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Which tail matters? Inequality and growth in Brazil

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Abstract
We estimate the effect of initial income inequality on subsequent income per capita growth using sub-national data from Brazil over the period 1970–2000. Holding initial income per capita and standard confounders constant, we find that sub-national units with a higher share of income going to the middle quintile at the expense of the bottom quintile grow more rapidly, while places with a higher share of income going to the top quintile at the expense of the middle quintile get no growth boost at all. We document that both physical and human capital accumulation in places with higher inequality in the lower tail of the initial income distribution outpace capital accumulation in more equal places, while inequality in the upper tail of the distribution is uncorrelated with subsequent physical or human capital growth. These results are consistent with theories on credit constraints and setup costs for human and physical capital investments.

Keywords Income inequality · Economic growth · Physical capital · Human capital

JEL Classification D3 · O1 · O4

1 Introduction

A series of seminal theory papers propose different channels through which a society's degree of initial economic inequality might impact subsequent income per capita growth. These channels include aggregate savings and investment (Bourguignon 1981), human and physical capital accumulation (Galor and Zeira 1993; Banerjee and Newman 1993; Aghion and Bolton 1997; Galor and Moav 2004), and income redistribution and social

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unrest (Persson and Tabellini 1994; Alesina and Rodrik 1994; Benabou 1996; Esteban and Ray 2000; Campante and Ferreira 2007). Existing cross- and within-country studies on the relationship between inequality and growth have produced effect estimates ranging from negative to zero and positive as further discussed below. While research design and data limitations may account for some of this variability, it is also possible that the effect of inequality on growth is genuinely heterogeneous. Indeed some of the mechanisms above have different implications for the effect of income inequality on growth, depending on whether the middle class is richer at the expense of the poor or the rich are richer at the expense of the middle class. Yet with the exception of Voitchovsky (2005), empirical work has ignored this issue.

This paper investigates whether inequality originating from the lower as opposed to the upper tail of the income distribution has different effects on subsequent income per capita growth. Greater inequality as measured by commonly used metrics (e.g. the Gini coefficient) can result from higher dispersion in different parts of the income distribution, as illustrated in Fig. 1. In Panel A, a theoretical redistribution of income from the bottom to the middle quintile (i.e., the transition from the Lorenz curve displayed in the solid line to that of the dashed line) implies higher overall income inequality as captured by the Gini coefficient. However, the exact same increase in overall inequality can be achieved by redistributing a portion of total income from the middle to the top quintile, as shown in Panel B. Most existing empirical work does not distinguish whether inequality originates from the lower or upper tails of the distribution, even though growth theory suggests that impacts on subsequent growth may well differ. For example, in the presence of credit constraints and setup costs for human (Galor and Zeira 1993) or physical capital investments (Banerjee and Newman 1993), it is conceivable that only inequality in one of the tails matters for growth.

Consider a stylized economy with three groups of equal size (the poor, the middle class, and the rich) and the same income within each group. Now assume that the incomes of the poor and the middle class are initially too low to overcome the setup costs for investing in either human or physical capital. Put differently, both the poor and the middle class cannot borrow enough to make the relatively large investments that would be required to make a profit. Now consider another economy with the same income per capita but with higher inequality at the bottom, i.e. the middle class is richer while the poor are poorer. In this second economy, the middle class might be rich enough to overcome the setup costs and make profitable investments in human and physical capital, thus making the second economy richer than the first economy in the long run. Finally consider a third economy, again with identical income per capita but higher inequality at the top, i.e. the rich are richer at the expense of the middle class. Since human and physical capital investments are as constrained as in the more equal first economy, investment and growth will be similarly limited.

Using sub-national data from Brazil over the 1970–2000 period, we first establish that holding initial income per capita and a host of standard confounders constant, places with higher initial income inequality as measured by the Gini coefficient exhibit higher subsequent income per capita growth. Most of the effect materializes by 1991, i.e. there is only a level effect, not permanently higher growth. We then propose a simple approach to distinguish between the growth effects of inequality originating from the bottom versus the top of the initial income distribution. The key idea is to include quintile income shares instead of the Gini coefficient in an otherwise standard cross-sectional growth regression. This allows for hypothetical income redistributions from the two tails towards the (omitted) middle quintile while holding other income shares and mean income constant. We find that the positive effect of overall inequality on subsequent growth is entirely driven by inequality in the lower tail of the income distribution: compared to more equal places, sub-national units with a 3 percentage points (one standard deviation) higher share of 1970 income going to the middle quintile at the expense of the bottom quintile experience about 3 percent higher income per capita by 2000. In contrast, places with a higher share of income going to the top quintile at the expense of the middle quintile get no growth boost at all compared to more equal places.

The differential effects of bottom versus top inequality are remarkably in line with our evidence on human and physical capital accumulation. We find that places with a higher share of income held by the middle quintile at the expense of the bottom quintile experience higher subsequent growth in both the number of business establishments and the value of their capital stocks. On the other hand, a higher share of income held by the top quintile at the expense of the middle quintile is not associated with increased physical capital accumulation. We also find that places with higher bottom inequality have a higher share of entrepreneurs (employers or self-employed) at the outset of our sample period compared to more equal places, while places with higher inequality at the top have slightly fewer entrepreneurs. Similarly, a higher share of the population attains more than a primary school education in places with higher inequality in the lower tail of the initial income distribution compared to places where the bottom quintile is richer. Inequality at the top of the distribution on the other hand is uncorrelated with subsequent human capital growth. Overall, these results suggest that in Brazil in the 1970s, income inequality at the bottom mattered for investment and growth, while inequality at the top did not.

The most plausible explanation for this pattern of results is the presence of credit constraints. Opportunities for investment were rather limited for households at the bottom of the wealth distribution in 1970, since access to credit was not widespread. For example, only 12% of agricultural establishments received credit in 1970, and only 5% of households in the 1970 census had a mortgage. Moreover, the result that bottom inequality has a positive effect on growth and investment also points to the importance of investment indivisibilities. Credit constraints alone would lead to the opposite prediction that places where the middle class is richer at the expense of the poor should exhibit lower quantity and average profitability of investment compared to more equal places (Galor and Zeira 1993). In order to further test the credit constraints cum setup costs mechanism, we split the sample by the average income of the middle quintile in 1970. Since investment indivisibilities matter in relation to the distribution of absolute income, we would expect effects to be concentrated in only a subset of our sample. Our results suggest indeed that the entire effect of lower-tail inequality on growth comes from the group with the poorest middle quintiles in 1970.

Another potential mechanism leading to differential effects of top versus bottom inequality is aggregate savings. Since the propensity to save is increasing and perhaps convex in income (Dynan et al. 2004; Gandelman 2017), higher inequality at the bottom might increase aggregate savings only little, while higher inequality at the top might increase available savings substantially. The savings channel would actually suggest that inequality at the top should matter more than inequality at the bottom, which is the opposite of what we find. Increased savings only leads to increased investment in at least partially closed economies, however, and data for Brazil from the end of our sample period suggest that capital was already highly mobile across municipalities at that time (Bustos et al. 2017). According to available evidence, the differential growth effects we find are therefore unlikely to be attributable to differential aggregate savings. Other channels, such as redistributive policies carried out at the local level, may have been at work. However, we are not

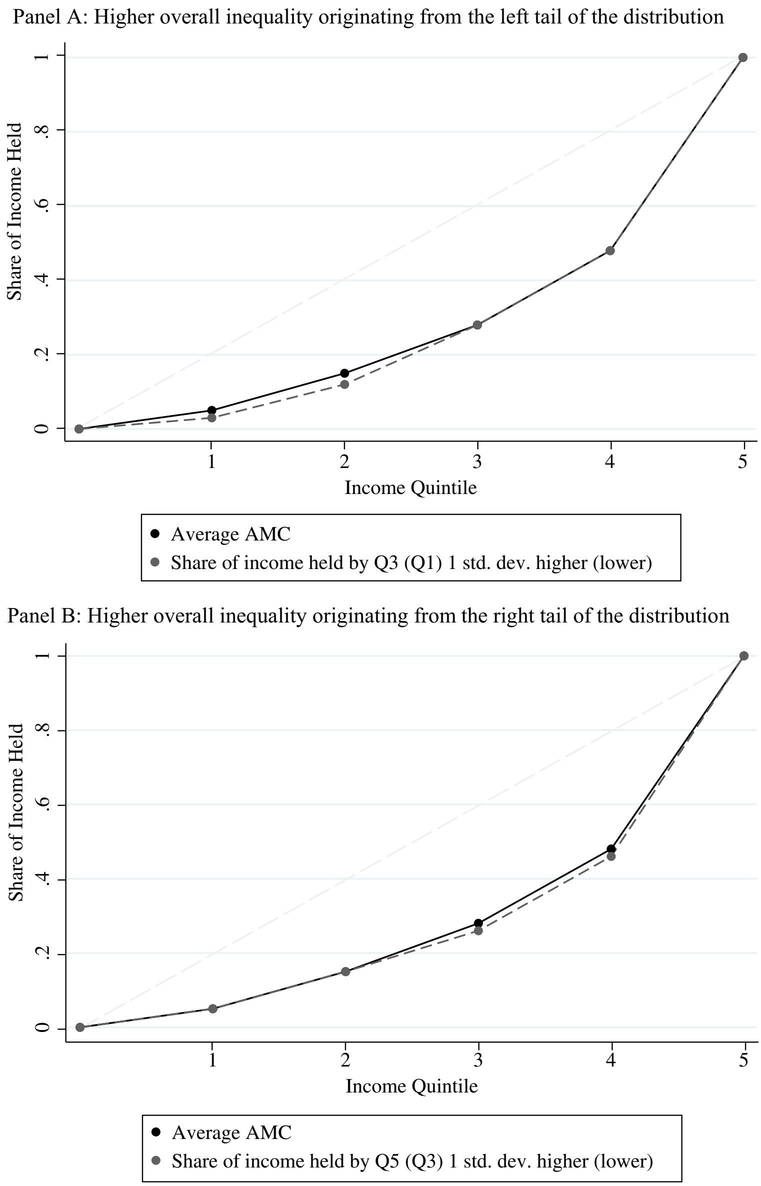

Fig. 1 Gini coefficient and inequality at the top and bottom of the income distribution. *Notes*: The solid lines display the Lorenz curve of an AMC with average quintile shares in 1970. Áreas Mínimas Comparáveis (AMCs) are roughly equivalent to Brazil's municipalities in 1970. In Panel A, the dashed line shows the Lorenz curve of another AMC where the share of income held by the third quintile is 1 standard deviation (3 percentage points) higher, at the expense of the first quintile, holding the other quintile shares constant. In Panel B, the dashed line shows the Lorenz curve of yet another AMC where the share of income held by the fifth quintile is 1 standard deviation (3 percentage points) higher, at the expense of the middle quintile, again holding the other quintile shares constant

aware of any theory leading to the differential growth effects we find and we lack data to investigate potential political economy mechanisms further.

