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Abstract

A fundamental unsolved question in economics is whether inequality is good or bad for growth. We argue here that this lack of consensus is due to the cholesterol hypothesis. This hypothesis states that the part of inequality generated by factors beyond the individuals' control, referred to as inequality of opportunity (IO), is growth-deterring, while the type of inequality generated by the difference in the willingness to exert effort, referred to as inequality of pure effort (IE), is growth-enhancing. We first build an overlapping generation model with human capital to derive a reduced-form growth equation consistent with this hypothesis, and the existing interaction between poverty and inequality. Then, given the inherent difficulty to decompose total inequality into IO and IE, we develop a strategy to test the cholesterol hypothesis: by extending the standard inequality-growth equation with a proxy of IO, the estimated coefficient of inequality must increase, while the coefficient of the IO proxy must be negative. Next, we use the best available data at worldwide level and, given the limitations of the existing IO indices, we construct an alternative proxy of IO by considering that the quality of institutions and ethnic and religious tensions are relevant macroeconomic drivers of IO. Using an instrumental variable approach and different samples and IO measures, our results do not reject the cholesterol hypothesis at worldwide level.

Keywords: growth, inequality, inequality of opportunity, poverty, human capital.

JEL Classification: O40, D63, E24, I32.

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1. Introduction

Since the pioneering work by Kuznetz (1955), a challenging question in economics has been whether inequality is good or bad for growth (Barro, 2000; Panizza 2002; Banerjee and Duflo, 2003; or Voitchovsky, 2011, among many others). Recent results point out that this effect is positive in the short-run (Halter et al., 2014) and negative in the mid- and long-run (Berg et. al., 2018; Dabla-Norris et al., 2015), but there is still no consensus on this issue. This lack of robustness has traditionally been attributed to the co-existence of a variety of channels –some of them growth-enhancing and others growth-deterring– through which inequality is affecting growth.[2] We argue here that the *cholesterol hypothesis* (Ferreira, 2007) is behind this lack of robustness.

Since inequality can be seen as a composite measure of at least two components (Roemer, 1993; Fleurbaey, 2008), inequality of opportunity (IO) and inequality of pure effort (IE), the cholesterol hypothesis states that IO is bad for growth while IE is good for growth. Consequently, the final effect of total inequality on growth depends on the type of inequality that dominates. The IO is attributed to the heterogeneity in individual circumstances, which are factors beyond the individual's control, such as family background, race, gender, health endowments or macroeconomic conditions. The IE is associated with the diversity in individual preferences and personal attitudes toward effort (i.e., free-will actions).

There are three main contributions in this paper. First, we derive a reduced-form growth equation that explicitly highlights the different effects of alternative types of inequality on growth, from a model that does not depend on any particular channel. Thus, no assumptions about market imperfections, rent-seeking activities, political economy function, unobservable effort or individual talent are made. Our setting consequently provides a broader perspective to understanding the existing ambiguity between overall inequality and growth. In addition to this, we consider the existence of poverty trap in

[2] The positive channels are related to the incentives for saving and investing (Kaldor, 1956; Stiglitz, 1969; Bourguignon, 1981; Barro 2000), asymmetric information (Mirrlees, 1971; Rebelo, 1991), and the generation of productivity premiums (Goldin and Katz, 2008; Mankiw, 2013). The negative channels are related to imperfect capital markets (Galor and Zeira, 1993; Banerjee and Newman, 1993), political economy issues (Gupta, 1990; Alesina and Rodrik, 1994; Stiglitz, 2012), and the development process (Dasgupta and Ray, 1987; Murphy et al., 1989; Kremer and Chen, 2002).

our setting since both inequality and poverty are closely interrelated aspects of the income distribution (Bourguignon, 2003; Bourguignon et al., 2007).[3]

Second, given the inherent difficulty to decompose total inequality into IO and IE, we develop an empirical strategy to test the cholesterol hypothesis.[4] Apart from being able to explain the existing controversy about the sign of the inequality-growth relationship, this proposal finds that when the standard inequality-growth equation is extended with any proxy of IO, the estimated coefficient of inequality must increase, while the coefficient of the IO proxy must be negative.

Third, for the first time we obtain robust empirical support for the cholesterol hypothesis at worldwide level. Previously, some support to the cholesterol hypothesis at regional level has been obtained for the U.S. (Marrero and Rodríguez, 2013; Bradbury and Triest, 2016; Marrero et al., 2016a) and for Brazil (Teyssier, 2017). However, the only existing study at worldwide level, Ferreira et al. (2018), did not find a robust negative and significant effect of IO on growth.[5] We extend the inequality-growth setting from Berg et. al. (2018) with alternative IO proxies. We first use those measures from Ferreira et al. (2018) and, given their limitations, we construct an alternative proxy of IO by considering that the quality of institutions and ethnic and religious tensions are relevant macroeconomic drivers of IO. Using an instrumental variable approach (Brueckner at al., 2012) and alternative samples and IO measures, our results do not reject the cholesterol hypothesis at worldwide level.

Taking human capital as the main engine of development, our model combines the basic principles of wage determination and human capital accumulation (Glomm and Ravikumar, 1992) with that of inequality of opportunity (Roemer, 1993; Fleurbaey, 2008; Roemer and Trannoy, 2016) and poverty traps (Azariadis and Stachurski, 2005). The economy is populated by a continuum of dynasties with warm-glow preferences,

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[3] In the poverty trap literature (Azariadis and Stachurski, 2005), López and Servén (2009), Ravallion (2012) and Marrero and Servén (2018) have found a negative effect of poverty on growth.

[4] The difficulty comes from different sources. First, the whole set of individual circumstances (family background, race, place of birth, health endowments, etc.) is difficult to observe. As a result, the analysis usually relies on a lower-bound estimate of the IO component (Ferreira and Gignoux, 2011), and an IE component that contains unobserved circumstances. Second, databases with a large number of circumstances are typically available only for developed countries (Rodríguez, 2008, Marrero and Rodríguez, 2012 and 2016b). Third, databases that contain measures of IO for a large number of countries tend to be heterogeneous across countries: different number and type of circumstances, different dependent variables − income or expenditure –, and different sources – survey or taxes – (Ferreira et al., 2018).

[5] Our analysis differs from Ferreira et al. (2018) in several relevant aspects, as will be discussed in Section 5.

where effort is considered as a non-monetary factor that generates disutility but is needed for the individual to accumulate human capital. The set of circumstances includes parental human capital, parental bequests and exogenous factors (i.e., health endowments, macroeconomic conditions, race, etc.), which affect individual human capital and wages directly but also indirectly through the return of individual effort. The ultimate source of heterogeneity comes from the set of exogenous circumstances, the initial stock of human capital in the dynasty and an idiosyncratic (dynasty-specific) parameter related to preferences toward effort.[6] Following Roemer (1998), the two first sources of inequality are associated with IO, while the last source is related to IE.

For expository reasons, we first solve the model without poverty trap (convex human capital accumulation process). Under these conditions, we show that human capital accumulation is increasing and concave with respect to the set of exogenous circumstances and decreasing and convex with respect to the parameter representing the preference to exert effort. As a result, a more equal distribution of exogenous circumstances (related to IO) increases transitory growth, while the opposite happens for the preferences to exert effort (related to IE). Hence, the final impact of total inequality on growth is ambiguous and its sign depends on which component dominates.

By assuming the existence of a poverty trap, each dynasty faces two potential equilibria, a low and a high one. Poverty, measured as the percentage of dynasties trapped in the low equilibrium, is found to be harmful for growth and, again, the results are consistent with the cholesterol hypothesis. In addition, we find that the effect of the two aforementioned components of inequality on growth decreases with poverty, becoming zero when all individuals are poor. For very high levels of poverty, therefore, the direct impact of these two components on growth becomes irrelevant and reducing the percentage of people trapped is the only way to foster growth. Finally, under this multiple-equilibria framework, the initial level of parental human capital becomes a relevant factor. We show that the inequality of this circumstance has an ambiguous impact on transitory growth, although, for economies with non-extremely high poverty rates, its long-run effect on growth is negative.

[6] The important role of circumstances on inequality of opportunity has been emphasized in the literature: Even if individuals have high inborn talent and strong preferences for effort, the likelihood of their being able to realize the benefits of that talent (in terms of admission to university or employment) is significantly affected by social conditions (Arrow et al., 2000).

From the model, we derive a reduced-form growth equation that includes the two aforementioned components of inequality, poverty and their interactions. It is observed that the coefficient of overall inequality depends on the magnitude of each component and their marginal effect on growth so it can be positive, negative or null. Moreover, given the impossibility of a perfect decomposition of total inequality into IO and IE, we show that the cholesterol hypothesis can be tested by extending the standard inequality-growth equation with a proxy of IO. In this case, the estimated coefficient of inequality must increase and, simultaneously, the coefficient of the IO proxy must be negative.

For the empirical exercise, we use growth and inequality data from Berg et al. (2018): per capita GDP from the Penn World Table (PWT 7.1) and income inequality from the Standardized World Income Inequality Database (SWIID 3.1; Solt, 2016). Our headcount poverty rates are from the POVCAL-Net (Ferreira et al., 2016). As a proxy of IO, we first consider the two best available sets of IO series at worldwide level from Ferreira et al. (2018): 118 country-years estimates from the Income and Expenditure Surveys (IES), and 134 country-years estimates from the Demographic and Health Surveys (DHS). However, due to the limitations of these two data sets, we propose an alternative approach to obtain a proxy of IO. We base our strategy on two ideas from the previous literature. First, Milanovic (2015) has found that macroeconomic factors, which are beyond the individual's control, are very important for *global* inequality of opportunity. Second, Alesina et al. (2003), Stiglitz (2012) and Acemoglu et al. (2015), among others, have observed that institutional setup and ethnic-linguistic and religious tensions may significantly influence the level of nepotism in an economy and the capacity of individuals to achieve a given socioeconomic status. Hence, in the same spirit as Fatás and Mihov (2003), we estimate a political economy model and construct an alternative proxy of IO. We regress overall inequality on the degree of democracy, the level of law enforcement, corruption and the existing ethnic-linguistic and religious tensions −all these variables are from the Political Risk Module of the International Country Risk Database (ICRD)− and take the fitted value as our proxy of IO.

