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Abstract
Theoretical and empirical studies exploring the effects of income inequality upon growth reach a disappointing inconclusive result. This paper postulates that one reason for this ambiguity is that income inequality is actually a composite measure of at least two different sorts of inequality: inequality of opportunity and inequality of returns to effort. These two types of inequality affect growth through opposite channels, so the relationship between income inequality and growth is positive or negative depending on which component is larger. We test this proposal using inequality-of-opportunity measures computed from the PSID database for 23 states of the U.S. in 1980 and 1990. We find robust support for a negative relationship between inequality of opportunity and growth, and a positive relationship between inequality of returns to effort and growth.

Keywords: income inequality; inequality of opportunity; economic growth.
JEL Classification: D63, E24, O15, O40.

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1. Introduction

A surge of literature on income inequality and growth has emerged over the last two decades.[2] On one hand, this literature addresses the causation from growth to inequality, and disputes about the Kuznets (1955) and the "augmented" Kuznets hypothesis (Milanovic, 1994), according to which economic development (and other socio-economic and political aspects) should eventually reduce income inequality. On the other hand, the reverse causation is studied, i.e., the effects of income inequality on growth. We concentrate on this second channel of influence, whose related literature has lead to controversial conclusions.

The analysis of the relationship between inequality and growth suggests many channels through which inequality can affect growth. Accumulation of savings (Galenson and Leibenstein, 1955), unobservable effort (Mirrless, 1971), and the investment project size (Barro, 2000) are some of the main routes through which inequality may enhance growth. On the contrary, inequality can negatively affect growth through the following channels: unproductive investments (Mason, 1988), levels of nutrition and health (Dasgupta and Ray, 1987), demand patterns (Marshall, 1988), capital market imperfections (Banerjee and Newman, 1991), fertility (Galor and Zang, 1997), domestic market size (Murphy et al., 1989), political economy (Persson and Tabellini, 1994), and political instability (Alesina and Perotti, 1996). Thus, overall inequality would affect growth positively or negatively depending on the channels that dominate.

However, the existing empirical literature does not indicate that any of these channels has a predominant influence. As a result, the relationship between inequality

[2] Surveys on this issue can be found in Bénabou (1996), Bourguignon (1996), Aghion et al. (1999), Bertola et al. (2005) and Ehrhart (2009).

and growth turns out to be ambiguous.[3] Empirical papers tend to justify this ambiguity through the quality of data (Deininger and Squire, 1996), the inconsistent nature of inequality measures (Knowles, 2001), the type of inequality index (Székely, 2003), the econometric method (Forbes, 2000) or the set of countries considered and their degree of development (Barro, 2000). Thus, Ehrhart (2009, p. 39) acknowledges that the overall rather inconclusive econometric results suggest that either the data and the instruments are not sufficient to estimate the true relationship between inequality and growth or the transmission mechanisms really at work are different from those mentioned in the literature.

In this paper, we defend the idea that this ambiguity can be due to the concept of inequality that has been used in the literature. We base our argument in the idea that income inequality is actually a composite measure of at least two different sorts of inequality: *inequality of opportunity* (IO) and inequality of returns to effort (IE) (Roemer, 1993; Van de Gaer, 1993).[4] Inequality of opportunity refers to that inequality stemming from factors (called circumstances) beyond the scope of individual responsibility like race and socioeconomic background. Inequality of returns to effort defines the income inequality caused by individual responsible choices. This concept reflects the consequences of factors for which individuals can be held responsible like the number of hours worked and occupational choice. Thus, overall inequality can be seen as the result of heterogeneity in social origins and other factors such as the exerted effort. We hypothesize that these two types of inequality may affect growth in an opposite way. On one hand, IO can reduce growth as it favors human capital accumulation by individuals with better social origins or circumstances, rather than by

[3] See Banerjee and Duflo (2003) on the inconclusiveness of the cross-country empirical literature on inequality and growth.
[4] Though not considered in this paper, another possible source of inequality is luck (Lefranc et al., forthcoming).

individuals with more talent or skills (Loury, 1981; Chiu, 1998). The greater the IO, the stronger the role that background plays, rather than responsibility.[5] On the other hand, income inequality among those who exert different effort can stimulate growth because it may encourage people to invest in education and effort (Mirrless, 1971). In sum, the relationship between income inequality and growth can be positive or negative depending on which kind of inequality prevails on the overall measure.

The main goal of this paper is to revisit the relationship between inequality and growth, distinguishing between the IO and IE components. To the best of our knowledge, the current paper is the first attempt to evaluate the relationship between IO and growth. For this task, we combine the growth literature from macroeconomics and the inequality-of-opportunity literature from microeconomics. A discussion on both these literatures is presented in Section 2.

Data requirements for comparing inequality of income across states or countries are severe (Deininger and Squire, 1996), but comparisons of IO are even more stringent (Lefranc et al*.*, 2008). This is because empirical analysis of IO requires not only comparable measures of individual disposable income but also individual background measured in a comparable and homogeneous way. Unfortunately, there are only a few databases with information on individual circumstances or social origins. Furthermore, the number of circumstances is usually small. In addition, to test for long-term effects on growth, we also need the value of IO for at least two distant periods of time, generally 10 years (Barro and Sala-i-Martin, 1991). This last requirement limits even more the availability of databases. As far as we are aware, the Panel Survey Income Dynamics (PSID) database is the only exception that satisfies both requirements and is rich enough in terms of cross-sectional heterogeneity, variables and observations. In

[5] A similar reasoning is found in World Bank (2006) and Bourguignon et al. (2007).

Section 3, we use depurated data of the PSID database to estimate total inequality and IO for a selected set of 23 states in the U.S. in the 1980s and 1990s. Nevertheless, note that any observed vector of circumstances is by construction a subset of the theoretical vector of all circumstances. Consequently, our empirical estimates should be interpreted as lower-bound estimates of IO.[6]

Section 4 shows the empirical model and studies the effect on growth of income inequality, IO and other widely used control variables. Furthermore, we decompose total inequality into IO and IE components. We find robust support for a negative relationship between IO and growth and a positive relationship between IE and growth. Given these findings, the lesson for economic policy is clear. Redistributive policies may, in general, increase investment across individuals and thus may increase growth, but also may discourage unobservable effort borne by agents. On the contrary, policies that equalize opportunities will improve individual investments without deterring individual effort. Hence, a general redistributive policy does not guarantee any result, and growth may increase or decrease depending on which effect prevails. However, selected distribution policies reducing IO will promote growth-enhancing conditions for the economy. Finally, Section 5 concludes.

2. Inequality of Opportunity and the Inequality–Growth Debate

The last decade has witnessed an intensive debate about the effects of inequality on growth. Meanwhile, the inequality-of-opportunity literature has also increased in

[6] See Ferreira and Gignoux (2008), among others.

importance during the last decade.[7] This section attempts to bring the inequality-of-opportunity issue into the inequality–growth debate.

Two different conceptions of equality of opportunity appear in the literature. The first one is about meritocracy (Lucas, 1995, Arrow et al., 2000). In this approach, individuals are completely responsible for their outcome (income, health, employment status, or utility). As a consequence, total inequality is due to individual responsible choices. The second conception, which has been developed over the last two decades, considers that equal opportunity policies must create a "level playing field", after which individuals are on their own.[8] The "level playing field" principle recognizes that an individual's outcome is a function of variables *beyond* and *within* the individual's control, called circumstances (e.g., socioeconomic, cultural background or race) and effort (e.g., investment in human capital, number of hours worked and occupational choice), respectively.[9] IO refers to those outcome inequalities that are exclusively due to different circumstances. Individuals are, therefore, only responsible for their effort. The meritocracy approach is an extreme case for which circumstances are not considered. In this paper, we adopt the more general second approach, which distinguishes between total inequality and IO.

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[7] Using the *Google Academic Search* tool, the term "inequality and growth" appears 608 times between 1990 and 1999 but 3,690 times between 2000 and 2009. The term "inequality of opportunity" is shown 696 times between 1990 and 1999 but 1,460 times between 2000 and 2009. However, the entry "inequality of opportunity and growth" is shown zero times. There is one academic document for each of the following entries: "inequality of opportunities and growth", "equality of opportunities and growth" and "equality of opportunity and growth". This search was made on May 26th, 2009.

[8] See Roemer (1993, 1996, 1998 and 2002), Van de Gaer (1993), Fleurbaey (1995 and 2008), Roemer et al. (2003), Ruiz-Castillo (2003), Peragine (2002 and 2004), Checchi and Peragine (2005), Betts and Roemer (2007), Moreno-Ternero (2007), Ooghe et al. (2007), Fleurbaey and Maniquet (2007), Bourguignon et al. (2007), Lefranc et al. (2008 and forthcoming), Rodríguez (2008) and Ferreira and Gignoux (2008).

[9] Talent could be considered a circumstance, however, this variable is controversial as it might reflect past effort of a person (while being a child) and hence is not obviously something for which a person should not be held accountable.

Two sets of models have been proposed in the inequality–growth literature: models where inequality is beneficial for growth and models where inequality is harmful for growth.

On one hand, we find three main reasons for a positive relationship between inequality and growth. First, income inequality is fundamentally good for the accumulation of a surplus over present consumption regardless of whether the rich have a higher marginal propensity to save than the poor do (Kaldor's hypothesis). Then, more unequal economies grow faster than economies characterized by a more equitable income distribution if growth is related to the proportion of national income that is saved.[10] Second, following Mirrless (1971), in a moral hazard context where output depends on the unobservable effort borne by agents, rewarding the employees with a constant wage, which is independent from output performance, will discourage them from investing any effort (Rebelo, 1991). Third, since investment projects often involve large sunk costs, wealth needs to be sufficiently concentrated in order for an individual to be able to initiate a new industrial activity. Barro (2000) proposes a similar argument for education. Accordingly, investments in physical or human capital have to go beyond a fixed degree to affect growth in a positive manner.

