Inequality ... of Opportunity and Economic Performance*
preliminary and incomplete version. Please, do not quote

Gustavo A. Marrero[†]
Universidad de La Laguna (Spain)

Juan G. Rodríguez[‡]
Universidad Complutense de Madrid (Spain)

March 4, 2015

Abstract

The study of the impact of inequality on economic performance is again in the agendas of pundits and policymakers. The high inequality reach by some economies after the Great Recession and the renovated debate on the main sources of overall inequality have trigger the interest for this topic. This work delves into a recent proposal of this literature according to which total inequality is actually a composite measure of inequality of opportunity (bad for growth) and inequality of effort (good for growth). To evaluate this theory, we first analyze the necessity of distinguishing between the two components of total inequality and revise the nascent literature on this topic. Based on the theoretical model proposed in Marrero and Rodríguez (2014), we derive a growth equation that relates economic performance with the different components of overall inequality. This model serves to better understand the existing controversy in the inequality-growth literature, and guide us to develop an alternative empirical less data-consuming cross-country empirical strategy. . Applying a

*The authors acknowledge the financial support of the Ministerio de Economía y Competitividad of Spain: Rodríguez through project ECO2013-46516-C4-4-R and Marrero through project ECO2013-48884-C3-3-P. Both authors acknowledge financial support from Fundación Caja Canarias (Spain).

[†]Departamento de Análisis Económico, University of La Laguna, Campus de Guajara, 38071, Tenerife (Canary Islands), Spain. E-mail: gmarrero@ull.es. Tel: 0034.922.317123; Fax: 0034.922.317204.

[‡]Departamento de Fundamentos del Análisis Económico I, Universidad Complutense de Madrid, Campus de Somosaguas, Pozuelo de Alarcón, 28223 Madrid, Spain. E-mail: juangabr@pdi.ucm.es. Tel: 0034.91.3942515; Fax: 0034.91.3942561

long-run cross-country analysis (growth is measured in a 20-years and 10-years basis between 1990 and 2010, and the cross-section is composed by 77 countries) our main conclusion is that inequality of opportunity always harms growth, while total inequality has an unclear impact on subsequent growth.

JEL Classification: D63, E24, O15, O40.

Keywords: growth; inequality; inequality of opportunity; human capital.

1 Introduction

A major discussion on the primary driving force behind inequality has recently captured the attention of pundits and policymakers. If the root cause of inequality is the change in technology (Goldin and Katz, 2008), incomes at the top grow much faster than average because talented and hard-worked individuals make significant economic contributions and, therefore, the implied increasing inequality should not be a concern (Mankiw, 2012). However, if rent-seeking is the fundamental factor for the growing incomes of the rich (Stiglitz, 2012), the resultant increase in inequality would be harmful for posterior development and growth (Piketty et al., 2011). Hence, inequality promotes or deters economic performance depending on the origin of inequality.

The key to address properly this debate on the impact of inequality upon growth is, we believe, to make a distinction between the different types of inequality, which is a common wisdom in the inequality-of-opportunity literature (Roemer, 1993; 1998). Thus, individual income and implied inequality is mainly determined by two factors:[1] first, free-will actions related to the level of exerted effort; second, opportunities, which are beyond the individual's control because they depend on circumstances like gender, race, family background or health endowments. A deeper analysis on this issue emphasizes that the relevance of these individual circumstances for determining personal income is strongly related with other non-personal circumstances like the macroeconomic conditions of the country where individuals perform their economic activities. For example, the importance of race and gender as major circumstances depends largely on the quality of economic and political institutions (Acemoglu and Robinson, 2015); the impact of parental contacts or networks on individuals' income rest deeply on the degree of corruption and rent-seeking (Stiglitz, 2012); the allocation of talent and effort is always conditioned by the conditions for credit to people with unfavorable circumstances (Galor and Zeira, 1993).

The crucial hypothesis is that these two types of inequality, inequality of opportunity (IO) and inequality of effort (IE), affect economic performance in an opposite way (World Bank, 2006; Bourguignon et al., 2007; Marrero and Rodríguez, 2013). On one hand, IO reduces growth as, for example, it favors human capital accumulation by individuals with better social origins, rather than by individuals with more talent. The greater the IO, the stronger the role that background plays, rather than responsibility. On the other hand, income inequality among those who exert different effort (IE) stimulates growth because, for example, it encourages people to invest in education and effort. Thus, if inequality of effort increases due to technological change or better economic institutions, not only inequality but also growth increases. However, if inequality of opportunity increases due to a pervasive level of corruption, or a worsening of the credit markets, inequality will increase but economic performance will be dampened. Since both types of inequality act at the same time, they may offset to each other and the discussion on the impact of total inequal-

[1] See Ferreira and Gignoux (2011) and Marrero and Rodríguez (2011) and (2012) for applications.

ity on growth could be misleading. Thus, in order to avoid this problem, we should distinguish between both kinds of inequality and focus our attention on the problematic one, inequality of opportunity.

Following this line of enquiry, we present here a panoramic view on the relationship between inequality of opportunity and economic performance. This literature is quite recent but has already produced a growing consensus: inequality of opportunity has significantly harm growth in the U.S.. Despite that they follow different approaches and use different databases, four papers have studied this issue for the U.S.: Marrero and Rodríguez (2013), Hsieh et al. (2013), Bradbury and Triest (2014) and Marrero et al. (2015). All of them highlight the same main result: relaxing barriers to opportunity is a viable strategy for promoting future economic growth.[2]

Likewise, using an overlapping generation model with human capital, Marrero and Rodríguez (2014) have shown that the negative impact of inequality of opportunity on growth is always fulfilled in a developed economy. However, if there exists a trap in the accumulation of human capital (Azariadis and Stachurski, 2005), an increase in any kind of inequality (including IO) might be good for growth in poor countries because that would help dynasties with better conditions to move upward and get out of the trap (López and Servén, 2009; Castelló-Climent and Mukhopadhyay, 2013). Nevertheless, using simulations, Marrero and Rodríguez (2014) show that this situation only occurs when the economy is extremely poor and the absolute poverty rate is initially very high. In any case, empirical research should be careful when mixing economies with large differences in poverty rates and other crucial characteristics like the degree of meritocracy.

Building on a literature that distinguishes individual circumstances which are beyond the individual's control, and individual effort, which stands in for the range of factors influencing economic success that an individual can make decisions about (Roemer, 1993), we develop in the next section the necessary distinction between the two components of overall inequality, inequality of opportunity and inequality of effort. In addition, we briefly review the nascent empirical literature on the relationship between inequality of opportunity and economic performance. In Section 3, based on the theoretical model proposed in Marrero and Rodríguez (2014), we derive a growth equation that relates income growth with the different types of inequality. This equation will serve to understand the existing controversy in the inequality-growth literature, and will guide us in the development of an alternative cross-country, less data-consuming empirical strategy than the one used in Ferreira et al. (2014). In Section 5, we carry out a long-run cross-country analysis where growth is measured in a 20-years and 10-years basis between 1990 and 2010, and the cross-section is composed by 77 countries. The main conclusion is robust: inequality of opportunity al-

[2]Marrero and Rodríguez (2012) analyzes the other way around of the causality. They study how macroeconomic determinants affect inequality of opportunity and inequality of effort in the U.S. along the 1970-2009 period. Marrero and Rodríguez (2011) analyzes the evolution of IO in U.S. between 1970 to 2009, and Palomino et al. (2014) analyzes the evolution of intergenerational mobility in U.S.

ways harms growth, while total inequality has an unclear impact on subsequent growth. Finally, Section 6 concludes and comments on some promising avenues of future research.

2 Inequality of opportunity and inequality of effort: a necessary distinction

The modern theories of justice emphasize that income inequality is actually a composite measure of inequality of opportunity (IO) and inequality of effort (IE).[3] In keeping with this literature, IO refers to that inequality stemming from factors, called circumstances, beyond the scope of individual responsibility like gender, race, socioeconomic background and macroeconomic conditions (corruption, quality of institutions, etc.). Meanwhile, IE defines the income inequality caused by individual responsible choices, like the number of hours worked or the occupational choice. Overall inequality is, therefore, a combination of IO and IE because individual's outcome (income, wealth, etc.) is a function of variables beyond and within the individual's control. According to this literature, inequality due to circumstances, IO, would be unfair and should be compensated for, while inequality due to individual effort is fair and should be acceptable.

This distinction between fair inequality (IE) and unfair inequality (IO) might be considered irrelevant by a pure positive economist, but fairness affects economic incentives and alters individual behavior (Fehr and Schmidt, 1999; Fehr and Fischbacher, 2003) so it also matters for efficiency. In fact, the literature has recently proposed that each component of total inequality could have a different effect on economic growth (the World Bank, 2006; Bourguignon et al., 2007; Mejia and St-Pierre, 2008; Marrero and Rodríguez, 2013). On one hand, IO would reduce economic growth as it favors human capital accumulation by individuals with better social origins, rather than by individuals with more talent. Disadvantageous initial circumstances would reduce the opportunity to acquire higher levels of human capital which would generate a misallocation of talent, underinvestment in human capital and a negative consequence on growth. On the other hand, income inequality among those who exert different effort would incentive people to invest in education and to hard work, which would stimulate growth.

If this hypothesis is true, the impact of total inequality on growth should be ambiguous and the sign would depend on which type of inequality, opportunity or effort, dominates aggregate inequality. Existing theoretical and empirical evidence supports indirectly this view. On the theoretical side, we find many channels through which inequality affects growth in opposite ways.[4] The main proposed routes through which inequality might enhance growth are the larger

[3] See, among others, Roemer (1993), Van de Gaer (1993) and Fleurbaey (2008).

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

accumulation of savings by the rich (Kaldor, 1956; Stiglitz, 1969; Bourguignon, 1981), unobservable effort (Mirrlees, 1971; Rebelo, 1991) and the investment project size (Barro, 2000). On the contrary, inequality in the presence of credit market imperfections would have a negative impact on growth through the investment in human capital channel (Galor and Zeira, 1993) and the entrepreneurial channel (Banerjee and Newman, 1993). Other channels through which inequality could have a negative effect on growth are unproductive investments (Mason, 1988), demand patterns (Marshall, 1988), fertility (Galor and Zang, 1997; Kremer and Chen, 2002), domestic market size (Murphy et al., 1989), political economy (Alesina and Rodrik, 1994; Alesina and Perotti, 1994; Persson and Tabellini, 1994), and political instability (Gupta, 1990).

On the empirical side, the vast empirical literature is also ambiguous.[5] This ambiguity has been justified by: the quality of data (Deininger and Squire, 1998); the econometric method (Forbes, 2000); the degree of development of the countries under consideration (Barro, 2000; Bleaney and Nishizama, 2004); the model specification (Panizza, 2002); the type of inequality measures (Székely, 2003; Knowles, 2005); and, the replacement of physical capital by human capital accumulation as a prime engine of growth along the process of development (Galor and Moav, 2004).

This ambiguous result about the impact of overall inequality on growth might be reflecting the fact that some or all of the channels highlighted before are working at the same time but in different directions. Following this reasoning, Voitchovsky (2005) estimates inequality among the poor (the 50/10 ratio) and among the rich (the 90/50 ratio), and finds that inequality among the poor deters growth while inequality among the rich enhances growth. In this manner, Voitchovsky (2005) is able to reconcile three alternative theories that relate inequality to growth: existence of constraints in the credit market, political instability and the accumulation of savings by the rich. The first two ideas would justify the negative effect of inequality among the poor on growth, while the third one would explain the positive effect of inequality among the rich on growth.[6]

Alternatively, one could consider all the channels quote above to be actually symptoms of two more encompassing concepts, inequality of opportunity and inequality of effort. For example, considering the credit market imperfections theory (Galor and Zeira, 1993; Banerjee and Newman, 1993), one could make the claim that people with unfavorable initial circumstances will face considerable barriers for accessing credit, regardless of their talent and degree of effort exerted. As a result, IO would imply suboptimal levels of investment in human capital, with a negative consequence on growth. By the same reasoning, we could advocate the models proposed by Easterly and Levine (1997) and Grad-

[5] See Banerjee and Duflo (2003), among others, on the inconclusiveness of the cross-country empirical literature on inequality and growth.