Our paper builds on an extensive empirical literature linking overall income inequality and subsequent income per capita growth surveyed in Galor (2011). While the studies to date are largely inconclusive, a recent study by Brueckner and Lederman (2018) finds evidence consistent with theories on credit constraints and setup costs. Using an instrumental variable approach with country fixed effects, they show that the correlation between the Gini coefficient and subsequent income and human capital growth is positive in poor countries and negative in rich countries. Another recent study by Berg et al. (2018) finds that higher inequality reduces growth through reduced education and increased fertility. The study which is most closely related to ours is Voitchovsky (2005), which uses the 90/75 income percentile ratio as a proxy for inequality at the top of the income distribution, and the 50/10 income percentile ratio to proxy inequality at the bottom. For a sample of 21 developed countries, the study shows that under some specifications, inequality at the bottom is negatively correlated with growth, and inequality at the top has a positive correlation. The main conceptual difficulty with the Voitchovsky (2005) study is that the regression specifications typically include percentile ratios along with the Gini coefficient in the same equation. But a higher 90/75 income percentile ratio while keeping the Gini coefficient constant necessarily implies that inequality must be lower in other parts of the distribution. As a result, it is not clear what the coefficient on the 90/75 income percentile ratio is picking up. A similar issue arises in Ravallion (2012), which explores the impact of various parameters of the initial income distribution on income per capita growth and poverty reduction in a large sample of developing countries. The regression specification sometimes includes the initial poverty rate along with the Gini coefficient in the same equation. But holding initial income per capita constant, countries with a higher poverty rate are also those with higher overall inequality, as discussed in that study. Moreover, holding both average income and overall inequality constant implies that countries with a higher poverty rate must have less inequality somewhere else in the distribution, which further complicates the interpretation of the coefficients.

The main contribution of our study is its conceptually straightforward approach to analyze the relationship between left- and right-tail inequality and subsequent outcomes. By replacing the Gini coefficient with the quintile income shares as our main regressors, we exploit variation in inequality originating from either tail while keeping initial average income and the other income shares constant. As illustrated in panels A and B of Fig. 1, we exploit quantitatively identical differences in income inequality arising from opposite sides of the income distribution. This implies that the differential effects of bottom versus top inequality we find are not driven by treating inequality in the two tails differently. And because our regressions hold income per capita constant, places with a lower share of income going to the poor and a higher share going to the middle class are places where the poor are poorer and the middle class is richer not only in relative but also in absolute terms. This is important because the credit market imperfections cum setup cost theory is based on absolute income levels. Another advantage of our setting is that we draw on homogeneously collected census data from a single country. Thus, unlike existing cross-country studies, we do not face a tradeoff between data quality and sample size, and our results are less prone to measurement error bias. Ours is also the first study to look at the effects of bottom versus top income inequality in a developing country context. An additional advantage of our setting is that by comparing sub-national units within the same country and state, we can abstract from differences in institutions at the federal and state level which might be correlated with initial inequality and income growth. Last but not least, our study also provides the first direct evidence on physical capital accumulation linking initial income distribution to subsequent economic growth.

A potential drawback compared to cross-country studies is that our results could be driven by migration. For example, places with high initial inequality at the bottom may experience higher emigration of the poor and thus higher income per capita in future periods among remaining residents. It turns out, however, that the effect of initial income inequality on immigration or emigration is close to negligible in practice as further discussed below. Another caveat is that the sub-national units we analyze are relatively small (the median population is 11,192) and thus results may not generalize to the cross-country level. However, education is a positive predictor of growth and Brazilian sub-national units also experience income convergence as predicted by growth theories, suggesting that there are at least some common mechanisms linking inequality and growth both within and across countries. We also show that our results are unlikely to be driven by differential measurement error at the bottom versus at the top of the initial income distribution. And as in any observational study there is the possibility that our results are driven by some unobserved confounder, such as heterogeneity in local tastes for equality. We show, however, that our estimates change very little if we adjust them to account for potential selection on unobservables as proposed in Oster (Forthcoming). An important final robustness check is that we also get quantitatively very similar results when we include entity-level fixed effects and account for potential dynamic panel bias using lagged regressors as instruments.

The paper is organized as follows. Section 2 describes the Brazilian setting, and Sect. 3 describes the data and presents summary statistics. Section 4 discusses our approach to analyze the relationship between left- and right-tail inequality and growth and how we deal with potential confounding factors. Section 5 presents and discusses our main results, and Sect. 6 presents evidence on mechanisms. Section 7 presents the results of multiple robustness checks, and Sect. 8 concludes with a discussion of external validity.

2 The Brazilian setting

The starting point of our analysis is 1970, which is dictated by the availability of comparable income data over time as further discussed below. Our units of analysis are the 3659 Brazilian *Áreas Mínimas Comparáveis* (AMCs), which are roughly equivalent to Brazil's municipalities in 1970. On average, AMCs had about 25 thousand inhabitants at that time, while the median population was about 11 thousand. 97% of individuals who worked or studied in 1970 did so in their municipality of residence and so it is reasonable to think of each AMC as a small separate economy. Although today Brazil is a middle-income country with a large urban population, this was by no means true in 1970 when a large fraction of the population lived in poverty, and almost half resided in rural areas. The level of education was also extremely low. In particular, AMCs had an average educational attainment of individuals above 25 years old of only 1.37 years, and an illiteracy rate of 44% for people above 15.

Several mechanisms driving the relationship between income inequality and growth might operate within AMCs. First, there was ample room for growth driven by the accumulation of human and physical capital. However, opportunities for investment were rather limited for households at the bottom of the wealth distribution, since access to credit was not widespread. For example, in the agricultural sector where 42% of the workforce was employed in 1970, only 12% of establishments received credit during that year.[1] Moreover,

[1] We obtained the share of the workforce employed in agriculture from the 1970 population census, and the share of agricultural establishments that received credit from a report summarizing the findings of the 1970

a recent paper by Skoufias et al. (2013) shows that a microfinance access expansion in the northeast of Brazil in 1998–2003 increased the total use of credit and firm profits, consistent with the existence of binding credit constraints for small enterprises. The firms in their sample are self-employed entrepreneurs with less than five employees and in 1997 less than 4% of these firms had borrowed in the last 3 months from formal or informal sources.[2] The existence of credit constraints for relatively poor microentrepreneurs is also confirmed in other developing countries by a series of recent papers that randomly allocate grants to small firms. In particular, the studies of McKenzie and Woodruff (2008), De Mel et al. (2008), and Fafchamps et al. (2014) in Mexico, Sri Lanka and Ghana find that the marginal returns to capital for these small firms exceed the market interest rates, indicating the presence of binding credit constraints.[3] As can be seen in Appendix Table A.2, the firms targeted by these studies are comparable to the small firms in the Brazilian study of Skoufias et al. (2013), and this is especially true in the Mexican study by McKenzie and Woodruff (2008). The available evidence thus suggests that credit constraints were likely binding for a large fraction of Brazilians in our period of study. Together with setup costs, inequality in the lower or upper tail of the income distribution might therefore lead to very different growth dynamics as argued in Galor and Zeira (1993), for example.

An important part of the literature has devoted attention to the role of political forces in explaining the relationship between inequality and economic development (Persson and Tabellini 1994; Alesina and Rodrik 1994; Benabou 1996, among others). In particular, these studies posit that more unequal societies face higher pressure for redistribution, which in turn generates distortions and hampers growth. Although Brazil was under a military dictatorship from 1964 until 1985, local elections were still held in most municipalities. Furthermore, while only 2.6% of total revenues were raised by municipal taxes, around 12–17% of total public spending was done by municipal governments (Hagopian 1996). So even though within-AMC inequality in the 1970s could not impact local taxation in a relevant way, it might still affect the composition of spending and thus economic development. While we do not mean to downplay the role of redistributive policies in mediating the effect of local inequality on subsequent growth, it is not clear from a theoretical perspective how inequality generated at the bottom as opposed to the top of the income distribution would interact with spending decisions at the AMC level. Furthermore, lack of information on spending at the local level for this period does not allow us to explore this issue further.

3 Data and descriptive statistics

Our analysis relies on the 25% sample of the 1970 and 1980 Brazilian censuses obtained from the Brazilian Statistical Agency (*Instituto Brasileiro de Geografia e Estadística*, IBGE), and on AMC-level statistics published by IPEA (*Instituto de Pesquisa Econômica*

Footnote 1 (continued)

agricultural census. Although there is no information on credit for firms in other sectors of the economy, the fact that only 5% of households in the 1970 census had a mortgage (i.e., the owners were still paying for it) provides further evidence on how limited access to credit was in this period.

2 The authors of this study rely on a survey called "Economia Informal Urbana" that surveys more than 40,000 individuals which reported owning a micro-enterprise with up to five employees in 1997.

3 Other studies examining the impact of making microcredit more accessible for poor households (mostly business owners or people who intended to start a business) find positive impacts on business profits, indicating the presence of binding credit constraints as well (Banerjee et al. 2015).

