Inequality and Growth:

Why Physical and Human Capital Interactions Matter

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Abstract

We investigate the relationship between economic growth and income inequality under the influence of human and physical capital accumulation, using a panel of US state-level data. Our empirics account for cross-section dependence and parameter heterogeneity, in non-stationary series. We find that the inequality-growth relationship is characterized by non-linearities, as inequality dampens growth in states with low physical capital, while high physical capital states enjoy a growth boost. In both cases, the influence of inequality on growth diminishes with human capital.

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1. Introduction

During the last decades United States witnessed an increase in both income inequality and economic growth. In this framework, important policy-related questions are still pending: what generates inequality? Is inequality linked with growth and if so, how? The evolution of the empirical literature offers no consensus on the above questions. In the US context, positive relationships between income inequality and economic growth have been found by Frank (2009) and Partridge (1997, 2005), a negative association is supported by Panizza (2002), while Atems & Jones (2014) argue that its magnitude varies over time.

This study attempts to shed light on the above questions by focusing on how physical and human capital accumulation affect the relationship between income inequality and economic growth. We take advantage of a recent theoretical model by Galor and Moav (2004) which provides a 'unified' framework and merges two approaches available in the earlier literature. Specifically, according to the "classical" approach, income inequality stimulates economic growth by channeling resources towards individuals whose marginal propensity to save is higher (i.e. wealthier households) and thus increases the rate of capital formation (see among others Smith, 1776; Keynes, 1920; Kaldor, 1957 and Bourguignon, 1981). According to the 'unified' theory of Galor and Moav (2004), this approach is rather dominant in the early stages of economic development. In contrast, the "credit market imperfection" approach suggests that equality enhances growth by facilitating access to credit towards human capital financing (Galor & Zeira, 1993). Galor and Moav (2004) argue that this approach corresponds relatively advanced economies where human capital accumulation becomes a major growth determinant and credit constraints are largely binding. Finally, in the late course of economic development the "classical" and "credit market imperfection" approaches are less important and inequality does not affect economic growth.

The 'unified' theory proposed by Galor and Moav (2004) incorporates both approaches by capturing the endogenous replacement of physical capital accumulation by human capital accumulation as the prime engine of economic growth, that is the transition to advanced economies. This is where the main hypothesis of this theory lies: human capital and physical capital accumulation are fundamentally asymmetric, that is by nature. The aggregate productivity of the physical capital stock is essentially independent of its overall distribution in the society, while human capital stock is maximized when its ownership is widely spread among individuals. Thus, in the presence of binding credit constraints, equality favors human capital accumulation, while inequality is beneficial for physical capital accumulation, given that marginal propensity to save increases with income. Specifically, the marginal productivity of physical capital is greater than that of human capital during the early stages of economic development and, thus income inequality is growth-enhancing through physical capital accumulation. As physical capital accumulation rise, the marginal product of human capital gradually increases – due to capital-skill complementarity – thus reducing the initial positive growth effect of inequality. Ultimately, the marginal product of human surpasses that of physical capital. In the latest stages of economic development the inequality-growth link becomes unimportant, as accumulating skills is not impeded by credit market imperfections, mainly due to higher household income in the form of wages.

The fundamental assumptions of the theory offered by Galor and Moav (2004) can be hypothesised as follows (Chambers & Krause, 2010): (1) the marginal propensity to save increases with household wealth (following the "classical" approach), (2) investments in human capital are impeded by credit market constraints in the presence of restrained household wealth and income inequality, (3) diminishing marginal returns characterize human capital accumulation and thus – given the "credit market imperfections" approach – income inequality reduces human capital accumulation, (4) economies are characterized by capital-skill complementarity, since the accumulation of physical capital increases the marginal product of human capital and induces its accumulation.

In this paper, the implications of the aforementioned hypotheses provided by Galor and Moav (2004) are empirically tested. Our aim is to examine the effect of inequality on growth through its dependence on human and physical capital. Is inequality growth promoting in economies where the levels of both physical capital and human capital are low? Does the marginal effect of higher inequality on growth declines as physical capital increases? Similarly, does the marginal effect of higher inequality on growth declines as human capital is enhanced, given binding credit market constraints? Finally, does the effect of higher inequality on growth become insignificant in economies which exhibit high levels of both physical capital and human capital?

This study provides for the first time an empirical investigation of the Galor and Moav (2004) 'unified' theory of inequality and growth using a multiplicative interaction model. We do so, because the growth-inequality relationship is conditional in nature depending on both physical and human capital according to Galor-Moav. In other words, the effect of inequality on growth is non-linear depending on physical and human capital stocks. To this end, we employ a single country framework and thus addressing weaknesses of the related literature as regards the quality of income inequality data and the econometric methodology. First, the use of a comprehensive panel of annual US state-level data (1960-2000) provided by Frank (2009) tackles limitations inherent in standard cross-country regressions such as the implicit assumption of common economic structures, production technologies, institutions and policies across nations (Herzer & Vollmer, 2012). Indeed, corruption levels, labor market flexibility, tax systems, entrepreneurial culture and other factors are poorly measured (Barro, 2000), and these sources of heterogeneity are much more likely to contribute to omitted variable bias across countries than across states (Frank, 2009). As noted by a number of scholars, it is particularly useful to increasingly focus research on determining the impact of income inequality on economic growth using single-country data at the regional level (Partridge, 1997; Dominicis et al. 2008). Human and physical capital in the US states, though high by international standards, exhibit noticeable variation, so there is quite a bit of overlapping of the US and world distributions of these variables. In view of that, we believe that the empirical testing of Galor-Moav theory with US states data is a legitimate exercise. Second, we apply an econometric methodology which jointly examines the role of cross-section dependence and parameter heterogeneity in a non-stationary panel framework. These issues arise due to common shocks, spillovers and production technology heterogeneity (Costantini and Destefanis, 2009; Eberhardt and Teal, 2011). These are crucial given the high degree of interdependency and cross-section variation prevalent in state-level data employed in this work. Overall, the quality of the data employed in our empirical estimations allows us to overcome the above limitations and make robust inferences on the inequality-growth nexus. We take advantage of seven inequality measures offered by Frank (2009) and three education indicators that proxy human capital, including average years of schooling (Turner, 2007) together with high school and college graduates (Frank, 2009).

So, physical and human capital accumulation is incorporated in our analysis, given that data on factor returns are not available. Overall, our results provide only partial support for the 'unified' theory proposed by Galor and Moav (2004). Our estimations reveal that income inequality is non-linearly related to growth, as it reduces growth at low physical capital levels and enhances growth at higher ones, irrespective of human capital level. This is in contrast to the Galor-Moav hypothesis, where higher physical capital increases returns to human capital thus reducing the initially positive effect of inequality on growth, due to capital-skill complementarity. However, we confirm that when large physical capital stocks and high education levels are present, the marginal effect of inequality on growth becomes insignificant. This is part of the Galor and Moav (2004) hypothesis which states that inequality has no substantive impact during the late stages of the development process. Turning to region-specific results, we infer that inequality does not affect growth in the vast majority of the US states, which is consistent with the Galor-Moav predictions for the late stages of economic development. Our results are only comparable with the empirical study offered by Chambers & Krause (2010), where the effects of physical and human capital accumulation on the inequality-growth link follow a similar pattern, in a world panel of countries.

The paper is organized as follows. Section 2 explains the specification of our empirical model. Section 3 describes the data and the econometric methodology. In Section 4, we discuss the empirical results and Section 5 offers some concluding comments.