[6] A similar result has been found by van der Weide and Milanovic (2014) using the US IPUMS database at the State level for the period of time 1960-2010. In addition, these authors have disaggregated growth by quantiles and have obtained that overall inequality hurts the growth of the poor, while it improves the growth of the rich.

stein and Justman (2002), which report a negative impact of racial and ethnic heterogeneity on growth; or the model by Galor et al. (2009), where land concentration, which is highly correlated with the proportion of wealth inequality explained by individual circumstances, adversely affects the implementation of human capital promoting institutions like public schooling and child labor regulations; or the proposals by Stiglitz (2012) and Mankiw (2012), where inequality is mainly explained by rent-seeking activities and technological change, respectively. In the first case, bad macroeconomic conditions (corruption, low quality of institutions and the like) would raise IO, while in the second case IE would increase because top incomes grow much faster than average when the change is technology get faster.

The problem with this hypothesis, that income inequality has two distinct offsetting avenues – IO and IE – affecting subsequent growth in opposite ways, is that direct evidence is difficult to find. On the theoretical side, total inequality has to be decomposed into the IO and IE components and then it has to be shown that more dynasties with bad circumstances raises IO and then harms growth, while higher exerted pure effort – effort not influenced by circumstances – increases IE and then enhances growth. As far as we are aware, Marrero and Rodríguez (2014) is the only theoretical model that shows the distinct impact on growth of the two alternative though complementary concepts of IO and IE.[7] Taking human capital as the main engine of development, they show that a more equal distribution of opportunity increases growth, while the opposite happens when inequality of effort raises. And their model does not rely in a particular channel (credit markets, accumulation of savings, land ownership, unobservable effort, political economy, etc.), but it just relies on the set of circumstances and the incentives to effort that people have and the way both factors affect human capital accumulation and wages. Hence, we believe that this framework is a good starting point to be used as benchmark to characterize, theoretically and empirically, the relationship between inequality, inequality of opportunities and growth.

On the empirical side, the literature has progressed at a high pace during the last years despite that testing empirically the IO-IE hypothesis is difficult because the decomposition of overall inequality into the IO and IE components requires not only comparable measures of individual disposable income but also individual circumstances measured in a comparable and homogeneous way. In a first empirical attempt, Marrero and Rodríguez (2013), using refined data of the PSID database for 26 U.S. states in 1970, 1980 and 1990, and applying system-GMM and, as a matter of robustness, alternative pooled-OLS, long-run cross-sectional and fixed effects regressions, found robust evidence that inequality of effort is growth enhancing, while inequality due to differences in opportunities is growth deterring. We reproduce in the Appendix (Table 1) the main table of results in Marrero and Rodríguez (2013): under any specification and econometric approach considered, the impact of the IO component is signifi-

[7]The closest model to Marrero and Rodríguez (2014) is Mejia and St-Pierre (2008). They proposed a static model where all circumstances are exogenous and there is no trade-off between the average level of human capital and equality of opportunity.

cantly negative, while the impact of the IE component is significantly positive; moreover, the coefficient associated with IE is greater and more significant than the one associated with overall inequality.[8] The scatter plots in Figures 1a-1c illustrate the estimated coefficients of total inequality, IE and IO in the Table. Conditioning growth and the inequality variables on all other explanatory variables, the slopes are exactly the estimated coefficients for the extended model: 31.4, positive and significant for total inequality; 93.8 for IE, greater and clearly more significant than for total inequality; and, -107.9 for IO, negative and also significant. These results indicate that increasing IE by one standard deviation could raise decade growth between 2.3 and 4.1 percentage points depending on the method (the average decade growth in the 1970-2000 period was 20.2%), and between 209 and 834 real US$ per person (the average income in the 1970-2000 period was 14,363 US$ per person). On the other hand, decreasing IO by one standard deviation could raise growth between 1.1 and 1.7 percentage points and steady-state income between 124 and 229 real US$ per person.

This initial result for the case of the United States has been confirmed by posterior studies. Thus, Hsieh et al. (2013) while adopting a complete different approach have found that changes in occupational barriers facing women and blacks potentially explain 15 to 20 percent of growth in US between 1960 and 2008. In both cases, Marrero and Rodríguez (2013) and Hsieh et al. (2013), the impact of IO on growth is found to be not only damaging but also quite significant. Bradbury and Triest (2014) examine the relationship between inequality of opportunity and growth in a cross-section of U.S. "commuting zones", geographic areas representing aggregations of counties (which coincide with metropolitan areas where they exist, and exhaust U.S. territory by also including rural areas). Using the measures of absolute and relative intergenerational mobility in Chetty et al. (2014a) as proxies of equality of opportunity, they show a strongly positive effect of absolute mobility on economic growth, while the impact of relative mobility is also positive but weaker. Interestingly, the effect on growth of overall inequality is generally indistinguishable from zero. Finally, Marrero et al. (2015) find again that IO deters growth. The novelty here is that using the IPUMS database for the US states from 1960 to 2010 and only two circumstances (race and gender), they measure IO in the acquisition not only of income, but also of education and occupation, and the total effect on growth is analyzed by quantiles. In this respect, they find that the negative impact of IO on growth is not equally distributed because it is mainly concentrated at the bottom of the distribution (see Table 2 in the Appendix). All these works focus on a single country, the United States, but Geoffrey (2015) focusing on the Brasilian *municípios* finds the same result, i.e. inequality of opportunity

[8] The dependent variable is the growth rate of real personal income divided by total midyear population in the entire decade. The explanatory variables are real per capita lagged income, inequality indices (total inequality, IE and IO), and a set of additional control variables, such as human capital, industry mix, farm employment, welfare public expenditures, lag employment growth and fertility rate. Time and regional-fixed effects are also included.

harms growth.

For a cross country setting we find only two studies. In the first one, Molina et al. (2013) making use of a measure of educational opportunities that incorporates inequality between circumstance groups, find that inequality of educational opportunities affects negatively development outcomes such as economic growth, institutional quality and infant mortality. In particular, their results support the prediction that agricultural endowments – specifically the relative abundance land suitable for wheat to that suitable for sugarcane – predict unequal educational opportunities and this, in turn, predicts development outcomes. In the second one, Ferreira et al. (2014) construct two new databases consisting of 118 household surveys (of income and expenditure) and 134 Demographic and Health Surveys to examine whether IO has a negative effect on subsequent growth. They find that while overall income inequality is generally negatively associated with growth in the household survey sample, there is no evidence that this is due to the IO component. In the DHS sample, both overall wealth inequality and IO have a negative effect on growth in some of their preferred specifications, but the results are not robust to relatively minor changes. Trying to understand these results, they comment on the possibility of having substantial amounts of inequality of opportunity contaminating the residual component (the IE component) due to omitted circumstances. Because observing all individual circumstances is not plausible, empirical research on this topic has to deal with this problem. We will come back to this issue later (Section 4).

With all these models and empirical works in mind, we sketched the model in Marrero and Rodríguez (2014) in the next section, and developed an original empirical exercise to measure the impact of inequality of opportunity and inequality of effort on growth in Section 4.

3 Inequality, inequality of opportunity and growth: a basic model of human capital

In this section, based on Marrero and Rodríguez (2014), we take human capital as the main engine of development and present an overlapping generations economy with heterogeneous agents to characterize the relationship between economic performance, human capital and the different types of inequality, inequality of opportunity and inequality of (pure) effort.

The framework is a small, open economy, with perfect competitive markets, inhabited by a continuum of dynasties, each one indexed by $i \equiv [0, 1]$. Time t is discrete and each dynasty i consists of a common individual who lives two periods, childhood and adulthood. During adulthood, the individual gives birth to another individual so the overall population remains constant over time.

3.1 Technology

A single homogenous good, y, is produced every period according to the neoclassical production function

$$y_t = A_t{\cdot}k_t^{\lambda}\widetilde{l}_t^{1-\lambda},\ A_t > 0,\ \lambda \in (0,1) \tag{1}$$

using physical capital, k_t, and efficient units of labor, $\widetilde{l}_t = l_t{\cdot}\widetilde{h}_t$, where l_t is raw labor (normalized to one) and $\widetilde{h}_t$ is the average human capital of the working population, $\widetilde{h}_t = E\left[\widetilde{h}_t(i)\right]$, which can be proxy by a function of the average years of schooling in the economy, $h_t = E\left[h_t(i)\right]$ (Barro and Lee, 2013),

$$\widetilde{h}_t = \exp(\pi{\cdot}h_t),\ \pi > 0 \tag{2}$$

where π can be interpreted as the quality of h_t (Psacharopoulos, 1994). The Arrow-neutral technological term A_t is assumed to grow at a constant rate $\varsigma > 0$.

The small open economy has unrestricted international borrowing and lending, thus the real interest rate is exogenous and equal to the stationary world interest rate $\overline{r}$.[9] Since producers operate in a perfectly competitive environment, $\overline{r}$ determines the $k_t/\widetilde{h}_t$ constant ratio,

$$\overline{r} = y_k' = A_t{\cdot}\lambda{\cdot}\left(\frac{k_t}{\widetilde{h}_t}\right)^{\lambda-1} \Rightarrow \left(\frac{k_t}{\widetilde{h}_t}\right) = \left(\frac{A_t{\cdot}\lambda}{\overline{r}}\right)^{1/(1-\lambda)}, \tag{3}$$

and the wage per unit of human capital (or effective labor) is given by,

$$w = y_{\widetilde{l}}' = A_t{\cdot}(1-\lambda){\cdot}\left(\frac{k_t}{\widetilde{h}_t}\right)^{\lambda} = A_t^{1/(1-\lambda)}{\cdot}(1-\lambda){\cdot}\left(\frac{\lambda}{\overline{r}}\right)^{\lambda/(1-\lambda)}, \tag{4}$$

which increases with A_t and decreases with $\overline{r}$.[10] Thus, given A_t and $\overline{r}$, real per capita income is fully determined by the dynamics of average human capital [plugging (3) into (1)]:

$$y_t = \left(\frac{\lambda}{\overline{r}}\right)^{\lambda/(1-\lambda)} A_t^{1/(1-\lambda)}\widetilde{h}_t = \left(\frac{\lambda}{\overline{r}}\right)^{\lambda/(1-\lambda)} A_t^{1/(1-\lambda)}\exp(\pi{\cdot}h_t). \tag{5}$$

3.2 Preferences

Individuals show warm-glow preferences, which depend positively on consumption, c_t, and bequests devoted to offprings, x_t, and negatively on exerted effort, e_t, during adulthood

$$u_t(i) = \pi(\eta){\cdot}c_t(i)^{\eta}{\cdot}x_t(i)^{1-\eta} - \gamma(i){\cdot}e_t(i)^{1+\beta}. \tag{6}$$

[9] The choice of a small open economy simplifies the model and is based on the fact that interest rates do not change significantly in the course of growth (Galor and Tsidon, 1997).

[10] We assume that A_t grows at a constant exogenous rate, but do not consider the presence of global technological externalities, which would require A_t to be a function of h_t (Benabou, 1996; Galor and Tsidon, 1997). This assumption is not needed to obtain the main results of the paper.

Without loss of generality, we assume that consumption during childhood is included in the consumption of the parents (Benabou, 2000), $\eta \in (0,1)$ is a parameter of relative preferences between c_t and x_t, and $\pi(\eta) = \eta^{-\eta}(1-\eta)^{-(1-\eta)}$ is a normalization factor. Labor is inelastically supplied. Effort is a non-monetary factor that generates disutility, but is needed to accumulate human capital (Aghion and Bolton, 1997; Roemer, 1998), with $\beta > 0$ so that the marginal disutility of effort is increasing. Finally, the cost of effort $\gamma(i) > 0$ is dynasty-specific (Niehues and Peichl, 2014) but independent of any factor in the economy (this fact will allow us to interpret this parameter as a proxy of pure effort or free-will, see below).

3.3 Human capital, circumstances and wages

As for the aggregate economy, we consider that human capital at the dynasty level is one-to-one related with the average years of schooling, i.e., $\widetilde{h}_t(i) = \exp[\pi h_t(i)]$. We assume that human capital is accumulated according to a convex process that depends on two non-purchasable but complementary factors (Sen, 1980; Roemer, 1993): circumstances, $\theta_t(i)$, which are generally associated with factors beyond the individual's control but affect their actions (Roemer, 1993; Fleurbaey, 2008) and effort, $e_t(i)$, which is associated with factors within personal responsibility,

$$\widetilde{h}_t(i) = \theta_t(i)^{\psi} \cdot e_t(i)^{1-\psi}, \ \psi \in (0,1), \text{ or equivalently} \quad (7)$$

$$h_t(i) = \frac{\psi}{\pi} \ln \theta_t(i) + \frac{1-\psi}{\pi} \ln e_t(i) \quad (8)$$

where ψ denotes the relative importance of personal circumstances with respect to effort in determining human capital. Hence, it proxies the (lack) of meritocracy in the economy (Lucas, 1995), the higher ψ, the greater the degree of nepotism.