To estimate our inequality-growth models, we follow the Instrumental Variable (IV) approach in Brueckner et al. (2012) to avoid the bias caused by potential reverse causality between income, inequality and the IO proxy. In this strategy, we use the lagged levels of the saving rate (Acemoglu et al., 2008) and of the growth rate (Fatás and Mihov, 2003; Aiyar and Ebeke, 2019) as instruments for per capita real GDP.

Alternative instruments like the lagged trade-weighted world income (Acemoglu et al., 2008) and the oil price shocks (Brueckner et al., 2012; 2015) were also considered, but they did not pass the corresponding tests. To check for robustness, we also estimate our models by pooled-OLS and system-GMM (Blundell and Bond, 1998; Roodman, 2009).

We find robust evidence consistent with the cholesterol hypothesis: the effect of the IO proxy on economic growth is significantly negative and the estimated coefficient of overall inequality becomes higher when the IO proxy is included in the regression. When the sample contains a majority of developed countries (i.e., the IES sample), we obtain these results for the restricted model without poverty. However, when the sample contains a large set of less developed and developing countries (i.e., the DHS and the alternative samples), we find this result for the general model that also considers the influence of poverty. For the last two samples, poverty is found to be growth-deterring (Ravallion, 2012; Marrero and Servén, 2018).

The rest of the paper is structured as follows. In Section 2, we present the main characteristics of the model, solve it for a convex and a non-convex human capital accumulation process and derive the corresponding reduced form growth equation. Section 3 presents our empirical approach to test the cholesterol hypothesis. In Section 4, we explain the uses of databases and the alternative measures of IO, paying special attention to the construction of an alternative proxy for IO. In Section 5, we show the econometric approaches used in the empirical exercise and the main results. Finally, Section 6 contains the concluding remarks.

2. The theoretical framework

We present a dynamic general equilibrium economy inhabited by a continuum of heterogeneous dynasties, each one indexed by $i \equiv [0,1]$. We assume a small and open economy, with perfect competitive markets, time t is discrete and each dynasty i consists of a common individual who lives for two periods: childhood and adulthood. During adulthood, the individual gives birth to another individual so the overall population remains constant over time. We take human capital as the main engine of development. Heterogeneity comes from differences in the preferences to exert effort, initial parental human capital of the dynasty, and other exogenous factors, all of them affecting the individual productivity to accumulate human capital.

Technology and aggregate output

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

$$y_t = Ak_t^{\lambda}\tilde{l}_t^{1-\lambda},\ A > 0,\ \lambda \in (0,1), \tag{1}$$

using physical capital, k_t, and efficient units of labor, $\tilde{l}_t = l_t\tilde{h}_t$, where l_t is raw labor (normalized to one) and $\tilde{h}_t = e^{\pi h_t}$ is the human capital of the working population, which is proxied by the mean years of schooling, h_t, corrected by its quality, π (Barro and Lee, 2013; Psacharopoulos, 1994). The mean years of schooling is $h_t = \int_0^1 h_t(i)dF[h_t(i)]$, where $F[h_t(i)]$ is the distribution function of the years of schooling at time t.[7] The arrow-neutral technological term A is assumed to be constant.[8]

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, $\bar{r}$.[9] Since producers operate in a perfectly competitive environment, $\bar{r}$ determines the k_t/h_t constant ratio,

$$\bar{r} = y_k' = A\lambda\left(\frac{k_t}{\tilde{h}_t}\right)^{\lambda-1} \Rightarrow \left(\frac{k_t}{\tilde{h}_t}\right) = \left(\frac{A\lambda}{\bar{r}}\right)^{\frac{1}{1-\lambda}}, \tag{2}$$

and the real wage per unit of effective labor, w_t, is given by,

$$w_t = y_{\tilde{l}}' = A(1-\lambda)\left(\frac{k_t}{\tilde{h}_t}\right)^{\lambda} = A^{\frac{1}{1-\lambda}}(1-\lambda)\left(\frac{\lambda}{\bar{r}}\right)^{\frac{\lambda}{1-\lambda}}, \tag{3}$$

which increases with A and decreases with $\bar{r}$. Thus, given A and $\bar{r}$, real per capita income is fully determined by human capital [plugging (3) into (1)]:

$$y_t = \left(\frac{\lambda}{\bar{r}}\right)^{\frac{\lambda}{1-\lambda}} A^{\frac{1}{1-\lambda}}\tilde{h}_t. \tag{4}$$

Preferences and circumstances

[7] The exponential formulation of the human capital function is consistent with the extensive literature on schooling and wages (Mincer, 1974; Bils and Klenow, 2000).

[8] Assuming that A_t grows at a constant positive rate does not change the main results of the paper.

[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).

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

$$u_t(i) = v(\eta)c_t(i)^{\eta}x_t(i)^{1-\eta} - \gamma(i)e_t(i)^{1+\beta}. \quad (5)$$

Without loss of generality, we assume that consumption during childhood is included in the parents' consumption (Benabou, 2000), $\eta \in (0,1)$ is a parameter of relative preferences between c_t and x_t, and $v(\eta) = \eta^{-\eta}(1-\eta)^{-(1-\eta)}$ is a normalization factor (Acemoglu, 2010). Labor is inelastically supplied. Effort e_t is a non-monetary factor that generates disutility but is needed to accumulate human capital (Aghion and Bolton, 1997; Roemer, 1998). We assume $\beta > 0$ so that the marginal disutility of effort is increasing.[10] Finally, preferences for bundles of effort and consumption (and bequest) are determined by the dynasty-specific parameter $\gamma(i) > 0$. While $e_t(i)$ is a control variable that might depend on many factors at the individual and aggregate level, $\gamma(i)$ is related to individual's preference for effort and is independent of any other characteristic of the dynasty (Roemer, 1998).

When born, each individual inherits a set of factors (circumstances), which are beyond the individual's control but would affect their posterior human capital accumulation decisions. We assume the set of circumstances is a composite index,[11]

$$\theta_t(i) = a(i)^{1-\alpha-\varphi}x_{t-1}(i)^{\alpha}\tilde{h}_{t-1}(i)^{\varphi};\ \alpha,\ \varphi \in (0,1),\ \alpha + \varphi < 1, \quad (6)$$

where $a(i)$ collects exogenous factors to the individual such as race, gender, health endowments, or macroeconomic factors like the quality of institutions and religious tensions in the country;[12] $x_{t-1}(i)$ is the bequest devoted to offspring (Card and Krueger, 1992; Glomm and Ravikumar, 1992); and $\tilde{h}_{t-1}(i)$ represents home externalities generated by parental human capital (Galor and Tsidon, 1997).[13]

[10] Note that the convexity of the effort function guarantees the concavity of the utility function.

[11] Because inborn ability or talent is less than perfectly correlated between generations, a model that explicitly represents how it evolves over time in the dynasty would be required (Hasler and Rodriguez-Mora, 2000). Another source of inequality beyond the scope of this paper is luck (Lefranc et al., 2009). Mejía and St-Pierre (2008) consider a single exogenous variable to represent personal circumstances.

[12] Country-specific factors like the quality of institutions and religious tensions are macro factors which cannot be changed by people at an individual level. Moreover, the importance of these macro factors is not mitigated by migration since less than 3% of the world's population lives in countries where they were not born (Milanovic, 2015). This idea is the base of our proposal to construct a proxy of IO in Section 4.

[13] 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

Human capital, wages and the sources of inequality

At the individual level, human capital is accumulated according to a process that depends on two non-purchasable but complementary factors: circumstances and effort (Roemer, 1993; Fleurbaey, 2008),

$$\tilde{h}_t(i) = R[\theta_t(i), e_t(i)], \tag{7}$$

with $R'_\theta \geq 0$ and $R'_e \geq 0$. As for the aggregate level, we assume that human capital and years of schooling at the individual level have a one-to-one relationship, i.e., $\tilde{h}_t(i) = e^{\pi h_t(i)}$.

Individuals work during their adulthood (supplying one unit of labor inelastically) and earn labor income,

$$w_t(i) = w\tilde{h}_t(i), \tag{8}$$

where $w > 0$ represents a minimum salary in the economy for individuals with zero years of schooling. From (8), it is obvious that inequality comes from differences in the way individuals accumulate human capital.

As we will show below, the ultimate sources of this heterogeneity come from differences in $\gamma(i)$, $a(i)$ and the initial level of parental human capital $\tilde{h}_{-1}(i)$. Following Benabou (1996), we assume that γ, a and $\tilde{h}_{-1}$ follow mean-invariant log-normal independent distributions, i.e., $\ln\gamma \sim N\left(\ln\hat{\gamma} - \frac{\Delta_\gamma^2}{2}, \Delta_\gamma^2\right)$, $\ln a \sim N\left(\ln\hat{a} - \frac{\Delta_a^2}{2}, \Delta_a^2\right)$ and $\ln\tilde{h}_{-1} \sim N\left(\ln\hat{h} - \frac{\Delta_{-1}^2}{2}, \Delta_{-1}^2\right)$.[14] In this manner, γ, a and $\tilde{h}_{-1}$ have constant means equal to $\hat{\gamma}$, $\hat{a}$ and $\hat{h}$, respectively, which 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 coefficient or the Mean Logarithmic Deviation (MLD). In fact, the MLD index, T_0, is exactly half the variance, i.e., $T_0(a) = \frac{\Delta_a^2}{2}$, $T_0(\gamma) = \frac{\Delta_\gamma^2}{2}$, $T_0(\tilde{h}_{-1}) = \frac{\Delta_{-1}^2}{2}$. For illustrative purposes, we use this property to introduce IO, in connection with $T_0(a)$ and $T_0(\tilde{h}_{-1})$,

relatively little importance in determining individual achievement (Coleman et al., 1966; Hanushek, 1996).