On the other hand, we find three main sets of models in which inequality can discourage growth. The first set refers to models of economic development where three general arguments can be found (Todaro, 1994): unproductive investment by the rich (Mason, 1988); lower levels of human capital, nutrition and health by the poor (Dasgupta and Ray, 1987); and biased demand pattern of the poor towards local goods (Marshall, 1988). The second set groups models of imperfect capital markets, fertility and domestic market size. Wealth and human capital heterogeneity across individuals

[10] See Galenson and Leibenstein (1955), Stiglitz (1969) and Bourguignon (1981).

produces a negative relationship between income inequality and growth whether capital markets are imperfect and investment indivisibilities exist.[11] According to the endogenous fertility approach, income inequality reduces per capita growth because of the positive effect that inequality exerts on the rate of fertility.[12] Moreover, the production of manufactures is only profitable if domestic sales cover at least the fixed setup costs of plants. Consequently, redistribution of income may increase future growth by inducing higher demand of manufactures.[13] Finally, the third set of models refers to the political economy literature, where two arguments can be found. First, in a median-voter framework, a more unequal distribution of income leads to a larger redistributive policy and thus to more tax distortion that deters private investment and growth.[14] Second, strong inequality may result in political instability.[15]

As a conclusion from the last two paragraphs, inequality may affect growth through a large variety of opposite routes. Therefore, from a theoretical perspective, the prevalence of a positive or negative relationship between overall inequality and growth depends on which channel predominates. This fact is clearly reflected by the empirical evidence linking income inequality to economic growth: cross-sectional and panel data studies are generally inconclusive. Cross-sectional analysis showing a negative relationship between both dimensions include, among others, Alesina and Rodrik (1994), Persson and Tabellini (1994), Clarke (1995), Perotti (1996), Alesina and Perotti (1996) and Alesina et al. (1996). However, other authors find a positive relationship between growth and income inequality, such as Partridge (1997) and Zou and Li

[11] See Banerjee and Newman (1991), Galor and Zeira (1993), Bénabou (1996), Aghion and Bolton (1997) and Piketty (1997).
[12] See Galor and Zang (1997), Dahan and Tsiddon (1998), Morand (1998), Khoo and Dennis (1999) and Kremer and Chen (2002).
[13] See Murphy et al. (1989), Falkinger and Zweimüller (1997), Zweimüller (2000) and Mani (2001).
[14] See Perotti (1992 and 1993), Alesina and Rodrik (1994), Alesina and Perotti (1994) and Persson and Tabellini (1994).
[15] See Gupta (1990), Tornell and Velasco (1992), Alesina and Perotti (1996), Alesina et al. (1996), Svensson (1998) and Keefer and Knack (2002).

(1998). Barro (2000) shows a very slight relationship between both variables when using panel data, while Forbes (2000) finds a positive relationship.

Given these different findings in the literature, we propose to analyze the inequality and growth relationship using the IO concept. In particular, models *à la* Mirrless, where a positive relationship between inequality and growth is found, have to do with incentives to merits and effort, so they can be associated with inequality of returns to effort. On the other hand, models where inequality is harmful for growth have to do with the negative impact that certain adverse circumstances may have on growth. In this case, these models are closed related to the inequality-of-opportunity concept. Consequently, by considering the IO component, we can discriminate between some positive and negative influences upon growth. In Sections 4, we test our proposal with an inequality–growth empirical analysis for the U.S. economy but before, we estimate IO in the next section.

3. **Inequality of Opportunity in the U.S.**

In this section we estimate the IO in the U.S. by using depurated data of the Panel Survey Income Dynamics (PSID) database for 23 states in the 1980s and 1990s. First, we present the method; next, we describe the database; and finally, we show the main results.

3.1. The conceptual approach

This section is based on Roemer (1993) and Van de Gaer (1993). Consider a finite population of discrete individuals indexed by $i \in \{1, \ldots, N\}$. As is standard in the inequality-of-opportunity literature, the individual income, y_i, is assumed to be a function of the amount of effort, e_i, that is expended and the set of circumstances, C_i, that the individual faces, and it is denoted by $y_i = f(C_i, e_i)$. Circumstances are traits beyond the individual responsibility, while effort represents those factors for which the individual is responsible. In this context, effort is not only the extent to which a person exerts herself, but all the other background traits of the individual that might affect her success, but that are excluded from the list of circumstances. We treat effort as a continuous variable, while, for each individual i, C_i is a vector of J elements, each element corresponding to a particular circumstance. Finally, circumstances are exogenous because they cannot be affected by individual decisions, while effort is influenced, among other factors, by circumstances. Consequently, individual income can be rewrite as $y_i = f(C_i, e_i(C_i))$.

In order to estimate IO, we partition the population into a mutually exclusive and exhaustive set of types $\Gamma = \{H_1, \ldots, H_M\}$, where all individuals in each type m share the same set of circumstances. That is, $H_1 \cup H_2 \cup \ldots \cup H_M = \{1, \ldots, \mathrm{N}\}$, $H_\mathrm{r} \cap H_\mathrm{s} = \varnothing$, $\forall$ r and s, and $C_\mathrm{i} = C_\mathrm{k}$, $\forall$ i and k $|i \in H_m$ and $k \in H_m$, $\forall$ m. Furthermore, assume that the distribution of effort exerted by individuals of type m is F^m and that $e^m(\pi)$ is the level of effort exerted by the individual at the π^{th} quantile of that effort distribution. Given the type m, we can, hence, define the level of income obtained by the individual at the π^{th} quantile as follows:

$$v^m(\pi) = y^m(e^m(\pi)). \qquad (1)$$

In this manner, the income rank and the effort rank are the same within each type because, given a particular type, income is fully and monotonically determined by effort. We follow Van de Gaer (1993) in considering the set of incomes available to the members of each type as the opportunity set of each type.

Let $\pi \in [0,1]$, and consider

$$\bar{v} = \left(\int_0^1 v^1(\pi)\, d\pi, ..., \int_0^1 v^M(\pi)\, d\pi \right), \tag{2}$$

the M-dimensional vector of average incomes. We can interpret each element of the vector $\bar{v}$ as the expected income of each type or category of origin.

At this point, Roemer (1993) proposed the "mean of mins" approach: take the minimum at each centile of the conditional distribution of income (across types), and then average across centiles. Alternatively, Van de Gaer (1993) proposed the "min of means" approach: average income for each type, and then take the minimum across types. Because of the limited size of our samples, as discussed below, we adopt the second method because it is much less restrictive in terms of data requirements.[16] Consequently, Van de Gaer (1993) proposed to maximize the minimum average income:

$$Min\,(\bar{v}) = \min_m \left\{ \int_0^1 v^m(\pi)\, d\pi \right\}. \tag{3}$$

Van de Gaer favored the minimum function to keep with the *Rawlsian* maximin principle. However, his proposal is exposed to extreme values because it focuses only on the minimum average income. To reduce this problem, we adopt an inequality index,

[16] Roemer's approach requires measuring income differences between types by centiles, while Van de Gaer's method only measures income differences between types at the mean. Nevertheless, both mechanisms produce the same rankings when the transition matrices between origins and income quantiles are "Shorrocks monotonic". See Van de Gaer et al. (2001) for more details on this point.

which considers the whole vector $\bar{v}$ of average incomes.[17] In particular, we use the Theil 0 (T) and Gini (G) indices.[18] Moreover, in Section 4 we show that considering the Theil 0 index has a major advantage, namely, it allows us to decompose the overall inequality into inequality-of-opportunity and inequality-of-returns-to-effort components.

In the rest of the section, we compute, after presenting the data, overall inequality and IO according to the Theil 0 and Gini indices.

3.2. The data

The PSID database provides data for U.S. states during the period 1968–2007. This database contains information not only on individual income and circumstances but also on the state of residence. However, there is still a problem: data are representative at the national level, but they do not have to be necessarily at the state level. To minimize this problem, we have made a reasonable selection of data, states and decades. Nevertheless, some robustness analysis has been carried out in order to mimic the sample selection bias.

Samples refer to individuals who are male heads of household, 25–50 years old, which are the cohorts with the highest proportion of employed persons. This sample selection rule allows us to avoid the so-called composition effect (individuals with

[17] The use of an inequality index instead of the minimum function is also proposed in Checchi and Peragine (2005), Moreno-Ternero (2007), Rodríguez (2008) and Ferreira and Gignoux (2008).

[18] The Theil 0 index is positively related to total inequality and has a value between 0 and ln(N), where N is the sample size. The Gini coefficient is also positively related to total inequality and has a value between 0 and 1. For a distribution X, with mean μ_X, the Theil 0 index is defined as:

$$T(X) = \frac{1}{N}\sum_{i=1}^{N} \ln\frac{\mu_X}{x_i},$$

while the Gini coefficient is defined as:

$$G(X) = \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N}\frac{|x_i - x_j|}{N^2\mu_X}.$$

different ages are in different phases of the wage-earning time series). Another advantage of this rule is that individual earnings will be more representative of the individual's lifetime income (Grawe, 2005). Income is calculated as the individual's labor income plus the household capital income divided by the number of adults in the household.

We consider race and the father's education as the individual's circumstances, which is standar in the inequality-of-opportunity literature.[19] Notice that the observed vector of circumstances, which depends on the available data, is by construction a subset of the theoretical vector of all possible circumstances. As a result, our empirical estimates should be interpreted as lower-bound estimates of IO. Naturally, this implies that the *non-estimated* IO (due to unobserved circumstances) would still remain in the IE component (see Section 4.4 below).