The set of circumstances is related with three types of factors: factors totally exogenous to the individual, such as race, gender, the quality of institutions and level of corruption (or rent-seeking) in his country during childhood and adulthood, etc., which, by simplicity, are all grouped in $a(i)$; home externalities generated by parental human capital, $\widetilde{h}_{t-1}(i)$ (Galor and Tsidon, 1997); and the bequest devoted to the quality of the offpring's education, $x_{t-1}(i)$ (Card and Krueger, 1992; Glomm and Ravikumar, 1992).[11] Following Roemer (1998), $\theta_t(i)$ can be expressed as a composite index of these three components:[12]

$$\theta_t(i) = a(i)^{1-\alpha-\varphi} \cdot x_{t-1}(i)^{\alpha} \cdot \widetilde{h}_{t-1}(i)^{\varphi}; \ \alpha, \varphi \in (0,1), \ \alpha + \varphi < 1. \quad (9)$$

[11] Scholars have extensively shown that parental education and resources devoted to the offspring's education have significant effects on the individual's human capital, while school characteristics have relatively little importance in determining individual achievement (Coleman et al., 1966; Hanushek, 1996). We interprete here that h_{t-1} creates a better environment for the accumulation of human capital (Galor and Tsidon, 1997), while x_{t-1} favors the bequest to the offspring in the form of quality of schooling.

[12] Because inborn ability or talent is less than perfectly correlated between generations, a model that explicitly models how it evolves in the dynasty over time would be required (Hasler and Rodriguez-Mora, 2000). Another source of inequality beyond the scope of this

Given $\widetilde{h}_t(i)$, individuals work during their adulthood (supplying one unit of labor inelastically) and earn labor income,

$$w_t(i) = w \cdot \widetilde{h}_t(i). \tag{10}$$

Therefore, the ultimate sources of heterogeneity come from differences in $a(i)$, $\gamma(i)$ and the initial level of parental human capital $\widetilde{h}_{-1}(i)$. Following Benabou (1996), we assume that a, γ and $\widetilde{h}_{-1}$ follow mean-invariant log-normal independent distributions:[13]

$$\begin{aligned} \ln a &\sim N\left(\ln \hat{a} - \frac{\Delta_a^2}{2}, \Delta_a^2\right), & (11) \\ \ln \gamma &\sim N\left(\ln \widehat{\gamma} - \frac{\Delta_\gamma^2}{2}, \Delta_\gamma^2\right), & (12) \\ \ln \widetilde{h}_{-1} &\sim N\left(\ln \widehat{h} - \frac{\Delta_{-1}^2}{2}, \Delta_{-1}^2\right). & (13) \end{aligned}$$

In this manner, a, γ and $\widetilde{h}_{-1}$ have constant means equal to $\hat{a}$, $\widehat{\gamma}$ and $\widehat{h}$, that are independent of the corresponding variances. Moreover, the variance term is closely related to the class of relative inequality indices consistent with the Lorenz curve (Cowell, 2009), such as the Gini or Mean Logarithmic Deviation (MLD). In fact, the MLD index, T_0, is exactly half the variance under log-normality.[14] Accordingly, we relates inequality of opportunity with Δ_a^2 and Δ_{-1}^2, while inequality of pure effort is associated with Δ_γ^2 (recall that $\gamma(i)$ is assumed to be independent of any factor in the economy, in particular of the set of circumstances).

3.4 Solving the model

Each individual takes $\theta_t(i)$ as given and maximizes (6) subject to

$$c_t(i) + x_t(i) = w_t(i). \tag{14}$$

paper is luck (Lefranc et al., 2009). Mejía and St-Pierre (2008) consider the whole set of $\boldsymbol{\theta}(i)$ as exogenous.

[13] Two reasons justify the use of the lognormal distribution. First, this distribution captures reasonably well the negative skewness of income distributions in practice. Second, the product of independent normal distributions converges to a lognormal (Gibrat, 1957). Thus, we can view income as the product of multiple factors.

[14] The MLD index has a path-independent additive decomposition (Foster and Shneyerov, 2000) and, for this reason, it is the inequality index used most in the empirical literature on inequality of opportunity (i.e., see Ferreira and Gignoux, 2011 or Marrero and Rodríguez, 2012).

For simplicity, time subscript is omitted from now on whenever it is not strictly necessary. We obtain conditions for all endogenous variables in the model:[15]

$$
\begin{aligned}
c(i) &= \eta \cdot w \cdot \widetilde{h}(i), & (15)\\
x(i) &= (1-\eta) \cdot w \cdot \widetilde{h}(i). & (16)
\end{aligned}
$$

$$
\begin{aligned}
e(i) &= \left[\frac{(1-\psi)\cdot w}{\gamma(i)\cdot(1+\beta)}\right]^{\frac{1}{\beta+\psi}} \theta(i)^{\frac{\psi}{\beta+\psi}}, & (17)\\
\widetilde{h}(i) &= \left[\frac{(1-\psi)\cdot w}{\gamma(i)\cdot(1+\beta)}\right]^{\frac{1-\psi}{\beta+\psi}} \theta(i)^{\frac{(1+\beta)\cdot\psi}{\beta+\psi}}, & (18)\\
w(i) &= \left[\frac{(1-\psi)\cdot w^{\frac{1+\beta}{1-\psi}}}{\gamma(i)\cdot(1+\beta)}\right]^{\frac{1-\psi}{\beta+\psi}} \theta(i)^{\frac{(1+\beta)\cdot\psi}{\beta+\psi}}. & (19)
\end{aligned}
$$

Three comments are in order. First, effort depends on aspects of the aggregate economy, w, which are common to all individuals but country-specific, and on dynasty-specific characteristics, $\theta(i)$ and $\gamma(i)$. Second, the parameter $\gamma(i)$ affects personal effort but it is independent of circumstances. In this manner, the parameter $\gamma(i)$ can be interpreted as pure effort or free-will (Roemer, 1998; Fleurbaey, 2008), that is, the part of total effort not influenced by individual circumstances. Third, circumstances affect human capital and wages through a direct channel (the return-to-effort $\theta(i)^{\psi}$ in (7)), but also by an indirect channel through its impact on total effort, given by the term $\theta(i)^{\frac{\psi}{\beta+\psi}}$ in (17).

3.5 Human capital dynamics

Using (16), we can rewrite $\theta_t(i)$ in terms of $\widetilde{h}_{t-1}(i)$ and derive a dynamic equation for $\widetilde{h}_t(i)$,

$$
\begin{aligned}
\widetilde{h}_t(i) &= \Phi[\widetilde{h}_{t-1}(i)] = \exp^{\frac{G}{\beta+\psi}} \left[\frac{a(i)^{[(1+\beta)\cdot\psi-\vartheta]}\widetilde{h}_{t-1}(i)^{\vartheta}}{\gamma(i)^{1-\psi}}\right]^{\frac{1}{\beta+\psi}}, & (20)\\
G &= (1-\psi)\ln\left(\frac{(1-\psi)\cdot w}{1+\beta}\right) + (1+\beta)\psi \ln\left[(1-\eta)^{\alpha} w^{\alpha}\right], \\
\vartheta &= (1+\beta)\psi\,(\alpha+\varphi),
\end{aligned}
$$

where $\Phi[0] = 0$, $\Phi[\cdot]$ is C^2 on $(0, +\infty)$ and, because $\vartheta/(\beta+\psi) < 1$, $\Phi[\widetilde{h}_{t-1}(i)]$ is strictly increasing and strictly concave in $\widetilde{h}_{t-1}(i)$ (marginal human capital is decreasing with parental human capital). It depends also on dynasty characteristics ($\gamma(i)$ and $a(i)$), the real wage w and all other parameters of the

[15] The problem is solved in two steps. First, taking $\widetilde{h}(i)$ as given, utility is maximized subject to (14) and (10). The resulting expressions, (15) and (16), are substituted in (10) to obtain the indirect utility function which is maximized, in a second step, with respect to $\widetilde{h}(i)$.

economy. Strictly concavity is always fulfilled, hence existence and uniqueness of steady-state is guaranteed by solving the fixed point $\widetilde{h}_\infty(i) = \Phi[\widetilde{h}_\infty(i)]$,

$$\widetilde{h}_\infty(i) = \exp^{\frac{G}{\beta+\psi-\vartheta}} \left[\frac{a(i)^{[(1+\beta)\psi-\vartheta]}}{\gamma(i)^{1-\psi}} \right]^{\frac{1}{\beta+\psi-\vartheta}}, \tag{21}$$

which is globally stable.

Taking logs in (20), it is easy to show that $\widetilde{h}(i)$ follows a log-normal distribution for all t, $\ln \widetilde{h}_t(i) \sim N\left[\mu_{\widetilde{h}_t}, \Delta^2_{\widetilde{h}_t}\right]$ (or equivalently, $h(i)$ follows a normal distribution for all t), with $\mu_{\widetilde{h}_t} = E\left[\ln \widetilde{h}_t(i)\right] = \pi \cdot h_t$, where recall that $h_t = E\left[h_t(i)\right]$ is the average years of schooling in (2); $\Delta^2_{\widetilde{h}_t} = \pi^2 Var(h_t(i)) = \pi^2 \Delta^2_{h_t}$ would be our proxy of the inequality of wages and human capital, i.e., $T_0(w_t) = T_0(\widetilde{h}_t) = \Delta^2_{\widetilde{h}_t}/2 = \pi^2 \Delta^2_{h_t}/2$.

Now, we characterize the dynamics of the average years of schooling, h_t, and of the variance $\Delta^2_{h_t}$. First, taking logs and expectations in (20), we obtain

$$h_t = \frac{G}{\pi\left(\beta+\psi\right)} + b_h h_{t-1} + \frac{b_a}{\pi} E \ln a - \frac{b_\gamma}{\pi} E \ln \gamma, \tag{22}$$

where $b_h = \frac{\vartheta}{\beta+\psi}$, $b_a = \frac{[(1+\beta)\cdot\psi-\vartheta]}{\beta+\psi}$ (which is always positive), and $b_\gamma = \frac{(1-\psi)}{\beta+\psi}$ which strongly depends on the meritocracy of the economy $(1-\psi)$. It is worth noting that b_h can be interpreted as the elasticity of intergenerational mobility in average years of schooling (or alternatively in human capital) for an extended version of the canonical model.[16] Thus, the relationship between b_h and the level of meritocracy is evident: given $\alpha + \varphi > 0$, a society with perfect intergenerational mobility, i.e., $\vartheta / \left(\beta+\psi\right) = 0$, is a pure meritocratic society, i.e., $\psi = 0$. Moreover, the strict concavity of the $\widetilde{h}(i)$ function (20) is equivalent to $b_h < 1$, which is fully consistent with the empirical evidence found in the related literature (Corak, 2013; Bishop et al., 2014). This equivalence provides confidence about the results set out next since they are based on the concavity of the $\widetilde{h}(i)$ function. Solving this equation at the steady-state, $h_t = h_{t-1} = h_\infty$, we have

$$h_\infty = \frac{G}{\pi\left(\beta+\psi-\vartheta\right)} + \frac{[(1+\beta)\cdot\psi-\vartheta]}{\pi\left(\beta+\psi-\vartheta\right)} E \ln a - \frac{(1-\psi)}{\pi\left(\beta+\psi-\vartheta\right)} E \ln \gamma. \tag{23}$$

Second, taking logs in (20), we can compute the variance and solve the resulting linear equation in first differences to characterize the dynamics of the

[16] The canonical model (Galton, 1869) is the regression model $\ln w_{i,t} = \upsilon + \xi \ln w_{i,t-1} + \varepsilon_i$ where the coefficient ξ is the so-called elasticity of intergenerational mobility.

second moment:[17]

$$\Delta^2_{h_t} = \Delta^2_a \left(\frac{(1+\beta)\psi - \vartheta}{\pi\left(\beta+\psi-\vartheta\right)}\right)^2 \left[1-b_h^{t+1}\right]^2 + \Delta^2_\gamma \left(\frac{1-\psi}{\pi\left(\beta+\psi-\vartheta\right)}\right)^2 \left[1-b_h^{t+1}\right]^2 + \Delta^2_{-1}\left(\frac{b_h^{t+1}}{\pi}\right)^2, \tag{24}$$

which for the steady-state, when $t \to \infty$, is

$$\Delta^2_{h_\infty} = \Delta^2_a \left(\frac{(1+\beta)\psi - \vartheta}{\pi\left(\beta+\psi-\vartheta\right)}\right)^2 + \Delta^2_\gamma \left(\frac{1-\psi}{\pi\left(\beta+\psi-\vartheta\right)}\right)^2. \tag{25}$$

The result in (24) reproduces the classical decomposition of total (labor) income inequality, $T_0(w_t)$, into inequality of opportunity (represented by Δ^2_a and Δ^2_{-1}) and inequality of (pure) effort (related to Δ^2_γ) (Ruíz-castillo, 2003). Thus, first, we are able to reproduce this important result of the inequality-of-opportunity literature in our macro framework; second, this decomposition will allow us to introduce into the model the intuition in Voitchovsky (2005), Bourguignon et al. (2007) and Marrero and Rodríguez (2013): inequality has distinct offsetting avenues that affect subsequent growth in different ways.