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

and IE, in connection with $T_0(\gamma)$ into our theoretical framework.[15] As we show below, γ affects individual effort regardless the set of individual circumstances, and this is the required condition to define pure effort (Roemer, 1998).

For illustrative purposes, we consider two cases for the accumulation of human capital: a convex process and a non-convex process. The latter generates a poverty trap and multiplicity of equilibria. For simplicity, time subscript is omitted from now on whenever it is not strictly necessary.

2.1. ***A convex process for human capital***

We assume that the human capital process in (7) is:

$$\tilde{h}(i) = \theta(i)^{\psi} e(i)^{1-\psi}, \tag{9}$$

where the parameter $\psi \in (0,1)$ represents the relative importance of personal circumstances with respect to effort in the determination of human capital, hence it can proxy the lack of meritocracy in the economy.

Each individual belonging to the i-th dynasty takes $\theta(i)$ as given and maximizes (5) subject to $c(i) + x(i) = w(i)$. The problem is solved in two steps. First, taking $\tilde{h}(i)$ as given, utility is maximized subject to the previous restriction and (8), obtaining $c(i) = \eta w \tilde{h}(i)$ and $x(i) = (1-\eta) w \tilde{h}(i)$. These expressions are then substituted in (5) to obtain the indirect utility function, which, in a second step, is maximized with respect to $e(i)$ subject to (9). We obtain the following:

$$e(i) = \left[\frac{(1-\psi)w}{\gamma(i)(1+\beta)}\right]^{\frac{1}{\beta+\psi}} \theta(i)^{\frac{\psi}{\beta+\psi}}, \tag{10}$$

$$\tilde{h}(i) = \left[\frac{(1-\psi)w}{\gamma(i)(1+\beta)}\right]^{\frac{1-\psi}{\beta+\psi}} \theta(i)^{\frac{(1+\beta)\psi}{\beta+\psi}}, \tag{11}$$

$$w(i) = \left[\frac{(1-\psi)w^{\frac{1+\beta}{1-\psi}}}{\gamma(i)(1+\beta)}\right]^{\frac{1-\psi}{\beta+\psi}} \theta(i)^{\frac{(1+\beta)\psi}{\beta+\psi}}. \tag{12}$$

[15] The connection between the Gini coefficient and the variance for any log-normal variable x is: $G(x) = 2\Phi\left(\frac{\Delta_x}{\sqrt{2}}\right) - 1$, where Φ is the standard normal distribution function. Because its connection with the variance is simpler, and solely for illustrative purposes, we focus on the MLD in this section. However, our empirical strategy will consider a proxy of IO based not only on the MLD, but also on the variance and the Gini coefficient depending on the sample under consideration (see Section 4).

These optimal conditions are consistent with a set of well-known results in the inequality-of-opportunity literature. First, according to (10), individual effort $e(i)$ depends on the following aspects: the aggregate economy, w, which is common to all individuals but is country-specific; personal circumstances, $\theta(i)$; the individual preferences to effort, $\gamma(i)$. Second, since the parameter $\gamma(i)$ affects personal effort but is independent of individual circumstances and the aggregate economy, it is a proxy of pure effort, as commented above.[16] Third, individual circumstances $\theta(i)$ affect human capital and wages not only by a direct channel (the return-to-effort term in (9), given by $\theta(i)^{\psi}$), but also an indirect channel through its impact on effort, represented by the term $\theta(i)^{\frac{\psi}{\beta+\psi}}$ in (10).

For each dynasty i, we use the expression $x(i) = (1-\eta)w\tilde{h}(i)$ to rewrite $\theta(i)$ in terms of $\tilde{h}_{t-1}(i)$ and then use (11) to derive a dynamic equation for human capital,

$$\tilde{h}_t(i) = \zeta\left[\tilde{h}_{t-1}(i), a(i), \gamma(i), w\right] = \left[e^{S}\frac{a(i)^{(1+\beta)\psi(1-\alpha-\varphi)}\tilde{h}_{t-1}(i)^{\psi(1+\beta)(\alpha+\varphi)}}{\gamma(i)^{1-\psi}}\right]^{\frac{1}{\beta+\psi}}, \qquad (13)$$

$$S = (1-\psi)ln\left(\frac{(1-\psi)w}{1+\beta}\right) + (1+\beta)\psi ln[(1-\eta)^{\alpha}w^{\alpha}],$$

where $\zeta[0] = 0$, $\zeta[\cdot]$ is C^2 on $(0, +\infty)$ and, because $\frac{\psi(1+\beta)(\alpha+\varphi)}{\beta+\psi} < 1$, $\zeta[\cdot]$ is strictly increasing and strictly concave in $\tilde{h}_{t-1}(i)$, i.e., marginal human capital is decreasing with parental human capital. Hence, the existence and uniqueness of a steady-state is guaranteed by solving the fixed point $\tilde{h}_{\infty}(i) = \zeta\left[\tilde{h}_{\infty}(i)\right]$ (see Figure 1),

$$\tilde{h}_{\infty}(i) = \left[e^{S}\frac{a(i)^{(1+\beta)\psi(1-\alpha-\varphi)}}{\gamma(i)^{1-\psi}}\right]^{\frac{1}{\beta+\psi[1-(1+\beta)(\alpha+\varphi)]}}, \qquad (14)$$

which is globally stable and depends not only on the dynasty characteristics $\gamma(i)$ and $a(i)$, but also on the aggregate economy, i.e., the real wage per unit of effective labor w.[17]

INSERT FIGURE 1 ABOUT HERE

[16] From the literature on inequality of opportunity, pure effort is defined as the part of total effort that is not influenced by individual circumstances and other exogenous factors beyond the individual's control (Roemer, 1998).

[17] Taking logs in (13), it is easy to show that $\tilde{h}(i)$ follows a log-normal distribution, $ln\tilde{h}_t(i) \sim N\left[\mu_{\tilde{h}_t}, \Delta^2_{\tilde{h}_t}\right]$ for all t, with $\mu_{\tilde{h}_t} = E\left[ln\tilde{h}_t(i)\right] = \pi h_t$ and $\Delta^2_{\tilde{h}_t} = Var\left[ln\tilde{h}_t(i)\right] = \pi^2\Delta^2_{h_t}$ where $\Delta^2_{h_t}$ is $Var[lnh_t(i)]$. As a result, $w_t(i)$ also follows a log-normal distribution, $lnw_t(i) \sim N\left[lnw + \pi h_t, \pi^2\Delta^2_{h_t}\right]$ for all t. Hence, $T_0(w_t) = T_0(\tilde{h}_t) = \pi^2\Delta^2_{h_t}/2$.

Finally, we derive a growth equation that relates income growth to the different sources of inequality, i.e., $T_0(\gamma)$, $T_0(a)$ and $T_0(\tilde{h}_{-1})$. This equation will help us to understand the existing controversy about the inequality-growth relationship and to define an empirical strategy to test for the cholesterol hypothesis (Section 4).

Let $g_{y_t} = lny_t - lny_{t-1}$ be the growth rate of income per capita in period t. Since A is assumed to be constant, g_y is equal to the growth rate of human capital $g_{\tilde{h}}$ which is, in turn, a function of the change in the mean years of schooling $\pi(h_t - h_{t-1})$. By definition $h = E[h(i)]$ and, because $E[h(i)] = \frac{1}{\pi}E[ln\tilde{h}(i)]$, we can take logs and expectations in (13) to obtain the following aggregate equation:

$$h_t = \frac{S}{(\beta+\psi)\pi} + b_h h_{t-1} + \frac{b_a}{\pi}E(\ln a) - \frac{b_\gamma}{\pi}E(\ln \gamma), \tag{15}$$

where $b_h = \frac{(1+\beta)\psi(\alpha+\varphi)}{\beta+\psi}$, $b_a = \frac{(1+\beta)\psi(1-\alpha-\varphi)}{\beta+\psi}$, and $b_\gamma = \frac{1-\psi}{\beta+\psi}$, which are always positive. The parameter b_h, which represents the persistence of human capital dynamics −and therefore of income− in the economy, is lower than one, which is consistent with the strict concavity property of the $h(i)$ function in (13).[18] Solving for the steady-state, i.e., $h_t = h_{t-1} = h_\infty$, we obtain:

$$h_\infty = \frac{S}{(\beta+\psi)\pi(1-b_h)} + \frac{b_a}{\pi(1-b_h)}E(\ln a) - \frac{b_\gamma}{\pi(1-b_h)}E(\ln \gamma). \tag{16}$$

Now, using the definitions of $E(\ln a) = \ln \hat{a} - \frac{\Delta_a^2}{2}$ and $E(\ln \gamma) = \ln \hat{\gamma} - \frac{\Delta_\gamma^2}{2}$, and the relationship between y_{t-1} and h_{t-1}, we can derive an extended growth equation that relates income growth to lagged income and the different sources of inequality:

$$g_{y_t} = b_0 - (1-b_h)lny_{t-1} - b_a T_0(a) + b_\gamma T_0(\gamma), \tag{17}$$

where $b_0 = \frac{S}{(\beta+\psi)} + b_a ln\hat{a} - b_\gamma ln\hat{\gamma} + \frac{(1-b_h)\left[\lambda ln\left(\frac{\lambda}{\bar{r}}\right)+lnA\right]}{1-\lambda}$, $T_0(a) = \frac{\Delta_a^2}{2}$ and $T_0(\gamma) = \frac{\Delta_\gamma^2}{2}$.

Equation (17) predicts conditional convergence in per capita income because the coefficient associated to lny_{t-1} is always negative, with a speed of convergence that is inversely related to b_h.

[18] Note that the persistence represented by b_h is strongly related to the level of meritocracy of the economy. In fact, given $\alpha + \varphi > 0$, a pure meritocratic society ($\psi = 0$) implies null inertia in the human capital accumulation process, i.e., $b_h = 0$.