2. The Econometric Specification and Data

2.1 The Model

We employ a multiplicative interaction model, because the growth-inequality relationship is conditional in nature, depending on both physical and human capital according to the Galor & Moav (2004) unified theory. In other words, the inequality effect on growth depends on both physical and human capital stocks. In this framework, we specify the growth-inequality relationship as follows:

$$yg_{it} = (a_0 + a_3 k_{it} + a_4 h_{it}) ineq_{it} + a_1 k_{it} + a_2 h_{it} + a_5 * k_{it} * h_{it} + a_6 * k_{it} * h_{it} * ineq_{it} + e_{it} \quad (1)$$

Model (1) can be rewritten in a multiplicative interaction form as follows:

$$\begin{aligned} yg_{it} &= a_0 ineq_{it} + a_1 k_{it} + a_2 h_{it} + a_3 * ineq_{it} * k_{it} + a_4 * ineq_{it} * h_{it} + a_5 * k_{it} * h_{it} + \\ &+ a_6 * k_{it} * h_{it} * ineq_{it} + e_{it} \end{aligned} \quad (2)$$

Note that we include all constitutive terms in our empirical specification, as we should do in multiplicative interaction models (Brambor et al., 2006). If we omitted some terms, the estimates of the remaining coefficients would be biased and inconsistent, due to omitted variable bias. Consequently, labor productivity growth depends on inequality, physical and human capital separately, as well as all possible two-way and three-way combinations of the three variables. Thus, the effect of a unit change in inequality on productivity growth is given by:

$$\frac{\partial yg_{it}}{\partial ineq_{it}} = a_0 + a_3 k_{it} + a_4 h_{it} + a_6 * k_{it} * h_{it} \quad (3)$$

Therefore, the inequality growth impact is conditional on physical and human capital stocks acting separately as well as their interaction. In order to identify the influence of each one of the capital stocks on growth, we must condition on a specific value of the other. In this work, we compute the growth impact of inequality for all relevant values of human capital at specific values of physical capital covering all the range of physical capital stocks present in our sample. At the same time, we compute the standard error of (3) in each case in order to make inferences on the statistical significance of the estimated growth effect. This is equal to:

$$\sqrt{\begin{matrix}\mathrm{var}(a_0)+k_{it}^2\,\mathrm{var}(a_3)+h_{it}^2\,\mathrm{var}(a_4)+k_{it}^2h_{it}^2\,\mathrm{var}(a_6)+2k_{it}\,\mathrm{cov}(a_0a_3)+2h_{it}\,\mathrm{cov}(a_0a_4)\\+2k_{it}h_{it}\,\mathrm{cov}(a_0a_6)+2k_{it}h_{it}\,\mathrm{cov}(a_3a_4)+2k_{it}^2h_{it}\,\mathrm{cov}(a_3a_6)+2k_{it}h_{it}^2\,\mathrm{cov}(a_4a_6)\end{matrix}} \quad (4)$$

So, it may be the case that most or all the individual coefficients are insignificant, but the overall effect of inequality on growth is still significant.

Moreover, we estimate model (2), where all variables are centered around the cross-sectional, i.e. state-specific, means. So, the interpretation of the marginal effects changes compared to the case where data are uncentered. Specifically, expression (3) measures the marginal growth impact of a one-unit change in inequality when human capital stock is at its mean for each value of physical capital considered. If we kept human capital at specific values and let physical capital vary, Eq. (3) would measure the effect of a one-unit variation in inequality on growth when physical capital is at its mean for each value of the human capital considered. In both cases, the growth impact of inequality differs from the case where physical and human capital are absent from Eq. (3), i.e. this effect is constant, therefore unconditional (Brambor et al., 2006). Therefore, the presentation of typical results tables is not sufficient in order to judge the statistical significance, sign and magnitude of the impact of inequality on growth, because they only present findings on the individual coefficients. It may be the case that the latter are not individually significant, while the overall inequality growth effect is.

2.2. Data

We use a recent comprehensive panel of state-level income inequality measures to re-evaluate empirically the growth-inequality relationship in the US (Frank, 2009). This is characterized by both large *N* and *T*, as it contains annual observations for 48 US states during the period 1960-2000. The greater homogeneity of state-level compared to national data mitigates the difficulty of capturing structural differences, since these are much smaller within rather than across countries. As stated in the Introduction, corruption, labor and product market regulations, tax and transfer systems as well as institutions are more likely to create omitted variable bias in the latter case compared to the former. We use six inequality indicators, namely the Atkinson index, Gini index, Theil entropy index, top 10%, top 1% and top 90-99% income shares. The inequality measures are derived from tax data reported in Statistics of Income published by the Internal Revenue Service (IRS) (Frank, 2009). Atkinson index is social welfare function based, uses an inequality aversion parameter and is bound between 0 and 1. Gini index describes the whole income distribution, it is the average distance between all pairs of proportional income in the population and lies between 0 and 1. Theil index is derived from statistical information theory and it is unbound. Higher values of the indices indicate higher inequality. Note that the relative mean deviation variable which Frank (2009) offers is note included in our analysis, as it is the least analytically attractive. This is so, because a reallocation of income within the population is not reflected in a change of this index (weak principle of transfers) (Frank, 2014).

Furthermore, the main limitation of the IRS income data is the underrepresentation of individuals earning less than a threshold gross income level, which depends on age as well as marital status and changes every year. For this reason, we consider top 10%, top 1% and top 90-99% income shares the most reliable inequality measures in our dataset (for details on the definitions and construction of these measures, see Frank (2009; 2014). This limitation does not allow us to study the growth impact of bottom-end inequality, which might differ from that of overall or top-end inequality (Voitchovsky, 2005). However, the large time series and cross-section dimensions of our dataset mitigate collinearity, allow to control for unobserved heterogeneity and improve efficiency. They also permit testing of complicated econometric models, control for time-specific and state-specific effects, enhance study of dynamics and facilitate parameter identification.

Turning to the other variables, we construct real GDP (in 2000 dollars) by dividing nominal GDP obtained from the Bureau of Economic Analysis (BEA) by state-specific CPI (Berry et al., 2000). Next, we calculate labor productivity dividing real GDP by labor force, since state employment data do not exist before 1969. Our choice of the human capital variables is dictated by the relevant literature. First, we employ the most commonly used human capital measure, i.e. average years of schooling. Average schooling years take into account the total amount of formal education acquired by the workforce, so they proxy human capital stock quite accurately (Benhabib and Spiegel, 1994; Engelbrecht, 1997). Data on schooling years and labor are provided by Turner et al. (2007). Schooling years in the US states, even at their minimum value, are high by international standards, but nevertheless span over the top quintile of the world distribution of this variable (Barro & Lee, 2014). So, there is quite a bit of overlapping of the US and world distributions of average schooling years. We check the robustness of our findings using two more measures of educational attainment; the proportion of the population with at least a high school degree and the proportion of the population with at least a college degree, which we collected from Frank (2009). Private capital stock is measured in millions of dollars and is obtained from Garofalo and Yamarik (2002) and Yamarik (2013) and is normalized using the labor force.

Fixed time effects are eliminated by taking the difference of all variables from their cross-section (state-specific) means. This is crucial given the long time span of our sample and year-to-year incremental changes in tax legislation associated with the IRS income data. We perform cross-section demeaning in order to facilitate meaningful interpretation of the results, given that we estimate a multiplicative interaction model (see Section 2, above). Descriptive statistics are reported in Table 1 below. All variables display large variation. Beginning with the inequality indicators, the Atkinson index varies between 0.15 and 0.38 with a mean value of 0.21. Gini is on average 0.51, but ranges between 0.41 and 0.66. The Theil Entropy index ranges from 0.13 to 1.33, being on average 0.5. Regarding our preferred inequality indicators, the top 10% income share equals on average 34%, but ranges between 27% and 57%. The top 1% averages 10%, but varies between 6% and 28%. The respective numbers for the top 90-99% income share are 24%, 19% and 31%. The above variation occurs both across states and through time, but approximately three-fourths occur in the time dimension and one-fourth in the cross-section dimension. Overall, inequality was relatively stable from the beginning of our sample period up to the mid-1980s and is steadily increasing since then in all states, although at varying rates.