3.6 Growth, human capital and inequality

Now, we derive a growth equation that relates income growth with the different types of inequality. It will help us to understand the existing controversy about the inequality-growth relationship and to define the empirical strategy that we will follow in the next section.

Let $g_{y_t} = \ln y_t - \ln y_{t-1}$ be the income growth rate and $\Delta h_t = h_t - h_{t-1}$ the change in the average years of schooling. Taking logs in (5), we obtain the relationship between g_{y_t} and Δh_t,

$$g_{y_t} = \frac{\varsigma}{(1-\lambda)} + \pi \cdot \Delta h_t, \tag{26}$$

where recall that ς is the exogenous growth rate of A_t.

Substracting h_{t-1} in the left and right hand sides of (22) and using the definitions of $E\ln a = \ln\hat{a} - \frac{\Delta^2_a}{2}$ and $E\ln\gamma = \ln\widehat{\gamma} - \frac{\Delta^2_\gamma}{2}$, we obtain the expression for the change in the average years of schooling,

$$\Delta h_t = \frac{G}{\pi\left(\beta+\psi\right)} - (1-b_h)h_{t-1} + \frac{b_a}{\pi}\left(\ln\hat{a} - \frac{\Delta^2_a}{2}\right) - \frac{b_\gamma}{\pi}\left(\ln\widehat{\gamma} - \frac{\Delta^2_\gamma}{2}\right). \tag{27}$$

[17]The complete procedure can be found in the Appendix A.1. in Marrero and Rodríguez (2014).

Introducing this expression in (26) and taking logs in (5) to obtain the average years of schooling at period $t-1$, we obtain the growth equation we are looking for:

$$g_y = b_0 + b_1(t-1) - (1-b_h)\ln y_{t-1} - b_a T_0(a) + b_\gamma T_0(\gamma), \qquad (28)$$

where $b_0 = \frac{\varsigma}{(1-\lambda)} + \frac{G}{\beta+\psi} + \frac{(1-b_h)\lambda\ln(\lambda/\overline{r})}{(1-\lambda)} + b_a \ln \hat{a} - b_\gamma \ln \widehat{\gamma}$, $b_1 = \frac{(1-b_h)\ln(1+\varsigma)}{(1-\lambda)}$

and A_0 is normalized to 1.

As it is typical in neoclassical growth models, equation (28) predicts conditional convergence (i.e., the coefficient associated to $\ln y_{t-1}$ is negative), with a speed of convergence coefficient that is inversely related to b_h (the elasticity of intergenerational mobility). In a cross-country analysis this makes a lot of sense because lack of convergence would be equivalent to lack of mobility between countries. More importantly, noting that b_a and b_γ are positive, we obtain our main result: the impact of inequality on growth depends on the type of inequality under consideration, negative for inequality of opportunity (i.e., $T_0(a)$) and positive for inequality of pure effort (i.e., $T_0(\gamma)$). Their corresponding short-term elasticities are $-b_a$ and b_γ, respectively, while their accumulated long-term elasticities are $-b_a/(1-b_h)$ and $b_\gamma/(1-b_h)$, respectively, which are higher because $b_h \in (0,1)$. Thus, at the country level, the transmission of the the initial impacts of $T_0(a)$ and $T_0(\gamma)$ in growth depends crucially on the intergenerational mobility.

Our model highlights that inequality of opportunity harms economic performance, while inequality of pure effort enhances growth. This result comes from the properties of (20) and (21). On one hand, $\widetilde{h}_t(i)$ is strictly increasing and strictly concave with respect to $\widetilde{h}_{t-1}(i)$ and $a(i)$, therefore, compensating for bad circumstances is growth enhancing since marginal returns to human capital are higher for those individuals who have less favorable circumstances. On the other hand, $\widetilde{h}_t(i)$ is decreasing and strictly convex with respect to $\gamma(i)$, so rewarding the free-will to exert effort would enhance growth because the marginal returns to human capital are now larger for those individuals with a lower aversion to effort. This result is obtained without relying on any particular channel because assumptions on market imperfections, political economy, savings and the like are not imposed. Since the concepts of IO and IE encompass many different avenues through which inequality could affect growth (as proposed by the literature), this result provides a broader perspective to understand the existing ambiguous empirical relationship between overall inequality and economic performance. It is also interesting to note that the concavity of the human capital accumulation function is endogenously obtained and the result holds for any distribution of a and γ (log-normality is assumed only to link the variance with the MLD index and for illustrative purposes).

As said above, the lack of robustness regarding the impact of total inequality on growth is evident from (28). When estimating the typical equation of the empirical inequality-growth literature:

$$g_{y_t,j} = \alpha + \beta_0 \ln y_{t-1,j} + \beta_1 I_{t-1,j} + \beta_2 Z_{t-1,j} + \varepsilon_{tj}, \qquad (29)$$

where I is an index of overall inequality, Z is an array of other controls and the subscript j refers to a country or region, now it is easy to understand that the impact of inequality on growth depends on which component, opportunity or pure effort, dominates the change of total inequality. For this reason, when the change in total inequality comes from a simultaneous variation in both components, $T(a)$ and $T(\gamma)$, the impact of total inequality on growth cannot be predicted a priory and it will strongly depend on the relative magnitude of their changes and their elasticities. For example, the degree of meritocracy is a parameter affecting both elasticities. If the degree of meritocracy is very high (i.e., $\psi \simeq 0$), then $b_a \simeq 0$ and $b_\gamma \simeq 1/\beta$ and according to (28) the impact of inequality on growth will be always positive, while the opposite will happen when $\psi \simeq 1$.

Another relevant implication for empirical studies when comparing equations (29) and (28) is that the set of controls included (or not included) in (29) could play an important role in the determination of the sign of β_1. If the controls in Z are more correlated with IO, then their inclusion in the regression together with I will cause that the coefficient of Z, β_2, will capture the effect of inequality of opportunity, while the coefficient of I, β_1, will better capture the impact of the inequality-of-pure-effort component. The opposite would happen when Z is more correlated with pure effort inequality. In this case, the coefficient β_1 is expected to become more negative (or less positive) because now I behaves as a better proxy of inequality of opportunity. In this respect, it is interesting to note that some empirical studies have found that the effect of income inequality on growth is sensitive to the inclusion of alternative explanatory variables (Birdsall et al., 1995). Furthermore, the impact of initial land inequality, which captures more closely opportunity than income, on growth is negative and robust to the introduction of different explicative variables (Deininger and Squire, 1998). These ideas are used in the next section to propose an alternative empirical strategy to estimate the impact of the different concepts of inequality on growth.

4 Inequality, inequality of opportunity and growth: a cross-country empirical analysis

Estimating the equation in (28) is difficult because it requires to decompose total inequality into inequality of opportunity and inequality of (pure) effort. In this respect, Marrero and Rodriguez (2013) for a panel of U.S. States and Ferreira et al. (2014) for a panel of countries are the most prominent exceptions. The main problem with Marrero and Rodríguez (2013) is that they used refined data of the PSID database for 26 states in the 1970s, 1980s and 1990s to have enough information to estimate IO. In spite of this, the smallness of their survey samples makes IO estimates vulnerable to sampling error. The failure of Ferreira et al. (2014) to find robust support for the main hypothesized relationship, inequality of opportunity harms growth, might be reflecting, as highlighted by Bradbury and Triest (2014), the very spotty set of circumstance variables they eke out of their income and expenditure survey sample and their demographic and health survey sample. Of course, it could also reflect that the relationships estimated by Marrero and Rodriguez (2013) do not apply across nations with different levels of development and institutional backdrops.

To elucidate this important issue, we propose next an alternative empirical strategy to estimate the relationship between growth and the components of overall inequality based on the theory developed in the previous section.

4.1 The strategy

First, we consider a large database of inequality indices with a big cross-section dimension. In particular, we combine the Gini coefficients from the UN-WIID2 and Povcal-Net databases as in López and Servén (2012). Following Dollar and Kraay (2002) and Serven and Marrero (2014), the existing heterogeneity of Gini coefficients within the databases is corrected. For robustness, we also consider the (market) Gini coefficients in the Standardized Income Inequality Database (SWIID) (Solt, 2009).

Second, we define a set of variables, X, that, according to the theory, can proxy circumstances at the aggregate level. We consider the following variables: i. parental background, proxy by the 20-years lag of human capital (HC); ii. opportunity for women to accumulate human capital, measured by the country fertility rate (*fertility*); iii. the existance of ethnic-linguistic tensions (*ethnic*); iv. degree of religious tensions (*religion*); v. level of nepotism and rent-seeking proxy by an index of corruption that measures the capacity of people to assume positions of power through patronage rather than effort and ability (*corruption*), and an index of military in power that estimates the presence of military in government positions (*military*); vi. quality of institutions proxy by an index of democratic accountability that measures how responsive government is to its people (*democracy*). For human capital, we use the human capital index recently developed in the PWT8.0, which is based on the average years of schooling corrected by its quality (using information from Barro and Lee, 2013); the fertility rates come from the World Bank database; while all other variables come from the the Political Risk Module of the International Country Risk Database.

Once this set of variables has been defined, we adapt the strategy proposed by Ferreira and Gignoux (2011) to our case. Making use of micro data, these authors run an OLS regression to estimate individual income as a function of circumstances and then use the fitted part to proxy inequality of opportunity (actually a lower bound of inequality of opportunity). To adapt this proposal to cross-country aggregate data, we run an OLS regression between total inequality (Gini coefficient) and the set of variables X as follows:

$$Gini_j = \alpha_0 + \alpha_1 X_j + v_j. \tag{30}$$

At the country-level, the fitted part, $\widehat{\alpha}_0 + \widehat{\alpha}_1 X_j$, would be taken as a proxy of inequality of opportunity, while the OLS residual, $\widehat{v}_j$, would be the residual part of inequality. This residual picks up the inequality-of-effort component, although it is contaminated by inequality of opportunity due to unobserved circumstances and luck. For this reason, the interpretation of the sign and significance of its coefficient must be done with caution.

After decomposing the Gini coefficient in its fitted (IO) and residual (referred here as IE by simplicity) components, we run the following four sequential regressions:

$$g_{yj} = \alpha + \beta \ln y_{0j} + \rho_{11} Gini_{0j} + \varepsilon_{1j}, \tag{31}$$

$$g_{yj} = \alpha + \beta \ln y_{0j} + \rho_{12} Gini_{0j} + \rho_{21} IO_{0j} + \varepsilon_{2j}, \tag{32}$$

$$g_{yj} = \alpha + \beta \ln y_{0j} + \rho_{13} Gini_{0j} + \rho_{31} IE_{0j} + \varepsilon_{3j}, \tag{33}$$

$$g_{yj} = \alpha + \beta \ln y_{0j} + \rho_{22} IO_{0j} + \rho_{32} IE_{0j} + \varepsilon_{4j}. \tag{34}$$

Equation (31) will be our regression of reference. Equations (32) and (33) are actually alternative versions of (29), while equation (34) is a particular version of (28). According to the theory developed in the previous section, the relationships between the different estimates of ρ should be the following:

R1. The sign and significance of the coefficients of overall inequality, ρ_{11}, ρ_{12} and ρ_{13}, are not determined a priory because they depend on the control specified in the regression. The sign of the coefficient ρ_{11} depends on which component, opportunity or effort, drives the Gini index. If $Z = IO$ we should find that $\rho_{12} > \rho_{11}$ and desirable $\rho_{12} > 0$ since the Gini coefficient now get closer to inequality of effort. On the contrary, if $Z = IE$ we should observe that $\rho_{13} < \rho_{11}$ and desirable $\rho_{13} < 0$ because in this case the Gini index should now proxy inequality of opportunity.