The main result is, however, the following: since b_a and b_γ are always positive, the effect of inequality on the growth rate of the economy depends on the type of inequality under consideration, it is negative for $T_0(a)$, and positive for $T_0(\gamma)$. Their corresponding short-run elasticities are $-b_a$ and b_γ, respectively, while their accumulated long-run elasticities are $\frac{-b_a}{1-b_h}$ and $\frac{b_\gamma}{1-b_h}$, with $b_h \in (0,1)$. Because the steady-state of $\tilde{h}$ is globally stable, $T_0(\tilde{h}_{-1})$ does not have a direct impact on the long-run equilibrium. Nonetheless, it affects transitory growth through the level of lagged income. Thus, once the growth equation (17) is controlled by the convergence term lny_{t-1}, the influence of $T_0(\tilde{h}_{-1})$ on growth becomes null.[19]

The two sources of inequality have opposite effects on the transitory growth rate and on the steady-state equilibrium. The explanation of this result lies in the own human capital accumulation process in (13) and it is illustrated in Figure 2. On one hand (left panel), $\tilde{h}_t(i)$ is strictly increasing and strictly concave with respect to $a(i)$, 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 (right panel), $\tilde{h}(i)$ is strictly decreasing and strictly convex with respect to $\gamma(i)$, hence economies with higher heterogeneity in the preference to exert more effort are growing faster, since marginal returns to human capital are larger for those individuals with a lower aversion to effort.

Two last comments are in order. First, the effect of the different sources of inequality on the economy depends greatly on the degree of meritocracy of the economy. Assume, for example, the extreme case of a pure meritocratic society, i.e., $\psi = 0$. In this case, it is easy to show that $T_0(a)$ does not affect growth ($b_a = 0$), while the impact of $T_0(\gamma)$ is maximum ($b_\gamma = 1/\beta$). Second, our main results do not depend on the log-normality assumption for $a(i)$, $\gamma(i)$ and $\tilde{h}_{-1}(i)$ and do not rely on any particular channel. Assumptions about market imperfections, rent-seeking activities, political economy functioning, unobservable effort or individual talent are not required. In this manner,

[19] Because of the concavity of the human capital accumulation function, there is zero growth in the steady-state. Regarding the steady-state level for y_t, y_∞, it can be shown that $ln\, y_\infty = \frac{1}{1-b_h}\left[b_0 - b_a T_0(a) + b_\gamma T_0(\gamma)\right]$. As for the growth rate along the transition, $T_0(a)$ is harmful for real per capita income in the long-run, while $T_0(\gamma)$ is beneficial. Moreover, since human capital is globally stable, its initial inequality, $T_0(\tilde{h}_{-1})$, has no effect on y_∞.

our setting provides a broader perspective to understand the existing ambiguous relationship between overall inequality and growth.

INSERT FIGURE 2 ABOUT HERE

2.2. *A non-convex process for human capital*

The previous section presented a model of human capital where initial inequality in parental human capital, $T_0(\tilde{h}_{-1})$, did not have any permanent effect on the economy. The reason is that the steady-state of human capital −and thus of income− is globally stable. While this characteristic of the model is reasonable for rich economies, an extensive literature has emphasized the relevance of considering non-convex frameworks with poverty traps for less developed and developing countries (Azariadis and Stachurski, 2005). Accordingly, we assume a simple non-convex accumulation process of individual human capital:

$$\tilde{h}(i) = \begin{cases} \bar{h} & w\tilde{h}_{-1}(i) \leq \bar{w} \\ \theta(i)^{\psi} e(i)^{1-\psi} & w\tilde{h}_{-1}(i) > \bar{w} \end{cases}, \tag{18}$$

where $0 < \bar{h} < \min_i \{\theta(i)^{\psi} e(i)^{1-\psi}\}$ is a sufficiently small value of human capital, common to all dynasties and economies, and $\bar{w}$ is an absolute poverty line.[20]

The dynasty is trapped when its initial human capital is not large enough, i.e., $\tilde{h}_{-1}(i)$ is not greater than $\bar{w}/w$. In this case, the optimal effort decision is $e(i) = 0$, and the solution is trivial (allocations denoted with a 0 superscript): $e^0(i) = 0$, $\tilde{h}^0(i) = \bar{h}$, $w^0(i) = w\bar{h}$, $c^0(i) = \eta w\bar{h}$, $x^0(i) = (1-\eta)w\bar{h}$ and $u^0(i) = w\bar{h}$.[21] In this non-convex setting, the probability of being trapped,

$$p = \Pr\left[w\tilde{h}_{-1}(i) \leq \bar{w}\right] \tag{19}$$

can be interpreted as a headcount ratio (Sen, 1997). When the individual is not trapped, the solution is given by (10)-(12). Hence, the dynamics of human capital is

$$\tilde{h}_t(i) = \Omega\left[\tilde{h}_{t-1}(i)\right] = \begin{cases} \bar{h} & w\tilde{h}_{-1}(i) \leq \bar{w} \\ \zeta\left[\tilde{h}_{t-1}(i)\right] & w\tilde{h}_{-1}(i) > \bar{w} \end{cases}, \tag{20}$$

[20] For the sake of simplicity, we assume that $\bar{h}$ is exogenous and common to all dynasties. A more sophisticated model, beyond the scope of this paper, would consider $\bar{h}$ to be related, for example, to funds provided by the public sector, and be dynasty and/or country specific.

[21] When using a nutrition-based history to motivate the existence of poverty trap (Banerjee and Duflo, 2011), we find that below certain levels of income the individual is unwilling to increase her capacity to produce.

where $\zeta\left[\tilde{h}_{t-1}(i)\right]$ is given by (13) with $\zeta' > 0$ and $\zeta'' < 0$, and $\Omega[0] = \bar{h}$. Because $\bar{h}$ is sufficiently small, it is true that $\zeta[\bar{h}] > \bar{h}$ so $\Omega[\cdot]$ is strictly increasing and concave in $\tilde{h}_{t-1}(i)$ (see Figure 3).

INSERT FIGURE 3 ABOUT HERE

A direct implication of the non-convexity of $\Omega\left[\tilde{h}_{t-1}(i)\right]$ is the multiplicity of steady-states in (20): one low, common to all dynasties, given by $\bar{h}$, and another high, dynasty specific, given by the solution of $\tilde{h}_{\infty}(i) = \zeta[\tilde{h}_{\infty}(i)]$, as provided in (14).[22] Thus, depending on whether $\tilde{h}_{-1}(i)$ is below or above $\bar{w}/w$, the dynasty will end up converging to either $\bar{h}$ or $\tilde{h}_{\infty}(i)$, respectively. Moreover, using the definition $h(i) = \frac{1}{\pi} ln\left(\tilde{h}(i)\right)$, the expected years of schooling of the economy is:

$$h_t = p\frac{1}{\pi} ln\left(\bar{h}\right) + (1-p)E\left[\xi[h_{t-1}(i)]/w\tilde{h}_{-1}(i) > \bar{w}\right], \tag{21}$$

where $\xi[h_{t-1}(i)] = \frac{s}{(\beta+\psi)\pi} + b_h h_{t-1}(i) + \frac{b_a}{\pi}\ln a\,(i) - \frac{b_\gamma}{\pi}\ln\gamma\,(i)$. Note that the headcount ratio, p, affects negatively the mean years of schooling h because $E\left[\xi[h_{t-1}(i)]/w\tilde{h}_{-1}(i) > \bar{w}\right] > \frac{1}{\pi} ln\left(\bar{h}\right)$.

Following a similar reasoning to the convex case, we obtain a growth equation for the non-convex setting (see Appendix A1 for details):

$$g_{y_t} = b_0 - [1-(1-p)b_h]ln(y_{t-1}) - b_p p - b_a(1-p)T_0(a)$$
$$+b_\gamma(1-p)T_0(\gamma) + b_h^{t-1}\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)\left[2T_o(\tilde{h}_{-1})\right]^{\frac{1}{2}}, \tag{22}$$

where $b_p = b_0 - \frac{\lambda ln\left(\frac{\lambda}{\bar{r}}\right)+lnA}{1-\lambda} - ln\bar{h}$ and $\phi(\cdot)$ is the standard normal density function of the random variable $X = ln\tilde{h}_{-1}(i) - ln(\bar{w}/w)$ with mean μ_X and standard deviation Δ_{-1}.

[22] Non-convexities and multiple steady-state equilibria have traditionally been justified in the context of imperfect credit markets (Banerjee and Newman, 1993; Galor and Zeira, 1993). However, multiple equilibria are also possible when there are no convexities if credit markets are imperfect and the marginal propensity to save is higher for richer dynasties (Galor and Moav, 2004). We assume instead the process in (18), which makes the role of parental human capital explicit.

First, notice that the result in (17) is a particular case of this more general framework when $p = 0$.[23] Accordingly, results derived from the human capital convex model can be associated to economies with zero headcount poverty rates.[24] Second, poverty is harmful for economic growth, i.e., $\frac{\partial g_{y_t}}{\partial p} < 0$ (see Appendix A2). This finding is consistent with the empirical result found by López and Servén (2009), Ravallion (2012) and Marrero and Servén (2018).

Third, for the general case $p < 1$, $T_0(a)$ and $T_0(\gamma)$ are again harmful and beneficial for growth, respectively. Hence, the result found for the convex setting is maintained. The short-run elasticities are now $-(1-p)b_a$ and $(1-p)b_\gamma$, while the long-run elasticities are equal to these terms divided by $1-(1-p)b_h$. However, notice that for extremely poor economies, where p is close to one, the impact of $T_0(a)$ and $T_0(\gamma)$ tends to disappear, therefore the only way to foster growth in this situation is by reducing the headcount poverty ratio.