[INSERT TABLE 1 HERE]

Concerning the remaining variables, labor productivity growth varies between -16.54% (state name) and 21.14% with a mean of 0.34%. Physical capital per worker equals 1.39 on average, ranging from 0.02 to 75.81. Schooling years also display huge variation being between 8.65 (less than high school completed) and 14.14 (more than half-college completed). Looking at the alternative human capital measures, the proportion of the population with at least high school education was on average 38.86%, but ranged between 14.45% and 60.75%, a more than 4-fold difference. The variation is even larger when we observe the percentage of the population having completed college, which is 9.4% on average, but varies between 2.35% and 24.79%, a higher than 10-fold difference.

3. Empirical Methodology

3.1. Cross-section dependence and parameter heterogeneity

To overcome the issue of spurious regression, which characterized earlier studies on the relation between education and regional productivity – due to the neglect of the time series properties– we follow a four-step approach: first, we assess the cross-section dependence of the series; second, we test them for stationarity; third, depending on the order of integration of the series, we decide whether to test for cointegration; if we do so and cointegration exists, an error correction model (ECM) is estimated, which permits to analyze the long-run relationship between the variables jointly with the short-term adjustment towards the long-run equilibrium; if we do not apply cointegration testing, we estimate the growth-inequality relationship allowing for non-cointegration.

Specifically, time-varying heterogeneity due to unobserved common shocks, which affect all units (in our case US states), introduces cross-section correlation or dependence in the error terms, which can lead to inconsistency and incorrect inference in standard panel econometric approaches (Phillips and Sul, 2003; Pesaran, 2006). At the same time, the assumption of cross-section independence is strong for regional data; cross-region co-movements of economic variables are most likely due to common shocks and spillover effects (Economides, 1996). So, we test for cross-section dependence and model it using unobserved common factors, but not spatial effects.[1] We do this, because if we use the latter method, we may not account for endogenous time-varying variables (i.e. trade, FDI and policy), which can not be approximated by distance measures (Pesaran, 2004). We model cross-section dependence by postulating:

$$B_{it} = e^{\eta_i + \theta_i' f_t + e_{it}} \tag{5}$$

$$x_{mit} = \pi_{mi} + p_{mi}' g_{mt} + q_{1mi} f_{1mt} + \ldots + q_{nmi} f_{nmt} + v_{mit} \tag{6}$$

$$f_t = \rho' f_{t-1} + e_t \text{ and } g_t = \kappa' g_{t-1} + \upsilon_t \tag{7}$$

where, η_i idiosyncratic regional technology term, e_{it} idiosyncratic random shock, x_{it} right-hand side observed variables in (2), *m=1,…k*, f_t, g_t unobserved common factors and $f_{mt} \subset f_t$. If we substitute (6) in (5), denoting natural logs by lower-case letters, we get:

$$y_{it} = \beta_i' x_{it} + u_{it} = \beta_i' x_{it} + \eta_i + \theta_i' f_t + \varepsilon_{it} \tag{8}$$

[1] Baltagi (2008) in a detailed review of the panel unit root and cointegration literature, points towards the vital importance of controlling for cross-sectional dependence.

The variables y_{it}, x_{it} are possibly nonstationary, β_i are region-specific elasticities of labor productivity with respect to the various inputs, θ_i, p_i, q_t are region-specific factor loadings, η_i, π_{mi} are region-specific fixed effects and $e_{it}, v_{it}, \varepsilon_{it}, \upsilon_{it}$ stand for i.i.d errors.[2] The factors f_t, g_t can be nonlinear and nonstationary. The presence of f_t in (6) - (8) induces endogeneity, because the regressors are correlated with the unobservables of the production function (u_{it}). If we do not account for f_t, g_t during estimation*,* we will produce biased estimates of β_i and incorrect inferences (Pesaran, 2006). Additionally, if these factors are nonstationary, estimation approaches neglecting heterogeneous common factors do not identify β_i (Kapetanios et al., 2011; Eberhardt and Bond, 2009).

The above empirical framework allows for parameter heterogeneity across states in the impact of observables (inputs) and unobservables (TFP) on output. "New growth theory", which emphasizes technology differences across cross-sections, justifies heterogeneous technology parameters (Durlauf et al., 2001). It argues that technology heterogeneity may mean that cross-section units can choose an 'appropriate' technology from many possible options.

Also, our empirical framework deals appropriately with any business cycle effects, i.e. idiosyncrasies of regional economies or global shocks with heterogeneous impacts (Chudik et al., 2011). Our model is intended for use with annual data, enabling us to deal properly with their time-series and cross-section properties (Eberhardt and Teal, 2011).

To test for cross-section dependence, we apply the CD test by Pesaran (2004), which uses the correlation coefficients between the time series for each panel member. In our case, for *N=48* states, this would be the 48 x 47 correlations between region *i* and all other regions, for *i=1* to *N-1*. Denoting the estimated correlation between the time-series for region *i* and *j* as $\hat{\rho}_{ij}$, the Pesaran CD statistic is given by:

$$\sqrt{\frac{2T}{N(N-1)}}\left(\sum_{i=1}^{N-1}\sum_{j=i+1}^{N}\hat{\rho}_{ij}\right) \tag{9}$$

where *T* is the time-series dimension of the panel. Under the null of cross-section independence, the above statistic follows the standard normal distribution. The statistic is robust to nonstationarity, parameter heterogeneity and structural breaks and performs well even in small samples. The test statistics imply decisive rejection of the cross-section

[2] Here, we note that the above common factor specification cannot discriminate among possible channels of cross-section dependence.

independence hypothesis for all variables.[3] Therefore, it provides strong evidence that cross-section dependence exists for them. Given that the observed variables are correlated across regions, it is natural to expect that the unobservables, which are contained in the error term, will also be correlated across regions.

3.2 Unit root tests

In the long run, series such as output or capital stock often display strong persistence, so it is reasonable to test if our series are 'non-stationary' processes (Nelson and Plosser, 1982; Lee *et al.*, 1997; Pedroni, 2007). This is important, because in the case of a non-stationary variable more observations do not help to learn about its distribution, e.g. mean, variance etc., since the latter do not converge to constant values. As time-averaging does not alter the order of integration, any macro production function is likely to include at least some cross-sections with non-stationary variables, and their time series properties must be accounted for to avoid bias and/or inefficiency (Granger, 1988; Granger and Siklos, 1995).

In light of these, we examine if our data are stationary. If the variables are not stationary in levels, we check for stationarity in differences. The recent literature has concluded that inference on the time series properties of data can be improved when applying integration and cointegration tests to the whole panel rather than to each unit separately. This way we address the problem of low power of conventional time series tests, since we increase the sample size considerably.

We apply the Pesaran (2007) panel unit root test for multiple variables and lags in models with and without a region-specific trend term.[4] It allows for heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression and a single unobserved common factor with heterogeneous factor loadings in the data. Therefore, it takes into account cross-section dependence.[5] The statistic is constructed from panel-member-specific (A)DF regressions where cross-section averages of the dependent and independent variables (including lagged differences to account for serial correlation) are included in the model (CADF regressions). Testing for the null of a unit root is based on the t-ratio of the first-order autoregressive parameter. To construct a panel statistic, the *t*-values are pooled across cross sections. A standardized version of the test is asymptotically distributed as standard normal

[3] Results on cross-section dependence are available from the authors upon request.
[4] There should be a careful use of a deterministic trend or "*…otherwise results can be misleading…*" (see, Ahking, 2002; p.51).
[5] Tests which do not account for dependence, when is exists, suffer from huge size distortions, which increase with the number of cross sections (Banerjee et al., 2004; 2005).

under the joint null hypothesis of nonstationarity for all cross sections. If the null is rejected, the series is stationary at least for one panel member. Under the null of nonstationarity the test statistic has a non-standard distribution. The test is found to have good size and power properties, even when *N* and *T* are relatively small.