R2. The coefficients ρ_{21} and ρ_{22} must be negative since they are capturing the (lower bound) inequality of opportunity component.

R3. The coefficients ρ_{31} and ρ_{32} should be positive but, as commented, this component is actually a residual (contaminated by some unobserved inequality of opportunity), hence we only expect that they are higher that the corresponding coefficients of the aggregate Gini, ρ_{11}.

4.2 Results

In Table 3 we present the estimates of equation (30) using the entire sample. We want to decomposed overall inequality into inequality of opportunity and inequality of effort according to the variables included in X so we do not include regional nor time dummies, as in Ferreira and Gignoux (2011). We run three versions of the regression (30) and find that the results are robust. In the first model we only consider the variables of the Political Risk Module (corruption, military, democracy, ethnic and religion). In the second model we introduce fertility; and in the last model we also include the 20-years lagged level of human capital. As expected, we observe that a higher average of parental human capital reduces overall inequality, while more corruption, more military in power and higher rates of fertility increase total inequality. The literature has found that ethnic-linguistic fractionalization is bad for growth, while religious fractionalization enhances growth (Alesina et al, 2003). In a similar manner, we find different effects for these two types of tensions, ethnic-linguistic tensions have no significant effects on inequality, while religious tensions reduce overall inequality. The quality of democracy has no significant influence on inequality.

The time index t in equation (28) refers to a generation so $t-1$ applies to the parental era. For this long-run analysis, and for data availability, we consider an interval of 20 years, so setting the initial period in 1990 the growth rate is measured between 1990 and 2010. Data availability restricts the final sample to a cross-country section of 68 observations. All explicative variables in the regressions (31)-(34) are dated at 1990. However, notice that the average of human capital necessary to estimate IO at 1990 in the regression (30) dates at 1970 which restricts our initial sample.

Table 4a shows long-run estimated results of equations (31)-(34) for our cross-section. The left panel only includes the explicative variables in (31)-(34), while the right panel includes also regional dummies. We observe that results are robust to both specifications and they are in all cases consistent with prediction from the theory (the R1, R2 and R3 predictions exposed above). To check that our results do not rely fundamentally on the set of regressors in (30), we disconsider the lag of human capital from the regression (30). We observe in Table 4b that nothing relevant changes when this explicative factor is not taken into account.

For illustrative purposes, Figures 2a-2c show the main intuition of our results (they are similar to those presented from Marrero and Rodriguez, 2013, using a totally different approach). They show the different scatter plots between growth and the alternative measures of inequality (after adjusting by time and regional dummies and initial log of per capita GDP). The first scatter plot relates growth with initial total inequality and its relationship is slightly positive but clearly non-significant. Figure 2b shows how the relationship with our measure of inequality of opportunity is clearly negative, while the third scatter plot relates growth with initial residual inequality and finds a positive slope.

In order to increase the number of observations, we reduce the interval of time to calculate the growth rates and construct a panel of data. First, we consider intervals of 10 years, so we increase the number of observations to 145 (2 waves in most cases). Table 5 shows the estimates under alternative econometric approaches: pool-OLS (first panel); fixed effects (second panel); and G2SLS to correct for potential endogeneity problems (Balestra and Varadharajan-Krishnakumar, 1987). We find again that the empirical results are consistent with the expectations from the theory.

Finally, we check whether our long-run (10 and 20 years interval) analysis applies also to a 5-years interval, mid-term growth model (as in Forbes, 2000). In this case, the time series dimension increases to 358 observations and hence more sophisticated econometric approaches to correct for endogeneity can be applied, such as the system-GMM technique developed by Blundell and Bond (1998). The results for pooled-OLS and system-GMM shown in Table 6 conclude, once again, that the initial inequality-of-opportunity component exerts a negative and significant effect on subsequent growth.

5 Conclusions

To be done ...

References

Acemoglu, D. and J.A. Robinson (2015). The Rise and Decline of General Laws of Capitalism, forthcoming at Journal of Economic Perspectives.

Alesina, A. and Rodrik, D. (1994), "Distributive politics and economic growth", Quaterly Journal of Economics, 109, 465-490.

Alesina, A. and Perotti, R. (1994), "The political economy of growth: a critical survey of the recent literature", The World Bank Economic Review, 8, 350-371.

Aghion, P. and Bolton P. (1997), "A trickle-down theory of growth and development with debt overhang", Review of Economic Studies, 64, 151–162.

Azariadis, C. and Stachurski, J. (2005), "Poverty traps", in Handbook of Economic Growth, P. Aghion and S. Durlauf (Eds.), vol. 1 (Ch. 5), Elsevier.

Balestra, P. and Varadharajan-Krishnakumar, J. (1987), Full information estimations of a system of simultaneous equations with error components structure", Econometric Theory, 3, 585-612.

Banerjee, A. and Newman, A. (1993), "Occupational choice and the process of development", Journal of Political Economy 101, 274–298.

Banerjee, A. and Duflo, E. (2003), "Inequality and growth: what can the data say?", Journal of Economic Growth, 8, 267–299.

Barro, R.J. (2000), "Inequality and Growth in a Panel of Countries", Journal of Economic Growth, 5, 5–32.

Barro, R.J. and Lee, J.W. (2013). "A new data set of educational attainment in the world, 1950–2010", Journal of Development Economics, 104, 184–198.

Bénabou, R. (1996), "Equity and efficiency in human capital investment: the local connection", Review of Economic Studies, 63, 237–264.

Bénabou, R. (2000), "Unequal Societies: Income Distribution and the Social Contract", American Economic Review, 90, 96–129.

Bertola, G., Foellmi, R. and Zweimüller, J. (2005), Income distribution in macroeconomic models. Princeton: Princeton University Press.

Bishop, J. A., Liu, H. and Rodríguez, J.G. (2014a): "Cross-country intergenerational status mobility: is there a Great Gatsby Curve?",Research on Economic Inequality, 22, 237-249.

Birdsall, N., Ross, D. and Sabot, R. (1995), "Inequality and growth reconsidered: lessons from East Asia", World Bank Economic Review, 9, 477–508.

Bourguignon, F. (1981), "Pareto-superiority of unegalitarian equilibria in Stiglitz' model of wealth distribution with convex savings function", Econometrica, 49, 1469-1475.

Bourguignon, F., Ferreira, F. and Walton, M. (2007), "Equity, efficiency and inequality traps: a research agenda", Journal of Economic Inequality, 5, 235–256.

Bradbury, K. and R. Triest (2014). "Inequality of Opportunity and Aggregate Economic Performance", Paper prepared for conference on "Inequality of Economic Opportunity", Federal Reserve Bank of Boston, October 2014.

Card, D. and Krueger A. (1992), "Does School Quality Matter? Returns to Education and the Characteristics of Public Schools in the United States", Journal of Political Economy, 100, 1–40.

Castelló-Climent, A. and Mukhopadhyay, A. (2013). "Mass education or a minority well educated elite in the process of growth: The case of India," Journal of Development Economics, 105, pp. 303-320.

Coleman, J., Campbell, E., Hobson, C., McPartland, J., Mood, A., Weinfeld, F. and York, R. (1966), Equality of educational opportunity. Department of health, education, and welfare, Washington D.C.

Corak, M. (2013), "Income Inequality, Equality of Opportunity, and Intergenerational Mobility", Journal of Economic Perspectives, 27, 79–102.

Cowell, F. A. (2009), Measuring Inequality (2nd Edition). Hemel Hempstead: Prentice Hall / Harvester Wheatsheaf.

Deininger, K. and Squire, L. (1998), "New ways of looking at old issues: inequality and growth", Journal of Development Economics, 57, 259–287.

Easterly, W. and Levine, R. (1997), "Africa's growth tragedy: policies and ethnic divisions", Quarterly Journal of Economics, 112, 1203-1250.

Ehrhart, C. (2009), "The effects of inequality on growth: a survey of the theoretical and empirical literature", ECINEQ WP 2009-107.

Fehr, E., and Fischbacher U. (2003). "The Nature of Human Altruism", Nature, 425, 785–791.

Fehr, E., and Schmidt, K.M. (1999). "A Theory of Fairness, Competition and Cooperation", Quarterly Journal of Economics, 114, 817–68.

Ferreira, F. and Gignoux, J. (2011), "The measurement of inequality of opportunity: theory and an application to Latin America", Review of Income and Wealth, 57, 622–657.

Ferreira, F., L. Christoph, M. Lugo and B. Ozler (2014). "Inequality of opportunity and economic growth : a cross-country analysis," Policy Research Working Paper Series 6915, The World Bank.

Fleurbaey, M. (2008), Fairness, responsibility, and welfare, Oxford University Press.

Forbes, K. (2000), "A reassessment of the relationship between inequality and growth", American Economic Review, 90, 869-887.

Galor, O. and Moav, O. (2004), "From Physical to Human Capital Accumulation: Inequality and the Process of Development", Review of Economic Studies, 71, 1001–1026.

Galor, O. and Tsiddon, D. (1997), "The Distribution of Human Capital and Economic Growth", Journal of Economic Growth, 2, 93–124.

Galor, O. and Zeira, J. (1993), "Income Distribution and Macroeconomics", Review of Economic Studies, 60, 35–52.

Galor, O. and Zang, H. (1997), "Fertility, income distribution and economic growth: theory and cross-country race obviousness", Japan and the world economy, 9, 197-229.

Gradstein, M. and Justman, M. (2002), "Education, social cohesion and growth", American Economic Review, 92, 1192-1204.

Gibrat, R. (1957), "On economic inequalities", International Economic Papers, 7, 53–70.

Goldin, C. and Katz, L.F. (2008), The Race between Education and Technology. Cambridge, MA: Harvard University Press.

Glomm, G. and B. Ravikumar (1992), "Public versus private investment in human capital endogenous growth and income inequality", Journal of Political Economy, 100, 818–34.

Gupta, D.K. (1990), The economics of political violence. The effect of political instability on economic growth. New York: Praeger Publishers.

Hanushek, E. (1996), "Measuring investment in education", Journal of Economic Perspectives, 10, 9–30.

Hassler, J. and Rodríguez-Mora, J. V. (2000), "Intelligence, Social Mobility, and Growth", American Economic Review, 90, 888–908.

Knowles, S. (2001), "Inequality and economic growth: the empirical relationship reconsidered in the light of comparable data". Discussion Paper 105, Department of Economics, University of Otago (Dunedin), New Zealand.

Kremer, M. and Chen, D. (2002), "Income distribution dynamics with endogenous fertility", Journal of Economic Growth, 7, 227-258.

Krueger, A. (2012), "The Rise and Consequences of Inequality", Presentation made to the Center for American Progress, January 12th. Available at http://www.americanprogress.org/events/2012/01/12/17181/the-rise-and-consequences-of-inequality/.

Lefranc, A., Pistolesi, N. and Trannoy A. (2009), "Equality of opportunity and luck: Definitions and testable conditions, with an application to income in France", Journal of Public Economics, 93, 1189–1207.

Lopez, H. and L. Serven (2009). "Too poor to grow," Policy Research Working Paper Series 5012, The World Bank.

Lucas, J. R. (1995), Responsibility. Oxford: Clarendon Press.

Mankiw, N.G. (2013), "Defending the one percent", Journal of Economic Perspectives, 27, 21–34.

Marshall, A. (1988), "Income distribution, the domestic market and growth in Argentina", Labour and Society, 13 (1), 79-103.

Marrero, G.A. and J.G. Rodríguez (2011). "Inequality of Opportunity in the U.S.: trends and decomposition", Research on Economic Inequality, vol 19, pp 217-46.