Thus, for the selected set of circumstances, the sample is partitioned into 8 groups (i.e., M = 8): four related to the father's education (no education, primary, secondary and tertiary education), and two related to race (white and others).[20] In this case, the estimated inequality-of-opportunity index is called "8-*groups*". Note that estimates of IO may increase (but cannot decrease) with the number of types, though an excessive number of types may cause few observations in some types. For the sake of robustness, we will estimate in Section 4 IO using separately the categories of race ("*IO-race index*") and father's education ("*IO-edu index*").

To have enough degrees of freedom to estimate IO, we disregard those states with less than 50 observations. Using this criterion, there are only 17 states in 1970 with

[19] See references in footnote 8.

[20] Information on mother's education is not available for the whole period. "No education" means 5 grades or less; "primary" education goes from 6 grades to 11 grades; "secondary" education refers to 12 grades and 12 grades plus non-academic training; and, "tertiary" education refers to college with or without degree. Results do not change significantly if we modify the partition of father's education.

at least 50 observations. Moreover, there were 2,116 observations for the U.S. as a whole in 1970, whereas the numbers of observations were 3,091 and 3,843 in 1980 and 1990, respectively. Hence, to assure a large enough sample size for each state, we disregard the 1970s and focus on the 1980s and 1990s. For these two decades, our final sample reduces to the following 23 states: Arkansas, California, Florida, Georgia, Illinois, Indiana, Iowa, Kentucky, Louisiana, Maryland, Massachusetts, Michigan, Mississippi, Missouri, New Jersey, New York, North Carolina, Ohio, Pennsylvania, South Carolina, Tennessee, Texas, and Virginia.

3.3. Inequality of income and opportunity in the U.S. states

For the 23 selected U.S. states, Tables 1 and 2 show income inequality and IO estimates for 1980 and 1990, respectively.[21] They show results for the Theil 0 and Gini indices and for the IO 8-groups estimates. We also provide the standard error estimates calculated by bootstrapping according to the formula (Davison and Hinkley, 2005):

$$\sigma(\hat{I}) = \sqrt{\frac{1}{R-1}\sum_{r=1}^{R}\left(I^{*} - \bar{I}^{*}\right)^{2}}\ , \tag{4}$$

where I is the corresponding index and R is the number of replications.[22] Bearing in mind the limited size of our samples, the estimated standard errors for the income inequality and IO indices are rather precise.

INSERT TABLES 1 AND 2 ABOUT HERE

[21] Note that we work with truncated samples of male heads of household, so direct comparisons of our estimations with the published inequality indices by states would be misleading.

[22] In our calculations, we have assumed R = 1000. Cowell and Flachaire (2007) find that bootstrap tests usually improve numerical performance. Moreover, with small sample sizes it could be better to use a bootstrap approach that guarantees a better level of approximation to the nominal confidence intervals (Davison and Hinkley, 2005).

Now, we give a brief descriptive analysis of the inequality-of-opportunity results. Figures 1a and 1b represent, respectively, inequality of income and the 8-groups IO for the selected 23 U.S. states in 1990 for the Theil 0 and Gini indices. We have ranked the U.S. states by the Gini index. Comparing the income inequality and IO results, we observe substantial differences between their rankings. For example, there exists a group of states with high total inequality and rather low IO, such as Florida and Pennsylvania; the opposite happens in states like Virginia and Indiana. Nevertheless, there exist some states whose relative position remains. For example, New York and Kentucky are at the lowest levels of both dimensions, while Maryland, New Jersey and Tennessee are at the top of the two rankings. These results confirm that inequality of income and IO, though related concepts, measure different things.

We also observe that IO estimates represent a modest percentage of the total inequality, above all for the Theil 0 index.[23] The existence of additional representative circumstances capturing differences in opportunity, other than race and parent's education, could explain this result.[24] Finally, it is worth noting that the Theil 0 and Gini indices reach similar, but not the same, rankings.

INSERT FIGURES 1a AND 1b ABOUT HERE

Figures 2a and 2b show the relationship between the 1980–1990 variation of total inequality and IO for the Theil 0 and Gini indices, respectively. Only one state, New York, has reduced income inequality and IO when looking at both indices, while the opposite is found in many states, for example, Maryland, Tennessee, Illinois, New

[23] Ferreira and Gignoux (2009) find that between one fifth and one third of all income inequality is explained by opportunities in six countries in Latin America. Checchi and Peragine (2005) find that less than ten percent of all income inequality is explained by opportunities in Italy.

[24] Another possibility is that income-based IO tends to underestimate IO because the higher measurement error and variance for transitory components in the distribution of income (in comparison with the distribution of consumption) may be effectively counted as inequality of returns to effort (see Ferreira and Gignoux, 2009).

Jersey and Texas. Besides, Indiana and Iowa experienced an increase in IO while showing little change in total dispersion. Kentucky increased income inequality, whereas IO decreased notably. Lastly, Pennsylvania, Massachusetts and North Carolina have not displayed a significant change in their inequality measures.

INSERT FIGURES 2a AND 2b ABOUT HERE

Finally, we emphasize the positive relationship between total inequality change and inequality-of-opportunity change. However, this correlation is far from being perfect (see the coefficients of determination). This result points out that those factors affecting the evolution of these two dimensions can be different. As a consequence, the impact on growth of each variable could be distinct, as is discussed in more detail in the next section.

4. Inequality, Inequality of Opportunity and Growth: An Empirical Analysis

In this section, we carry out the main task of this paper, which is to characterize the effects of IO on growth. We assume two consecutive decades, from 1980 to 1990 (the 80s) and from 1990 to 2000 (the 90s), and our analysis is limited to the selected set of 23 U.S. states. An advantage of this panel is that heterogeneity within states is not coming from the political process because, for the most part, it is similar across the different states. More importantly, institutional, cultural, religious and other differences are less intensive for U.S. states than for different countries.

The dependent variable is the growth rate in the ensuing 10 years of real personal income (adjusted by CPI) divided by total midyear population. Inequality indices and other explanatory variables are all measured at the beginning of each decade

(1980 and 1990). This strategy saves us from endogeneity and measurement errors. In this manner, we can apply standard pooling regressions techniques, such as in Barro and Sala-i-Martin (1991), Partridge (1997) and many others.

To measure the relationship between inequality, IO and growth properly, the model must include additional variables that also affect growth. We use the controls that were significant in Partridge (1997). In a first and more parsimonious specification - specification (1) -, we consider a convergence term, time and regional dummies and the average skills of the labor force. In a second specification - specification (2) -, we also include variables capturing sectoral composition and past labor growth.[25]

More specifically, the lagged level of real per capita income is included in the model to control for conditional convergence across states.[26] In addition, we consider a time dummy for the 80s, and we omit the dummy for the 90s. We also use a standard and broad classification for regional variables: *West*, *Midwest*, *South* and *Northeast*.[27] The omitted regional dummy is the *Northeast* region. We consider three categories to measure the average skills of the labor force: the percentage of the population over 24 years old who have graduated from high school but do not have a four-year college degree (*high school*); the percentage who have graduated from a four-year college (*college*); and the omitted category, which is the percentage of individuals who have not graduated from high school.[28] To control for the initial economic sectoral mix of each

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[25] Population and personal income data come from the Regional Economic Accounts of the Bureau of Economic Analysis (*U.S. Department of Commerce*, http://www.bea.gov/regional/spi/drill.cfm), while CPI data come from the U.S. Department of Labor (*All Urban Consumers CPI series*: http://www.bls.gov/data/#prices); employment data (total and by type of industry) come from the Current Employment Statistics of the Bureau of Labor Statistics (*U.S. Department of Labor*: http://www.bls.gov/data/#employment).

[26] As is the norm in the convergence literature, an implicit assumption is that economic growth is converging to an equilibrium growth path that is a function of initial conditions (Barro and Sala-i-Martin, 1991)

[27] Regional dummies consider those fixed factors that are time invariant and inherent to each area but are not observed or not included in the model, such as geographical, social or local policy regional aspects or initial technology efficiency.

[28] Historical Census Statistics on Education Attained in the U.S., 1940 to 2000 (U.S. Census Bureau):

state, the shares of nonagricultural employment are included for *mining*, *construction*, *manufacturing*, *transportation and public utilities*, *finance*, *insurance and real estate*, and *government*. *Traded goods and services* are the omitted sector, and thus the employment share coefficients should be interpreted as being relative to this sector. The percentage of the population who worked on a farm (*farm*) is included to account for the different importance of agriculture across states. Finally, in order to account for the possibility that growth in the previous decade could, in turn, influence growth in the following decade and be correlated with past inequality, we include the percentage change in nonagricultural employment in the preceding decade (e.g., employment growth in the 80s is used to explain per capita income growth in the 90s).

4.1. Income inequality and growth

The benchmark analysis is based on regressions between growth, lagged income, an overall inequality index (Theil 0 and Gini) and the set of control variables:

$$GY_{it} = \beta \cdot y_{it-s} + \phi \cdot I_{it-s} + \alpha' T_t + \delta' R_i + \lambda' X_{it-s} + \varepsilon_{it}, \tag{5}$$

where GY_{it} is real per capita income growth in the decade, y_{it-s} is the real per capita income of state i at the beginning of the decade, I_{it-s} is the overall inequality index at the beginning of the decade, T_t is the time dummy corresponding to the 80s, R_i is a set of regional dummies, X_{it-s} groups the rest of control variables measured at the beginning of the decade, and finally ε_{it} encompasses effects of a random nature that are not considered in the model and is assumed to have the standard error component structure. Results for this benchmark setting are shown in Table 3. As in the rest of the paper,

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http://www.census.gov/population/www/socdemo/education/introphct41.html.

results are based on the standard OLS pooling regression and White cross-sectional standard errors and covariance matrix.