Aplicada).[4] The starting point of our analysis is 1970 since this is when the first round of the Brazilian census with precise information on individual incomes was conducted.[5] Our units of analysis are the 3659 Brazilian AMCs, which are themselves based on all existing municipalities from 1970 to 2000. Since many municipalities split or merged with others after 1970, performing our analysis at the AMC-level allows us to keep the borders constant and follow the same geographical units over time.[6]

When working with the 1970 25% census sample we first match the 3974 municipalities appearing in this census to their corresponding AMCs.[7] This census investigated the monthly monetary income for all individuals 10 years and older and asked for: (i) the income of the last month for those who earn a fixed income (e.g., salaries, pensions, etc.); (ii) the average monthly income in the last 12 months for those who receive variable income (e.g. professionals' fees, sale and brokerage commissions, payments for services rendered, etc.); and (iii) the monthly average of other regular sources of income such as routine donations, rents, dividends, etc. Income in kind was not included. We construct the per capita family income distribution for each AMC in 1970 by dividing the sum of the individual incomes of all family members living in the same household by the number of family members.[8] This way, all family members living under the same roof have the same per capita income. We exclude from our analysis those individuals living in collective dwellings (e.g. hotels, hospitals, nursing homes), which amount to 1.89% of our sample. We also exclude individuals living in a private dwelling who are unrelated to the family head (tenants and domestic servants) and who account for 2.19% of all individuals. As a robustness check, we include individuals living in collective dwellings and non-family members living in private dwellings. We then construct three main indicators from each AMC's per capita family income distribution, using the appropriate expansion weights provided by IBGE. First, we calculate the average per capita family income in 1970, which we express in R$ of 2000. Second, we construct the 1970 AMC Gini coefficient,[9] and third the share of total AMC income held by each of the quintiles. We also calculate an approximation to the Gini coefficient using these quintiles shares.[10] Unlike subsequent censuses, incomes above Cr$ 9998 are top-coded at this value,[11] affecting 0.04% of employed individuals. As a robustness check, we adjust top-coded incomes, multiplying them by a factor of 2.15 so that individual incomes in the top 20% follow a Pareto distribution.[12] We also use the 1970 census to compute the share of occupied individuals working in each of the

[4] Available at http://www.ipeadata.gov.br/.

[5] In the previous census round in 1960, income was reported in only eight categories.

[6] Brazil had 3974 municipalities in 1970, and 5507 by 2000.

[7] We match municipality and AMC codes using the Data Zoom program developed by the Department of Economics at PUC-Rio, available at http://www.econ.puc-rio.br/datazoom/english/.

[8] Only 1.68% of individuals who report having a source of income do not report their earnings.

[9] We use the ineqdec0 code written by Stephen Jenkins for this calculation.

[10] Define Qn as the share of total AMC income held by quintile n. Then Gini ≈ 0.8*[Q5 + 0.5Q4 - 0.5Q2 - Q1].

[11] All figures in the 1970 and 1980 census are reported in Cruzeiros (Cr$), Brazil's currency at the time. We converted all figures to Brazilian Reais (R$) of 2000 using the guidelines employed by the 1998 "Atlas de Desenvolvimento Humano no Brasil."

[12] This methodology is commonly used by researchers working with CPS data in the U.S. Examples include Katz and Murphy (1992), Autor et al. (2008), and Autor and Dorn (2013).

16 economic sectors detailed in the census, which we use as controls in the robustness checks we perform in Sect. 7.2.[13]

We apply the same procedure to the microdata from the 1980 25% long-form sample to obtain the per capita family income distribution of each AMC. We then compute a series of per capita income percentiles and poverty rates for each AMC. For computing poverty rates, we use three different poverty lines: (i) half of the Brazilian minimum wage in September 1991; (ii) US$ 2 a day at 2005 PPP, which is the median poverty line amongst developing countries based on a compilation of national poverty lines in Ravallion et al. (2009); and (iii) US$ 1.25 a day at 2005 PPP, the mean poverty line for the poorest 15 countries. The first of these was obtained from IPEA, whereas the others were taken from Ravallion (2012). We also rely on the 1980 census 25% sample to study the migration patterns across AMCs between the 1970 and 1980 censuses. More specifically, we compute immigration and emigration rates for each AMC between 1970 and 1980. Since the 1980 census asks individuals how long they have been living in their current municipality, we count all individuals in a particular AMC who report that they were not living in their current municipality in 1970 as immigrants. Individuals who are younger than 10 years old in 1980 and belong to a family in which the head is an immigrant are considered immigrants as well. We calculate an AMC's immigration rate as the ratio between the number of immigrants in 1980 and the AMC's total population in 1970. Furthermore, the census also asks people who have been living in their current municipality for less than 10 years to specify the municipality in which they were previously residing. Thus, for each AMC, we can calculate the number of people who were living there in 1970 and left. We use this to calculate the emigration rate, which is simply the number of emigrants of an AMC divided by the 1970 population. A caveat for this measure is that the municipality of origin is missing for approximately 19% of all immigrants. Since we cannot trace these people to their municipality of origin, our emigration rate does not include these observations in the numerator. We also calculate AMCs' fertility and mortality rates, to uncover the population dynamics in this period. The fertility rate is the ratio between the number of AMC natives who are less than 10 years old in 1980 and the population in 1970. The mortality rate is therefore the ratio between the change in population between 1970 and 1980 not accounted for by fertility and migration, divided by 1970 population.[14]

From IPEA we obtain the following 1970 AMC-level control variables, which we use in all our regressions: average years of schooling of individuals aged 25 and above, illiteracy rates for people 15 years and older, total population, the percentage of people living in urban areas, and life expectancy. We also obtain a set of time-invariant AMC-level controls such as latitude, longitude, distance to the state and federal capitals, and an indicator for whether the AMC is located on the coast. Our main outcome variables consist of mean per capita family income at the AMC-level for 1980, 1991 and 2000, which are based on the corresponding population censuses. We also obtained several outcome measures of educational attainment in 1980 at the AMC-level, which are based on the education level

[13] These sectors are agriculture and forestry; gathering of wild growing products; hunting and fishing; mining and quarrying; manufacturing; construction; public utilities; wholesale and retail trade; services; transporting and communications; education, health and social activities; public administration, legislation and justice; national defense and public safety; real estate, financial and insurance activities; liberal professions; and other activities.

[14] This also includes individuals who emigrated from an AMC but do not report their municipality of origin.

of individuals 25 years and older. Specifically, we use average years of education and the share of individuals with less than 4, between 4 and 8, and with 8 or more years of education for each AMC.

Other IPEA data include the number of businesses and the value of capital stocks held by businesses in each AMC in 1970 and 1980 in the agricultural, commercial, manufacturing and service sectors, all based on the respective economic censuses.[15] Up until 1980, Brazil's statistical agency carried out periodic economic censuses covering all firms in each of these sectors. As explained in detail by the academics in charge of performing these calculations at IPEA (Reis et al. 2005), the value of capital stocks for agricultural establishments include farmland, buildings, long-term crops,[16] vehicles, machinery, agricultural instruments, and livestock. They deduct the value of residential buildings within farms, and only consider livestock used for traction or reproduction. Firms in the agricultural sector include all establishments dedicated to farming, cattle, poultry or rabbits, beekeeping, raising silk worms, horticulture, floriculture, forestry, and extraction of vegetable products. When calculating the value of capital stocks for manufacturing, commercial and service industry establishments, they take into account the value of firms' capital employed in buildings, land, machinery and equipment as reported in the corresponding economic censuses. The firms covered by the commercial census are all the establishments dedicated to the purchase, sale, exchange or distribution of merchandise through retail.[17] Activities considered in the manufacturing census include the processing and packaging of food products, metallurgical activities, production of pharmaceutical products, clothes items, etc. Finally, firms in the service sector include all establishment whose activity involves providing services to people, such as hotels, repair shops, restaurants, and so on.[18] After calculating the value of each establishment's capital stock, IPEA aggregates these figures at the municipality level, separately for each sector. In performing this calculation, they consider an establishment as belonging to a municipality if it is located there. As with all of our income figures, capital stocks are expressed in real terms (in 2000 R$).

We summarize the main variables for our analysis in Table 1. In 1970 Brazil was an extremely poor country. The average AMC monthly mean per capita family income in 1970 was 56 R$ (in R$ of 2000), which was approximately 31 US dollars in 2000. Inequality rates were high with an average Gini coefficient of 0.47 and standard deviation 0.07. Inequality also displayed a considerable degree of spatial variation across AMCs, as shown in Fig. 2.[19] During the 1970–2000 period income per capita more than doubled on average across AMCs. Most of these gains occurred in the first decade and were accompanied by large increases in physical capital stocks across sectors.

[15] A detailed account on how the value of capital stocks at the AMC-level was backed out from the corresponding economic censuses by IPEA can be found in Reis et al. (2005).

[16] Long-term crops are those that do not need to be replanted after each harvest, such as coffee, oranges, bananas, etc.

[17] For example, the sales activities of a firm that produces machinery is accounted for in the commercial census only if the firm sells its products through its own retail establishments, but not if it does so through a wholesaler. Further explanations can be found in the reports by IBGE on the commercial censuses. For example, at https://biblioteca.ibge.gov.br/visualizacao/periodicos/63/cc_1980_v4_n15_ba.pdf.

[18] Further details can be found in IBGE's reports on the results of the service industry census. See https://biblioteca.ibge.gov.br/visualizacao/monografias/GEBIS%20-%20RJ/censodosservicos/1980_v05_n03_AC.pdf.

[19] Appendix Figures A.1 and A.2 depict the spatial variation in the share of income held by the bottom and top quintiles in 1970, respectively.