Marrero, G.A. and Rodríguez, J.G. (2012). "Inequality of opportunity in Europe", Review of Income and Wealth, 58, 597–621.

Marrero, G.A. and Rodríguez, J.G. (2012). "Macroeconomic determinants of inequality of opportunity and effort in the US: 1970-2009," WP-249, ECINEQ, Society for the Study of Economic Inequality.

Marrero, G.A. and Rodríguez, J.G. (2013), "Inequality of opportunity and growth", Journal of Development Economics, 104, 107–122.

Marrero, G.A. and Rodríguez, J.G. (2014). "Inequality and development: the role of opportunities and free-will," WP-327, ECINEQ, Society for the Study of Economic Inequality.

Marrero, A.G., Rodríguez, J.G., van de Weide, R. (2015). "Inequality of opportunity and growth: a quintile analysis for the U.S. (1960-2010)", Mimeo.

Marrero, G.A. and L. Servén (2014). "Does poverty deters growth?", Mimeo.

Mason, A. (1988), "Savings, economic growth and demographic change", Population and Development Review, 14, 113-144.

Mejía, D. and St-Pierre, M. (2008), "Unequal Opportunities and Human Capital Formation", Journal of Development Economics, 86, 395–413.

Murphy, K. M., Schleifer, A. and Vishny, R. (1989), "Income distribution, market size, and industrialization", Quaterly Journal of Economics, 104, 537-564.

Palomino, J.C., Marrero, G.A. and J.G. Rodríguez (2014). One size doesn't fit all: a quantile analysis of intergenerational income mobility in the US (1980-2010). WP-2014–349 ECINEQ.

Panizza, U. (2002), "Income inequality and economic growth: evidence from American data", Journal of Economic Growth, 7, 25-41.

Partridge, M. D. (1997), "Is Inequality Harmful for Growth? Comment", American Economic Review, 87, 5, 1019-1032.

Persson, T. and Tabellini, G. (1994), "Is inequality harmful for growth?: theory and evidence", American Economic Review, 84, 600-621.

Piraino P. (2012), "Inequality of opportunity and intergenerational mobility in South Africa", paper presented at the 2nd World Bank Conference on Equity. June 27th, 2012; Washington DC, USA.

Piketty, T., Saez, E. and Stantcheva, S. (2011), "Optimal taxation of top labor incomes: a tale of three elasticities", NBER Working Paper N. 17616.

Rodríguez, J.G. (2008), "Partial equality-of-opportunity orderings", Social Choice and Welfare, 31, 435–456.

Roemer, J.E. (1993), "A pragmatic approach to responsibility for the egalitarian planner", Philosophy & Public Affairs, 20, 146–166.

Roemer, J.E. (1998), Equality of opportunity. Harvard University Press, Cambridge, MA.

Ruiz-Castillo, J. (2003). "The measurement of the inequality of opportunities", Research on Economic Inequality, 9, 1-34.

Sen, A. (1980), "Equality of what?", in Tanner Lectures on Human Values, Vol. I, Crambridge University Press.Singh A. (2011), "Inequality of opportunity in earnings and consumption expenditure: The case of Indian men", Review of Income and Wealth, 58, 79–106.

Stiglitz, J.E. (1969), "The distribution of income and wealth among individuals", Econometrica, 37, 382-397.

Stiglitz, J.E. (2012), The Price of Inequality: How Today's Divided Society Endangers Our Future. W.W. Norton and Company.

Solt, F. (2009). "Standardizing the World Income Inequality Database", Social science Quarterly 90, 231-242.

Székeli, M. (2003), "The 1990s in Latin America: Another decade of persistent inequality, but with somewhat lower poverty", Journal of Applied Economics, VI, 317-339.

Van de Gaer, D. (1993), “Equality of opportunity and investment in human capital”, Catholic University of Leuven, Faculty of Economics, no. 92.

Van der Weide, R. and B. Milanovic (2014). "Inequality is bad for growth of the poor (but not for that of the rich)," Policy Research Working Paper Series 6963, The World Bank.

Voitchovsky, S. (2005), “Does the profile of income inequality matter for economic growth?: distinguishing between the effects of inequality in different parts of the income distribution”, Journal of Economic Growth, 10, 273–296.

World Bank (2006), "World development report 2006: equity and development", Washington, DC: The World Bank and Oxford University Press.

APPENDIX: Tables and Figures

Inequality . . . of Opportunity and Economic Performance

Gustavo A. Marrero and Juan G. Rodríguez

Table 1.a. Growth, inequality and inequality of opportunity (Theil 0)
Source: Marrero and Rodríguez (JED, 2013)

	THEIL (pooled-OLS)		THEIL + IO (pooled-OLS)		THEIL + IO/THEIL (pooled-OLS)		IE + IO (pooled-OLS)		IE + IO (long-run, cross-section OLS)	
	Small	Base	Small	Base	Small	Base	Small	Base	Small	Base
Intercept	52.01***	131.10***	50.372***	91.688***	54.261***	118.25***	50.372***	91.688***	132.01***	54.07
	(7.77)	(4.05)	(7.43)	(2.80)	(8.18)	(3.77)	(7.43)	(2.80)	(6.24)	(0.583)
Total inequality	14.778*	31.388***	72.152***	93.775***	31.579***	42.413***	--	--	--	--
(Theil 0)	(1.34)	(3.17)	(2.66)	(4.47)	(2.80)	(3.91)				
Inequality of returns to	--	--	--	--	--	--	72.152***	93.775***	64.660	212.660**
Effort (IE)							(2.63)	(4.47)	(0.62)	(2.46)
Inequality of	--	--	-178.02**	-201.71***	-14.69*	-11.68**	-105.87*	-107.93***	-148.37**	-277.87**
Opportunity (IO)			(-1.84)	(-3.26)	(-1.48)	(-1.65)	(-1.50)	(-2.48)	(-1.89)	(-2.37)
Income lag	-0.006***	-0.005***	-0.006***	-0.005***	-0.006***	-0.005***	-0.006***	-0.005***	-0.0056*	-0.0132***
	(-6.22)	(-6.78)	(-6.66)	(-6.91)	(-6.72)	(-6.91)	(-6.66)	(-6.91)	(-1.43)	(-6.94)
High school (% total	-0.229	-0.418*	-0.075	-0.244	-0.132	-0.367	-0.075	-0.244	-0.3989	0.935
graduated)	(-1.07)	(-1.40)	(-0.38)	(-0.87)	(-0.66)	(-1.25)	(-0.38)	(-0.87)	(0.25)	(1.08)
College (% total	2.374***	1.976***	2.075***	1.950***	2.222***	1.976***	2.075***	1.950***	5.025	10.800***
graduated)	(5.46)	(6.35)	(5.49)	(6.05)	(5.85)	(6.50)	(5.50)	(6.06)	(2.74)	(7.02)
Farm population	--	-16.526	--	-24.420*	--	-24.671	--	-24.420*	--	39.950
(% total)		(-1.11)		(-1.58)		(-1.44)		(-1.58)		(1.08)
Mining empl.	--	-88.447	--	-77.460	--	-96.190	--	-77.460	--	-266.630
(% nonagric.)		(-1.07)		(-1.04)		(-1.18)		(-1.04)		(-1.23)
Construction empl.	--	162.600***	--	-44.217	--	-110.360*	--	-44.217	--	-407.180
(% nonagric.)		(-2.70)		(-0.69)		(-1.57)		(-0.69)		(-1.26)
Manufact. empl.	--	-45.034*	--	-11.616	--	-34.574	--	-11.616	--	106.390*
(% nonagric.)		(-1.58)		(-0.40)		(-1.23)		(-0.40)		(1.49)
Transp. & Pub. Util.	--	52.847	--	141.86**	--	86.176	--	141.860**	--	581.320**
empl. (% nonagric.)		(0.86)		(1.92)		(1.19)		(1.92)		(1.97)
Fin. Ins. & real Estate	--	-121.67	--	-90.532	--	-121.320*	--	-90.532	--	-228.69**
empl. (% nonagric.)		(-1.27)		(-0.96)		(-1.26)		(-0.96)		(-1.89)
Government empl.	--	-43.299	--	-17.474	--	-34.466	--	-17.474	--	-195.96**
(% nonagric.)		(-1.19)		(-0.48)		(-0.97)		(-0.48)		(-2.81)
Change nonagric.	--	-0.0697	--	-0.1010*	--	-0.0769	--	-0.101*	--	0.149
empl. previous decade		(-1.07)		(-1.56)		(-1.11)		(-1.56)		(0.44)
Welfare exp.	--	0.216	--	0.647	--	0.670	--	0.647	--	3.022
(% personal income)		(0.20)		(0.60)		(0.56)		(0.60)		(1.08)
Fertility rate	--	-0.380***	--	-0.376***	--	-0.362***	--	-0.376***	--	-0.218
		(-4.54)		(-4.36)		(-4.14)		(-4.36)		(-1.04)
Population age 65 or	0.443	--	0.0019	--	0.156	--	0.0019	--	-1.266*	--
above (% total)	(1.08)		(0.01)		(0.41)		(0.01)		(-1.47)	
Population in	0.146***	--	0.133***	--	0.140***	--	0.133***	--	-0.243	--
Metropolitan area (%)	(3.18)		(3.21)		(3.35)		(3.21)		(-1.23)	
Temporal Dummy:	1.505	-5.026*	1.071	-5.863**	1.159	-5.027**	1.071	-5.863**	--	--
Decade 80	(0.67)	(-1.74)	(0.46)	(-2.15)	(0.51)	(-1.76)	(0.46)	(-2.15)		
Temporal Dummy:	5.860**	-4.380	4.047*	-6.403*	4.845	-4.760	4.046	-6.403*	--	--
Decade 90	(2.31)	(-0.87)	(1.33)	(-1.36)	(1.75)	(-0.94)	(1.33)	(-1.36)		
Regional dummy:	-6.663***	-0.403	-3.537	3.563	-4.559**	1.175	-3.537	3.563	-12.468*	17.306
South	(-3.81)	(-0.12)	(-1.24)	(1.06)	(-1.79)	(0.33)	(-1.24)	(1.06)	(-1.66)	(-1.03)
Regional dummy:	-1.763	1.647	-1.906	2.765	-1.854	2.195	-1.906	2.765	-14.01***	-6.6509
Midwest	(-0.79)	(0.85)	(-0.88)	(1.30)	(-0.84)	(1.00)	(-0.88)	(1.30)	(-2.70)	(-2.09)
Regional dummy:	-5.696***	0.961	-6.533***	0.825	-6.295***	0.752	-6.533***	0.825	-21.92***	-26.555***
West	(-2.76)	(0.45)	(-2.94)	(0.43)	(-3.03)	(0.36)	(-2.93)	(0.43)	(-2.79)	(-3.09)
R2	0.4366	0.6013	0.4784	0.6409	0.4605	0.6125	0.4784	0.6409	0.6945	0.8954
Num. Observ.	78	78	78	78	78	78	78	78	26	26

Cross-sections included: 26; Total pool (balanced): 78; t-statistics in parenthesis.

(*) significant at the 10% level; (**) significant at the 5% level; (***) significant at the 1% level (one-sided test).

Table 1.b. Growth, IO and IE: alternative econometric methods
Source: Marrero and Rodríguez (JED, 2013).