For implementation of the panel unit root tests, we use the Bartlett kernel. All bandwidths and lag lengths equal $4\left(T/100\right)^{\frac{2}{9}} \approx 3.28$, where *T* = 41 in our case (Basher and Westerlund, 2007). So, the maximum lag length lies between 3 and 4. Too few lags reduce the size of a unit root test, while too many lags reduce its power (Campbell and Perron, 1991). We conduct the panel unit root tests with the lag length equal to 4, following Martins (2011) and Jaunky (2012). For comparison, we also present the findings from the Maddala and Wu (1999) test, which allows for heterogeneity in the autoregressive coefficient of the Dickey-Fuller regression, but ignores cross-section dependence.

Regarding inequality, the Atkinson, Gini, Top 1%, Top 10%, Top 90-99% variables are stationary in levels, while Theil is stationary in first differences[6]. Labor productivity growth is I(0) and physical capital-human capital ratio is I(1). Given these findings, we can not study the long-run relationship among levels of the variables. So, we do not conduct panel cointegration tests and proceed directly to the estimation of the relationship among levels of the variables with a methodology described below, which is robust to non-cointegration (Bronzini and Piselli, 2009).

3.3 Estimation methodology

Having established the order of integration of our variables, we proceed with the estimation of Equation (9) in levels, using panel econometric techniques. This way we mitigate endogeneity, since physical and human capital accumulation can be driven by labor productivity. Moreover, we are able to estimate the effect of inequality on growth, allowing for its possible dependence on physical and human capital stocks. We also allow for heterogeneity in the growth-inequality relationship across states by including region-specific fixed effects, input parameters and factor loadings.

There are alternative procedures for estimating Equation (9). The available estimators incorporate different assumptions about the underlying data generating process. Generally, the simple pooled estimators assume a fully homogeneous coefficient model in

[6] Results on unit root tests are available from the authors upon request.

which all slope and intercept parameters are identical across regions, meaning that regions follow the same underlying model relating productivity to the right-hand side variables. However, Durlauf and Johnson (1995), Lee et al. (1998) and Temple (1999a,b) among others, show that this is not a trivial assumption, so allowing parameter heterogeneity can change results of growth regressions in very important ways. For instance, errors are non-stationary if 'true' technology parameters are heterogeneous and input variables are non-stationary.

For instance, the fixed-effect estimator allows only the intercepts to differ across regions assuming common parameters on factor inputs and convergence rates and heterogeneity with respect to TFP growth across regions. Thus, it ignores cross-section dependence in the form of unobserved common factors. Alternatively, the Arellano and Bover (1995) - Blundell and Bond (1998) (AB-BB hereafter) estimator employs moment conditions in which lagged differences are instruments for the level equation, in addition to the moment conditions of lagged levels as instruments for the differenced equation. It can treat the explanatory variables as endogenous and accounts for heteroscedasticity in the data-generating process. This estimator still assumes common factor input parameters and common impact of unobservables, although it solves the identification problem due to the correlation between inputs and unobservables (TFP in our case) (see discussion in section 4.2).

For these reasons, we implement the Augmented Mean Group (AMG) estimator (Eberhardt and Teal, 2009, 2012a, 2012b), which allows for cross-section dependence. Also, it does not require pre-testing for cointegration. It was developed with production function estimation in mind, where unobservables represent TFP. We choose AMG to Common Correlated Effects Mean Group (CCEMG hereafter) estimator (Pesaran, 2006), because the latter treats f_t as a nuisance, which must be accounted for, but is not of particular interest for the empirical analysis. But in our empirical model, we view TFP as a 'measure of our ignorance' (Abramowitz, 1956), reflecting a wide set of factors which can shift the production possibility frontier (for instance "…resource endowments, climate, institutions, and so on…" Mankiw et al., 1992; pp.410-411).[7]

The AMG estimator first involves estimation of a pooled regression model with period dummies by first difference OLS and collection of the coefficients on the (differenced) dummies, which correspond to the estimated cross-region average of TFP evolution. This is

[7] In Monte Carlo simulations, the AMG performed similarly well as the CCEMG in panels with nonstationary variables (cointegrated or not) with common factor errors (Eberhardt and Bond, 2009).

called the "common dynamic process". Second, the group-specific regression model is augmented with this TFP process either: (a) as an explicit variable or (b) imposes on each group member a unit coefficient by subtracting the estimated process from the dependent variable. The regression model includes an intercept, which corresponds to time-invariant fixed effects (TFP levels). Third, the region-specific parameters are averaged across the panel. Therefore, AMG allows for heterogeneous technology parameters and heterogeneous factor loadings. The standard errors reported in the averaged regression results are constructed following Pesaran and Smith (1995) and test the significance of the average coefficients.

4. Estimation results

We estimate Equation (9), because variables cannot be cointegrated and the AMG estimator is robust to non-cointegration (Bronzini and Piselli, 2009). Overall, six models are estimated, which differ only in the inequality indicator used as the main independent variable. For each specification, we estimate two versions. In the first version we impose a common dynamic process (cdp hearafter) with a unit coefficient for TFP, subtracting the estimated process from the dependent variable, after having tested this assumption and verified it. In the second version the TFP process is included as a separate right-hand side variable. The findings are very similar both qualitatively and quantitatively in the two versions.

Using the specification analyzed in Section 2, we focus on economically relevant values of the growth effect. To this end, we estimate the above specification including the three human capital variables for each of the inequality indicators (see Tables 2-4 below). As explained in Section 2.1., individual coefficient do not have a meaningful interpretation in a multiplicative interaction model such as ours. In light of that, we focus on the growth effect of inequality which is given by Eq. 3. Specifically, we calculate the growth effect of each of the six inequality indicators and the three human capital variables. We do that for all in-sample values of educational attainment at five values of physical capital stock: (1) very low capital (minimum), low capital (10th percentile), medium capital (median capital stock), high capital (90th percentile), and very high capital (maximum). We interpret constitutive terms as conditional marginal effects, due to the multiplicative nature of our empirical specification. To this end, we calculate meaningful marginal effects and standard errors. The relevant plots are presented in Fig. 1-18 and show how the marginal growth effect of each inequality indicator changes across the whole range of observed schooling years. This effect is computed for specific values of observed physical capital, which also cover the whole range in our data (see discussion above). We choose to present findings over the data range in our sample in order to obtain interesting results from a policy point of view. The asterisks indicate statistically significant effects at the 5% level.

[INSERT TABLES 2-4 HERE]

[INSERT FIGURES 1-18 HERE]

First, we analyze the baseline estimations, where we use average schooling years as the human capital indicator (see Figure 1-6 below). We note that in the Figures provided each line corresponds to one of the five levels of physical capital and the asterisks denote statistical significance of the growth effect at the 5% level. When we employ the Atkinson index to measure inequality, we reveal that in states with very low and low levels of physical capital, the growth effect of inequality is negative, but decreases (becomes less negative) as human capital increases (see Figure 1 above). In turn, in states with median physical capital the growth impact is positive and remains approximately constant throughout education levels. Finally, in high and very high physical capital states, inequality boosts growth, but its influence diminishes as the education level grows. The behavior of inequality is the same when using average schooling years and the percentage of population with at least tertiary education as human capital variables (see Figure 2 above). When the secondary education indicator is considered, our results reveal that the growth impact of inequality remains positive, though increasing, as education rises in median and high physical capital states (see Figure 3 above).

Similarly, when we apply the Theil indicator, inequality enhances growth, but this impact subsides as human capital rises in median and high physical capital states, until it becomes insignificant. This is true when both average years of schooling and tertiary education variables are applied (see Figures 4 and 5, respectively). When we proxy human capital with secondary education graduates, inequality enhances growth as before, but the effect strengthens with education in median physical capital states (see Figure 6 above).

