States." *American Economic Review* 103 (6): 2121–68.
- Autor, D., D. Dorn, and G. Hansen. 2015. "Untangling Trade and Technology: Evidence from Local Labour Markets." *Economic Journal* 125 (584): 621–46.
- Autor, D., L. Katz, and M. Kearney. 2008. "Trends in US Wage Inequality: Revising the Revisionists." *Review of Economics and Statistics* 90 (2): 300–23.
- Banerjee, A. V., and E. Duflo. 2003. "Inequality and Growth: What Can the Data Say?" *Journal of Economic Growth* 8 (3): 267–99.
- Barro, R. 2000. "Inequality and Growth in a Panel of Countries." *Journal of Economic Growth* 5 (1): 5–32.
- Bartels, L. 2010. *Unequal Democracy*. Princeton, NJ: Princeton University Press.
- Bazzi, S., and M. Clemens. 2013. "Blunt Instruments: Avoiding Common Pitfalls in Identifying the Causes of Economic Growth." *American Economic Journal: Macroeconomics* 5 (2): 152–86.
- Bénabou, R. 1996a. "Inequality and Growth." In *NBER Macroeconomics Annual 1996*, edited by B. S. Bernanke and J. Rotemberg, 11–74. Cambridge, MA: MIT Press.
- Bénabou, R. 1996b. "Heterogeneity, Stratification, and Growth: Macroeconomic Implications of Community Structure and School Finance." *American Economic Review* 86 (3): 584–609.
- Bénabou, R. 2000. "Unequal Societies: Income Distribution and Social Contract." *American Economic Review* 90 (1): 96–121.
- Benjamin, D., L. Brandt, and J. Giles. 2011. "Did Higher Inequality Impede Growth in Rural China?" *Economic Journal* 121 (557): 1281–309.
- Binder, M., C. Hsiao, and H. Pesaran. 2005. "Estimation and Inference in Short Panel Vector Autoregressions with Unit Roots and Cointegration." *Econometric Theory* 21 (4): 795–837.
- Blundell, R., and S. Bond. 1998. "Initial Conditions and Moment Restrictions in Dynamic Panel Data Models." *Journal of Econometrics* 87 (1): 115–43.
- Bun, M., and J. Kiviet. 2006. "The Effects of Dynamic Feedbacks on LS and MM Estimator Accuracy in Panel Data Models." *Journal of Econometrics* 132 (2): 409–44.
- Bun, M., and V. Sarafidis. 2015. "Dynamic Panel Data Models." In *The Oxford Handbook of Panel Data*, edited by B. H. Baltagi, 76–110. Oxford: Oxford University Press.
- Chetty, R., N. Hendren, and L. Katz. 2016. "The Effects of Exposure to Better Neighborhoods on Children: New Evidence from the Moving to Opportunity Experiment." *American Economic Review* 106 (4): 855–902.
- Chetty, R., N. Hendren, P. Kline, and E. Saez. 2014. "Where Is the Land of Opportunity? The Geography of Intergenerational Mobility in the United States." *Quarterly Journal of Economics* 129 (4): 1553–1623.
- de Dominicis, L., H. L. F. de Groot, and R. J. G. M. Florax. 2006. "Growth and Inequality: A Meta-Analysis." Discussion Paper TI 2006–064/3, Tinbergen Institute, University of Amsterdam, Amsterdam, the Netherlands.

- Deininger, K., and L. Squire. 1996. "A New Dataset for Measuring Income Inequality." *World Bank Economic Review* 10 (3): 565–91.
- Easterly, W. 2007. "Inequality Does Cause Underdevelopment: Insights from a New Instrument." *Journal of Development Economics* 84 (2): 755–76.
- Ferreira, F. 2001. "Education for the Masses? The Interaction Between Wealth, Educational and Political Inequalities." *Economics of Transition* 9 (2): 533–52.
- Ferreira, F., C. Lakner, M. Ana Lugo, and B. Ozler. 2018. "Inequality of Opportunity and Economic Growth: A Cross-Country Analysis." *Review of Income and Wealth*, forthcoming.
- Forbes, K. 2000. "A Reassessment of the Relationship Between Inequality and Growth." *American Economic Review* 90 (4): 869–87.
- Galor, O. 2009. "Inequality and Economic Development: An Overview." Introduction to, *Inequality and Economic Development: The Modern Perspective*, by O. Galor, v–xxii. Cheltenham and Camberley, UK: Edward Elgar Publishers.
- Galor, O., and O. Moav. 2004. "From Physical to Human Capital Accumulation: Inequality and the Process of Development." *Review of Economic Studies* 71 (4): 1001–26.
- Galor, O., and J. Zeira. 1993. "Income Distribution and Macroeconomics." *Review of Economic Studies* 60 (1): 35–52.
- Gilens, M., and B. I. Page. 2014. "Testing Theories of American Politics: Elites, Interest Groups and Average Citizens." *Perspectives on Politics* 12 (3): 564–81.
- Halter, D., M. Oechslin, and J. Zweimuller. 2014. "Inequality and Growth: The Neglected Time Dimension." *Journal of Economic Growth* 19 (1): 81–104.
- Hegre, H., and N. Sambanis. 2006. "Sensitivity Analysis of Empirical Results on Civil War Onset." *Journal of Conflict Resolution* 50 (4): 508–53.
- Hobijn, B., and D. Lagakos. 2005. "Inflation inequality in the United States." *Review of Income and Wealth* 51 (4): 581–606.
- Jenkins, S. 2015. "World Income Inequality Databases: An Assessment of WIID and SWIID." *Journal of Economic Inequality* 13 (4): 629–71.