Table 1 Descriptive statistics

	Mean	SD	Min	Max
Dependent variables				
Ln (*mean per capita family income*)—(*in 2000 R$*)				
1980 mean	4.77	0.59	2.32	6.41
1991 mean	4.64	0.59	3.17	6.38
2000 mean	5.01	0.57	3.62	6.86
Ln (*value of capital stocks in 1980*)—(*in 2000 R$*)				
Agriculture	17.68	1.35	0.00	22.69
Commerce	15.07	1.91	0.00	23.18
Manufacturing	15.14	3.17	0.00	24.63
Services	14.41	2.13	0.00	24.08
Total	18.24	1.37	13.11	25.23
Ln (*number of establishments in 1980*)				
Agriculture	6.61	1.14	0.00	10.85
Commerce	3.95	1.29	0.00	10.97
Manufacturing	2.88	1.34	0.00	10.37
Services	3.02	1.58	0.00	10.94
Total	6.86	1.04	0.00	11.89
1980 educational attainment (*people 25 years and older*)				
Average years of schooling	2.07	1.06	0.10	7.20
Proportion with less than 4 years of schooling	0.74	0.16	0.15	0.99
Proportion with 4 or more and less than 8 years of schooling	0.20	0.12	0.01	0.75
Proportion with 8 or more years of schooling	0.06	0.05	0.00	0.48
Explanatory variables—all measured in 1970				
Gini coefficient	0.47	0.07	0.25	0.97
Gini approximation based on quintile income shares	0.42	0.07	0.15	0.80
Share of AMC income held by Q1	0.05	0.02	0.00	0.14
Share of AMC income held by Q2	0.09	0.02	0.00	0.30
Share of AMC income held by Q3	0.14	0.03	0.00	0.27
Share of AMC income held by Q4	0.20	0.03	0.00	0.45
Share of AMC income held by Q5	0.52	0.07	0.14	1.00
Ln (real mean per capita family income) (2000 R$)	3.89	0.54	0.57	5.70
Avg years of education	1.37	0.81	0.00	5.60
Illiteracy rate	0.44	0.18	0.03	0.92
Population (in 000 s)	25.45	132.47	0.83	5924.61
Share urban population	0.33	0.21	0.01	1.00
Life expectancy	51.11	4.27	38.40	64.46

The unit of observation is an Área Mínima Comparável (AMC) over the period 1970–2000. There are 3659 AMCs

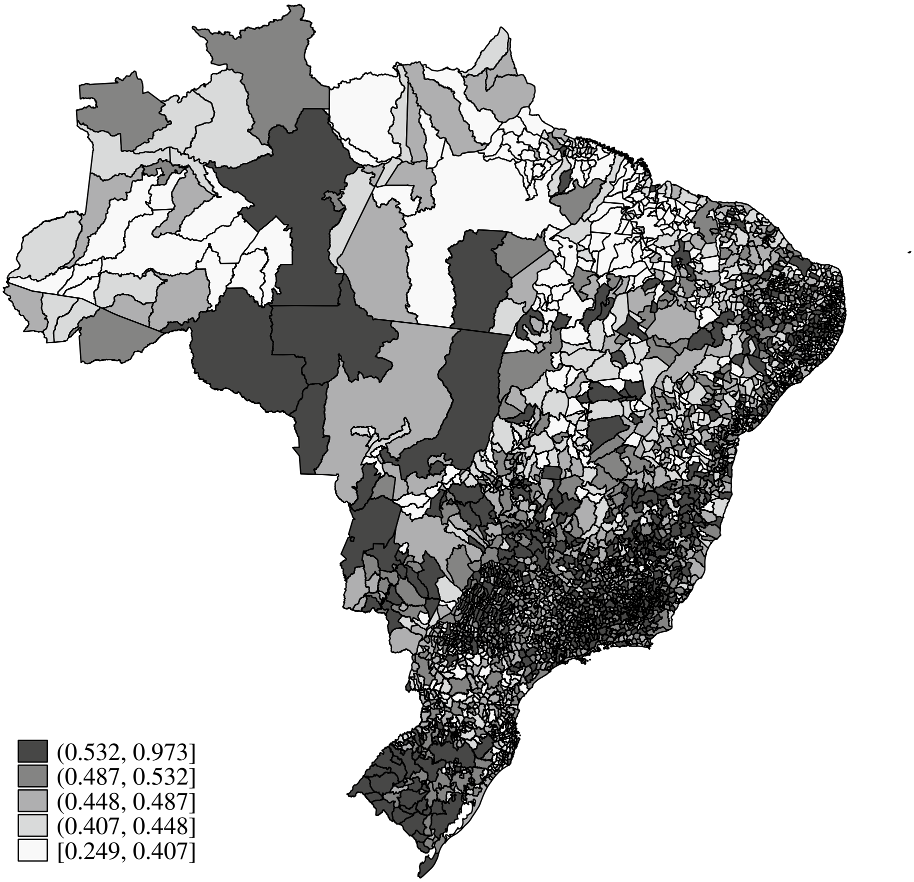

Fig. 2 Gini coefficient across Brazilian AMCs in 1970. *Notes*: Each unit is an Área Mínima Comparável (AMC) in 1970. Darker areas indicate greater income inequality as measured by the Gini coefficient in 1970

4 Estimation approach

In order to estimate the effect of initial overall income inequality on subsequent economic growth, we run the following OLS regression:

$$\ln\left(\bar{y}_{a,s,t}\right) = \beta_0 + \beta_1 \ln\left(\bar{y}_{a,s,1970}\right) + \beta_2 Gini_{a,s,1970} + X_{a,s,1970}\delta + \gamma_s + U_{a,s,t} \quad (1)$$

where $\bar{y}_{a,s,t}$ is the mean per capita family income in AMC a in state s and year t. We estimate separate regressions with the (natural) logarithm of average per capita family income in 1980, 1991 and 2000, $\ln\left(\bar{y}_{a,s,t}\right)$, as the dependent variable. Since we control for baseline income per capita it makes no difference whether the left-hand side is a future level or a growth rate (except for the coefficient estimate on baseline income per capita). $Gini_{a,s,1970}$ is the Gini coefficient in AMC a in state s in 1970, $X_{a,s,1970}$ is a vector of 1970 AMC-level controls, γ_s are state fixed effects and $U_{a,s,t}$ is the influence of unobserved factors on outcomes in year t.

Our coefficient of interest in these regressions is β_2, the effect of initial inequality on the future level of income per capita. There are many potential confounders at the AMC-level in 1970 that could correlate with both initial income inequality and subsequent economic growth, and the direction of the bias in $\hat{\beta}_2$ is unclear. For instance, AMCs with greater income inequality in 1970 might also be places where a higher percentage of the population has low levels of education, and low education is likely bad for economic growth, biasing $\hat{\beta}_2$ downwards. AMCs with high inequality in 1970 might also be more rural, and growth patterns of rural areas might be different from those of more urbanized AMCs for reasons unrelated to the society's initial income inequality. We address potential omitted variable bias by including standard growth determinants in all our regressions as well as state fixed effects.[20] In particular, $X_{a,s,1970}$ includes a set of AMC characteristics in 1970 (average years of schooling of individuals 25 years and older, illiteracy rate for people 15 years and older, population, share of urban population, and life expectancy), as well as other time-invariant features of each AMC (latitude, longitude, distance from the federal and state capitals, and an indicator for whether the AMC is located on the coast). In Sect. 7 below we also show results that include AMC fixed effects and account for potential dynamic panel bias using lagged regressors as instruments. Nonetheless, to the extent that reverse causality or heterogeneity in local tastes for equality are important, our effect estimates are best interpreted as partial correlations rather than causal effects of inequality.

In order to distinguish between effects of inequality originating from either tail of the income distribution, we take advantage of the fact that the Gini coefficient can be approximated with a formula based on the shares of income held by each of the quintiles.[21] This approximation is:

$$Gini_{a,s,1970} \approx 0.8 \times \left[Q5_{a,s,1970} + 0.5Q4_{a,s,1970} - 0.5Q2_{a,s,1970} - Q1_{a,s,1970}\right] \tag{2}$$

where $Qn_{a,s,1970}$ is the 1970 share of total income of AMC a in state s held by quintile n. As can be seen in the first column of Table 2, controlling for state fixed effects and our vector of 1970 AMC covariates, the Gini coefficient and its approximation based on quintile shares in 1970 vary almost one-to-one, with an R^2 of almost one. In light of this, decomposing differences in the 1970 AMC Gini coefficients into differences in quintile income shares as in Eq. (2) allows us to differentially focus on the growth effects of inequality in the left and right tails of the income distribution. Throughout our Gini decomposition exercise, the omitted quintile is the middle one. Thus, a lower share of income held by the first quintile implies a correspondingly higher share of income held by the middle one, and higher overall income inequality, as illustrated in Panel A of Fig. 1. Throughout the paper we refer to this as inequality in the left or bottom tail. The exact same increase in overall inequality occurs when a higher share of overall income is held by the top quintile at the expense of the middle one. This is what we call higher inequality in the right or upper

[20] Excluding *Distrito Federal* which is also a municipality in itself, Brazil has 26 states in total.

[21] As shown by Theil (1967), if there are n groups of individuals and they are ordered in terms of income, the Gini coefficient can be expressed as $\sum_{i=1}^{n} y_i \left(\sum_{j<i} x_j - \sum_{j>i} x_j \right)$, where x_i is the population share of group i, and y_i is its income share. If there are 5 groups, it follows that the Gini coefficient is approximated by Eq. (2).

Table 2 Income shares and income inequality in 1970

Dependent variable: 1970 Gini coefficient		
Gini approximation	1.099***	
	(0.006)	
Share of 1970 AMC income held by Q5		0.925***
		(0.015)
Share of 1970 AMC income held by Q4		0.350***
		(0.023)
Share of 1970 AMC income held by Q2		−0.332***
		(0.026)
Share of 1970 AMC income held by Q1		−0.696***
		(0.029)
Baseline controls	✓	✓
Observations	3659	3659
R^2	0.976	0.979

This table presents the results of OLS regressions where the unit of observation is an AMC and the dependent variable is the 1970 Gini coefficient. The explanatory variable of interest in column 1 is the 1970 Gini approximation based on quintile shares, calculated using the formula in (2). The explanatory variables of interest in column 2 are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

tail, as shown in Panel B of Fig. 1. With this intuition in mind, we distinguish between the growth effects of inequality in the left and right tails by running the following regressions:

$$\begin{aligned} \ln\left(\bar{y}_{a,s,t}\right) = \beta_0 + \beta_1 \ln\left(\bar{y}_{a,s,1970}\right) + \propto_1 Q5_{a,s,1970} + \propto_2 Q4_{a,s,1970} \\ + \propto_3 Q2_{a,s,1970} + \propto_4 Q1_{a,s,1970} + X_{a,s,1970}\delta + \gamma_s + U_{a,s,t} \end{aligned} \tag{3}$$

which is the specification in Eq. (1), but replacing the Gini coefficient with four of the quintile income shares and omitting the middle quintile share. In this regression, our coefficients of interest are $\propto_1$ (the coefficient for inequality in the right tail), and $\propto_4$ (the coefficient for inequality in the left tail, when multiplied by minus 1). When exploring the correlation between inequality in the left and right tails with subsequent growth in physical capital, we estimate Eq. (3) with log capital stock held by firms on the left-hand side. We do this separately for each sector of the economy (agriculture, manufacturing, commerce and services), and also for the total capital stock across sectors. In all these regressions we control for the log of the 1970 value of the capital stocks held by firms in every sector. We also run the same regressions with the total number of establishments in each sector as the dependent variable in 1980, controlling for 1970 levels.