Employing the Gini index, inequality boosts growth in very low and low physical capital states and its impact strengthens as human capital rises, that is tertiary education attainment (see Figure 8). On the contrary, the inequality effect on growth is negative and becomes more negative with rising education in high and very high physical capital states. This behavior coincides with the case where the proportion of population with secondary education is used as human capital variable (see Figure 9). However, when average years of schooling are employed the impact is small and positive only in median and high physical capital states and declines as the education level rises (see Figure 7).

If we employ the Top 10% income share, the growth impact of inequality is positive and declining as we proceed towards higher education levels in median and high physical capital states, when average years of schooling and tertiary education attainment are applied as human capital indicators (see Figures 10 and 11). Note that in the tertiary education case, the Top 10% share boosts growth also in very low and low physical capital states, while it turns negative in very high physical capital states, at an increasing rate. For secondary education attainment, inequality still boosts growth at an increasing rate, in in median and high physical capital states (see Figure 12).

In the same manner, the growth behavior of the Top 1% income share is the same with that of the Top 10% share's, with the exception that the positive growth effect increases with education in median physical capital states (see Figures 13-15). This holds for mainly all human capital indicators used, with the minor exception of secondary attainment, that is low and very low physical capital states where there is additionally a negative and decreasing growth impact of inequality

When we apply the Top 90-99% income share, inequality dampens growth and the penalty rises with human capital in median and high physical capital states, robustly in all human capital indicators estimated (see Figures 16-18). The only exception is the positive and decreasing growth impact in median and high physical capital states and low levels of education.

Overall, a rise in Atkinson and Theil indices as well as the Top 10% and Top 1% income shares boosts growth in high physical capital states and hurts growth in low physical capital states. These effects decline with education level until they become insignificant. On the contrary, a higher Top 90-99% share dampens growth at an increasing rate, as human capital rises in median and high physical capital states. Finally, the Gini coefficient does not have a robust growth impact, because the latter is sensitive to the level of physical capital as well as the human capital indicator used. For both the Top 90-99% share and Gini coefficient, the growth impact becomes insignificant for very high education levels.

Next, we compute the growth impact of inequality in each state separately based on the state-specific estimation results for the top 1% and top 90-99% income shares, since we consider the top inequality indicators as the most reliable in our dataset (see Section 2.2). We observe that the growth effect of inequality is significant in only 13 and 10 out of 48 states for the top 1% and top 90-99% indicators respectively (see Tables 5 and 6 below). So, inequality does not affect growth in the vast majority of the US states, which is consistent with the GM predictions for the late stages of economic development. The states where inequality is a significant growth determinant, are spread out across all Bureau of Economic Analysis regions. Turning to the top 1% indicator, its impact is positive in 11 of the 13 states (Rhode Island, Pennsylvania, Illinois, Wisconsin, Minnesota, Missouri, Nebraska, Alabama, Arizona, Colorado, Oregon). Both remaining states, which exhibit a negative inequality-growth relation (Mississippi, New Mexico), are located in Southern US. As far as the top 90-99% income share, its growth influence is positive in 5 of the 10 states (Michigan, Iowa, Idaho, California, Washington). None of these is located in the East or the Southern US; there are 2 states in each of these regions where inequality hurts growth (Connecticut, Maryland and Georgia, Oklahoma respectively), and only in Wyoming outside these regions, we observe the same phenomenon.

[INSERT TABLES 5 & 6 HERE]

5. Conclusions

In this paper we have empirically explored the implications of income inequality on the process of development by testing the 'unified' approach offered by Galor and Moav (2004) in a single-country framework. This data homogeneity provides advantages over previous literature as it mitigates structural differences among cross-sectional units. At the same time our methodology has emphasized cross-section dependence and parameter heterogeneity.

We find that key implications of the Galor and Moav (2004) 'unified' growth and inequality model are only partially consistent with the empirical evidence provided herein. Our results robustly exhibit that inequality and growth are linked with a non-linear relationship: high physical capital states enjoy a boost in growth due to inequality where the opposite holds in states with low physical capital. In both cases, the influence of inequality on growth diminishes as the education level grows. The former finding is in contrast with the Galor-Moav hypothesis, which states that the initially positive growth effect of inequality declines as physical capital increases. However, we confirm that the effect of inequality on growth evaporates in the presence of high physical and human capital stocks. The latter finding is in line with that of Chambers and Crause (2010) where an international sample is used.

Overall, our results partially challenge the theoretical arguments of Galor and Moav (2004), as most testable implications are not confirmed using a single-country framework. However, we should note that our empirics focus on the US, which is a developed country but it exhibits large disparities in terms of physical and human capital stocks. We believe that our results provide insights to relevant policy makers.

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Table 1 Descriptive statistics

Variables	Mean	Standard deviation	Min	Max
GSP/Labor Force Growth	0.0034	0.0333	-0.1654	0.2114
Atkinson Index	0.2058	0.0360	0.1470	0.3799
Gini Coefficient	0.5053	0.0507	0.4097	0.6557
Theil Entropy Index	0.4974	0.1797	0.1286	1.3258
Top 10% Income Share	0.3396	0.0438	0.2736	0.527
Top 1% Income Share	0.1026	0.0337	0.0594	0.2752
Top 90-99% Income Share	0.2370	0.0157	0.1908	0.3106
Physical Capital/Labor Force	1.3898	7.6548	0.0226	75.8122
Average Schooling Years	11.8414	1.1816	8.6474	14.141
Tertiary Education Graduates	0.3885	0.1174	0.1445	0.6074
High School Education Graduates	0.0940	0.0439	0.0235	0.2478

Table 2 Estimates of the Income Inequality Effect on Growth (AMG estimator; using Average Years of Schooling)

	Atkinson Index		Gini Coefficient		Theil Entropy Index		Top 10% Income Share		Top 1% Income Share		Top 90-99% Income Share	
	impose	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*
Inequality	0.347***	0.314***	-0.001	0.020	0.592**	0.052**	0.368***	0.414***	0.414***	0.366***	-0.208	-0.100
	(0.000)	(0.000)	(0.991)	(0.802)	(0.011)	(0.015)	(0.001)	(0.000)	(0.001)	(0.003)	(0.294)	(0.624)
Physical Capital	1.259***	1.108**	1.719***	1.788***	1.360**	1.230**	1.329***	1.118**	1.189**	1.040**	0.901**	0.718*
	(0.003)	(0.011)	(3.58)	(0.000)	(0.011)	(0.024)	(0.004)	(0.018)	(0.027)	(0.055)	(0.044)	(0.081)
Schooling	0.175***	1.775***	0.158***	0.161***	0.164***	0.171***	0.171***	0.172***	0.180***	0.179***	0.176***	0.179***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.005)
Inequality * Physical Capital	36.953**	33.277**	0.1796	7.444	5.530	7.190**	16.249	14.551	15.358	13.591	-15.335	-0.783
	(0.015)	(0.040)	(0.878)	(0.566)	(0.114)	(0.057)	(0.358)	(0.418)	(0.329)	(0.454)	(0.679)	(0.985)
Inequality * Schooling	-0.006	0.028	-0.153**	-0.196**	-0.041	-0.038	-0.086	-0.129	0.0260	-0.035	-0.541**	-0.539**
	(0.956)	(0.820)	(0.039)	(0.029)	(0.138)	(0.186)	(0.429)	(0.282)	(0.871)	(0.830)	(0.018)	(0.028)
Physical Capital* Schooling	-0.511	-0.312	0.595*	0.530	0.193	0.752	0.014	0.281	-0.525	-0.298	-0.020	-0.101
	(0.145)	(0.282)	(0.086)	(0.102)	(0.561)	(0.809)	(0.971)	(0.437)	(0.147)	(0.431)	(0.942)	(0.720)
Inequality *Schooling* *Physical Capital	13.375*	-12.897	-3.868	-5.712	-1.095	-2.380	-7.882	-5.430	-6.193	-5.967	-16.195	-16.690
	(0.093)	(0.127)	(0.323)	(0.181)	(0.574)	(0.247)	(0.277)	(0.448)	(0.444)	(0.487)	(0.467)	(0.478)
trend	0.001	0.001	0.001**	0.003***	0.001	0.001	0.001	0.001	0.001	0.002	0.001	0.001
	(0.779)	(0.281)	(0.020)	(0.003)	(0.336)	(0.151)	(0.580)	(0.227)	(0.534)	(0.177)	(0.329)	(0.322)
constant	0.287***	-0.282	0.246***	0.252***	-0.361***	-0.395***	0.284***	0.280***	0.284***	0.277***	0.279***	0.283***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
RMSE	0.0205	0.0201	0.0205	0.0200	0.0201	0.0198	0.0204	0.0200	0.0203	0.0202	0.0202	0.0198
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD test	0.37	-0.07	-0.33	0.11	0.37	-0.11	-0.08	-0.04	-0.22	-0.15	-1.14	-1.23
	(0.708)	(0.945)	(0.743)	(0.915)	(0.002)	(0.914)	(0.938)	(0.968)	(0.827)	(0.882)	(0.256)	(0.219)
Observations	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920