Finally, the initial inequality of human capital, $T_0(\tilde{h}_{-1})$, now influences growth through three alternative avenues. As in the setting without poverty trap, there is an indirect and transitory effect through lagged income, which favors conditional convergence since marginal returns to human capital are decreasing. The second is a direct effect (see the last term in (22)), which is transitory and positive: a higher $T_0(\tilde{h}_{-1})$ increases the human capital accumulated by the rich (non-trapped) individuals.[25] The third is an indirect effect (through poverty), which is permanent but ambiguous. We prove that $T_0(\tilde{h}_{-1})$ harms growth by increasing the poverty rate p if and only if $p < \Phi(\Delta_{-1})$, i.e., the economy is not extremely poor (see Appendix A3). Only for countries with a large proportion of poor people, $p > \Phi(\Delta_{-1})$, does an increase in the initial dispersion of human capital reduce the number of poor people and, consequently, economic growth

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[23] Note that $\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right) = 0$ when $p = 0$ because p is equivalent to the value of the standard normal cumulative distribution function, Φ, of X for 0, i.e., $p = \Phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)$, by definition.

[24] Using the widely used poverty line of 1.90 US$/person-day (at 2011 PPP values), all OECD countries show a zero level for p, while a big fraction of South American and South East Asian countries present small levels of p.

[25] Using standard calculus $\left(\frac{\partial \phi(z)}{\partial (z)} = -z\phi(z)\right)$, it can be proven that $\frac{\partial\left[b_h^{t+1}\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)[2T_0(\tilde{h}_{-1})]^{\frac{1}{2}}\right]}{\partial T_0(\tilde{h}_{-1})} > 0$. However, this effect is transitory because $b_h < 1$.

increases because the poor individuals with the highest initial human capital are able to escape from the trap.[26]

3. Empirical approach to test the cholesterol hypothesis

Following the recent empirical literature on inequality and growth (Berg et al., 2018; Brueckner and Lederman, 2018), the usual reduced form to test for the impact of inequality on growth is the following:

$$g_{it} = \alpha_i + \delta_t + \beta lny_{it-1} + \varphi I_{it} + \varepsilon_{it}, \quad (23)$$

where g_{it} denotes the growth rate in per capita income for country i between the periods $t-1$ and t (usually, 5 or 10 years), α_i and δ_t denote country- and time-specific effects, lny_{it-1} is the log of per capita income in country i at period $t-1$, I_{it} is an index of overall inequality in country i at year t, and ε_{it} is an *iid* error term.[27]

However, our theoretical framework suggests that we should estimate a different growth equation. For the case where the sample does not contain countries with high poverty rates, the econometric specification, based on (17), must be:

$$g_{it} = \alpha_i + \delta_t + \beta lny_{it-1} + \varphi_{IO} IO_{it} + \varphi_{IE} IE_{it} + \varepsilon_{it}, \quad (24)$$

where IO refers to the part of inequality arising from differences in exogenous circumstances, while IE is that part of inequality arising from pure effort. If the measures of IO and IE are accurate, the coefficients φ_{IO} and φ_{IE} will be closely related to b_a and b_γ in (17), so that we would have $\varphi_{IO} < 0$ and $\varphi_{IE} > 0$ under the cholesterol hypothesis. In fact, this is the result that Marrero and Rodríguez (2013) found for the U.S., where we estimated equation (24) for a panel of 26 U.S. states and three decades (1970-2000).

[26] For the steady-state, setting $g_{y_t} = 0$ and taking limits for $t \to \infty$ in (22), the level of income (in logs) is $ln\, y_\infty = \frac{1}{1-(1-p)b_h}\left[b_0 - b_p p - b_a(1-p)T_0(a) + b_\gamma(1-p)T_0(\gamma)\right]$. We find again that $T_0(a)$ and $T_0(\gamma)$ have, respectively, a negative and a positive impact on the per capita income at steady-state. In addition, it can be shown that $\frac{\partial ln\, y_\infty}{\partial p} = -\frac{1}{1-(1-p)b_h}\left[E[ln\zeta(h_\infty(i))] - ln\bar{h}\right]$ is always negative. Finally, for non-extremely poor economies (i.e., $p < \Phi(\Delta_{-1})$), $T_0(\tilde{h}_{-1})$ increases p and, therefore, harms per capita income levels in the long run.

[27] In addition to these variables, the literature usually includes an array of other controls. However, in this parsimonious setting, the estimated coefficients better capture the global (direct and indirect) effect of inequality and poverty on growth (Galor, 2009). Moreover, in the empirical application, we want to be close to our theoretical framework, which does not consider any channel and hence does not include any additional control in the reduced form growth equations (17) and (22).

For the case where the sample contains countries with high poverty rates, the econometric model, now based on (22), must be:

$$g_{y_{it}} = \alpha_i + \delta_t + \beta lny_{it-1} - \delta p_{it} + \varphi_{IO} IO_{it}(1 - p_{it}) + \varphi_{IE} IE_{it}(1 - p_{it}) + v_{it}, \quad (25)$$

where p_{it} is the headcount poverty ratio. In this specification, we include the effect of poverty and its interaction with the different components of inequality. Because the last term in (22) is transitory, we assume that its effect is captured by the fixed effects and the error term. In both cases (equations (24) and (25)), the cholesterol hypothesis implies that $\varphi_{IO} < 0$ and $\varphi_{IE} > 0$.

Obtaining accurate estimations of IO and IE is, however, very difficult in practice, especially for a large set of countries, because the relevant set of individual circumstances is never fully observed, so researchers must rely on a lower-bound estimation of IO (Ferreira and Gignoux, 2011). Another consequence of this fact is that the estimation of IE will be contaminated with unobserved circumstances, which in practice invalidates the use of this component as a proxy of inequality of pure effort.[28] Therefore, we face the following dilemma: we can estimate (23), but we must estimate (24) or (25), depending on the sample under consideration. In this situation, our greatest aspiration is to have proper measures of overall inequality and poverty, and a convenient proxy of IO. Is this information enough to test the cholesterol hypothesis? Our answer is positive, and to illustrate this, we focus, without loss of generality, on the model excluding poverty.

Suppose that $IO_{it} = Q_{it} + V_{it}$, where Q_{it} is a feasible proxy of IO for country *i* at time *t*, and V_{it} is the non-observed (or non-measurable) part of IO. Also, assume that both terms, Q_{it} and V_{it}, can be expressed as shares of overall inequality, i.e., $Q_{it} = q_{it} I_{it}$ and $V_{it} = v_{it} I_{it}$, where $q_{it}, v_{it} \in [0, 1]$. Then, by combining these definitions with (24), we obtain

$$g_{it} = \alpha_i + \delta_t + \beta lny_{it-1} + \varphi_{I1} I_{it} + \varepsilon_{it}, \quad (26)$$

where $\varphi_{I1} = [\varphi_{IE} + (\varphi_{IO} - \varphi_{IE})(q_{it} + v_{it})]$. Under the cholesterol hypothesis (i.e., $\varphi_{IO} < 0$ and $\varphi_{IE} > 0$), the coefficient of I_{it}, φ_{I1}, can be positive, negative or null,

[28] Databases with large number of circumstances are typically available only for developed countries (Marrero and Rodríguez, 2012). Meanwhile, databases that contain measures of IO for a large number of countries tend to be heterogeneous across countries with a different number and type of circumstances, different dependent variables (income and expenditure), and different sources (survey and taxes) (Ferreira et al., 2018).

depending on the relative strength of the IO and the IE components. This result explains the existing controversy about the sign of the inequality-growth relationship, as highlighted in the Introduction.

From the previous expression, we can also derive the following inequality-growth equation:

$$g_{it} = \alpha_i + \delta_t + \beta lny_{it-1} + \varphi_{I2} I_{it} + \varphi_Q Q_{it} + \varepsilon_{it}, \tag{27}$$

where $\varphi_{I2} = \varphi_{IE} + (\varphi_{IO} - \varphi_{IE})v_{it}$ and $\varphi_Q = \varphi_{IO} - \varphi_{IE}$. Again, under the cholesterol hypothesis, the coefficient φ_{I2} of I_{it} can be positive, negative or zero, although it is larger than φ_{I1}. In addition, the coefficient of Q_{it}, φ_Q, is always negative.[29]

Hence, despite the fact that expressions (24) and (25) cannot be estimated, we can test for the cholesterol hypothesis because under the null that $\varphi_{IO} < 0$ and $\varphi_{IE} > 0$, we should find that $\varphi_{I2} > \varphi_{I1}$ and $\varphi_Q < 0$ when comparing (26) and (27).

When poverty is considered, the reduced forms would be:

$$g_{it} = \alpha_i + \delta_t + \beta lny_{it-1} + \lambda p_{it} + \varphi_{I1}(1 - p_{it})I_{it} + \varepsilon_{it} \tag{28}$$

and

$$g_{it} = \alpha_i + \delta_t + \beta lny_{it-1} + \lambda p_{it} + \varphi_{I2}(1 - p_{it})I_{it} + \varphi_Q(1 - p_{it})Q_{it} + \varepsilon_{it}. \tag{29}$$

In this case, the tests for the cholesterol hypothesis are the same but, in addition, we can test whether poverty is harmful for growth, i.e., $\lambda < 0$, in line with the related literature (López and Servén, 2009; Ravallion, 2012; Marrero and Servén, 2018).

4. Data: growth, inequality and the IO proxy

In this section we describe the dataset used, paying special attention to the construction of an alternative proxy for IO to those existing in the literature. We use the basic inequality-growth model in Berg et al. (2018) as our starting point. Thus, as these

[29] In the literature on inequality and growth, measures of IO and IE are hardly used. Our results suggest that the sign and size of the coefficient of total inequality could depend on the set of controls included in the regression. Thus, if this set of controls is more related to IO, the coefficient of total inequality will increase (in comparison with the value obtained when these controls are not included) because now overall inequality captures the effect of IE to a greater extend. On the contrary, if the set of controls is more related to IE, the opposite will happen. In this line of enquiry, Birdsall et al. (1995) found that the sign of the coefficient may depend on the controls under consideration, however, they did not provide any theoretical explanation for this result.

authors, we take the per capita real output from the PWT 7.1, and the inequality measure (net income Gini coefficient) from the SWIID 3.1 (Solt, 2016). In addition, the poverty indices (absolute headcount ratio with 1.90 US$ poverty line) are from the POVCAL-Net (Ferreira et al., 2016).[30] Using information every 5 years between 1960 and 2010, we initially construct a strongly balanced panel with 688 observations, for a total of 140 countries and 10 periods.