INSERT TABLE 3 ABOUT HERE

Regardless of the model specification, the results for the control variables are fairly robust and are in line with the related literature. The negative coefficient for lagged per capita income reflects conditional convergence, and its magnitude is in accordance with Barro and Sala-i-Martin (1991). Future economic growth is expected to be positively correlated with the labor force's human capital. As is commonly found in growth models augmented for human capital, the relevant variable of education is *college*, which is highly positive and significant with respect to the omitted category (non-graduated). However, we find that the effect of *high school* on growth is negative, but small, with respect to this category. The coefficients on most of the initial industrial mix variables are negative, though only *construction* is significant. The exception is *manufacturing*, whose coefficient is positive and significant. These findings suggest that states with greater initial shares in *services and traded goods* (the omitted category) and manufacturing have experienced higher economic growth.

The estimates for the *farm* variable are negative and no significant, while the coefficient associated with labor growth in the preceding year is positive and significant, which corroborates the idea that growth in the previous decade influences growth in the following decade. Regarding the cross-regional dummies, the coefficient for *South* is positive and significant for a full-specified model, while that for *West* is negative and significant; the coefficient for *Midwest* is no significant. Finally, the dummy for the 80s is positive and significant for a full-specified model.

At last, regarding the overall inequality indices, we first notice that Partridge (1997) found a positive relationship between overall inequality and per capita income growth. However, we find that the initial *Theil 0* and *Gini* coefficients are no significant.[29] Based on this result, a poor conclusion would be that distributive policies would not affect growth. Next, we test whether this result is due to the non-distinction between income inequality and IO. As we will see below, controlling by an inequality-of-opportunity measure changes the policy message dramatically.

4.2. Inequality of opportunity and growth

Now, we introduce IO into the model. In particular, we include the IO term into the expression (5) to estimate the following model:

$$GY_{it} = \beta \cdot y_{it-s} + \phi_1 \cdot I_{it-s} + \phi_2 \cdot IO_{it-s} + \alpha' T_t + \delta' R_i + \lambda' X_{it-s} + \varepsilon_{it} \tag{6}$$

where IO_{it-s} is the corresponding inequality-of-opportunity index (8-groups) at the beginning of the decade.

When including the IO term into the regression, we control for the observed circumstances, i.e. father's education and race. As a result, the coefficient of total inequality would now show the effect of effort and those circumstances that are not observed. Thus, we would expect that our estimated IO has a negative effect on growth, and the positive coefficient of total inequality found in Table 3 turns out significant. These results are confirmed for the Theil 0 and Gini indices, as it is shown in Table 4. These findings support the thesis that IO and inequality of returns to effort have opposite effects upon growth. Inequality is good for growth when that comes from

[29] Note that our results are not directly comparable with Partridge's; because we use the PSID database, our samples refer to male heads of households 25 to 50 years old, and we focus on the 80s and 90s and 23 selected states.

differences in the returns to effort, while it is harmful for growth when that comes from differences in opportunity. Accordingly, policies that equalize opportunity and promote individual effort will enhance growth.

INSERT TABLE 4 ABOUT HERE

The importance of this result deserves a careful analysis of robustness. The number and type of circumstances used, the way that income inequality and IO are combined into the same regression and the number of states considered, are the factors that we analyze to be more confident in our main result.

4.3. Inequality-of-opportunity estimates: the role of circumstances

Peculiar non-linearity effects on growth of the educational structure might lead to erroneous conclusions when using father's education as a circumstance. For instance, let's assume that race is not representative because it does not explain much IO and the explicative variables that measure the average skills of the labor force do not completely capture the effect of education upon growth. Then, it is possible that the estimated IO term, which relies on the distribution of people among four educational groups, is actually capturing part of the effect that education may have on growth. This fact might cause that the estimated impact of IO would be misleading.[30] To check this possibility, we analyze the explicative power of every circumstance alone.

First, we estimate dispersion in opportunity using separately the circumstance of race (*IO-race*) and father's education (*IO-edu*). Table 5 shows the indices of IO for our selected U.S. states in 1980 and 1990. We observe that both circumstances are relevant for explaining differences in opportunity. For example, when using the Theil 0 index we

[30] We are grateful for this suggestion from François Bourguignon.

find that IO-race and IO-edu dominate to each other approximately in the same number of states in 1990. Therefore, the negative impact of IO on growth found in the previous section (see Table 4) cannot be completely ascribed to father's education. Even if the proposed alternative channel through which education may affect growth is true, there is still room for a negative and significant impact of IO due to race on growth.

INSERT TABLE 5 ABOUT HERE

Table 6 shows the regression results using the IO-race and IO-edu indices under the full specified model. We first notice that the coefficient for the IO-race measure is highly significant and negative for both the Theil 0 and the Gini indices. However, the impact of IO-edu is unclear because its coefficient is negative but non-significant for the Theil 0 and Gini indices. In respect to the coefficient of total inequality, it is positive and significant for the 2-groups case (IO-race), and positive but non-significant for the 4-groups case (IO-edu). Consequently, we can be confident in the estimated impact of IO (8 groups), as long as race has been shown to be the driving force explaining the negative influence that IO has on growth.

INSERT TABLE 6 ABOUT HERE

4.4. Overall inequality decomposition

Thus far, we have included in the regressions indices of total inequality and IO. However, the total inequality and IO terms are not independent, which may affect the estimated coefficient of IO and its significance. In order to avoid this inconvenience, a further refinement is possible: we can exactly decompose overall inequality into inequality-of-opportunity and inequality-of-returns-to-effort components. In this manner, the two sources of income differences, circumstances and effort, will be included separately in the regressions.

As is well known, an inequality index is additively decomposable by population subgroups if and only if it is a positive multiple of a member of the Generalized Entropy class (Bourguignon, 1979 and Shorrocks, 1980 and 1984). This means that for every partition, any member of the Generalized Entropy class can be expressed as the sum of two terms: a weighted sum of within-group inequalities, plus a between-group inequality component. Only the Theil 0 index, among the members of the General Entropy class, uses weights based on the groups' population shares and has a path-independent decomposition (Foster and Shneyerov, 2000).[31] For both reasons we consider the Theil 0 index throughout this Section.

Thus, given a particular set of circumstances, consider any partition of income v into M groups, $v=\left(v^1,...,v^M\right)$, and $\bar{v}$ as defined in expression (2), then the Theil 0 index can be decomposed as follows:

$$T(v)=T(\bar{v})+\sum_{m=1}^{M}p_m T(v^m)\,, \tag{7}$$

where p_m is the frequency of type m in the population. The first term, $T(\bar{v})$, is a between-group index, which captures the income inequality due to different circumstances. As it was done in Section 3, this component is calculated by applying the Theil 0 index to an income vector in which each individual in a given group receives the corresponding group's mean income. Thus, this component is, by construction, an

[31] The rest members of the General Entropy class use weights based not only on the groups' population shares but also on the groups' income shares. In this manner, these indices give more importance to rich people.

inequality-of-opportunity index. As said above, its accuracy is conditioned by the set of circumstances being selected, which, in practice, depends on the available data. The second component is a within-group term, which captures the income inequality within each type *m*, weighted by the demographic importance of the corresponding type. Because income is a function of effort and circumstances, the within-group component then can be considered as an inequality-of-returns-to-effort index (the IE variable). Unfortunately, the estimated IE and IO terms will not be completely orthogonal because the *non-estimated* IO (due to unobserved circumstances) would still remain in the IE component.[32]

After decomposing total inequality into inequality-of-opportunity and inequality-of-returns-to-effort components, we estimate the following model:

$$GY_{it} = \beta \cdot y_{it-s} + \phi_1 \cdot IE_{it-s} + \phi_2 \cdot IO_{it-s} + \alpha' T_t + \delta' R_i + \lambda' X_{it-s} + \varepsilon_{it} . \qquad (8)$$

Table 7 shows the results for this model, using the IO (8 groups), IO-race and IO-edu estimates. The IE coefficient is positive and significant, while the IO coefficient is negative and significant for the IO (8 groups) and IO-race estimates. For the IO-edu index, the coefficients for the IE and IO variables are positive and negative, respectively, but they are not significant. These results are consistent with previous findings. In particular, the two components of total inequality, IO and IE, have significant but opposite effects upon growth. Moreover, race is more important than father's education in explaining the negative influence of IO on growth.

[32] The Gini index generally fails to decompose additively into between- and within-group components. Thus, the Gini decomposition is (see, among others, Lambert and Aronson, 1993):

$$G(v) = G(\bar{v}) + \sum_{m=1}^{M} p_m q_m G(v^m) + R ,$$

where q_m is the income share for type *m*. The first term is the between-groups Gini coefficient, the second term is the within-group component, and *R* is a residual that is zero only in the case that group income ranges do not overlap, which does not occur in our case.

INSERT TABLE 7 ABOUT HERE

4.5. States

Now, we change the states considered in the regressions. Because of the limited size of our samples, we eliminate those states with fewer observations in 1990.[33] Using the specification in (8), we show in Table 8 the IO and IE coefficients when reducing recursively the number of states in the regression. Thus, the first line shows the results when using all 23 states; the second line shows the results when Arkansas, which is the state with lowest number of observations in 1990, is excluded; in the next row, we exclude Arkansas and Tennessee, which is the next state with lowest number of observations; and so on and so forth for the next rows until we keep with 10 states (20 observations).[34] Results confirm the positive and significant coefficient for IE and the negative and significant coefficient for IO. Reducing the number of states, therefore, neither affects our main result.