When analyzing growth in human capital, we run the above regression for a set of outcomes capturing the 1980 levels of educational attainment in an AMC, such as average years of education of individuals above 25 years old, the percent of such individuals with less than 4 years of education (i.e., less than a primary school degree), between 4 and 8 years (i.e., more than primary but less than middle school), and 8 or more years of education (i.e., at least a middle school diploma). In addition to the baseline controls included in $X_{a,s,1970}$, we also control for the 1970 proportion of individuals 25 and older with less than 4, between 4 and 8, and 8 or more years of education.

5 Main results

5.1 Overall inequality and income per capita growth

Table 3 shows that there is positive correlation between the Gini coefficient in 1970 and income per capita in 1980, 1991 and 2000. In particular, AMCs with a 0.07 (one standard deviation) higher Gini in 1970 had about 3% higher income per capita in 2000. It is clear that the results are concentrated in the first two decades. Income per capita increased by about 2% by 1980 and by about 3% by 1991 in places where the Gini coefficient was 7 percentage points higher in 1970, with only negligible additional growth by the year 2000. The results are very similar when using the Gini approximation based on quintile shares, as can be seen in Appendix Table A.1, which validates the regressions based on Eq. (3) below. Taken together, the results suggest that holding 1970 income per capita and standard confounders constant, AMCs with higher inequality in 1970 end up with higher average income in 2000, but do not experience permanently higher growth.

Even though our study explores within-country (across sub-national unit) variation, the coefficients on control variables are very similar to those in cross-country studies. For example, education is a strong positive predictor of growth and Brazilian AMCs also experience income convergence as predicted by growth theories. These results speak to the external validity of our study and suggest that there are at least some common mechanisms linking inequality and growth both within and across countries. We also note that our regressions account for most of the variation in subsequent income per capita levels, (R^2 of 0.877 in column 5 of Table 3), leaving little room for unobserved confounders to dramatically alter our estimates of interest.[22]

5.2 Quintile income shares and income per capita growth

Having established a positive correlation between inequality as measured by the Gini coefficient in 1970 and subsequent economic growth, we now explore whether this effect is different when inequality originates from the lower as opposed to the upper tail of the income distribution. As explained in Sect. 4, the third quintile is omitted in our regressions with quintile shares. Thus, a lower share of income held by the first quintile is matched by an equivalent higher middle quintile income share, implying higher inequality in the left tail. Therefore, multiplying the coefficient associated with the share of 1970 AMC income held by Q1 by -1 gives us the effect of higher left-tail inequality in 1970 on future levels of

[22] The high R^2 in our level regressions is not a mere statistical artifact. If we run this same regression using the growth in AMC income between 1970 and 2000 instead of the income level as the dependent variable, we still get an R^2 of 0.673.

Table 3 Income inequality in 1970 and subsequent income

	Ln (income)		
	1980	1991	2000
Gini coefficient	0.313***	0.415***	0.447***
	(0.073)	(0.072)	(0.060)
Ln (1970 income)	0.386***	0.296***	0.229***
	(0.023)	(0.021)	(0.017)
Avg years of education	0.083***	0.097***	0.094***
	(0.015)	(0.016)	(0.014)
Illiteracy rate	− 0.170**	− 0.224***	− 0.468***
	(0.069)	(0.068)	(0.059)
Population (in 000s)	0.000	0.000*	0.000
	(0.000)	(0.000)	(0.000)
Share urban population	0.363***	0.380***	0.290***
	(0.030)	(0.034)	(0.030)
Life expectancy	0.004***	0.006***	0.008***
	(0.001)	(0.001)	(0.001)
Coastal AMC	0.064***	0.070***	0.078***
	(0.016)	(0.018)	(0.019)
Observations	3659	3659	3659
R^2	0.857	0.849	0.877

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variable is the mean per capita family income in 1980, 1991 and 2000 (in ln). The 1970 Gini approximation based on quintile shares is calculated using the formula in (2), and Ln (1970 income) is the mean per capita family income in 1970 (in ln). All regressions also include state fixed effects and control for latitude, longitude, and distance from state and federal capital. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

income per capita. On the other hand, a higher share of income held by the top quintile implies a lower share of income held by the middle quintile, and thus higher inequality in the right tail. Thus, the coefficient on the share of 1970 AMC income held by Q5 directly gives the partial effect of higher inequality in the right tail on subsequent outcomes.

The first row in columns 1 through 3 of Table 4 shows that a higher 1970 share of income held by Q5 at the expense of Q3 had a small and statistically insignificant effect on income per capita in 1980, 1991 and 2000. Thus, holding the other quintile shares, 1970 income per capita and standard confounders constant, AMCs with higher right-tail inequality did not experience higher growth compared to more equal AMCs. Similarly, the coefficient estimates on Q4 and Q2 are also small and insignificant, suggesting that the distribution of income among the three middle quintiles has no implications for future growth. On the other hand, the negative coefficient for the share of income held by Q1 means that AMCs with higher inequality in the left tail of the distribution did experience higher growth compared to more equal places. In particular, AMCs with a 3 percentage points (one standard deviation) higher income share of Q3 in 1970 at the expense of Q1 had about 3% higher income per capita by the year 2000. Income per

Table 4 Income shares in 1970 and subsequent income

	Ln (income)		
	1980	1991	2000
Share of 1970 AMC income held by Q5	0.183	0.092	0.243
	(0.226)	(0.198)	(0.170)
Share of 1970 AMC income held by Q4	0.126	−0.026	0.216
	(0.328)	(0.255)	(0.229)
Share of 1970 AMC income held by Q2	0.359	−0.125	−0.349
	(0.336)	(0.320)	(0.277)
Share of 1970 AMC income held by Q1	−1.440***	−1.591***	−1.065***
	(0.469)	(0.453)	(0.380)
Ln (1970 income)	0.393***	0.302***	0.234***
	(0.024)	(0.022)	(0.017)
Avg years of education	0.085***	0.098***	0.094***
	(0.015)	(0.016)	(0.014)
Share illiterate	−0.151**	−0.205***	−0.454***
	(0.069)	(0.067)	(0.059)
Population (in 000s)	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)
Share urban population	0.347***	0.364***	0.276***
	(0.031)	(0.034)	(0.030)
Life expectancy	0.005***	0.006***	0.008***
	(0.001)	(0.001)	(0.001)
Coastal AMC	0.060***	0.067***	0.076***
	(0.016)	(0.018)	(0.019)
Observations	3659	3659	3659
R^2	0.858	0.849	0.877
P-value (Q4 + Q2 = 0)	0.362	0.748	0.746
P-value (Q5 + Q1 = 0)	0.055	0.014	0.110

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variable is the mean per capita family income in 1980, 1991 and 2000 (in ln). The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. All regressions also include state fixed effects and control for latitude, longitude, and distance from state and federal capital. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

capita increased by about 4% by 1980 with little additional growth by 1991 and a slight and statistically insignificant drop by year 2000. As with overall inequality, higher left-tail inequality therefore did not lead to permanently higher income growth. The last row of Table 4 shows that the impacts of left- and right-tail inequality are not only economically but also statistically different in most specifications. We therefore conclude that the overall effect of inequality picked up by the Gini coefficient is essentially driven by the lower tail of the initial income distribution: compared to more equal places, AMCs with a higher share of income going to the middle quintile at the expense of the bottom quintile grow more rapidly, while places with a higher share of income going to the top quintile at the expense of the middle quintile get no growth boost at all.

5.3 Quintile income shares and subsequent income distribution

Which income groups benefited from higher income per capita as a result of greater left-tail inequality? It would be surprising if increased mean income were driven exclusively by the lower tail of the 1980 income distribution for example. While our repeated cross-sectional data do not allow us to track incomes of specific quintiles over time, we can nonetheless investigate whether increased mean income in subsequent periods reflects a general or more localized upward shift of the income distribution. Since higher growth already materialized by 1980, we focus on this period and substitute income per capita with various 1980 income percentiles on the left-hand side of the regression equation. As shown in Table 5, more inequality in the left tail in 1970 is correlated with a positive shift in the top half of the 1980 income distribution. More specifically, in AMCs where the share of income held by Q3 (Q1) was 3 percentage points higher (lower) in 1970, the 50th, 60th and 80th per capita income percentiles were all about 6% higher. The 90th and 95th percentiles were respectively 5% and 4% higher in 1980, while at the bottom of the distribution the shift was if anything negative. Figure 3 plots the magnitude of the shift compared to the average AMC in 1980.

A similar distributional shift emerges when we look at poverty rates in 1980. Table 6 shows that higher initial inequality in the left tail is associated with significantly lower poverty rates in 1980, but only for relatively broad definitions of poverty. Under our two broadest definitions, for which the average poverty rates were 60% and 45%, respectively, AMCs where the share of income held by Q3 in 1970 was 3 percentage points higher had a roughly 1 percentage point lower poverty rate in 1980. Higher initial left-tail inequality does not correlate with lower poverty rates in 1980 for our strict definition of poverty, under which the average poverty rate in 1980 was 32%. Overall, these results suggest that higher initial inequality at the bottom was good for the middle and upper quintiles, and neutral for the bottom quintiles, which is remarkably consistent with the credit market imperfections cum setup costs theory outlined above.