	FE Panel Regression		RE Panel Regression		System GMM	
	Small	Base	Small	Base	Small	Base
Intercept	46.886***	137.612**	44.8564***	109.468***	352.135***	594.732***
	(4.56)	(1.91)	(9.53)	(4.91)	(3.73)	(5.16)
Inequality of returns to Effort (IE)	72.026***	52.455***	77.725***	77.939***	50.289**	54.868***
	(3.81)	(3.01)	(3.68)	(4.07)	(1.92)	(2.66)
Inequality of Opportunity (IO)	-97.370**	-87.462***	-117.624**	-85.130**	-107.092**	-69.933**
	(-2.01)	(-2.76)	(-2.10)	(-1.97)	(-1.90)	(-2.05)
Income lag	-0.0148***	-0.0109***	-0.0047***	-0.0048***	0.6209***	0.4362***
	(-10.11)	(-11.16)	(-7.04)	(-6.90)	(5.55)	(3.53)
High school (% total graduated)	0.484**	-0.383	-0.208**	-0.329***	-0.110	-0.152
	(2.08)	(-0.98)	(-2.24)	(-2.58)	(-1.02)	(-0.92)
College (% total graduated)	6.099***	5.034***	1.566***	1.815***	0.881***	1.445***
	(7.73)	(5.72)	(7.12)	(5.42)	(3.24)	(3.91)
Farm population (% total)	--	45.626	--	-18.797	--	-44.568**
		(0.38)		(-0.89)		(-1.75)
Mining empl. (% nonagric.)	--	-78.579	--	-94.818	--	-128.277**
		(-0.75)		(-1.25)		(-2.12)
Construction empl. (% nonagric.)	--	-163.587*	--	-67.085	--	-101.598*
		(-1.53)		(-1.09)		(-1.35)
Manufact. empl. (% nonagric.)	--	-78.958	--	-28.703	--	-49.722**
		(-1.02)		(-1.18)		(-2.23)
Transp. & Pub. Util. empl. (% nonagric.)	--	344.277*	--	94.809	--	91.652
		(1.65)		(1.14)		(1.07)
Fin. Inst. & real Estate empl. (% nonagric.)	--	-580.218***	--	-131.678 *	--	-182.244 **
		(-2.44)		(-1.41)		(-1.95)
Government empl. (% nonagric.)	--	40.357	--	-25.463	--	-31.452
		(0.48)		(-0.65)		(-0.88)
Change nonagric. empl. previous decade	--	0.014	--	-0.097**	--	-0.127***
		(0.25)		(-1.75)		(-2.44)
Welfare exp. (% personal income)	--	1.398	--	-0.012	--	-0.815
		(0.83)		(-0.01)		(-0.72)
Fertility rate	--	-0.259**	--	-0.341***	--	-0.379***
		(-1.95)		(-5.38)		(-4.46)
Population age 65 or above (% total)	2.162**	--	0.169	--	0.075	--
	(2.04)		(0.65)		(0.34)	
Population in Metropolitan area (%)	0.204	--	0.118***	--	0.097**	--
	(1.15)		(3.07)		(1.61)	
Temporal Dummy: Decade 80	-13.312 ***	-5.743	2.620*	-4.035**	3.575**	-4.801**
	(-3.06)	(-1.01)	(1.30)	(-1.80)	(2.23)	(-1.82)
Temporal Dummy: Decade 90	-10.120*	1.105	4.917**	-3.851	5.219***	-5.713**
	(-1.46)	(0.12)	(2.17)	(-1.29)	(2.75)	(-1.73)
Tests[1]						
F-test	9.32 (0.00)	136.80 (0.00)	--	--	--	--
Breusch-Pagan test	--	--	1.53 (0.22)	0.74 (0.39)	--	--
Hausman test	105.52 (0.00)	51.67 (0.00)	--	--	--	--
m1 test	--	--	--	--	-2.62 (0.01)	-2.20 (0.03)
Sargan test	--	--	--	--	26.07 (0.00)	30.33 (0.00)
Hansen test	--	--	--	--	14.04 (0.05)	15.47 (0.03)

Cross-sections included: 26; Total pool (balanced): 78; t-statistics in parenthesis.

(*) significant at the 10% level; (**) significant at the 5% level; (***) significant at the 1% level (one-sided test).

FE and RE regressions: robust cluster standard errors; System GMM: robust one step.

(1) p-values in parenthesis.

Table 2. Impact of inequality and IO on growth by quantiles in the US (1960-2010) (System-GMM estimates)
Source: Marrero, Rodríguez and Van der Weide (2015).

	p05	p10	p25	p50	p75	p90	p95	p99
MLD + IO								
Inequality	0.403**	0.265**	0.163**	0.174***	0.161***	0.0913**	0.0522	0.126*
	(2.59)	(2.64)	(2.44)	(3.32)	(3.63)	(2.30)	(1.31)	(1.90)
IO (Inc_Race)	-1.204***	-0.916***	-0.430***	-0.267**	-0.147	0.0393	0.135	0.0549
	(-3.73)	(-4.13)	(-2.74)	(-2.55)	(-1.48)	(0.45)	(1.47)	(0.53)
Hansen (p)	0.349	0.334	0.333	0.288	0.391	0.457	0.322	0.375
Inequality	0.347**	0.195*	0.123*	0.165***	0.176***	0.104**	0.0732	0.148*
	(2.48)	(1.88)	(1.95)	(3.45)	(4.08)	(2.49)	(1.51)	(1.89)
IO (Inc_Race & Sex)	-1.171***	-0.777***	-0.349**	-0.283**	-0.207**	-0.00485	0.0778	-0.00157
	(-3.80)	(-3.36)	(-2.23)	(-2.56)	(-2.18)	(-0.05)	(0.70)	(-0.01)
Hansen (p)	0.374	0.345	0.286	0.288	0.370	0.450	0.342	0.337
Inequality	0.313***	0.191**	0.176***	0.173**	0.167***	0.109***	0.0877*	0.128*
	(2.89)	(2.34)	(2.95)	(2.60)	(3.46)	(2.98)	(1.92)	(1.98)
IO (Occ_Race)	-8.623***	-6.470***	-3.635***	-2.072**	-1.302*	-0.197	0.172	0.320
	(-4.45)	(-4.07)	(-3.12)	(-2.19)	(-1.69)	(-0.39)	(0.28)	(0.37)
Hansen (p)	0.367	0.305	0.209	0.228	0.383	0.407	0.339	0.300
Inequality	0.236**	0.126	0.135**	0.172***	0.166***	0.128***	0.108***	0.164**
	(2.44)	(1.64)	(2.61)	(3.04)	(3.66)	(3.88)	(2.79)	(2.33)
IO (Occ_Race & Sex)	-6.214***	-4.614***	-2.742**	-1.941*	-1.196	-0.235	0.0537	-0.169
	(-4.23)	(-3.03)	(-2.62)	(-1.98)	(-1.59)	(-0.55)	(0.11)	(-0.20)
Hansen (p)	0.329	0.309	0.279	0.170	0.323	0.454	0.326	0.346
Inequality	0.101	0.0232	0.0525	0.0946***	0.102***	0.0974***	0.102***	0.144***
	(1.04)	(0.38)	(1.31)	(3.23)	(4.17)	(4.14)	(4.28)	(3.74)
IO (Drop_Race)	-0.564**	-0.467*	-0.232	-0.102	0.00699	0.0826	0.110	0.197*
	(-2.45)	(-1.96)	(-1.48)	(-0.73)	(0.07)	(0.82)	(1.07)	(1.95)
Hansen (p)	0.358	0.229	0.233	0.216	0.273	0.454	0.408	0.217
Inequality	0.0474	0.0123	0.0544	0.0966***	0.106***	0.0882***	0.0915***	0.121***
	(0.50)	(0.20)	(1.33)	(3.30)	(3.99)	(4.15)	(3.39)	(3.29)
IO (Drop_Race & Sex)	-0.572***	-0.469**	-0.256*	-0.130	-0.0192	0.0490	0.0634	0.0975
	(-3.20)	(-2.63)	(-1.96)	(-1.19)	(-0.23)	(0.71)	(0.94)	(1.37)
Hansen (p)	0.351	0.317	0.307	0.301	0.290	0.411	0.331	0.214
Inequality	0.0938	0.0333	0.0736*	0.163***	0.175***	0.153***	0.151***	0.202***
	(1.26)	(0.54)	(1.95)	(4.81)	(5.06)	(5.53)	(4.42)	(3.04)
IO (Immob_Occ)	-0.174***	-0.136***	-0.109***	-0.0811***	-0.0585***	-0.0313*	-0.0297	-0.0454
	(-3.88)	(-3.07)	(-2.80)	(-3.61)	(-3.12)	(-1.95)	(-1.47)	(-1.44)
Hansen (p)	0.321	0.379	0.343	0.356	0.495	0.422	0.352	0.321

Note: t statistics in parentheses, * p<0.10, ** p<0.05, *** p<0.01.

Other controls included: lag of log GDP; population>25 years with at least a bachelor degree (%); people out of labor force (%); people below 15 years (%); people above 65 years (%); people working in the agricultural sector (%)

Table 3. Decomposition of the Gini coefficient

	(1)	(2)	(3)
Corruption	0.0138***	0.0149***	0.0163***
	(3.73)	(4.30)	(4.03)
Military	0.0164***	0.00785**	0.00795*
	(4.51)	(2.10)	(1.90)
Democracy	-0.00610	0.000809	0.00434
	(-1.61)	(0.24)	(1.07)
Ethnic	0.00128	-0.00178	-0.00183
	(0.37)	(-0.57)	(-0.53)
Religion	-0.0166***	-0.0219***	-0.0242***
	(-4.66)	(-6.48)	(-6.46)
Fertility		0.0248***	0.0205***
		(8.37)	(5.38)
L4.HC			-0.0320***
			(-2.77)
_cons	0.371***	0.292***	0.359***
	(14.76)	(12.41)	(9.79)
N	480	474	400
adj. R-sq	0.179	0.297	0.328

t statistics in parentheses
Significance: * p<0.10, ** p<0.05, *** p<0.01.

Table 4a. Impact of inequality and IO on growth (20 years: 1990-2010) (OLS; decomposition (3) of the Gini coefficient)

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Simple model				Simple model (with reg. dummies)			
L4.ly	-0.00146	-0.00557*	-0.00557*	-0.00557*	-0.00541	-0.00939*	-0.00939*	-0.00939*
	(-0.71)	(-1.85)	(-1.85)	(-1.85)	(-1.16)	(-1.77)	(-1.77)	(-1.77)
L4.Gini	-0.0288	-0.00964	-0.126***		-0.0296	-0.0234	-0.137***	
	(-1.40)	(-0.46)	(-3.01)		(-1.02)	(-0.81)	(-2.78)	
L4.IO		-0.117**		-0.126***		-0.114**		-0.137***
		(-2.59)		(-3.01)		(-2.41)		(-2.78)
L4.Resid			0.117**	-0.00964			0.114**	-0.0234
			(2.59)	(-0.46)			(2.41)	(-0.81)
_cons	0.0451*	0.120***	0.120***	0.120***	0.0935**	0.170***	0.170***	0.170***
	(1.87)	(2.85)	(2.85)	(2.85)	(2.08)	(2.84)	(2.84)	(2.84)
N	68	68	68	68	68	68	68	68
adj. R-sq	0.001	0.061	0.061	0.061	0.210	0.259	0.259	0.259

Table 4b. Impact of inequality and IO on growth (20 years: 1990-2010) (OLS; decomposition (2) of the Gini coefficient)

	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Simple model				Simple model (with reg. dummies)			
L4.ly	-0.00148	-0.00560*	-0.00560*	-0.00560*	-0.00523	-0.00874	-0.00874	-0.00874
	(-0.74)	(-1.76)	(-1.76)	(-1.76)	(-1.16)	(-1.67)	(-1.67)	(-1.67)
L4.Gini	-0.0289	-0.0104	-0.134***		-0.0299	-0.0248	-0.131**	
	(-1.41)	(-0.51)	(-2.74)		(-1.04)	(-0.85)	(-2.49)	
L4.IO		-0.123**		-0.134***		-0.107**		-0.131**
		(-2.40)		(-2.74)		(-2.12)		(-2.49)
L4.Resid			0.123**	-0.0104			0.107**	-0.0248
			(2.40)	(-0.51)			(2.12)	(-0.85)
_cons	0.0453*	0.123**	0.123**	0.123**	0.0920**	0.162**	0.162**	0.162**
	(1.92)	(2.65)	(2.65)	(2.65)	(2.11)	(2.60)	(2.60)	(2.60)
N	69	69	69	69	69	69	69	69
adj. R-sq	0.002	0.064	0.064	0.064	0.211	0.251	0.251	0.251

Table 5. Impact of inequality and IO on growth (10 years: 1990-2000 & 2000-2010) (POOL-OLS, FE, G2SLS; decomposition (3) of the Gini coefficient)