To obtain a proxy of IO (Q in equations (27) and (29)), we adopt two strategies. First, we use the largest set of available IO indices across countries obtained by Ferreira et al. (2018) from two panel data sets, the Income and Expenditure Survey (IES) and the Demographic and Health Survey (DHS). Second, we propose an approach to construct an alternative IO proxy to cover a larger set of countries and years. Thus, our final dataset results from merging these three proxies of IO (from the IES, the DHS and the alternative samples) with our previously collected inequality, growth and poverty measures.

For each sample, Table 1 shows the descriptive statistics of the key variables (growth, poverty, inequality and the IO proxy) in the regressions (26)-(29). While descriptive statistics for growth, poverty (the headcount rate) and inequality (the Gini index) are directly comparable for the three samples, they are not for the alternative IO proxy because they are constructed using different sources, methodologies and indices, as discussed shortly. Far from being a problem, this fact will allow us to develop an additional robustness check for the cholesterol hypothesis.

The first sample (IES) contains 42 countries −both developed and developing– for a total number of 115 observations.[31] The variable used to calculate IO was net household income per capita for 32 countries and household expenditure per capita for the other 10 countries. The whole set of circumstances was gender, race or ethnicity, the language spoken at home, religion, caste, nationality of origin, immigration status and region of

[30] If there is no information about poverty in a given year, we use the nearest available year to maximize the number of observations.

[31] The authors used three harmonized meta-databases: 23 (mostly developed) countries from the Luxembourg Income Study (LIS), 6 Latin American countries from the Socioeconomic Database for Latin America and the Caribbean (SEDLAC), and another 10 developing economies from the International Income Distribution Database from the World Bank (I2D2). For the remaining three countries, they used the respective national household surveys.

birth.[32] However, the number and kind of circumstances and the number of types (groups of people with the same circumstances) differed significantly across countries.

The second sample (DHS) contains 39 developing countries from Africa, Asia and Latin America for a total number of 114 observations. For the DHS, since it does not contain estimates of household income or expenditure, the authors constructed a wealth index (the first principal component of a set of indicators on assets and durable goods owned, dwelling characteristics, and access to basic services). Here, the set of circumstances was region of birth, number of siblings, religion, ethnicity, and mother tongue. Again, the list of circumstances varied significantly from country to country.

In accordance with Table 1, the remarkable differences between these two samples are clear. For the IES sample, the average poverty rate is 7.9% (with a standard deviation of 14%); 55% of the country-years observations showing a poverty rate equal to zero and the 75% below 12%. However, for the DHS sample, the average poverty rate is above 40% (with a standard deviation of 23.1%); all observations show positive poverty rates and 25% of the observations show a rate above 60%. The average levels of the Gini coefficient are also quite different: 34.4% for the IES sample and 44.7% for the DHS sample, consistent with the fact that the highest levels of inequality are associated with less developed or developing countries. Finally, their average GDP growth rates are also consistent with the observed divergence between poor and rich countries over the last 50 years: 2.2% for the IES sample and 1.6% for the DHS.

INSERT TABLE 1 ABOUT HERE

These notorious differences put forth that, while it would be reasonable to use the model specification without poverty (equations (26) and (27)) for the IES sample, we must focus on the specification with poverty (equations (28) and (29)) for the DHS sample because, otherwise, we would incur misspecification problems.

However, these two samples have two limitations in common: a reduced coverage of countries for a worldwide analysis, and a small within-group variability of the IO proxy (around 20% of the between group variability, see Table 1). These shortcomings make it difficult to exploit the time dimension of the panel dataset. In addition, as emphasized

[32] The authors used the current region of residence for those countries where the birth region was unavailable.

above, the resultant IO indices lack homogeneity, in terms of data sources, variables of analysis, circumstances and types.

For all these reasons, to increase the reliability of our results, we try to find empirical evidence by using an alternative IO proxy. To this end, we propose a strategy to estimate an alternative IO proxy that more than triple the sample size and the within group variability of the sample (see column 3 in Table 1). Because this new sample contains countries belonging to the whole spectrum of the development process, its statistics are in between those for the IES and the DHS samples.

4.1. An institutional-induced inequality measure to proxy IO

Our proposal is supported by two results in the literature. As a first result, we know from Milanovic (2015) that macroeconomic factors, which are beyond the individual control, are important determinants of the *global inequality of opportunity*. As a second result, it has been found that certain macroeconomic variables, such as the quality of institutions and ethnic-linguistic and religious fractionalization, influence the capacity of individuals to assume positions of power through individual effort rather than patronage (nepotism) and to achieve a given socioeconomic status (Alesina et al., 2003; Stiglitz, 2012; Acemoglu et al., 2015). Consequently, bad institutions, as reflected by deficient levels of democracy or excessive levels of corruption, or the existence of ethnic-linguistic or religious division, could be the origin of part of the IO observed in a particular country.

Following these ideas and in the same spirit as Fatás and Mihov (2003), we propose a chain through which institutions and social (ethnic-linguistic and religious) division might affect IO and subsequently inequality and growth:

Institutional setup and social division
↓
Inequality of Opportunity
↓
Overall Inequality
↓
Growth

Differences in the institutional setup and social division generate IO. Since IO is a component of total inequality, the latter is indirectly affected by the institutional setup and social division. Finally, the institutional-induced IO component of overall inequality affects future economic growth. Since IO is not observed in this chain, our strategy explores an alternative way of judging the importance of part of IO in affecting growth through inequality. To this end, as in Fatás and Mihov (2003), we construct a fitted value for overall inequality (net income Gini coefficient) based on a political economy regression that includes: *democratic accountability* (how responsive the government is to its people); *law and order*; *corruption*; *religious division*; and, *ethnic-linguistic division*. All these variables −considered at 5-year intervals from 1985 through 2015− come from the Political Risk Module of the International Country Risk Database (ICRD), which is available from 1985 on.

We are conscious that the institutional setup and social division may affect growth through alternative channels other than the IO-inequality channel. To control for this possibility and, therefore, to isolate the IO-inequality channel, we also include in the political economy regression the growth rate of real GDP per capita. At the country-level, the part of overall inequality (Gini) fitted by the aforementioned variables from the ICRD database is taken as our alternative proxy of IO.[33]

Table 2 displays for different political economy regressions the estimates from pool-OLS and system-GMM.[34] Separately, the five variables are statistically significant (columns 1-5) and with the expected sign: negative for *democratic accountability* and *law and order, and positive for corruption, religious division* and *ethnic-linguistic division*. However, the high correlation of democratic accountability and law and order with corruption (-0.5175 and -0.6296, respectively) causes the last variable to be non significant when the three institutional variables are included together (column 6). When all the relevant variables are included in the same model (columns 8-11), democratic accountability and law and order maintain their significant and negative effects on overall inequality. Corruption and religious division have a positive and a negative effect on inequality, respectively, although these effects are significant only for pool-OLS. In sum, it seems that a society with better institutions and more diversity of religions can provide more opportunities to its citizens and, in this manner, reduce overall inequality (through IO).

INSERT TABLE 2 ABOUT HERE

[33] A similar procedure, but at an individual level, is typically applied in the IO literature: an OLS regression between income and a set of factors beyond individual's responsibility is run, and then, the fitted part of income is latterly used to calculate the proxy of IO (Ferreira and Gignoux, 2011; Marrero and Rodríguez, 2011 and 2017).

[34] System-GMM specifications are calculated with all lags starting at *t*-2 under the 2-stage version, and the variance-covariance matrix is computed using the small sample correction of Windmeijer (2005).

It is worth mentioning that, in spite of the fact that economic growth has a negative and significant effect on overall inequality (columns 9 and 11), the correlation between the institutional-induced inequality fitted levels (the IO proxy) for the results in columns (8) and (9) is 0.999, while the correlation between the models in columns (10) and (11) is 0.9610.[35] Thus, these minor differences imply that the results in the next section will be robust to any alternative IO proxy estimated from the results in columns (8)-(11). Also, as said, the alternative strategy allows us to obtain a homogeneous sample with a much larger sample size and a higher within-country variability (see column 3 in Table 1). For this sample, our IO proxy (the fitted level of inequality) positively correlates with overall inequality (the Gini), with a coefficient of determination (R^2) of 0.231 (Figure 4), which is a little bit lower than the correlations observed in the literature for developed economies (Marrero and Rodríguez, 2012 and 2013; Brunori et al., 2013).

INSERT FIGURE 4 ABOUT HERE

To end this section, we carry out a simple exercise to illustrate the potentiality and validity of our approach to obtain a proxy of IO. Remember that we are not looking for a perfect measure of IO, which is impossible, but for a proxy of it. In our case, the attempt is to estimate the fraction of the country IO that is generated by differences in the institutional setup and social divisions. When comparing overall inequality (Gini coefficient) with the IO proxy from the IES and DHS samples, it is observed a positive correlation in both cases with a coefficient of determination (R^2) equal to 0.402 (significant) for the IES and 0.014 (non significant) for the DHS (see Figure 5, top panel). However, when comparing our alternative IO proxy with the fitted part of the IO indices from the IES and DHS samples explained by the same macroeconomic factors, we find much higher correlations, 0.858 (strongly significant) for the IES sample and 0.159 (significant) for the DHS sample (Figure 5, bottom panel). Therefore, we can conclude that overall inequality is in general a poor predictor of IO, although its capacity to predict IO greatly increases when both inequality and IO are conditioned to the institutional setup and social division macroeconomic channels.