INSERT TABLE 8 ABOUT HERE

5. **Concluding Remarks**

Models exploring the incidence of income inequality upon economic growth do not reach a clear-cut conclusion. We postulate in this paper that one possible reason for this inconclusiveness is that income inequality indices are indeed measuring at least two different sorts of inequality: inequality of opportunity and inequality of effort. Though

[33] Similar results are obtained if we eliminate those states with fewer observations in 1980.
[34] We are aware of the few degrees of freedom that we have when reducing the number of states, but we now care only for the robustness of our results.

this distinction has already been emphasized in the inequality-of-opportunity literature, it has not yet been considered in the growth literature.

Using depurated data of the PSID database for 23 U.S. states in 1980 and 1990, we followed Van de Gaer's approach to compute inequality-of-opportunity and inequality-of-returs-to-effort indices. We ran standard OLS pooling regressions, finding robust support for a negative relationship between inequality of opportunity and growth and a positive relationship for the other sort of inequality. Hence, these two types of inequalities are affecting growth through opposite channels. On one hand, inequality of effort increases growth because it may encourage people to invest in education and to exert effort. On the other hand, inequality of opportunity decreases growth because it may not favor human capital accumulation of the more talented individuals. In fact, Van de Gaer et al. (2001) have pointed out that inequality of opportunity reduces the role that talent plays in competing for a position by worsening intergenerational mobility. Making a distinction between inequality of income and inequality of opportunity can throw some light upon several intriguing empirical facts in the growth literature. Two examples are pointed out.

Barro (2000) shows a positive relationship between growth and inequality within most developed countries, while this relationship is negative when looking at the poorest countries. He proposes, as a tentative explanation, the different role of capital markets. In particular, he considers that problems of information (moral-hazard and repayment enforcement problems) are larger in poor countries because they have less-developed credit markets. However, he does not find empirical evidence for this different role of capital markets. An alternative explanation that would arise from the present paper is that differences in opportunity are more important within less-developed countries. At this respect, some evidence is found in the inequality-of-opportunity literature as in Ferreira and Gignoux (2009), Checchi and Peragine (2005), Rodríguez (2008) and Cogneau and Mesplé-Somps (2009).

Secondly, some empirical studies have found that the effect of income inequality on growth is sensitive to the inclusion of some variables like regional dummy variables (Birdall et al., 1995). However, the relationship between initial land inequality and growth is negative and robust to the introduction of regional dummies and other explicative variables (Deininger and Squire, 1998). Our proposal offers an easy explanation for this empirical fact. Income inequality comes not only from unequal opportunities but also from different levels of effort. As a result, the effect of income inequality upon growth can have a different sign depending on the kind of controls that are introduced in the regressions. However, initial land inequality comes unambiguously from unequal opportunities (i.e., the socioeconomic conditions of parents) and has a clear-cut negative effect upon growth.

Further research concerning these issues is clearly needed. However, we believe that a complete understanding of the relationship between inequality and growth requires more effort in constructing appropriated databases that properly represent social origins.

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TABLES

Table 1. Inequality of income and opportunity (8 groups) in 1980

		Total Inequality		**IO (8 groups)**[a]		**Ratio**[b]	
State	**Obs.**	**Gini**	**Theil 0**	**Gini**	**Theil 0**	**Gini**	**Theil 0**
Arkansas	62	0.33424	0.22890	0.08650	0.02149	25.9	9.4
		(0.00792)	(0.01075)	(0.00651)	(0.00262)		
California	288	0.32272	0.21533	0.09366	0.01687	29.0	7.8
		(0.00382)	(0.00602)	(0.00476)	(0.00149)		
Florida	91	0.42466	0.33766	0.14481	0.04648	34.1	13.8
		(0.00801)	(0.01293)	(0.01149)	(0.00531)		
Georgia	96	0.27988	0.23834	0.12551	0.03086	44.8	12.9
		(0.00724)	(0.02882)	(0.01020)	(0.00529)		
Illinois	96	0.31883	0.19999	0.06997	0.01295	21.9	6.5
		(0.00557)	(0.00733)	(0.00583)	(0.00225)		
Indiana	87	0.32770	0.21875	0.10313	0.02693	31.5	12.3
		(0.00797)	(0.01040)	(0.00614)	(0.00246)		
Iowa	57	0.33646	0.20843	0.05522	0.02501	16.4	12.0
		(0.00705)	(0.00840)	(0.00910)	(0.00400)		
Kentucky	53	0.26658	0.12608	0.14123	0.03461	53.0	27.5
		(0.00479)	(0.00481)	(0.00697)	(0.00333)		
Luisiana	83	0.39985	0.44742	0.22624	0.08799	56.6	19.7
		(0.01128)	(0.02907)	(0.01380)	(0.01181)		
Maryland	126	0.30568	0.21192	0.13413	0.03478	43.9	16.4
		(0.01258)	(0.02000)	(0.01525)	(0.00734)		
Massachusetts	60	0.31730	0.17690	0.06081	0.00733	19.2	4.1
		(0.00478)	(0.00578)	(0.00819)	(0.00193)		
Michigan	147	0.34835	0.36653	0.13826	0.09811	39.7	26.8
		(0.00598)	(0.01553)	(0.00745)	(0.00986)		
Mississippi	122	0.38898	0.29497	0.24167	0.11049	62.1	37.5
		(0.01821)	(0.02564)	(0.02319)	(0.02069)		
Missouri	95	0.33638	0.27555	0.04738	0.01443	14.1	5.2
		(0.00689)	(0.01305)	(0.00747)	(0.00203)		
New Jersey	79	0.37963	0.31529	0.08450	0.03322	22.3	10.5
		(0.00661)	(0.01435)	(0.00771)	(0.00518)		
New York	144	0.34521	0.23178	0.09271	0.02401	26.9	10.4
		(0.00423)	(0.00623)	(0.00549)	(0.00250)		
N. Carolina	142	0.36258	0.24823	0.18670	0.06859	51.5	27.6
		(0.00826)	(0.01188)	(0.01107)	(0.00766)		
Ohio	136	0.29474	0.17561	0.04477	0.00845	15.2	4.8
		(0.00372)	(0.00638)	(0.00597)	(0.00156)		
Pennsylvania	162	0.36375	0.35750	0.10150	0.02217	27.9	6.2
		(0.00663)	(0.01534)	(0.00759)	(0.00261)		
S. Carolina	152	0.34084	0.22259	0.12916	0.03236	37.9	14.5
		(0.00711)	(0.01091)	(0.00815)	(0.00409)		
Tennessee	53	0.27433	0.16526	0.10089	0.01930	36.8	11.7
		(0.00597)	(0.00902)	(0.00674)	(0.00240)		
Texas	187	0.30064	0.18843	0.03604	0.00338	12.0	1.8
		(0.00426)	(0.00774)	(0.00594)	(0.00102)		
Virginia	116	0.28231	0.22889	0.07761	0.01344	27.5	5.9
		(0.00452)	(0.01668)	(0.00617)	(0.00218)		
USA	**3091**	**0.34084**	**0.25252**	**0.06212**	**0.01110**	**18.2**	**4.4**
		(0.00543)	(0.01036)	(0.00645)	(0.00275)		

Standard deviations in parentheses.

[a] Inequality of opportunity according to the father's education and race circumstances.

[b] Inequality of opportunity in relation to total inequality in percentage.

Table 2. Inequality of income and opportunity (8 groups) in 1990

		Total Inequality		IO (8 groups)[a]		Ratio[b]	
State	**Obs.**	**Gini**	**Theil 0**	**Gini**	**Theil 0**	**Gini**	**Theil 0**
Arkansas	67	0.29706	0.16818	0.09970	0.02648	33.6	15.7
		(0.00629)	(0.00934)	(0.00787)	(0.00295)		
California	332	0.38229	0.29217	0.10847	0.02388	28.4	8.2
		(0.00486)	(0.00831)	(0.00559)	(0.00191)		
Florida	129	0.42208	0.35338	0.09126	0.05391	21.6	15.3
		(0.00645)	(0.01165)	(0.00759)	(0.00605)		
Georgia	112	0.35784	0.26191	0.13932	0.03524	38.9	13.5
		(0.00725)	(0.01292)	(0.01095)	(0.00485)		
Illinois	115	0.34540	0.34581	0.13757	0.11171	39.8	32.3
		(0.00661)	(0.01626)	(0.00767)	(0.01385)		
Indiana	89	0.33431	0.22422	0.14120	0.03820	42.2	17.0
		(0.00798)	(0.01160)	(0.00674)	(0.00402)		
Iowa	72	0.32327	0.20573	0.10085	0.04312	31.2	21.0
		(0.00672)	(0.00943)	(0.01019)	(0.00710)		
Kentucky	69	0.32882	0.22694	0.09846	0.02041	29.9	9.0
		(0.00606)	(0.01171)	(0.00772)	(0.00301)		
Luisiana	78	0.38272	0.46783	0.21279	0.08455	55.6	18.1
		(0.01027)	(0.03272)	(0.01288)	(0.01163)		
Maryland	155	0.49677	0.47258	0.30793	0.16170	62.0	34.2
		(0.02059)	(0.03707)	(0.02393)	(0.02413)		
Massachusetts	89	0.33443	0.20076	0.05169	0.00630	15.5	3.1
		(0.00575)	(0.00663)	(0.00723)	(0.00123)		
Michigan	177	0.42317	0.43608	0.17375	0.07565	41.1	17.3
		(0.00771)	(0.01571)	(0.00835)	(0.00615)		
Mississippi	162	0.37041	0.33277	0.15032	0.03834	40.6	11.5
		(0.00857)	(0.01695)	(0.01044)	(0.00551)		
Missouri	113	0.33655	0.23957	0.11615	0.02702	34.5	11.3
		(0.00567)	(0.01008)	(0.00831)	(0.00339)		
New Jersey	101	0.47989	0.46021	0.21257	0.08379	44.3	18.2
		(0.01661)	(0.02897)	(0.01999)	(0.01491)		
New York	160	0.30540	0.18871	0.05037	0.01171	16.5	6.2
		(0.00425)	(0.00535)	(0.00479)	(0.00124)		
N. Carolina	214	0.37127	0.28901	0.19076	0.06407	51.4	22.2
		(0.00716)	(0.01244)	(0.00924)	(0.00598)		
Ohio	150	0.35475	0.35219	0.09544	0.03003	26.9	8.5
		(0.00524)	(0.01312)	(0.00608)	(0.00357)		
Pennsylvania	205	0.36963	0.34179	0.09930	0.02020	26.9	5.9
		(0.00441)	(0.00967)	(0.00517)	(0.00204)		
S. Carolina	225	0.35308	0.45366	0.15726	0.04323	44.5	9.5
		(0.00555)	(0.02604)	(0.00634)	(0.00354)		
Tennessee	69	0.43795	0.38964	0.22457	0.08887	51.3	22.8
		(0.01340)	(0.02403)	(0.01686)	(0.01285)		
Texas	235	0.39419	0.35183	0.13689	0.05153	34.7	14.6
		(0.00520)	(0.01028)	(0.00649)	(0.00368)		
Virginia	134	0.35629	0.27648	0.15890	0.04465	44.6	16.1
		(0.00548)	(0.01039)	(0.00806)	(0.00429)		
USA	**3843**	**0.38469**	**0.32666**	**0.10756**	**0.02398**	**28.0**	**7.3**
		(0.00718)	(0.01305)	(0.00712)	(0.00368)		