Notes: Dependent variable: *ΔlnGSPpw*. Time Period: 1960-2000. 48 states. ***Coefficient Significant at 1%; **Coefficient Significant at 5%; *Coefficient Significant at 10%. *p-values* are presented in parentheses. AMG: Augmented Mean Group estimator. RMSE: Root Mean Square Error; *Diagnostics*: The order of integration of the residuals is determined using the Pesaran (2007) CIPS test for H_o of nonstationarity; CD test: Pesaran (2004) test for H_o of cross-sectionally independent errors, test statistics are provided with p-values in parentheses.

Table 3 Estimates of the Income Inequality Effect on Growth (AMG estimator; Tertiary Education Graduates)

	Atkinson Index		Gini Coefficient		Theil Entropy Index		Top 10% Income Share		Top 1% Income Share		Top 90-99% Income Share	
	impose	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*
Inequality	0.287*** (0.000)	0.260*** (0.000)	-0.056 (0.367)	-0.047 (0.488)	0.058*** (0.000)	0.045*** (0.004)	0 .404*** (0.000)	0.418*** (0.000)	0.314** (0.022)	0.261** (0.047)	0.156 (0.396)	0.247 (0.178)
Physical Capital	1.373*** (0.001)	1.208*** (0.007)	2.090*** (0.000)	2.047*** (0.000)	1.878*** (0.000)	1.819*** (0.001)	1.588*** (0.001)	1.468*** (0.004)	1.695*** (0.002)	1.597*** (0.003)	0.784* (0.053)	0.743* (0.077)
Schooling	0.068 (0.466)	0.037 (0.721)	-0.068 (0.466)	-0.049 (0.653)	0.021 (0.825)	-0.006 (0.951)	-0.062 (0.459)	-0.047 (0.582)	0.007 (0.944)	-0.001 (0.926)	0.085 (.355)	0.068 (0.466)
Inequality * Physical Capital	11.160 (0.313)	14.852 (0.170)	-13.211** (0.034)	-9.207 (0.215)	0.109 (0.953)	0.654 (0.654)	-4.874 (0.706)	-2.680 (0.819)	17.005 (0.225)	13.892 (0.339)	-3.995 (0.846)	0.152 (0.128)
Inequality * Schooling	-0.223 (0.930)	0.441 (0.837)	-0.815 (0.624)	-1.446 (0.379)	-0.487 (0.341)	-0.060 (0.891)	-0.887 (0.691)	-1.477 (0.472)	-1.180 (0.740)	-1.344 (0.690)	-8.594 ** (0.05)	-10.669** (0.012)
Physical Capital* Schooling	18.066** (0.025)	15.290** (0.044)	42.601*** (0.000)	37.084*** (0.001)	34.093*** (0.000)	30.364*** (0.001)	40.801*** (0.000)	40.314*** (0.000)	15.149** (0.030)	11.342 (0.164)	15.43*** (0.005)	12.353** (0.038)
Inequality *Schooling* *Physical Capital	-199.879* (0.061)	-220.124** (0.041)	-373.035** (0.012)	-338.843** (0.015)	-71.283* (0.052)	-79.454** (0.046)	-353.938** (0.01)	-293.541** (0.037)	-287.105 (0.179)	-310.833 (0.136)	-573.680 (0.113)	-449.141 (0.183)
trend	-0.001*** (0.007)	-0.0009** (0.049)	-0.0007 (0.154)	-0.0007 (0.221)	0.001 (0.336)	-0.001** (0.015)	-0.0009* (0.063)	-0.0009 (0.077)	-0.001** (0.013)	-0.0009 (0.056)	-0.0004 (0.345)	-0.0006 (0.182)
constant	-0.008 (0.357)	-0.011 (0.180)	0.012 (0.280)	0.010 (0.431)	-0.001 *** (0.001)	-0.004 (0.706)	-0.024** (0.037)	-0.026** (0.026)	0.004 (0.773)	-0.003 (0.812)	0.003 (0.700)	0.007 (0.492)
RMSE	0.0229	0.0221	0.0224	0.0200	0.0225	0.0217	0.0224	0.0214	0.0221	0.0212	0.0221	0.0213
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD test	0.53 (0.598)	0.41 (0.684)	0.42 (0.675)	0.77 (0.441)	1.67 (0.094)	1.40 (0.163)	0.53 (0.594)	0.65 (0.513)	-0.11 (0.910)	-0.00 (0.997)	-1.07 (0.283)	-0.35 (0.726)
Observations	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920

Notes: Dependent variable: *ΔlnGSPpw*. Time Period: 1960-2000. 48 states. ***Coefficient Significant at 1%; **Coefficient Significant at 5%; *Coefficient Significant at 10%. *p-values* are presented in parentheses. AMG: Augmented Mean Group estimator. RMSE: Root Mean Square Error; *Diagnostics*: The order of integration of the residuals is determined using the Pesaran (2007) CIPS test for H_o of nonstationarity; CD test: Pesaran (2004) test for H_o of cross-sectionally independent errors, test statistics are provided with p-values in parentheses.

Table 4 Estimates of the Income Inequality Effect on Growth (AMG estimator; Secondary Education Graduates)