6 Evidence on mechanisms

6.1 Quintile income shares and physical capital growth

Given the positive correlation between 1970 inequality in the left tail and subsequent growth in mean per capita family income, we should observe a similar correlation with growth in physical and human capital if credit constraints and setup costs were holding back investment in more equal places. Panel A of Table 7 shows effect estimates for the value of capital stocks held by firms from different sectors in 1980, holding constant the 1970 value of both total and sector-specific capital stocks and our other controls. Consistent with the positive growth effect of left-tail inequality discussed above, we find a positive and sizable correlation between inequality in the left tail in 1970 and the value of capital stocks in 1980 for all four sectors as well as overall. Total capital stocks were about 12% higher in AMCs where the 1970 income share of Q3 was 3 percentage points (one standard deviation) higher at the expense of the bottom quintile. The effect of left-tail inequality on physical capital accumulation arises across sectors, ranging from about 9% in agriculture, to about 15% in the commercial sector, around 24% in manufacturing and 13% in services. On the other hand, we find much smaller and statistically less significant effects of inequality in the right tail on firms' capital stocks.

Table 5 Income shares in 1970 and 1980 income percentiles

	Ln (income percentile in 1980)							
	10th	20th	40th	50th	60th	80th	90th	95th
Share of 1970 AMC income held by Q5	−0.038	0.262	−0.421	−0.576	−0.790**	−0.655*	−0.123	0.382*
	(0.028)	(0.688)	(0.455)	(0.423)	(0.382)	(0.341)	(0.196)	(0.216)
Share of 1970 AMC income held by Q4	−0.043	0.713	0.278	0.097	−0.148	−0.407	0.050	0.339
	(0.065)	(0.921)	(0.662)	(0.626)	(0.570)	(0.593)	(0.274)	(0.305)
Share of 1970 AMC income held by Q2	−0.067	3.425***	1.160	0.937	0.342	0.351	0.101	0.134
	(0.051)	(1.165)	(0.827)	(0.727)	(0.691)	(0.312)	(0.295)	(0.329)
Share of 1970 AMC income held by Q1	−0.084	2.986**	−1.429	−2.056**	−2.173***	−2.316***	−1.707***	−1.325***
	(0.060)	(1.482)	(0.965)	(0.829)	(0.663)	(0.598)	(0.425)	(0.474)
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	3658	3658	3658	3658	3658	3658	3658	3658
R^2	0.807	0.415	0.665	0.726	0.791	0.856	0.867	0.854

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variables are the different AMC income percentiles in 1980 (in ln), based on per capita family incomes. The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

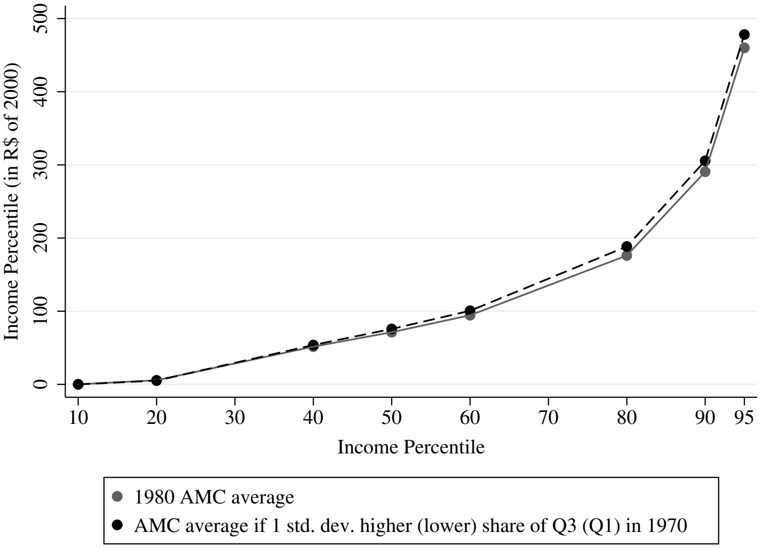

Fig. 3 Left-tail inequality in 1970 and 1980 income percentiles. *Notes*: The solid line plots the 1980 income percentiles of the average AMC in terms of per capita family income. The dashed line plots the 1980 income percentiles of an AMC with a 1 standard deviation higher (lower) share of income held by the third (first) quintile in 1970, which was calculated using the coefficients in Table 5

We next explore whether this increase in capital stocks was driven by the extensive margin (i.e., opening of new firms) or the intensive margin (i.e., expansion of existing firms) by running the same regressions as above but with the number of establishments in each sector in 1980 (in natural logs) as the dependent variable. Panel B of Table 7 shows that there is a positive and statistically significant association between left-tail inequality in 1970 and the number of firms in 1980 in all sectors except for agriculture. More specifically, AMCs in which the third quintile held one standard deviation higher income (at the expense of the bottom quintile) had between 7 and 8% more establishments in the commercial, manufacturing and services sectors by 1980. This implies that the expansion of capital stocks in AMCs with higher left-tail inequality in 1970 was at least partially driven by new business openings, which is reassuring since one would expect credit constraints to operate on both intensive and extensive margins.

In order to further corroborate the results on physical capital investments, we also investigate whether AMCs with higher bottom inequality had a higher share of entrepreneurs (either employers or self-employed) at the outset of our sample period in 1970. Column 1 of Appendix Table A.4 shows results for the share of entrepreneurs in the AMC in 1970, irrespective of income quintile. The negative and significant estimate on Q1 suggests that bottom inequality was associated with a higher share of entrepreneurs in 1970. Places with a three percentage points higher income share of the middle quintile at the expense of the bottom quintile had a 1 percentage point higher share of entrepreneurs. On the other hand, places with higher top inequality had about half a percentage point lower share of entrepreneurs in 1970. While the magnitude of this differential is small, its sign lines up with the lower capital accumulation associated with increased top inequality shown above. Column 2 shows similar results for a slightly reduced sample of

Table 6 Income shares in 1970 and 1980 poverty rates

	Share of people under poverty line in 1980		
	1/2 the Sep-91 min. wage (84.73 R$ a month)	US$ 2 a day (50.67 R$ a month)	US$ 1.25 a day (26.43 R$ a month)
Share of 1970 AMC income held by Q5	0.158***	0.084	0.014
	(0.057)	(0.061)	(0.062)
Share of 1970 AMC income held by Q4	0.004	−0.037	−0.070
	(0.073)	(0.082)	(0.088)
Share of 1970 AMC income held by Q2	−0.188**	−0.205**	−0.140
	(0.090)	(0.104)	(0.102)
Share of 1970 AMC income held by Q1	0.417***	0.326**	0.106
	(0.127)	(0.136)	(0.132)
Baseline controls	✓	✓	✓
Observations	3658	3658	3658
R^2	0.871	0.826	0.699
Dependent variable mean	0.604	0.447	0.319

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variable is the share of people in the AMC in 1980 below the poverty line in terms of their per capita family income. The poverty line used in column 1, obtained from IPEA, is half the Brazilian minimum wage in September 1991, whereas the poverty lines in columns 2 and 3 (US$ 2 and US$ 1.25 a day at 2005 PPP) were taken from Ravallion (2012). The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

AMCs for which the shares of entrepreneurs by 1970 income quintile can be constructed (in 12 AMCs the two bottom quintiles had zero income). Columns 3 through 7 show results for the 1970 share of entrepreneurs in Q1 through Q5, respectively. While higher bottom inequality is associated with a higher share of entrepreneurs in each quintile, the largest increase comes from the middle quintile, amounting to 1.6 percentage points in AMCs where Q3 enjoyed a 3 percentage points higher income share at the expense of Q1. Overall, the results for entrepreneurs in 1970 line up nicely with those on capital accumulation and suggest that higher inequality at the bottom allowed the middle class to overcome credit constraints and setup costs that were holding back investment in more equal places.

6.2 Quintile income shares and human capital growth

Turning to investments in education, Table 8 shows a similar pattern though with different magnitudes. The first column shows that there is no correlation between initial inequality in the right tail and average educational attainment in 1980. On the other hand, average years of schooling was higher in 1980 in AMCs that started out with higher inequality in the left tail. Though significant statistically, this effect is relatively small: AMCs in which the income held by the middle quintile in 1970 was 3 percentage points higher (at

Table 7 Income shares in 1970 and the value of firms' capital stocks and number of establishments in 1980

	Agriculture	Commercial	Manufacturing	Services	Total
Panel A: value of capital stocks					
Share of 1970 AMC income held by Q5	−0.079	−1.021	−4.905**	−0.548	−0.979*
	(0.600)	(0.856)	(1.991)	(1.219)	(0.529)
Share of 1970 AMC income held by Q4	0.072	−0.710	−5.201**	−0.259	0.174
	(0.750)	(1.212)	(2.500)	(1.729)	(0.719)
Share of 1970 AMC income held by Q2	0.293	−0.008	−3.288	−0.707	−0.174
	(1.006)	(1.440)	(3.839)	(2.032)	(0.992)
Share of 1970 AMC income held by Q1	−3.042**	−5.053***	−8.009**	−4.380*	−3.931***
	(1.339)	(1.897)	(3.839)	(2.398)	(1.222)
Baseline controls	✓	✓	✓	✓	✓
Lagged value of capital stocks	✓	✓	✓	✓	✓
Observations	3659	3659	3659	3659	3659
R^2	0.786	0.721	0.626	0.653	0.831
P-value (Q5 + Q1 = 0)	0.083	0.018	0.017	0.142	0.002
Panel B: number of establishments					
Share of 1970 AMC income held by Q5	0.587**	−0.060	−1.015*	0.370	−0.540
	(0.295)	(0.407)	(0.521)	(0.561)	(0.343)
Share of 1970 AMC income held by Q4	0.478	0.681	−1.042	1.232*	−0.139
	(0.395)	(0.544)	(0.703)	(0.739)	(0.464)
Share of 1970 AMC income held by Q2	0.762	0.548	−0.118	0.793	0.873
	(0.513)	(0.705)	(0.869)	(1.025)	(0.543)
Share of 1970 AMC income held by Q1	−0.359	−2.654***	−2.577**	−3.100**	−2.070***
	(0.632)	(0.909)	(1.181)	(1.248)	(0.732)
Baseline controls	✓	✓	✓	✓	✓
Lagged number of establishments	✓	✓	✓	✓	✓

Table 7 (continued)