Standard deviations in parentheses.

[a] Inequality of opportunity according to the father's education and race circumstances.

[b] Inequality of opportunity in relation to total inequality in percentage.

Table 3. Overall Inequality and growth within US States: 1980-2000

	(1) for Theil 0	(2) for Theil 0	(1) for Gini	(2) for Gini
Lagged per capita income	-0.0018*** (0.00004)	-0.0018*** (0.00022)	-0.0018*** (0.00006)	-0.0018*** (0.00027)
Inequality	-6.1229 (3.9589)	2.7926 (2.0451)	-1.5546 (6.6779)	6.6133 (4.6939)
Dum 80	0.4615 (0.4989)	0.8255** (0.3591)	0.7444 (0.5799)	0.7797*** (0.2313)
Midwest	-2.2353 (1.8756)	-1.0987 (1.7492)	-2.2323 (1.7096)	-1.0174 (1.7574)
West	-7.1877** (3.4245)	-6.1018* (3.5746)	-7.0111** (3.2642)	-6.0303* (3.5642)
South	-2.8078*** (0.5117)	2.4009*** (0.3819)	-2.9559*** (0.3824)	2.4225*** (0.2353)
High school	-0.1994*** (0.0595)	-0.1634*** (0.0235)	-0.1968*** (0.0513)	-0.1557*** (0.0180)
College	0.9484*** (0.0183)	1.0676*** (0.2308)	0.9696*** (0.0444)	1.0489*** (0.2172)
Mining	--	-0.5972 (0.7090)	--	-0.5372 (0.7380)
Construction	--	-1.8897* (0.9568)	--	-1.8892** (0.8996)
Manufacturing	--	0.2369** (0.1114)	--	0.2495** (0.0991)
Transportation and public utilities	--	-0.3630 (0.3021)	--	-0.3438 (0.3058)
Finance, insurance and real estate	--	0.4246 (0.7992)	--	0.4605 (0.7421)
Government	--	-0.2018 (0.2109)	--	-0.1624 (0.1811)
Farm/population	--	-0.1121 (0.0985)	--	-0.1375 (0.1198)
Lag change in employment	--	0.0426** (0.0178)	--	0.0384*** (0.0139)
Constant	39.9902*** (2.4078)	37.0799*** (12.2198)	39.2604*** (1.5186)	34.5748*** (10.6005)
R^2	0.4611	0.6658	0.4491	0.6495
R^2 Adjusted	0.3446	0.4629	0.3300	0.4562
F-stat (p-value in parenthesis)	3.9580 (0.0018)	3.6251 (0.0013)	3.7704 (0.0025)	3.3596 (0.0022)

OLS pooling regression; White cross-section standard errors and covariance estimates.

Cross-sections included: 23; Total pool (balanced): 46. Standard deviations in parenthesis.

(*) significant at the 10% level; (**) significant at the 5% level; (***) significant at the 1% level.

Table 4. Inequality, IO and growth within US States: 1980-2000

	(1) for Theil 0 and IO (8 groups)	(2) for Theil 0 and IO (8 groups)	(1) for Gini and IO (8 groups)	(2) for Gini and IO (8 groups)
Lagged per capita income	-0.0018*** (0.00004)	-0.0017*** (0.00012)	-0.0020*** (0.00006)	-0.0018*** (0.00023)
Inequality	-2.9524 (4.7388)	10.7953*** (0.4273)	13.7357* (7.1776)	14.8684*** (5.1708)
Inequality of opportunity	-12.5087*** (4.4638)	-26.3222*** (1.3883)	-17.3267*** (0.14066)	-9.3317*** (0.6125)
Dum 80	0.4016 (0.3760)	0.9122 (0.5877)	0.0018 (0.4092)	0.5339 (0.3685)
Midwest	-1.7147 (2.1762)	-0.0144 (1.9480)	-1.2743 (1.8469)	-0.6472 (1.7881)
West	-7.1479** (3.3166)	-6.1161* (3.5754)	-6.5852** (2.7838)	-5.7472* (3.4358)
South	-2.5458*** (0.8195)	2.9601*** (0.6996)	-2.5153*** (0.5859)	2.6031*** (0.3139)
High school	-0.2246*** (0.0680)	-0.2490*** (0.0231)	-0.2885*** (0.0320)	-0.1889*** (0.0063)
College	1.0005*** (0.0172)	1.2164*** (0.2297)	1.1223*** (0.0547)	1.0878*** (0.2319)
Mining	--	-0.6708 (0.5994)	--	-0.5129 (0.7081)
Construction	--	-2.0507*** (0.6465)	--	-1.8011** (0.7129)
Manufacturing	--	0.2019** (0.0876)	--	0.2679*** (0.0593)
Transportation and public utilities	--	-0.4370 (0.5164)	--	-0.2990 (0.4365)
Finance, insurance and real estate	--	0.3026 (0.7425)	--	0.4388 (0.7066)
Government	--	-0.2531 (0.2109)	--	-0.1027 (0.1693)
Farm/population	--	0.0303*** (0.0044)	--	-0.1090*** (0.0201)
Lag change in employment	--	0.0474*** (0.0017)	--	0.0310*** (0.0071)
Constant	40.0302*** (1.4149)	39.9815*** (7.9088)	40.7365*** (0.2585)	32.3179*** (6.3231)
R^2	0.4643	0.6601	0.4634	0.6529
R^2 Adjusted	0.3303	0.4537	0.3293	0.4422
F-stat (p-value in parenthesis)	3.4662 (0.0034)	3.1979 (0.0031)	3.4545 (0.0036)	3.0988 (0.0039)

OLS pooling regression; White cross-section standard errors and covariance estimates.

Cross-sections included: 23; Total pool (balanced): 46. Standard deviations in parenthesis.

(*) significant at the 10% level; (**) significant at the 5% level; (***) significant at the 1% level.

Table 5. Inequality of opportunity in 1980 and 1990 (2 and 4 groups)