INSERT FIGURE 5 ABOUT HERE

[35] Comparing the alternative econometric techniques, pool-OLS and system-GMM, the correlation is 0.8113 when income growth is not included (models (8) and (10)) and 0.8559 (models (9) and (11)) otherwise.

5. The empirical results: Testing the cholesterol hypothesis

In this section, we estimate the reduced forms in (26)-(29) and check if the cholesterol hypothesis is fulfilled by comparing the estimates under the models with and without the IO proxy. Following the strategy described in Section 3, we should observe a negative coefficient for the IO proxy, and a higher coefficient for the Gini coefficient when the IO proxy is included in the model. Next we describe the econometric approach, then, we present our main results.

5.1.- The econometric approach

To estimate the reduced-form equations, we consider an instrumental variable (IV) approach as our preferred procedure. For comparability reasons and for the sake of robustness, we also show results for pooled-OLS and system-GMM. We include time-fixed effects in all models, but do not consider country-fixed effects for the IES and the DHS samples because of their small within-country variability, as commented above (Table 1). For these two samples, country-fixed effects would capture almost 100% of the conditional relationship between the endogenous variable and the IO proxy. However, for our alternative sample of IO indices, which possesses a much higher within-country variability, we consider both time dummies and country-fixed effects.

First, we show results for pool-OLS. This approach generates, however, biased estimates when double causality exists between inequality and growth. To avoid this reverse causality bias, we adopt an IV approach following Brueckner et al. (2012; 2015) and Brueckner and Lederman (2018). Thus, we instrument our target variables −Gini (G) and IO-proxy (Q)− as follows: the instruments $Z_{G,it}$ and $Z_{Q,it}$ are the parts of the Gini coefficient and the IO-proxy that are not explained by the log of per capita income, i.e., $Z_{G,it} = G_{it} - \hat{\beta}_{G,IV} lny_{it}$ and $Z_{Q,it} = Q_{it} - \hat{\beta}_{Q,IV} lny_{it}$.

One key element when applying this approach is that $\hat{\beta}_{G,IV}$ and $\hat{\beta}_{Q,IV}$ must be obtained from the auxiliary regressions $G_{it} = \alpha_i + \delta_t + \beta lny_{it} + \varepsilon_{it}$ and $Q_{it} = \alpha_i + \delta_t + \beta lny_{it} + \varepsilon_{it}$ estimated by 2SLS. Otherwise, the aforementioned approach would lead to bias estimates. For these auxiliary regressions, we use the following instruments for

lny_{it}: the lagged ($t-1$ and $t-2$) levels of the saving rate (Acemoglu et al., 2008) and the income growth rate (Fatás and Mihov, 2003; Aiyar and Ebeke, 2019).[36]

For the three samples considered (IES, DHS and ICRD), the values of the first-stage Kleibergen-Paap F-statistic to test for the weakness of the set of instruments are: 21.98 for the IES sample, 13.82 for the DHS sample and 15.51 for the ICRD sample. These values are well above 10 (the rule of thumb) and also exceed the Stock and Yogo (2005) critical values. Consequently, we reject the null of weak instruments for lny_{it} in the three cases. In addition, we calculate the Hansen *J* overidentifying test. For the IES sample, the p-values are 0.5997 for the Gini coefficient and 0.7380 for the IO-proxy; for the DHS sample, the p-values are 0.7718 for the Gini and 0.9910 for the IO-proxy; and for the ICRD sample, the p-values are 0.4892 for the Gini and 0.4047 for the IO-proxy. Therefore, the p-value is well above 0.1 in all cases, which suggests that we cannot reject the hypothesis that the instruments are valid.[37]

In addition to pool-OLS and IV, we estimate our reduced forms by system-GMM to check for robustness. The system-GMM estimator employs internal instruments to deal with the endogeneity of regressors and their validity is tested using an overidentifying Hansen *J*-test. Moreover, the proliferation of instruments (a common fact in system-GMM) tends to introduce additional overidentifying problems, which may call for a reduction of the instruments count (Roodman, 2009). With this in mind, our system-GMM specifications consider only two lags of instruments, starting at t-2, and the variance-covariance matrix is computed using the small sample correction of Windmeijer (2005).

[36] For the DHS sample, we exclude the two GDP growth lags, because otherwise the estimation does not pass the overidentifying restriction test. In all cases, alternative instruments like the lagged trade-weighted world income (Acemoglu et al., 2008) and the oil price shocks (Brueckner et al., 2012; 2015) were also considered. The trade-weighted world income is calculated from a matrix of trade shares where the predicted income of each country is a function of the trade flows of the country with the rest of countries in the world. The oil price shocks are the changes in international oil prices interacted with countries' net-export shares of oil relative to GDP. However, they did not pass the corresponding weak instruments and/or overidentifying restriction tests.

[37] Our results for the alternative ICRD sample refer to the IO-proxy obtained from the results in column (11) in Table 2. Nonetheless, results are robust to the use of the IO-proxy estimates from the results in columns (8), (9) and (10) in Table 2. In addition, notice that for the inequality-growth regressions (26)-(29) we cannot apply an overidentifying test because these models are exactly identified. Nevertheless, the correlation between the residuals in (26)-(29) and the instruments Z_G and Z_Q is very small by construction. As shown in the corresponding tables of results (Tables 3, 4 and 5) these instruments are not weak.

5.2.- Estimation results

We present the estimation results of equations (26)-(29) for the three samples under consideration (IES, DHS and ICRD) and three alternative econometric methods (pooled OLS, IV and system-GMM). For each case, the first two columns correspond to the reduced forms in (26) and (27) without poverty trap. In the first column, we only include overall inequality, while in the second column we also consider the IO proxy. The next two columns show the results for the reduced forms in (28) and (29) which include poverty. Overall inequality interacts with poverty in the third column, while the interaction between the IO-proxy and poverty is also included in the fourth column.

First, Table 3 shows the results for the IES sample. Recall that this sample includes developed countries and developing countries with small absolute poverty rates. Hence, the relevant reduced forms for this sample are equations (26) and (27). Second, Table 4 shows the results for the DHS sample, which includes less developed countries and developing countries with high absolute poverty rates. Hence, in this case, the relevant reduced forms are (28) and (29), which include poverty and the interaction of poverty with inequality and the IO proxy. Finally, Table 5 shows the results for the alternative ICRD sample. The set of countries included in this sample covers the whole range of poverty, from zero to extreme poverty, so the pertinent reduced forms are also (28) and (29).

For the IES sample, the coefficient of the IO proxy is always negative and significant at the 5% level of significance (Table 3). Moreover, the coefficient of overall inequality that is negative for equation (26) (and significant for pool OLS) turns positive (and even significant under system-GMM, see last column in Table 3) when the IO proxy is included in the regression. In accordance with the empirical strategy described in Section 3, these results do not reject the cholesterol hypothesis. In addition, it is worth mentioning that for this sample, poverty is not significant in any specification. As Marrero and Servén (2018) found, the negative effect of poverty on growth is restricted to samples with sufficiently high poverty rates. Quantitatively, the estimated results point out that a decrease in one standard deviation of the IO proxy (0.0463, see Table 1), i.e., moving from an IO level similar to the one in Peru or Brazil to level related with countries like the U.S. or Italy, is associated with an increase in per capita annual GDP of 0.68 percentage points (0.0463 x -0.147) which would imply, for example, a change from the sample average 0.0220 to an annual growth rate of about 0.0288.[38]

For the DHS sample, the results are, in principle, not so evident in favor of the cholesterol hypothesis, most likely because of the lesser precision of the IO estimates in this case. Nonetheless, they reveal an interesting fact. When poverty is not included in the model, the coefficient of overall inequality is negative and significant for pooled OLS and system-GMM (non-significant for IV) and it changes little when the IO proxy is included; the estimated coefficient of the IO proxy is non-significant in this case. However, when the model includes poverty, these results become similar to those obtained for the IES sample. According to our theoretical framework, this latter specification is precisely the one that should be estimated when the sample contains a large fraction of countries with high poverty levels as is the case with the DHS sample. In this case, the coefficients of the IO proxy are negative and significant in all cases, while the coefficients of overall inequality now increase when the IO proxy is included in the model. Again, our results do not reject the cholesterol hypothesis. Quantitatively, the estimated results suggest that a decrease in one standard deviation of the IO proxy (0.4949, see Table 1), i.e., moving from an average level similar to the one observed in Cameroon or Madagascar to a level similar to that for Nepal or Ethiopia in 2005, is associated with an increase in per capita real GDP of 0.68 percentage points (0.4949 x -0.0137). This finding would imply, for example, moving from the observed average growth rate, 0.0159, to a growth rate level of about 0.0227. Although the precision of the estimations is lower, the impact is basically the same to the one obtained for the IES sample.

Unlike our results, the study carried out by Ferreira et al. (2018) using the IES and DHS samples did not find a robust negative and significant effect of IO on growth. Why might this happen? We find at least four main differences between their approach and ours. First, we use different data sources. In particular, following Acemoglu et al. (2008) and Berg et al. (2018), we use inequality indices from the SWIID 3.1 in Solt (2016) and per capita real output from the PWT 7.1. Second, the specification of our econometric model is also different. We adopt the specification suggested by the theoretical model developed in Section 2, which includes the interaction between

[38] Since the qualitative results are robust to the econometric approach under consideration, our quantitative comments are based on the IV results.

poverty and the inequality terms. Moreover, the controls are not lagged, following Berg et al. (2018) and Brueckner and Lederman (2018). Third, we use an Instrumental Variable approach (Brueckner et al., 2012) to control for a potential double causality problem in the inequality-growth relationship. Fourth, by focusing on the additive decomposition of overall inequality into IO and IE, Ferreira et al. (2018) tried to find a negative effect for IO and a positive effect for IE (residual inequality) on growth. On the contrary, for the reasons exposed in Section 3, we have proposed an alternative strategy to test the cholesterol hypothesis, which is less demanding than that in Ferreira et al. (2018).