	Agriculture	Commercial	Manufacturing	Services	Total
Observations	3659	3659	3659	3659	3659
R^2	0.904	0.883	0.816	0.854	0.868
P-value (Q5 + Q1 = 0)	0.790	0.028	0.023	0.103	0.010

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variables in Panel A and B are the value of the AMC's private sector capital stocks (in ln) and the number of establishments in 1980 (in ln), for each productive sector, respectively. All dependent variables were calculated by IPEA from the 1980 economic censuses. The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. All regressions also control for lagged dependent variables in all sectors. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

Table 8 Income shares in 1970 and educational attainment in 1980

	Average years of education	Share of people by years of education		
		< 4 years	≥ 4 and < 8 years	≥ 8 years
Share of 1970 AMC income held by Q5	0.323	− 0.002	− 0.024	0.026*
	(0.225)	(0.037)	(0.035)	(0.014)
Share of 1970 AMC income held by Q4	0.390	− 0.031	0.001	0.031*
	(0.311)	(0.052)	(0.049)	(0.018)
Share of 1970 AMC income held by Q2	0.388	− 0.055	0.062	− 0.006
	(0.373)	(0.064)	(0.059)	(0.023)
Share of 1970 AMC income held by Q1	− 1.091**	0.177**	− 0.148**	− 0.029
	(0.491)	(0.079)	(0.075)	(0.029)
Baseline controls	✓	✓	✓	✓
Lagged education controls	✓	✓	✓	✓
Observations	3659	3659	3659	3659
R^2	0.935	0.925	0.897	0.886
Dependent variable mean	2.073	0.742	0.196	0.062

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variables measure the average educational attainment in 1980 for individuals 25 years and older. The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. All regressions also control for lagged educational attainment variables (i.e., share of people according to their educational attainment in 1970). Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

the expense of the bottom quintile) saw an increase of 0.03 years in average educational attainment of individuals above 25 years of age. Turning to the regressions in columns 2 to 4, it is clear that this increase in educational attainment was driven by a smaller proportion of the population with less than 4 years of education (i.e., less than a primary school degree), and a higher proportion with educational attainment of between 4 and 8 years. Higher inequality at the top also increased the proportion of the population with more than 8 years of schooling, but the impact is negligibly small.

6.3 Effect heterogeneity by initial income

The leading explanation for higher growth in AMCs with higher left-tail inequality is that in these AMCs, individuals in the middle quintile were on the margin of overcoming the credit constraints and setup costs for investing in physical and human capital. While our regressions compare more equal to less equal places holding initial income per capita constant, our estimates so far represent average effects across many different levels of initial income per capita. But the marginal investor can only be located in the middle quintile in some AMCs, since the absolute level of initial income in the third quintile varies across AMCs. Following this logic, we split the sample into three groups according to the average income of individuals in Q3 in 1970. Appendix Table A.3 presents the average baseline characteristics of these three groups of AMCs. In the poorest group, the AMC-average of middle quintile average monthly income in 1970 was 19.52 R$ (in R$ of 2000). In contrast, the corresponding figures for middle quintile individuals in the middle and top terciles of the Q3 average income distribution were 34.20 R$ and 58.83 R$, respectively. Since these differences are rather large, we would expect growth effects to be concentrated in only one of the three groups if the credit constraints cum setup costs mechanism is driving the results.

The evidence in Table 9 suggests indeed that the entire effect of lower-tail inequality on growth comes from one of the groups of AMCs, namely those with the poorest middle quintiles in 1970. Columns 1–3 show that the correlation between higher inequality in the left tail and subsequent income per capita is only positive and statistically significant for AMCs in the bottom tercile. In the two other groups of AMCs, the coefficients are of the same sign but much smaller in magnitude and statistically insignificant (columns 4–9). Overall, these results are again remarkably in line with theories emphasizing credit constraints and investment indivisibilities as the main drivers of the inequality-growth relationship.

7 Robustness checks

7.1 Quintile income shares and migration

A first-order concern given our setting is that the results could be driven by differential migration patterns. For example, places with high initial inequality in the left tail might experience higher emigration of the poor and thus higher income per capita among remaining residents in future periods. Alternatively, AMCs with high initial left-tail inequality could be attracting workers with higher education and higher potential earnings, leading to a selection-driven increase in average income. AMCs with a higher Q3 income share in 1970 (and lower share of income held by Q1) indeed had about 4.5% more residents in 1980 as shown in column 1 of Table 10. However as shown in column 2, AMCs with higher inequality in the left tail in 1970 did not experience higher immigration between 1970 and 1980, and only slightly lower emigration rates as shown in column 3. A 3 percentage points higher share of total income held by the middle quintile (at the expense of the bottom quintile) was associated with an emigration rate reduction of 0.70 percentage points over the 1970–1980 decade relative to an average emigration rate of about 19%. In fact, the higher growth in population between 1970 and 1980 experienced by AMCs that started out with higher inequality in the left tail was mostly driven by a lower mortality rate, as shown in column 5 of Table 10.[23]

7.2 Controlling for 1970 sectoral labor force shares

While our main specification controls for the share of an AMC's 1970 population living in rural areas, as a robustness check we also account for differences in the initial structure of the economy in a more flexible manner. As detailed in Sect. 3, we control for the share

[23] What we refer to as mortality rate is actually a residual category, namely the ratio between the change in population between 1970 and 1980 not accounted for by fertility or migration. This includes not only people who passed away in 1970–1980, but also individuals who emigrated from the AMC but did not report their municipality of origin.

Table 9 Income shares in 1970 and subsequent income—heterogeneous effects by average income of third quintile in 1970

Dependent variable: Ln (income) in	Q3 in bottom Tercile			Q3 in middle Tercile			Q3 in top Tercile		
	1980	1991	2000	1980	1991	2000	1980	1991	2000
Share of 1970 AMC income held by Q5	0.027	−0.268	−0.003	0.220	0.118	0.253	0.350	1.006***	0.535*
	(0.321)	(0.290)	(0.237)	(0.427)	(0.378)	(0.347)	(0.351)	(0.353)	(0.313)
Share of 1970 AMC income held by Q4	0.416	−0.496	−0.033	0.385	0.194	0.498	−0.751	0.500	−0.104
	(0.432)	(0.386)	(0.304)	(0.564)	(0.470)	(0.426)	(0.557)	(0.454)	(0.421)
Share of 1970 AMC income held by Q2	0.144	0.032	−0.395	0.100	−1.178*	−0.822*	0.578	0.584	−0.462
	(0.572)	(0.444)	(0.372)	(0.555)	(0.606)	(0.496)	(0.570)	(0.634)	(0.606)
Share of 1970 AMC income held by Q1	−1.647**	−1.920***	−1.127**	−0.518	−0.595	−0.380	−0.653	−0.300	−0.610
	(0.646)	(0.635)	(0.506)	(0.849)	(0.784)	(0.721)	(0.761)	(0.880)	(0.756)
Baseline controls	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	1205	1205	1205	1205	1205	1205	1249	1249	1249
R^2	0.659	0.559	0.703	0.662	0.723	0.822	0.761	0.747	0.765

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variable is the mean per capita family income in the year specified in the column header (in ln). The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. The sample is split into three groups according to the average per capita household income of the individuals in the third quintile in 1970. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

Table 10 Income shares in 1970, population growth and migration from 1970 to 1980

	Population growth	Immigration rate	Emigration rate	Fertility rate	Mortality rate
Share of 1970 AMC income held by Q5	−0.397	−0.167	0.240***	−0.033	−0.043
	(0.383)	(0.317)	(0.053)	(0.051)	(0.107)
Share of 1970 AMC income held by Q4	−0.004	0.211	0.142*	−0.036	0.037
	(0.427)	(0.356)	(0.073)	(0.064)	(0.135)
Share of 1970 AMC income held by Q2	0.787	0.616	0.032	0.103	−0.101
	(0.661)	(0.466)	(0.100)	(0.105)	(0.223)
Share of 1970 AMC income held by Q1	−1.494**	−0.627	0.232**	−0.150	0.483**
	(0.643)	(0.506)	(0.113)	(0.105)	(0.210)
Baseline controls	✓	✓	✓	✓	✓
Observations	3659	3659	3659	3659	3659
R^2	0.210	0.194	0.524	0.596	0.276
Dependent variable mean	0.137	0.258	0.190	0.242	0.174

This table presents the results of OLS regressions based on Eq. (1). The unit of observation is an AMC. The dependent variable in column 2 is the immigration rate between 1970 and 1980, i.e., the ratio between the number of people living in the AMC in 1980 who were not living there in 1970 (or who belong to a family in which the head was not living there in 1970 if aged less than 10) and the AMC's population in 1970. The dependent variable in column 3 is the AMC's emigration rate in 1970–1980, calculated as the ratio between the number of people who reported the AMC as their previous residence but were not living there in 1980, and the AMC's population in 1970. The dependent variable in column 4 is the AMC's fertility rate in 1970–1980, computed as the ratio between the number of children less than 10 years old living in the AMC in 1980 whose parents are non-immigrants and the AMC population in 1970. The dependent variable in column 5, which we refer to as mortality rate, is the ratio between the change in population between 1970 and 1980 not accounted for by fertility and migration and the 1970 population; this is a residual category, including not only people who passed away in 1970–1980, but also individuals who emigrated from the AMC but did not report their municipality of origin. The explanatory variables of interest are the shares of 1970 AMC income held by each of the quintiles, with the third quintile being the omitted category. Baseline controls include state fixed effects and controls for 1970 mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, life expectancy, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. Robust standard errors are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

of individuals working in each of the 16 economic sectors defined by the 1970 census. As shown in Appendix Table A.5, the association between inequality in the left-tail in 1970 and subsequent economic growth is robust to the inclusion of these controls. Our evidence on physical and human capital accumulation featured in Appendix Tables A.6 and A.7 is also consistent with our results on inequality, although slightly weaker when it comes to physical capital accumulation.