- Kaldor, N. 1956. "Alternative Theories of Distribution." *Review of Economic Studies* 23 (2): 83–100.
- Keefer, P., and S. Knack. 2002. "Polarization, Politics and Property Rights: Links Between Inequality and Growth." *Public Choice* 111 (1-2): 125–54.
- Kierzenkowski, R., and I. Koske. 2012. "Less Income Inequality and More Growth—Are they Compatible? Part 8. The Drivers of Labour Income Inequality—A Literature Review." OECD Economics Department Working Papers No. 931, OECD Publishing, Paris.
- Kleibergen, F. 2005. "Testing Parameters in GMM without Assuming That They Are Identified." *Econometrica* 73 (4): 1103–123.
- Kleibergen, F., and R. Paap. 2006. "Generalized Reduced Rank Tests Using the Singular Value Decomposition." *Journal of Econometrics* 133 (1): 97–126.
- Knowles, S. 2005. "Inequality and Economic Growth: The Empirical Relationship Reconsidered in the Light of Comparable Data." *Journal of Development Studies* 41 (1): 135–59.
- Kraay, A. 2015. "Weak Instruments in Growth Regressions: Implications for Recent Cross-Country Evidence on Inequality and Growth." Policy Research Working Paper No. 7494, World Bank, Washington, DC.
- Li, H., L. Squire, and H.-Fu Zou. 1998. "Explaining International and Intertemporal Variations in Income Inequality." *Economic Journal* 108 (446): 26–43.
- Li, H., and H.-Fu Zou. 1998. "Income Inequality is not Harmful for Growth: Theory and Evidence." *Review of Development Economics* 2 (3): 318–34.
- Lloyd-Ellis, H. 2000. "Public Education, Occupational Choice, and the Growth-Inequality Relationship." *International Economic Review* 41 (1): 171–201.
- Malinen, T. 2007. "Comment on the Relationship between Inequality and Growth." Discussion Paper No. 193, HECER, University of Helsinki, Helsinki, Finland.
- Marrero, G., and J.-G. Rodriguez. 2012. "Inequality of Opportunity in Europe." *Review of Income and Wealth* 58 (4): 597–621.
- Marrero, G., and J.-G. Rodriguez. 2013. "Inequality of Opportunity and Growth." *Journal of Development Economics* 104: 107–22.

- Meltzer, A. H., and S. F. Richard. 1981. "A Rational Theory of the Size of Government." *Journal of Political Economy* 89 (5): 914–27.
- Meltzer, A. H., and S. F. Richard. 1983. "Tests of a Rational Theory of Size of Government." *Public Choice* 41 (3): 403–37.
- Milanovic, B. 2000. "The Median Voter Hypothesis, Income Inequality and Income Redistribution: An Empirical Test with the Required Data." *European Journal of Political Economy* 16 (3): 367–410.
- Moreira, M. 2003. "A Conditional Likelihood Ratio Test for Structural Models." *Econometrica* 71 (4): 1027–48.
- Ostry, J., A. Berg, and C. Tsangarides. 2014. "Redistribution, Inequality, and Growth." Staff Discussion Note SDN/14/02, International Monetary Fund, Washington, DC.
- Page, B., L. Bartels, and J. Seawright. 2011. "Democracy and the Policy Preferences of the Wealthy Americans." Paper presented at the annual meeting of the *American Political Science Association*, Seattle, Washington, August 31 to September 4, 2011.
- Panizza, U. 2002. "Income Inequality and Economic Growth: Evidence from American Data." *Journal of Economic Growth* 7 (1): 25–41.
- Partridge, M. 1997. "Is Inequality Harmful for Growth? Comment." *American Economic Review* 87 (5): 1019–32.
- Perotti, R. 1996. "Growth, Income Distribution, and Democracy: What the Data Say." *Journal of Economic Growth* 1 (2): 149–87.
- Persson, T., and G. Tabellini. 1994. "Is Inequality Harmful for Growth? Theory and Evidence." *American Economic Review* 84: 600–21.
- Piketty, T., and E. Saez. 2007. "How Progressive is the US Federal Tax System? A Historical and International Perspective." *Journal of Economic Perspectives* 21 (1): 3–24.
- Ravallion, M. 2012. "Why Don't We See Poverty Convergence?" *American Economic Review* 102 (1): 504–23.
- Roodman, D. 2009. "Practitioners' Corner: A Note on the Theme of too Many Instruments." *Oxford Bulletin of Economics and Statistics* 71 (1): 135–58.
- Roodman, D. 2012. "Doubts About the Evidence That Foreign Aid for Health Is Displaced into Non-Health Issues." *Lancet* 380 (9846): 972–73.
- Ruggles, S., J. Trent Alexander, K. Genadek, R. Goeken, M. B. Schroeder, and M. Sobek. 2010. *Integrated Public Use Microdata Series: Version 5.0 [Machine-readable database]*. Minneapolis: Minnesota Population Center.
- Sokoloff, K., and E. Zolt. 2005. "Inequality and Taxation: Evidence from the Americas on How Inequality May Influence Tax Institutions." *Tax Law Review* 59 (2): 167–241.
- Stock, J., and M. Yogo. 2005. "Testing for Weak Instruments in Linear IV Regression." In *Identification and Inference for Econometric Models: Essays in Honour of Thomas Rothenberg*, edited by D. Andres and J. Stock, 80–108. New York: Cambridge University Press.
- Voitchovsky, S. 2005. "Does the Profile of Income Inequality Matter for Economic Growth?" *Journal of Economic Growth* 10 (3): 273–96.
- West, D. M. 2014. *Billionaires: Reflections on the Upper Crust*. Washington, DC: Brookings Institution Press.