	1980				1990			
	IO (2 groups)[a]		IO (4 groups)[b]		IO (2 groups)[a]		IO (4 groups)[b]	
State	**Gini**	**Theil 0**	**Gini**	**Theil 0**	**Gini**	**Theil 0**	**Gini**	**Theil 0**
Arkansas	0.04525	0.01681	0.05985	0.00674	0.03522	0.00865	0.07593	0.02083
	(0.00426)	(0.00235)	(0.00658)	(0.00130)	(0.00356)	(0.00145)	(0.00775)	(0.00266)
California	0.05206	0.00866	0.05984	0.00735	0.06506	0.01829	0.06792	0.00797
	(0.00319)	(0.00109)	(0.00475)	(0.00111)	(0.00258)	(0.00139)	(0.00557)	(0.00127)
Florida	0.06870	0.01858	0.11434	0.02466	0.07764	0.04869	0.04832	0.00806
	(0.00623)	(0.00350)	(0.01237)	(0.00482)	(0.00448)	(0.00415)	(0.00910)	(0.00217)
Georgia	0.06891	0.01855	0.09283	0.01544	0.04440	0.00981	0.11313	0.02432
	(0.00677)	(0.00342)	(0.01055)	(0.00336)	(0.00436)	(0.00183)	(0.01189)	(0.00458)
Illinois	0.03618	0.00573	0.04220	0.00391	0.08241	0.04617	0.04538	0.00502
	(0.00460)	(0.00152)	(0.00611)	(0.00097)	(0.00503)	(0.00509)	(0.00778)	(0.00143)
Indiana	0.04658	0.01232	0.07117	0.01011	0.03750	0.01153	0.11986	0.02538
	(0.00410)	(0.00208)	(0.00586)	(0.00145)	(0.00366)	(0.00225)	(0.00622)	(0.00277)
Iowa	0.00030	0.00008	0.05503	0.02495	0.00214	0.00103	0.09869	0.04205
	(0.00000)	(0.00030)	(0.00913)	(0.00400)	(0.00092)	(0.00044)	(0.00950)	(0.00690)
Kentucky	0.01852	0.00316	0.11805	0.02502	0.01297	0.00102	0.08430	0.01204
	(0.00210)	(0.00047)	(0.00780)	(0.00326)	(0.00422)	(0.00066)	(0.00775)	(0.00230)
Luisiana	0.15171	0.04664	0.17443	0.05666	0.11288	0.02600	0.14185	0.03584
	(0.01289)	(0.00820)	(0.01394)	(0.00953)	(0.01232)	(0.00590)	(0.01254)	(0.00647)
Maryland	0.07397	0.01223	0.11305	0.02277	0.18455	0.09564	0.15154	0.05507
	(0.00824)	(0.00279)	(0.01496)	(0.00625)	(0.01087)	(0.01203)	(0.02217)	(0.01062)
Massachusetts	0.00234	0.00125	0.05889	0.00620	0.00607	0.00190	0.04637	0.00444
	(0.00000)	(0.00092)	(0.00820)	(0.00169)	(0.00105)	(0.00034)	(0.00713)	(0.00119)
Michigan	0.03693	0.00703	0.11648	0.08429	0.07972	0.04031	0.14242	0.03618
	(0.00376)	(0.00146)	(0.00819)	(0.00907)	(0.00453)	(0.00470)	(0.00872)	(0.00409)
Mississippi	0.15316	0.05286	0.15551	0.05609	0.10694	0.02396	0.09600	0.01629
	(0.01339)	(0.00988)	(0.02493)	(0.01622)	(0.01021)	(0.00473)	(0.01087)	(0.00378)
Missouri	0.01061	0.00060	0.02211	0.00095	0.01179	0.00070	0.09605	0.01713
	(0.00369)	(0.00044)	(0.00707)	(0.00087)	(0.00421)	(0.00056)	(0.00848)	(0.00296)
New Jersey	0.06578	0.03060	0.04415	0.01030	0.08626	0.03954	0.13820	0.03576
	(0.00499)	(0.00424)	(0.00749)	(0.00309)	(0.00515)	(0.00466)	(0.01930)	(0.00999)
New York	0.05187	0.01365	0.04941	0.00673	0.03654	0.00559	0.01334	0.00060
	(0.00450)	(0.00252)	(0.00483)	(0.00082)	(0.00428)	(0.00138)	(0.00453)	(0.00029)
N. Carolina	0.10302	0.03112	0.15196	0.05497	0.14671	0.05085	0.11258	0.02937
	(0.00610)	(0.00375)	(0.01208)	(0.00747)	(0.00565)	(0.00405)	(0.01027)	(0.00504)
Ohio	0.01288	0.00111	0.02974	0.00155	0.03081	0.00698	0.08070	0.02348
	(0.00342)	(0.00056)	(0.00580)	(0.00065)	(0.00323)	(0.00150)	(0.00583)	(0.00291)
Pennsylvania	0.02938	0.00610	0.07975	0.01307	0.01910	0.00235	0.07477	0.01317
	(0.00267)	(0.00113)	(0.00780)	(0.00235)	(0.00330)	(0.00086)	(0.00496)	(0.00156)
S. Carolina	0.10373	0.02700	0.00859	0.00026	0.11095	0.02901	0.08258	0.01726
	(0.00688)	(0.00362)	(0.00563)	(0.00044)	(0.00529)	(0.00286)	(0.00601)	(0.00196)
Tennessee	0.01165	0.00228	0.09497	0.01758	0.01828	0.00672	0.20515	0.07297
	(0.00202)	(0.00058)	(0.00688)	(0.00231)	(0.00356)	(0.00259)	(0.01688)	(0.01221)
Texas	0.01211	0.00046	0.03297	0.00290	0.08192	0.02525	0.03183	0.00184
	(0.00502)	(0.00040)	(0.00576)	(0.00089)	(0.00543)	(0.00353)	(0.00776)	(0.00094)
Virginia	0.01952	0.00260	0.06794	0.00925	0.07228	0.01837	0.12133	0.02922
	(0.00314)	(0.00084)	(0.00604)	(0.00157)	(0.00435)	(0.00219)	(0.00885)	(0.00390)
USA	**0.04048**	**0.00815**	**0.04049**	**0.00475**	**0.05721**	**0.01730**	**0.07966**	**0.01097**
	(0.00515)	(0.00265)	(0.00664)	(0.00180)	(0.00493)	(0.00318)	(0.00791)	(0.00290)

Standard deviations in parentheses.

[a] Inequality of opportunity according to race.

[b] Inequality of opportunity according to father's education.

Table 6. Inequality, IO and growth within US States: 1980-2000

	(2) for Theil 0 and IO (Race)	(2) for Gini and IO (Race)	(2) for Theil 0 and IO (Edu)	(2) for Gini and IO (Edu)
Lagged per capita income	-0.0017*** (0.00012)	-0.0021*** (0.00007)	-0.0017*** (0.00015)	-0.0018*** (0.00026)
Inequality	9.3202*** (1.0928)	27.0867*** (7.5324)	5.5371 (4.0638))	5.9249 (6.8464)
Inequality of opportunity	-48.4542** (20.1302)	-35.6361** (15.0021)	-18.5179 (18.7083)	1.4117 (4.5492)
Dum 80	0.6977 (0.8146)	-0.2530 (0.8465)	0.9934* (0.5829)	0.7861*** (0.1983)
Midwest	-0.4775 (1.8486)	-0.1042 (1.2722)	-0.9307 (1.7887)	-1.0428 (1.8469)
West	-6.0225* (3.5381)	-4.6839* (2.4592)	-6.2598* (3.3757)	-6.0345* (3.5892)
South	2.6166** (1.1559)	2.4926** (0.9341)	2.436 *** (0.2812)	2.4259*** (0.2474)
High school	-0.2534*** (0.0487)	-0.2213** (0.0920)	-0.1726*** (0.0322)	-0.1535*** (0.0254)
College	1.1997*** (0.1240)	1.1717*** (0.0899)	1.0927*** (0.2585)	1.0486*** (0.2159)
Mining	-0.7353 (0.7955)	-0.4299 (0.8447)	-0.6089 (0.6169)	-0.5349 (0.7400)
Construction	-1.7428* (0.9040)	-1.2154 (0.8859)	-1.9889** (0.9277)	-1.8851** (0.9288)
Manufacturing	0.2335*** (0.0818)	0.3819*** (0.0434)	0.2273* (0.1169)	0.2522 ** (0.1109)
Transportation and public utilities	-0.4569* (0.2549)	-0.2296** (0.1012)	-0.3886 (0.3888)	-0.3528 (0.3158)
Finance, insurance and real estate	0.4020 (0.6623)	0.8193 (0.5164)	0.3024 (0.9601)	0.4827 (0.8071)
Government	-0.2267 (0.1858)	0.1313 (0.2522)	-0.2098 (0.2163)	-0.1653 (0.1729)
Farm/population	-0.0598 (0.1074)	-0.2299*** (0.0007)	-0.0300 (0.0457)	-0.1365 (0.1347)
Lag change in employment	0.0472*** (0.0075)	0.0115 (0.0165)	0.0499** (0.0211)	0.0380** (0.0156)
Constant	38.0290*** (6.9734)	22.0069*** (6.1383)	37.618*** (11.6134)	34.499*** (11.1864)
R^2	0.6658	0.6796	0.6515	0.6497
R^2 Adjusted	0.4630	0.4851	0.4399	0.4370
F-stat (p-value in parenthesis)	3.2819 (0.0026)	3.4938 (0.0016)	3.079 (0.0041)	3.0543 (0.0043)

OLS pooling regression; White cross-section standard errors and covariance estimates.

Cross-sections included: 23; Total pool (balanced): 46. Standard deviations in parenthesis.

(*) significant at the 10% level; (**) significant at the 5% level; (***) significant at the 1% level.

Table 7. Inequality decomposition: IO, IE and growth within US States: 1980-2000

	(2) for IO 8 groups (Race and Education)	(2) for IO 2 groups (Race)	(2) for IO 4 groups (Edu)
Lagged per capita income	-0.0017*** (0.00012)	-0.0017*** (0.00012)	-0.0017*** (0.00015)
Inequality of effort (IE)	10.7953*** (0.4273)	9.3202*** (1.0928)	5.5371 (4.0637)
Inequality of opportunity (IO)	-15.5269*** (1.8156)	-39.1339** (19.0374)	-12.9808 (14.6446)
Dum 80	0.9122 (0.5877)	0.6977 (0.8146)	0.9934* (0.5829)
Midwest	-0.0144 (1.9480)	-0.4776 (1.8486)	-0.9307 (1.7887)
West	-6.1161* (3.5754)	-6.0225* (3.5381)	-6.2598* (3.3757)
South	2.9601*** (0.6996)	2.6167** (1.1559)	2.4361*** (0.2812)
High school	-0.2490*** (0.0231)	-0.2534*** (0.0487)	-0.1725*** (0.0322)
College	1.2164*** (0.2298)	1.1997*** (0.1240)	1.0928*** (0.2585)
Mining	-0.6707 (0.5994)	-0.7353 (0.7955)	-0.6089 (0.6169)
Construction	-2.0507** (0.6465)	-1.7428* (0.9040)	-1.9889** (0.9277)
Manufacturing	0.2019** (0.0876)	0.2335*** (0.0818)	0.2273* (0.1169)
Transportation and public utilities	-0.4370 (0.5164)	-0.4569* (0.2549)	-0.3886 (0.3888)
Finance, insurance and real estate	0.3026 (0.7425)	0.4020 (0.6623)	0.3023 (0.9601)
Government	-0.2531 (0.2109)	-0.2268 (0.1858)	-0.2098 (0.2163)
Farm/population	0.0303*** (0.0045)	-0.0598 (0.1074)	-0.0300 (0.0457)
Lag change in employment	0.0474*** (0.0018)	0.0472*** (0.0075)	0.0499** (0.0211)
Constant	39.9814*** (7.9087)	38.0290*** (6.9734)	37.6182*** (11.6135)
R^2	0.6601	0.6658	0.6515
R^2 Adjusted	0.4537	0.4630	0.4399
F-stat (p-value in parenthesis)	3.1979 (0.0031)	3.2819 (0.0026)	3.0791 (0.0040)

OLS pooling regression; White cross-section standard errors and covariance estimates.