7.3 Imputing top-coded incomes

Unlike subsequent censuses, incomes in the 1970 census are top-coded, a practice which affects 0.04% of employed individuals. In order to check whether our results are driven by differential measurement error at the bottom versus at the top of the initial income distribution, we impute top-coded incomes and construct new quintile shares. Following the methodology used by Katz and Murphy (1992), Autor et al. (2008), and Autor and Dorn (2013), among others, we multiply top-coded incomes by a factor of 2.15, so that individual incomes in the top 20% follow a Pareto distribution. As can be seen in Appendix Table A.8, our main results are robust to these imputations.

7.4 Alternative definition of the 1970 census universe

As explained in Sect. 3, the 1970 AMC income statistics used in our main specification exclude individuals living in collective dwellings and individuals who live in a private dwelling but are unrelated to the family head (i.e., tenants and domestic servants), which in total account for 4.10% of individuals in the 1970 census.[24] While the correlation between initial inequality in the left tail and subsequent growth in income per capita is robust to the inclusion of these individuals, as shown in Appendix Table A.9, inequality at the top is positively correlated with growth in income per capita in some specifications. However, the coefficients for inequality at the top are much smaller and not robust across specifications.

7.5 Adjusting for selection on unobservables

As discussed in Sect. 4, there could be many confounders at the AMC-level in 1970 correlating with both initial income inequality and subsequent economic growth. Although we address potential omitted variable bias by including standard growth determinants in all our regressions as well as state fixed effects, we cannot fully rule out the existence of unobservable determinants of AMC growth that correlate with initial income inequality even conditional on these controls.

In this subsection we follow the approach of Oster (Forthcoming), itself an extension of the methodology developed by Altonji et al. (2005), to evaluate the robustness of our estimates to potential omitted variable bias. Under the two assumptions that observable and unobservable variables are equally related to the regressor of interest and that the bias from unobservables is not so large that it biases the direction of the covariance between

[24] Almost 83% of individuals living in collective dwellings in 1970 do not live with their family. These people account for 1.6% of the total population. Since almost 42% of them do not have any income (as opposed to 4% in the general population), it is very likely that they are children living in orphanages, incarcerated individuals, etc., and so we exclude them from our analysis.

the observables and the regressor of interest, Oster (Forthcoming) develops an estimator that accounts for selection on unobservables. Since the quintile income shares only capture inequality in the left and right tails if they are conditioned on the other quintile shares and initial income, we include all of these in the "uncontrolled" regression.

Our estimates change very little if we adjust them to account for potential selection on unobservables. The bias-adjusted estimate for the first quintile income share in the regression using mean per capita family income in 2000 (in ln) as the outcome variable is equal to −0.796, down from −1.065 in the specification that controls for all our observables (column 3 of Table 4). This change is quite small because the coefficient in the uncontrolled regression is −1.490, which is close to the coefficient in the regression with the full set of controls.[25] In the case of Q5, which was small and statistically insignificant in our initial regression, controlling for potential selection on unobservables results in an impact estimate of 0.123, compared to 0.243 in column 1 of Table 4.

7.6 Estimations using panel data

Our main specification estimates the relationship between initial inequality and subsequent growth by exploiting cross-sectional differences in inequality across AMCs (after controlling for state fixed effects and standard confounders). In this section we evaluate the robustness of our main estimates to controlling for unobserved time-invariant AMC characteristics. In particular, we estimate the impact of within-AMC decadal changes in inequality on subsequent income by using our four census rounds (1970, 1980, 1991 and 2000).

The results are remarkably robust to alternative estimation approaches. Recall that the 10-year growth estimates from our cross-sectional estimation in Table 4 are close to zero for top-inequality and −1.44 for bottom inequality. In the first column of Table 11 we present OLS estimates of the relationship between AMC quintile shares in period t and mean per capita family income (in ln) in year t + 10. This regression includes year fixed effects, as well as our set of time-varying AMC controls measured in year t, state fixed effects, AMC geographical controls but no AMC fixed effects. The estimate for top inequality is close to zero, while the estimate for bottom inequality is −1.67. In column 2 we include AMC fixed effects and drop the lagged dependent variable, resulting in top-and bottom-inequality effect estimates of −0.40 and −1.42, respectively. As shown in Angrist and Pischke (2009), the true effect is likely bracketed by these two specifications.

A potential limitation of relying on within-AMC variation with a lagged dependent variable is that the estimates of interest may suffer from dynamic panel bias (Nickell 1981). We address this problem by using standard first difference GMM (Arellano and Bond 1991)

[25] If we perform this same adjustment using the growth in 1970–2000 instead of the income level as the outcome variable, our adjusted coefficient is −0.902, which is even closer to the one in the regression with full controls. The first reason for this is that the R^2 in the uncontrolled regression is much lower when the dependent variable is income growth (0.083 versus 0.655). And so in that regression, the increase in R^2 is massive compared to the change in coefficient estimates. The second reason is that as proposed in Oster (Forthcoming), we also assume that the hypothetical maximum R^2 from a regression of the dependent variable against all observable and unobservable controls is the minimum value between 1 and 1.3 times the R^2 of the regression with observable controls.

Table 11 Income shares and subsequent income—panel estimation

Dependent variable: Ln (Income)$_{t+10}$	OLS	Fixed effects		GMM	
		(excl. lag. dep.)	(incl. lag. dep.)	FD	System
Share of AMC income held by Q5$_t$	−0.126	−0.401**	−0.318*	−0.412*	−0.263
	(0.159)	(0.162)	(0.166)	(0.228)	(0.370)
Share of AMC income held by Q4$_t$	0.367	0.572**	0.568**	−0.033	0.356
	(0.244)	(0.263)	(0.262)	(0.329)	(0.523)
Share of AMC income held by Q2$_t$	−0.264	−0.279	−0.222	0.554	0.081
	(0.262)	(0.271)	(0.273)	(0.360)	(0.520)
Share of AMC income held by Q1$_t$	−1.668***	−1.416***	−1.175***	−1.439***	−1.782***
	(0.334)	(0.327)	(0.334)	(0.462)	(0.656)
Lagged dependent variable	✓		✓	✓	✓
Time-varying controls	✓	✓	✓	✓	✓
Time-invariant controls	✓				

This table presents the results of different panel estimations using AMC data for 1970, 1980, 1991 and 2000. Column 1 presents the results of an OLS regression where the dependent variable is the mean per capita family income (in ln) in year t + 10, and the explanatory variables of interest are the shares of AMC income held by each of the quintiles in year t, with the third quintile being the omitted category. Time-varying controls include year fixed effects, and controls for the AMC's mean per capita family income, average schooling attainment, illiteracy rate, population, share of urban population, and life expectancy in year t. Time-invariant controls include state fixed effects, latitude, longitude, distance from state and federal capital, and whether the AMC is located on the coast. The OLS regressions in columns 2 and 3 include AMC fixed effects, but the regression in column 2 also excludes the lagged dependent variable. Column 4 presents the results of a GMM estimation in which the regressors are expressed in first differences, and all explanatory variables are instrumented using their lagged levels. Column 5 presents the results of a system GMM estimation, where all regressors are assumed to be predetermined. All GMM estimations are conducted using the xtabond2 command developed by David Roodman. Standard errors clustered by AMC are reported in parentheses. *Significant at 10%; **significant at 5%; ***significant at 1%

and system GMM estimations (Arellano and Bover 1995; Blundell and Bond 1998).[26] Both the first difference and system GMM estimates are remarkably similar to our cross-sectional estimates. Specifically, we find that using the two dynamic panel GMM techniques, AMCs with a 3 percentage points higher share of income held by Q3 in 1970 at the expense of Q1 exhibit income per capita between 4 and 5% higher after 10 years. These estimates are significant at the 1% level. In line with our cross-sectional estimates, the coefficients for right-tail inequality are small and not consistently significant across the different estimation approaches shown in Table 11.

[26] Under the first difference GMM estimation procedure, we take first differences and instrument all explanatory variables using their lagged levels. The system GMM estimator augments the first-differenced estimations with the moment conditions of the equation in levels, instrumenting the lagged regressors with their first differences. We assume that all regressors are predetermined, and conduct all estimations with the xtabond2 command in Stata.

8 Conclusion

This study investigates whether inequality originating from the lower as opposed to the upper tail of the initial income distribution has different effects on subsequent income per capita growth. Using within-country variation in Brazil, we find that holding average income per capita and standard controls constant, AMCs with higher inequality in the left tail of the income distribution in 1970 exhibited higher growth in income per capita over the subsequent three decades. At the same time, there is no correlation between initial inequality in the right tail of the initial income distribution and growth. We show that our estimates are remarkably robust when we account for selection on unobservables. Moreover, our results are barely affected if we flexibly control for 1970 structural differences across sectors, impute incomes that were top-coded in the 1970 census, or use alternative definitions of the population underlying our inequality measures. Last but not least, we also get quantitatively very similar results when we include AMC fixed effects and account for potential dynamic panel bias using lagged regressors as instruments. Consistent with the existence of credit constraints and setup costs for investing in physical and human capital, we show that AMCs that started out with higher inequality in the left tail also accumulated physical and human capital at a faster pace, while right-tail inequality had no such effects.

Whether left-tail inequality would lead to higher growth in other contexts is likely to depend crucially on the distribution of initial income relative to setup costs. Consider once more a stylized economy in which the population is divided into three groups of equal size (the poor, the middle class, and the rich). In the first economy, the incomes of the poor and the middle class are initially too low to overcome the setup costs for investing in either human or physical capital and so higher inequality at the bottom boosts investment and growth. But consider a second economy where the average level of income is higher so that credit constraints only bind for the poorest group. Higher inequality in the left tail would have no impact on growth in this situation, which is precisely what we find for AMCs where the average income of the middle quintile is higher. In an even richer economy in which all groups can profitably invest in human and physical capital, it is conceivable that higher inequality in the lower tail could even be bad for growth if it results in the poor becoming credit constrained. This last case might be representative of the U.S. over the 1940–1980 period, for which Panizza (2002) provides some evidence of a negative cross-state relationship between inequality and growth. To be consistent with the theory however, the overall effect of inequality should be driven by the bottom tail and there should be some evidence of reduced human and physical capital accumulation. In sum, while under credit constraints and investment indivisibilities the relationship between overall inequality and growth may be genuinely heterogeneous, additional evidence from the U.S. and other within-country studies are required to further corroborate the theory.

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