	Atkinson Index		Gini Coefficient		Theil Entropy Index		Top 10% Income Share		Top 1% Income Share		Top 90-99% Income Share	
	impose	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*	*impose*	*non-impose*
Inequality	0.346***	0.326***	-0.1308*	-0.102	0.045**	0.041**	0.428***	0.470***	0.207	0.196	-0.099	-0.001
	(0.000)	(0.000)	(0.075)	(0.179)	(0.016)	(0.018)	(0.001)	(0.000)	(0.186)	(0.188)	(0.622)	(0.962)
Physical Capital	1.053**	0.947*	1.546***	1.642***	1.512***	1.529 ***	1.406***	1.228**	1.363**	1.081**	0.706*	0.613
	(0.026)	(0.051)	(0.001)	(0.001)	(0.002)	(0.005)	(0.008)	(0.022)	(0.012)	(0.027)	(0.070)	(0.112)
Schooling	0.096*	0.088*	0.038	0 .059	0.080	0.107*	0.076	0.080*	0.0003	-0.002	9.104**	0.151***
	(0.062)	(0.053)	(0.439)	(0.232)	(0.156)	(0.067)	(0.119)	(0.089)	(0.995)	(0.970)	(.046)	(0.007)
Inequality *	-4.939	0.099	-25.950**	-17.819*	-2.8841	-0.332	-7.859	-7.501	17.002	19.118	-56.180**	-37.835
Physical Capital	(0.607)	(0.991)	(0.011)	(0.092)	(0.419)	(0.918)	(0.503)	(0.532)	(0.298)	(0.235)	(0.04)	(0.202)
Inequality *	2.262**	2.307***	0.014	-0.514	0.286	0.276	1.292	0.847	0.019	-0.344	-0.431	-1.309**
Schooling	(0.013)	(0.007)	(0.985)	(0.486)	(0.176)	(0.158)	(0.175)	(0.362)	(0.988)	(0.783)	(0.812)	(0.476)
Physical Capital*	2.651	1.920	13.696***	10.414***	9.265**	6.562***	8.695***	9.446***	3.588	2.467	5.247***	3.998**
Schooling	(0.368)	(0.498)	(0.000)	(0.004)	(0.019)	(0.06)	(0.002)	(0.000)	(0.204)	(0.357)	(0.005)	(0.028)
Inequality *Schooling*	-48.378	-65.552	-12.417 **	-44.787	-12.782	-16.689**	-25.720	1.258***	-150.204*	-155.655*	57.217	19.596
*Physical Capital	(0.419)	(0.288)	(0.833)	(0.358)	(0.463)	(0.312)	(0.724)	(0.986)	(0.061)	(0.058)	(0.737)	(0.908)
trend	-0.002***	-0.002***	-0.002***	-0.002***	-0.002***	-0.002**	-0.001***	-0.002***	-0.001**	-0.001*	-0.001***	-0.002
	(0.001)	(0.000)	(0.006)	(0.007)	(0.002)	(0.015)	(0.003)	(0.003)	(0.043)	(0.074)	(0.008)	(0.001)
constant	-0.009	-0.013	0.030**	0 .035**	-0.0001	-0.004	-0.036***	-0.035 ***	0.007	0.0002	0.023**	0.036
	(0.407)	(0.172)	(0.014)	(0.015)	(0.992)	(0.706)	(0.002)	(0.002)	(0.647)	(0.988)	(0.015)	(0.001)
RMSE	0.0229	0.0220	0.0224	0.0215	0.0223	0.0216	0.0223	0.0215	0.0222	0.0214	0.0221	0.0213
Order of Integration	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)	I(0)
CD test	-0.19	-0.20	-0.79	-0.20	1.18	1.04	0.59	0.85	0.09	0.19	-0.83	0.25
	(0.582)	(0.842)	(0.432)	(0.839)	(0.238)	(0.30)	(0.554)	(0.394)	(0.928)	(0.853)	(0.408)	(0.802)
Observations	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920	1920

Notes: Dependent variable: $\Delta lnGSPpw$. Time Period: 1960-2000. 48 states. ***Coefficient Significant at 1%; **Coefficient Significant at 5%; *Coefficient Significant at 10%. *p-values* are presented in parentheses. AMG: Augmented Mean Group estimator. RMSE: Root Mean Square Error; *Diagnostics*: The order of integration of the residuals is determined using the Pesaran (2007) CIPS test for H_o of nonstationarity; CD test: Pesaran (2004) test for H_o of cross-sectionally independent errors, test statistics are provided with p-values in parentheses.

Fig. 1 Atkinson & Schooling Years

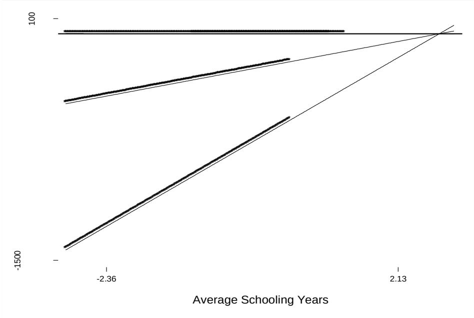

Fig. 2 Atkinson & Tertiary Grads.

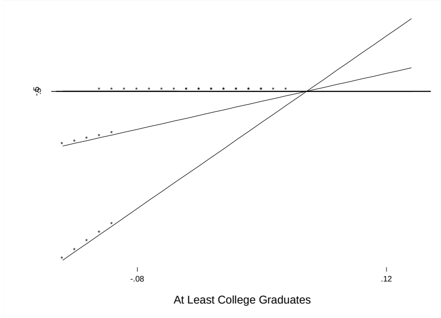

Fig. 3 Atkinson & Secondary Grads.

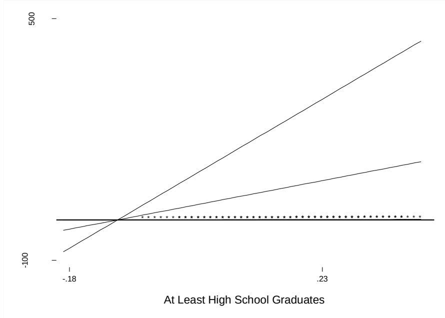

Fig. 4 Theil & Schooling Years

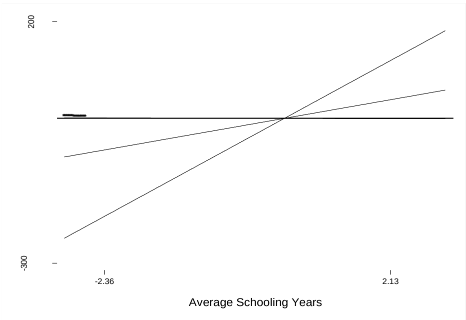

Fig. 5 Theil & Tertiary Grads.

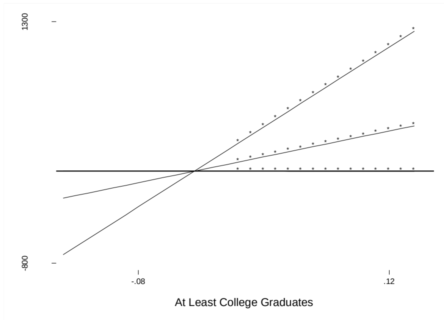

Fig. 6 Theil & & Secondary Grads.

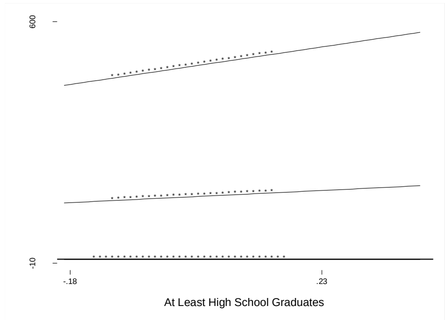

Fig. 7 Top 1% & Schooling Years

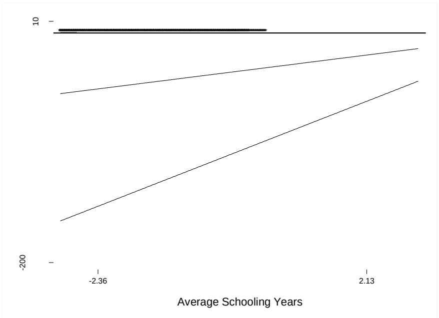

Fig. 8 Top 1% Tertiary Grads.

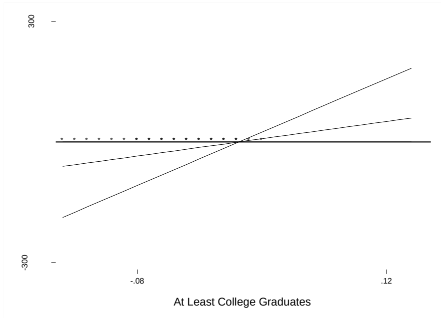

Fig. 9 Top 1% & Secondary Grads.