Cross-sections included: 23; Total pool (balanced): 46. Standard deviations in parenthesis.

(*) significant at the 10% level; (**) significant at the 5% level; (***) significant at the 1% level.

Table 8. The IO and IE components when reducing recursively the number of US States

	States	IE	std	p-value	IO	std	p-value
23	**All**	**10.795**	0.427	0.000	**-15.527**	1.816	0.000
22	Arkansas	7.705	1.602	0.000	-15.062	4.814	0.004
21	Tennessee	8.278	1.271	0.000	-13.729	5.760	0.025
20	Kentucky	11.727	5.581	0.047	-11.468	6.527	0.093
19	Iowa	10.591	5.977	0.092	-10.727	4.319	0.022
18	Louisiana	11.831	6.828	0.100	-8.579	4.883	0.096
17	Indiana	24.308	8.808	0.014	-11.051	2.501	0.000
16	Massachusetts	26.465	10.472	0.024	-27.679	16.342	0.112
15	New Jersey	30.515	6.565	0.001	-27.650	14.921	0.089
14	Georgia	46.874	0.7712	0.000	-34.795	7.814	0.001
13	Missouri	60.030	3.195	0.000	-56.266	16.068	0.008
12	Illinois	68.837	4.179	0.000	-154.787	6.209	0.000
11	Florida	70.015	3.933	0.000	-135.742	2.828	0.000
10	Virginia	35.866	4.980	0.019	-89.200	6.042	0.005

FIGURES

Figure 1a. Income Inequality in U.S. (1990)

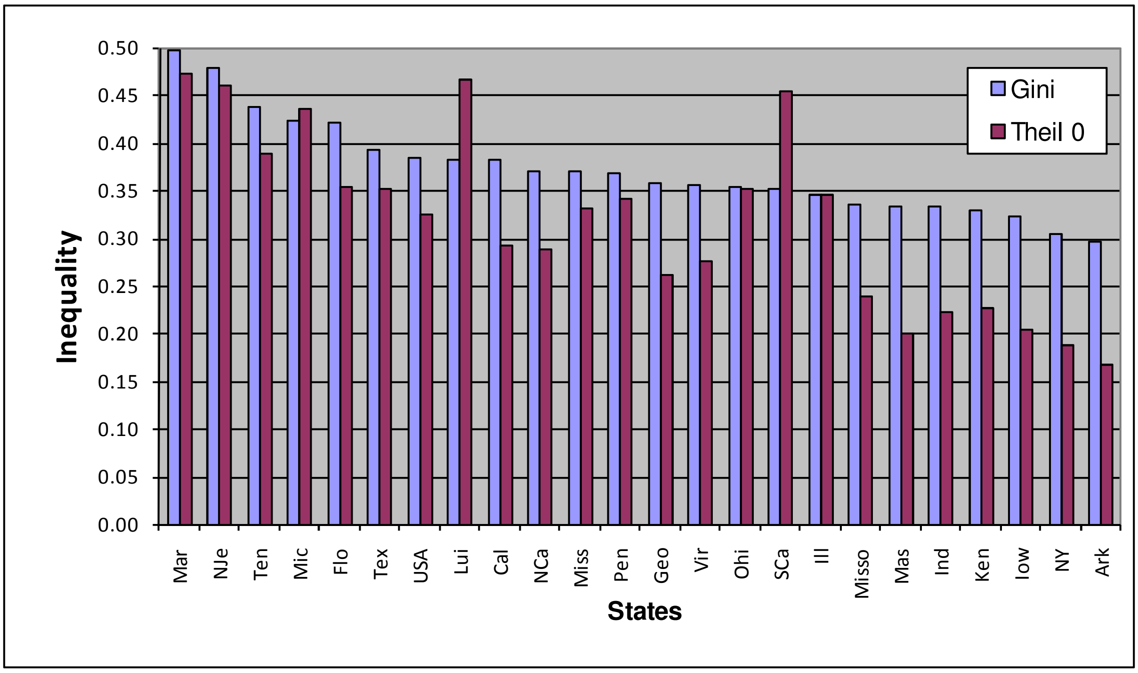

Figure 1b. Inequality of opportunity (8 groups) in U.S. (1990)

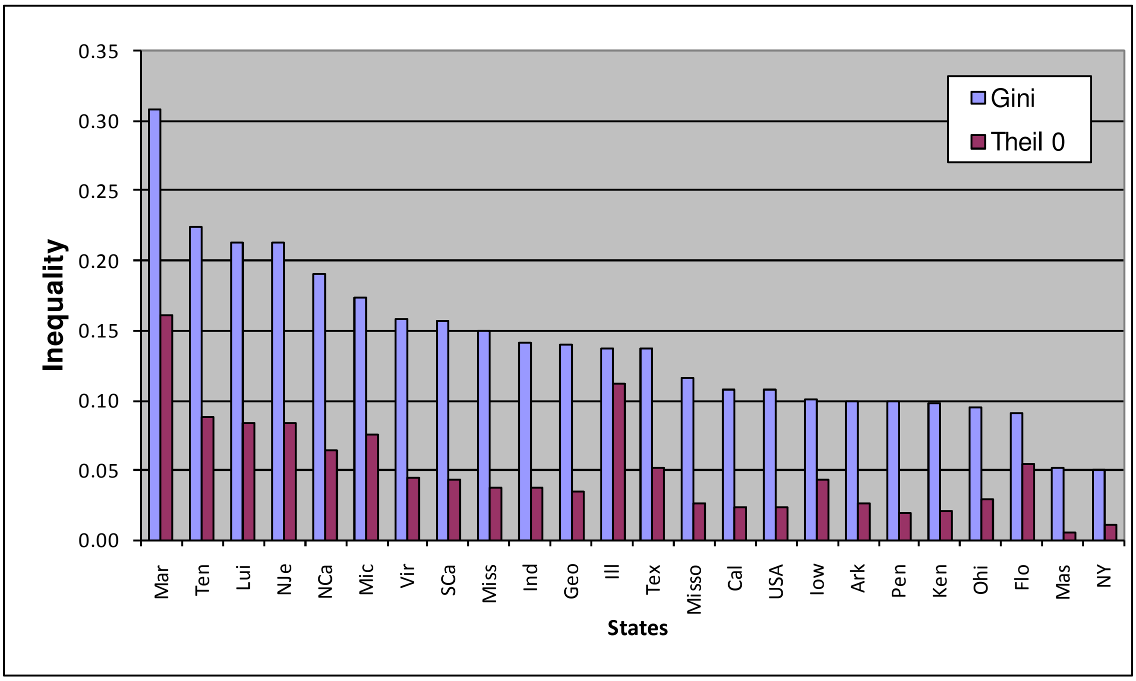

Figure 2a. Variation of total inequality and IO (8 groups) in U.S. (1980-90): Theil 0

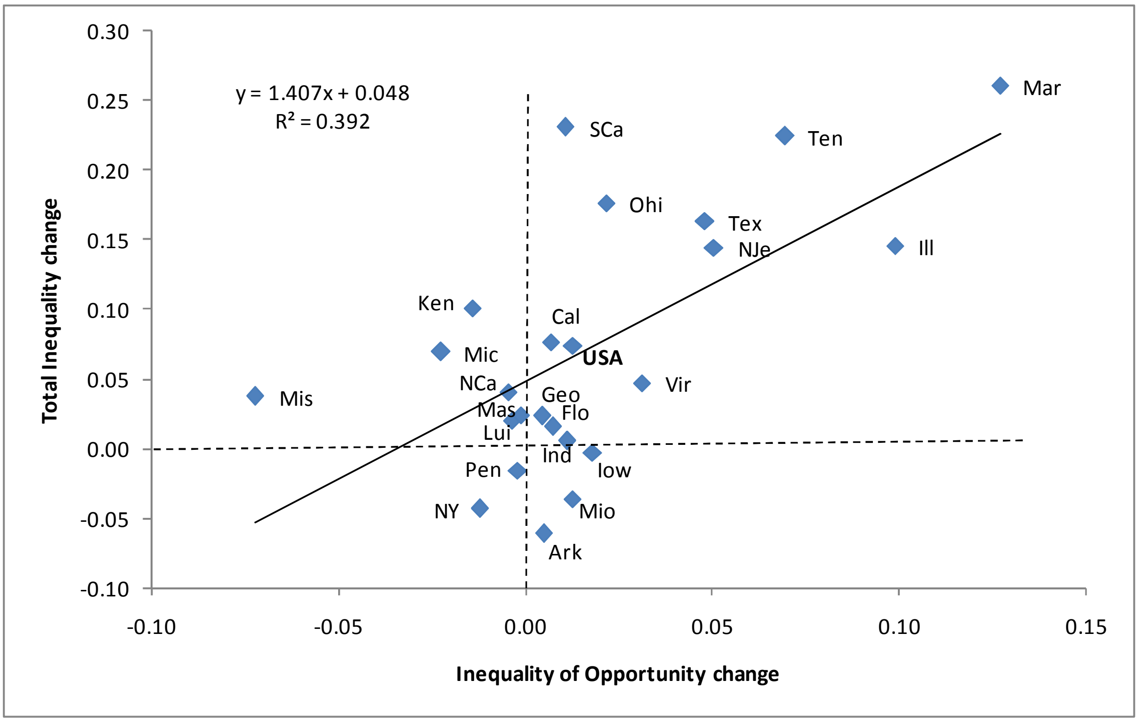

Figure 2b. Variation of total inequality and IO (8 groups) in U.S. (1980-90): Gini