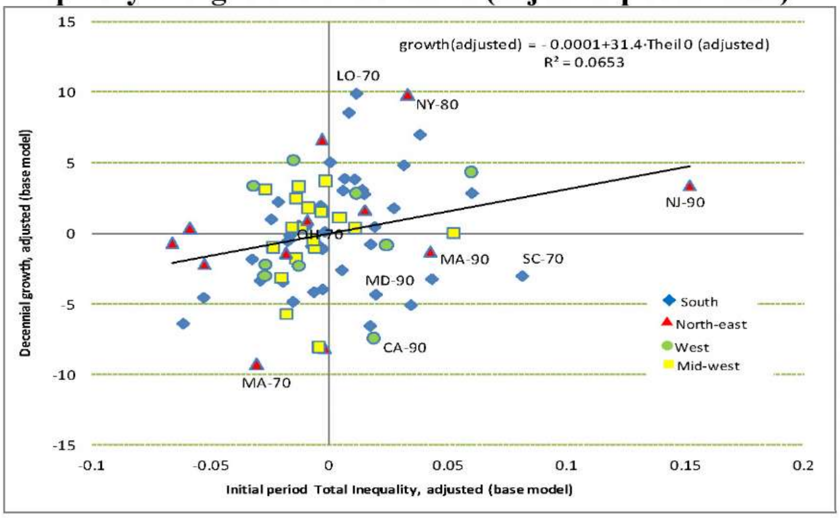
	POOL-OLS								FE				G2SLS			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Simple model (with time dummies)				Simple model (with time & reg. dummies)				Simple model (with time dummies)				Simple model (with time & reg. dummies)			
L2.ly	-0.00334**	-0.00899***	-0.00899***	-0.00899***	-0.00950***	-0.0137***	-0.0137***	-0.0137***	-0.0634***	-0.0614***	-0.0614***	-0.0614***	-0.0131***	-0.0208***	-0.0208***	-0.0208***
	(-2.20)	(-4.67)	(-4.67)	(-4.67)	(-3.67)	(-4.80)	(-4.80)	(-4.80)	(-3.23)	(-3.68)	(-3.68)	(-3.68)	(-3.93)	(-5.16)	(-5.16)	(-5.16)
L2.Gini	-0.0287*	0.000461	-0.179***		-0.0103	-0.00260	-0.156***		0.0425	0.0457	-0.133**		-0.0967	-0.0146	-0.391***	
	(-1.73)	(0.03)	(-5.36)		(-0.52)	(-0.13)	(-3.99)		(1.44)	(1.48)	(-2.01)		(-1.27)	(-0.35)	(-3.18)	
L2.IO		-0.180***		-0.179***		-0.153***		-0.156***		-0.179***		-0.133**		-0.377***		-0.391***
		(-5.00)		(-5.36)		(-3.94)		(-3.99)		(-2.85)		(-2.01)		(-3.26)		(-3.18)
L2.Resid			0.180***	0.000461			0.153***	-0.00260			0.179***	0.0457			0.377***	-0.0146
			(5.00)	(0.03)			(3.94)	(-0.13)			(2.85)	(1.48)			(3.26)	(-0.35)
_cons	0.0591***	0.168***	0.168***	0.168***	0.120***	0.212***	0.212***	0.212***	0.552***	0.605***	0.605***	0.605***	0.192***	0.367***	0.367***	0.367***
	(3.17)	(5.84)	(5.84)	(5.84)	(4.51)	(6.01)	(6.01)	(6.01)	(3.24)	(4.46)	(4.46)	(4.46)	(4.10)	(4.67)	(4.67)	(4.67)
N	145	145	145	145	145	145	145	145	145	145	145	145	109	109	109	109
adj. R-sq	0.044	0.159	0.159	0.159	0.219	0.281	0.281	0.281	0.336	0.405	0.405	0.405				

Table 6. Impact of inequality and IO on growth (5 years: 1985-2010) (POOL-OLS, System-GMM; decomposition (3) of the Gini coefficient)

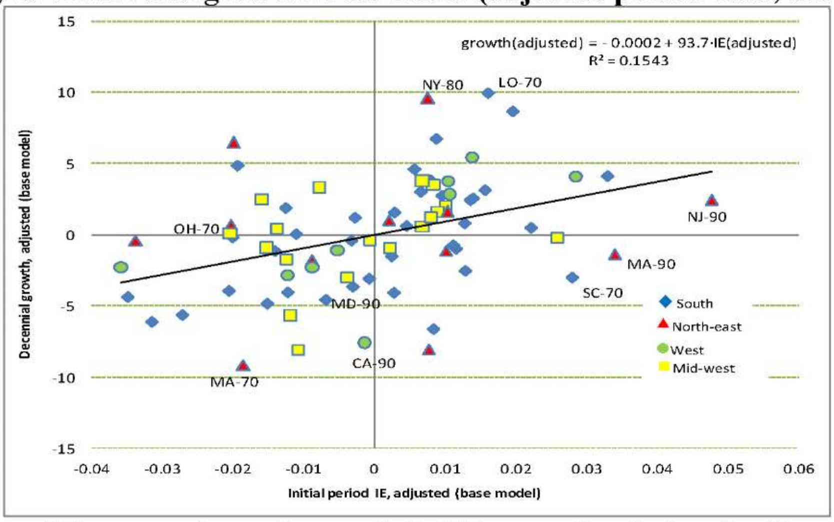
	POOL-OLS								System-GMM			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
	Simple model (with time dummies)				Simple model (with time & reg. dummies)				Simple model (with time dummies)			
L2.ly	-0.00224**	-0.00654***	-0.00654***	-0.00654***	-0.00689***	-0.00935***	-0.00935***	-0.00935***	0.00258	-0.00682*	-0.00754*	-0.00802*
	(-2.15)	(-4.64)	(-4.64)	(-4.64)	(-3.55)	(-4.19)	(-4.19)	(-4.19)	(0.76)	(-1.73)	(-1.77)	(-1.89)
L2.Gini	-0.0364***	-0.0117	-0.153***		-0.0130	-0.00812	-0.104***		-0.113**	-0.0357	-0.421***	
	(-2.82)	(-0.79)	(-5.37)		(-0.82)	(-0.48)	(-2.83)		(-2.53)	(-0.95)	(-3.55)	
L2.IO		-0.141***		-0.153***		-0.0962**		-0.104***		-0.374***		-0.443***
		(-4.30)		(-5.37)		(-2.52)		(-2.83)		(-3.84)		(-3.62)
L2.Resid			0.141***	-0.0117			0.0962**	-0.00812			0.386***	-0.0546
			(4.30)	(-0.79)			(2.52)	(-0.48)			(3.71)	(-1.35)
_cons	0.0548***	0.139***	0.139***	0.139***	0.102***	0.159***	0.159***	0.159***	-3.989**	-3.205	-3.255	-3.366
	(4.44)	(6.36)	(6.36)	(6.36)	(5.26)	(5.45)	(5.45)	(5.45)	(-2.28)	(-1.53)	(-1.55)	(-1.60)
N	358	358	358	358	358	358	358	358	358	358	358	358
adj. R-sq	0.015	0.055	0.055	0.055	0.121	0.133	0.133	0.133				
hansenp									0.433	0.513	0.497	0.236

Figure 1. Inequality, IO, IE and Growth
Source: Marrero and Rodríguez (JED, 2013)

a. **Total inequality and growth in US states (adjusted pooled data)**



b. Inequality of Effort and growth in US states (adjusted pooled data, base model)



c. Inequality of Opportunity and growth in US states (pooled and adjusted data)

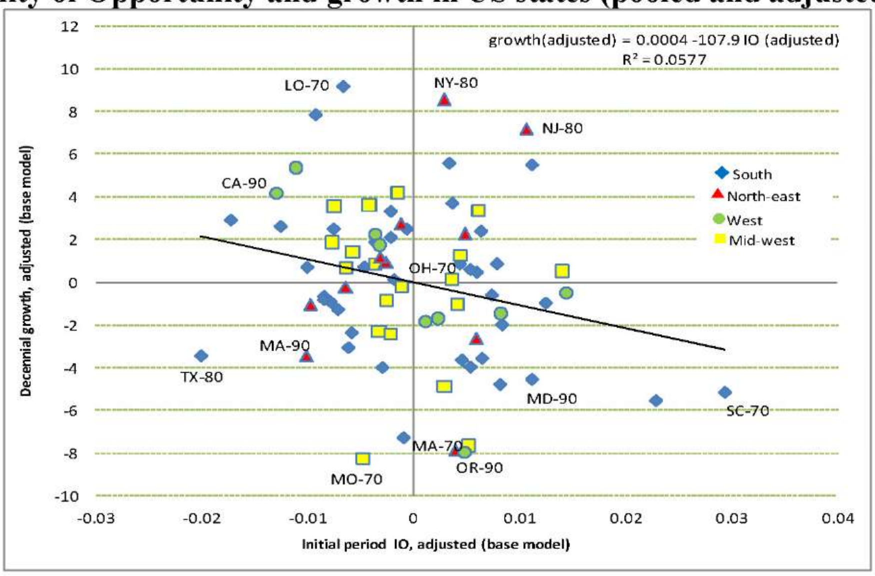
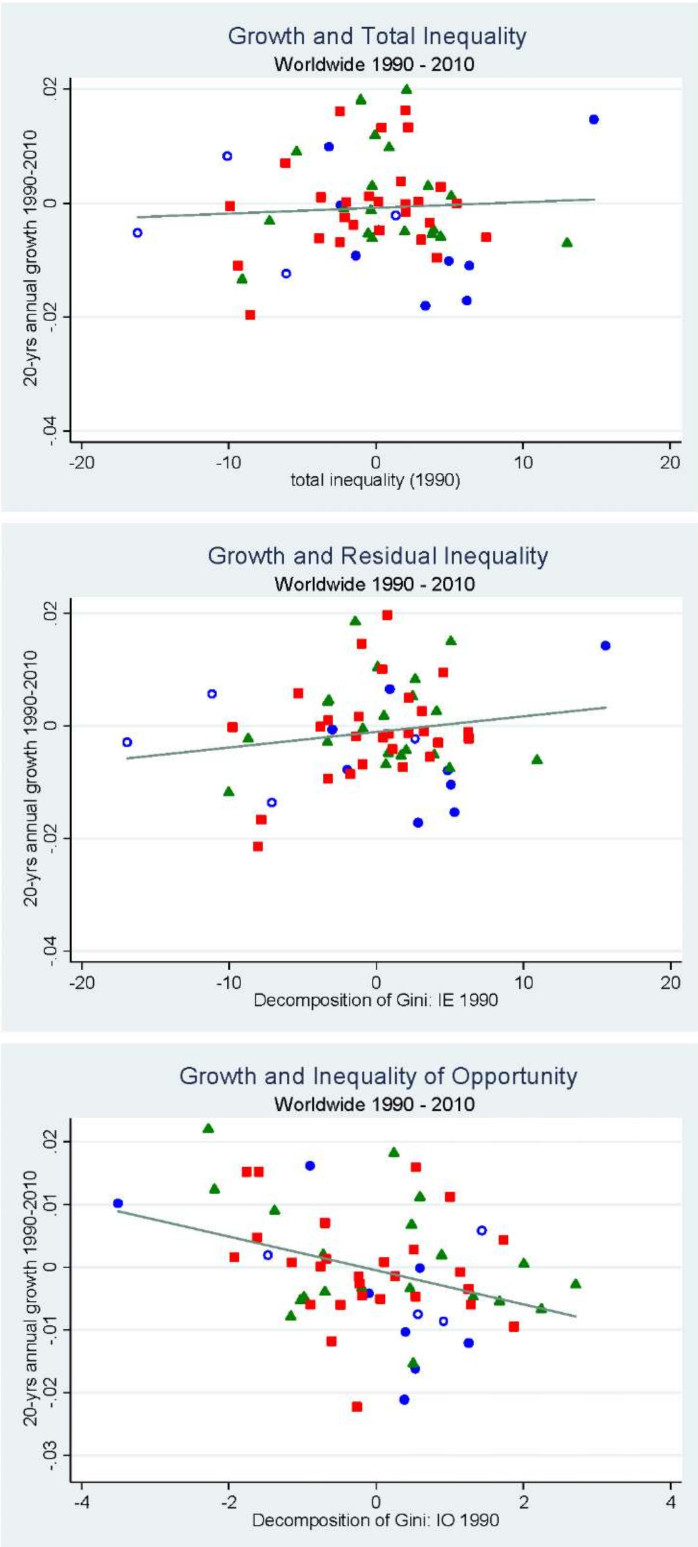


Figure 2. Inequality, IO, IE and Growth (long-run cross-country analysis – 20 years interval) (*)



(*) Variables in the axes are OLS adjusted by initial log of per capita GDP, time dummies and regional dummies.