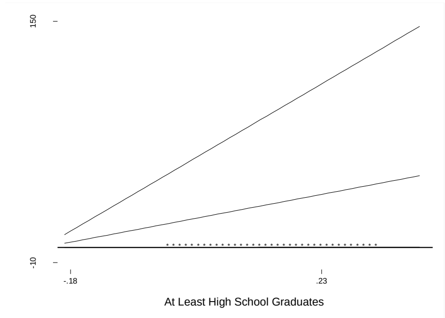

Fig. 10 Top 10% & Schooling Years

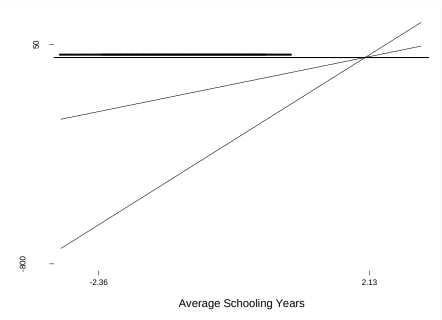

Fig. 11 Top 10% & Tertiary Grads.

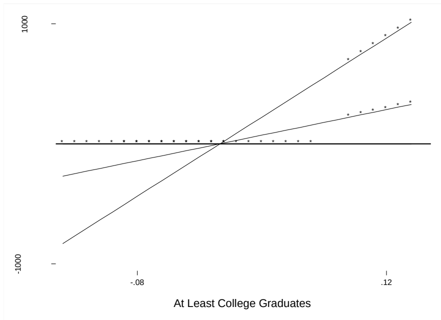

Fig. 12 Top 10% & Secondary Grads.

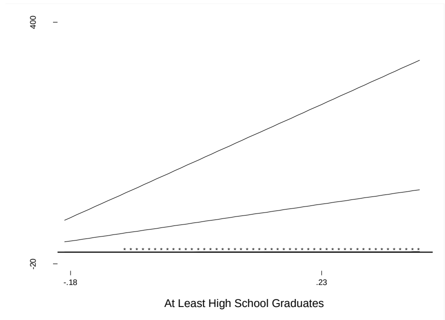

Fig. 13 Top 90-99% & Schooling Years

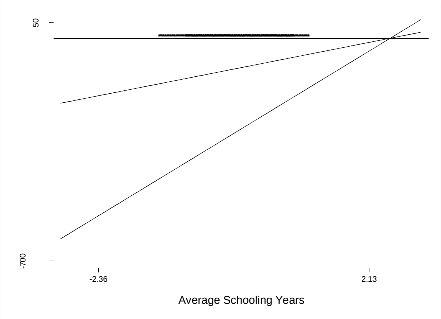

Fig. 14 Top 90-99% & Tertiary Grads.

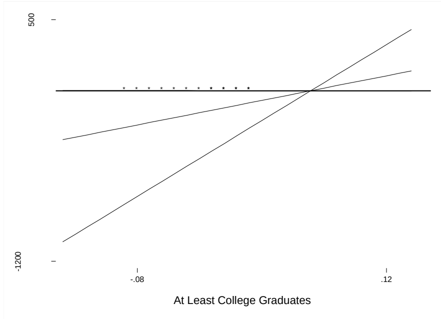

Fig. 15 Top 90-99% Secondary Grads.

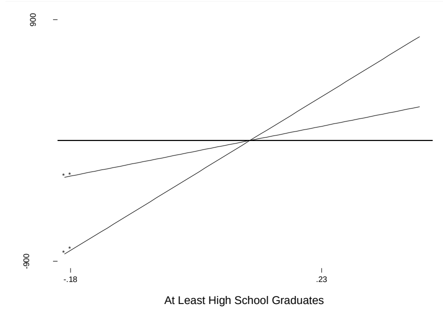

Fig. 16 GINI & Avg. Schooling Years

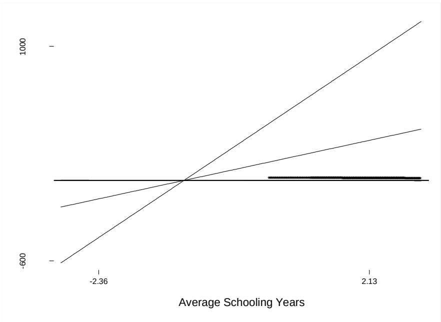

Fig. 17 GINI & Tertiary Grads.

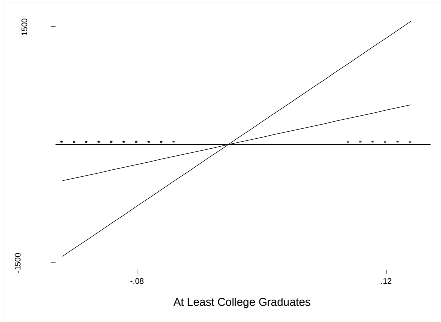

Fig. 18 GINI & Secondary Grads.

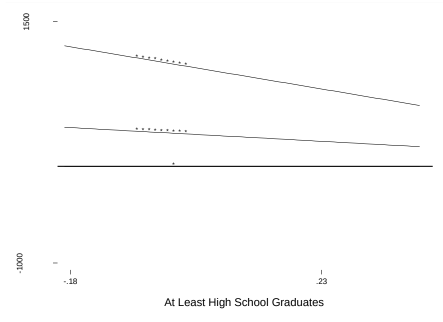

Table 5 State-Specific Inequality-Growth Effects (Top 1%)

New England		**Southeast**	
Connecticut	-0.313	Alabama	1.131**
Maine	0.324	Arkansas	-0.082
Massachusetts	-0.480	Florida	0.380
New Hampshire	0.641	Georgia	0.431
Rhode Island	0.596*	Kentucky	0.822
Vermont	-1.185	Louisiana	1.164
Mideast		Mississippi	-1.581***
Delaware	-0.735	North Carolina	-0.112
Maryland	-0.441	South Carolina	-0.550
New Jersey	0.244	Tennessee	0.801
New York	-0.176	Virginia	-0.208
Pennsylvania	1.062***	West Virginia	0.103
Great Lakes		**Southwest**	
Illinois	0.868***	Arizona	1.233*
Indiana	0.884	New Mexico	-1.345*
Michigan	-0.468	Oklahoma	0.941
Ohio	0.453	Texas	0.627
Wisconsin	1.885***	**Rocky Mountains**	
Plains		Colorado	0.823*
Iowa	0.484	Idaho	0.656
Kansas	0.175	Montana	-0.511
Minnesota	1.335**	Utah	0.658
Missouri	1.134***	Wyoming	226.201
Nebraska	0.842*	**Far West**	
North Dakota	-16.222	California	0.230
South Dakota	2.872	Nevada	1.465
		Oregon	1.655**
		Washington	0.265

Table 6 State-Specific Inequality-Growth Effects (Top 90-99%)

New England		**Southeast**	0.711
Connecticut	-1.873**	Alabama	-0.191
Maine	-0.135	Arkansas	0.802
Massachusetts	-0.767	Florida	-1.627**
New Hampshire	-2.150	Georgia	-0.786
Rhode Island	-0.797	Kentucky	-1.229
Vermont	3.105	Louisiana	0.767
Mideast	-4.601	Mississippi	-0.311
Delaware	-2.122***	North Carolina	-0.875
Maryland	-0.931	South Carolina	-0.203
New Jersey	0.541	Tennessee	0.135
New York	-0.107	Virginia	0.543
Pennsylvania		West Virginia	
Great Lakes	0.522	**Southwest**	-0.145
Illinois	-0.129	Arizona	0.725
Indiana	3.424***	New Mexico	-2.338***
Michigan	-0.317	Oklahoma	-0.163
Ohio	0.046	Texas	
Wisconsin	-4.601	**Rocky Mountains**	-0.611
Plains		Colorado	1.234*
Iowa	1.845***	Idaho	0.711
Kansas	0.468	Montana	-0.226
Minnesota	-0.077	Utah	0.015
Missouri	0.307	Wyoming	-2983.484**
Nebraska	0.263	**Far West**	
North Dakota	-2.702	California	1.908***
South Dakota	-1.245	Nevada	-3.841
		Oregon	-1.402
		Washington	2.721***