To end this section, we discuss the results for our alternative sample.[39] They are also consistent with the cholesterol hypothesis. Thus, the coefficient of the IO proxy is always negative and significant, while the coefficient of overall inequality tends to increase when the IO proxy is included in the regression. The coefficient of poverty is always negative and significant and the differences between the estimated coefficients of the IO proxy when including poverty or not in the model are small. Quantitatively, the results are similar to those obtained for the IES and DHS samples. Looking at the model with poverty for the IV approach, we obtain that a decrease in one standard deviation of the IO proxy (0.0511, Table 1), i.e., moving from an average level similar to the one observed in countries like Mali, Vietnam or Nigeria to a level observed in Italy or Lithuania is associated with an increase in per capita real GDP of 0.85 percentage points (0.0511 x -0.166). For example, this change would imply moving from the observed annual growth rate of 0.0185 to an annual growth level similar to 0.0270.

6.- Conclusions

The way overall income inequality affects economic growth is more complex than what the literature has commonly assumed. Thus, despite the huge number of papers devoted to studying this question, there is still no consensus in the literature. This lack of robustness has been typically attributed to the variety of channels –some of them growth-enhancing and others growth-deterring– through which inequality may affect

[39] Here we comment on the results for the IO proxy obtained from the results in column 11, Table 2 (system-GMM controlling by income growth). Nonetheless, the results for models in columns 8, 9 and 10 are similar as shown in Appendix A4 (Tables A4.1, A4.2 and A4.3).

growth. Instead, we have argued here that the cholesterol hypothesis is the main reason for this lack of robustness. This hypothesis states that the part of inequality generated by factors beyond the individuals' control, referred to as inequality of opportunity (IO), is growth-deterring, while the type of inequality generated by the difference in the willingness to exert effort, referred to as inequality of pure effort (IE), is growth-enhancing.

To defend this view, the proposal developed in this paper contributes to this key question in economics in three different ways. First, we propose a human capital model that explicitly highlights the different effects of alternative types of inequality on growth without relying on any particular channel. By including a poverty trap, our model also allows us to characterize the consequences for the cholesterol hypothesis of existing interactions between inequality and poverty. Second, because the decomposition of total inequality into the IO and IE components is in reality quite difficult, we propose an empirical strategy to test the cholesterol hypothesis at worldwide level. When the standard inequality-growth equation is extended with a proxy of IO, the estimated coefficient of inequality must increase, and the coefficient of the IO proxy must be negative. As a third contribution, we obtain the first empirical evidence at worldwide level for the cholesterol hypothesis. Despite some previous promising results at regional level (Marrero and Rodríguez, 2013; Bradbury and Triest, 2016; Teyssier, 2017), the only existing study at country level, Ferreira et al. (2018), was not decisive since no significant effect of IO on growth, either positive or negative, was found. However, our instrumental variable estimations did not reject the cholesterol hypothesis.

Compensating for bad circumstances would be growth enhancing given that marginal returns to human capital are higher for those individuals who have less favorable circumstances. Meanwhile, rewarding preferences for effort would enhance growth because the marginal returns to human capital are greater for those individuals with lower willingness to exert effort. Since total inequality is a combination of different types of inequalities with opposite impacts on growth, changes in inequality would be growth enhancing or growth deterring depending on which component of inequality dominates in the overall change. Moreover, poverty is found to be harmful to growth and the effect of the two aforementioned components of inequality on growth decreases with poverty. Thus, for very high levels of poverty, the impact of the inequality components on growth becomes irrelevant and reducing poverty is the only way to enhance growth.

This is not, however, the whole story extracted from this paper. To overcome the limitations of the existing IO indices at worldwide level, we have constructed an alternative proxy of IO by considering that the quality of institutions and ethnic-linguistic and religious division are relevant macroeconomic drivers of IO.

We have found that this is a relevant driver, and that the resultant IO proxy (an institutional adjusted level of inequality) harms growth. Given these results, improving the quality of institutions and reducing the ethnic-linguistic and religious division of a country could have a double benefit effect on the economy. It could reduce overall inequality (in fact, it seems to reduce the bad part of inequality) and, at the same time, through reductions in IO, could enhance economic growth. A detailed empirical analysis of this possibility at a more disaggregate level, is a promising avenue that future research should take for the sake of inclusive growth.

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Tables

Table 1. The descriptive statistics of the three samples.

		IES Sample	DHS Sample	Alternative Sample (ICRD)
Sample size		115	114	533
Number of countries		42	39	111
Growth rate:	Average	0.0220	0.0159	0.0185
	Standard deviation	0.0222	0.0275	0.0296
Headcount rate:	Average	0.0790	0.4080	0.1732
	Standard deviation	0.1436	0.2308	0.2363
Inequality – Gini:	Average	0.3440	0.4467	0.3878
	Standard deviation	0.0910	0.0814	0.1022
IO proxy:	Average	0.0250	0.5992	0.8252
	Standard deviation	0.0463	0.4949	0.0511
Std. within / between (%)		20.0%	16.5%	60.4%

Table 2. Inequality, quality of institutions, and social division.

(Dependent variable: net income Gini coefficient SWIID 3.1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Pooled-OLS									System GMM	
Democracy	-0.0284***					-0.00951***		-0.0110***	-0.0110***	-0.0146*	-0.0136**
	(-10.84)					(-3.16)		(-3.76)	(-3.85)	(-1.83)	(-2.25)
Law & Order		-0.0388***				-0.0305***		-0.0340***	-0.0315***	-0.0264***	-0.0257***
		(-17.38)				(-7.93)		(-9.17)	(-8.39)	(-2.99)	(-3.39)
Corruption			-0.0348***			-0.00492		-0.00720*	-0.00909**	0.0103	0.00139
			(-12.45)			(-1.16)		(-1.70)	(-2.11)	(1.20)	(0.20)
Religion division				-0.00507*			0.00129	0.0162***	0.0164***	-0.00957	-0.00885
				(-1.85)			(0.44)	(5.95)	(5.99)	(-1.06)	(-1.07)
Ethnic division					-0.0148***		-0.0153***	0.000600	0.00101	-0.000324	0.00647
					(-5.37)		(-5.11)	(0.22)	(0.38)	(-0.04)	(1.07)
GDP Growth									-0.433***		-0.397**
									(-3.19)		(-1.97)
Num. Obs	586	586	586	586	586	586	586	586	586	586	586
R2-adj	0.173	0.316	0.214	0.006	0.042	0.334	0.041	0.368	0.381		
Hansen (pvalue)										0.266	0.158
m2-pvalue										0.189	0.0874
Num. Cross-sections										127	127
Num. Instruments										71	112

Constant term and time dummies are included in all models.
Robust t statistics in parentheses. *** denotes significance at 1%, ** at 5%, * at 10%.
For system-GMM, estimations use instruments starting at *t*-2 and the variance covariance matrix is computed using the small sample correction of Windmeijer (2005).

Table 3. Growth, inequality and inequality of opportunity.
(IO proxy from the Income and Expenditure Surveys (IES) in Ferreira et al., 2018)

	Pooled-OLS				Instrumental Variable				System GMM			
log(y), lag	-0.00382**	-0.00305*	-0.00556	-0.00480	-0.00321*	-0.00241	-0.00443	-0.00378	-0.00609	-0.00265	-0.00719	-0.00559
	(-2.20)	(-1.77)	(-1.42)	(-1.30)	(-1.91)	(-1.45)	(-1.19)	(-1.08)	(-1.28)	(-0.69)	(-1.20)	(-0.62)
Gini	-0.0400*	0.00878			-0.0248	0.0271			-0.0809	0.114		
	(-1.79)	(0.32)			(-1.12)	(1.01)			(-1.06)	(1.23)		
IO-proxy		-0.135**				-0.147***				-0.546**		
		(-2.37)				(-2.64)				(-2.14)		
Gini(1-p0)			-0.0413	0.0128			-0.0212	0.0340			-0.0592	0.164*
			(-1.60)	(0.43)			(-0.83)	(1.14)			(-0.98)	(1.84)
IO-proxy(1-p0)				-0.164**				-0.177***				-0.655***
				(-2.36)				(-2.63)				(-2.65)
P0			-0.0324	-0.0144			-0.0214	-0.00376			-0.0260	0.0205
			(-0.91)	(-0.42)			(-0.63)	(-0.11)			(-0.38)	(0.21)
Num.Observations	114	114	114	114	114	114	114	114	114	114	114	114
R2-adj	0.081	0.134	0.070	0.133	0.126	0.185	0.123	0.191				
Kleibergen Paap F-stat					30603.8	15217.9	9319.2	5794.6				
Underidentification F-stat					45.09	35.69	46.24	36.21				
(P-value)					0.000	0.000	0.000	0.000				
Hansen (pvalue)									0.275	0.331	0.233	0.362
m2-pvalue									0.270	0.160	0.250	0.109
Num. Cross-sections									42	42	42	42
Num. Instruments									33	36	48	43

Note: constant term and time dummies are included in all models. For the instrumental variable (IV) approach, the instrument Z_x for the variable x (the Gini coefficient or the IO-proxy) is the level of the variable adjusted by per capita real GDP (in logs) using IV, i.e.,$Z_{x,it} = x_{it} - b_{IV} * \ln(y_{it})$, following Brueckner and Lederman (2018). Instruments for the interactions are calculated as $Z_{x,it} * (1 - p0_{it})$, where $p0$ is the headcount poverty rate. The instruments for per capita real GDP in the preliminary regression $x_{it} = a + b * \ln(y_{it}) + v_{it}$ are the lagged levels (t-1 and t-2) of the saving rate (Acemoglu et al., 2008) and the growth rate (Fatas and Mihov, 2003). Alternative instruments such as the lagged trade weighted world income (Acemoglu et al., 2008) and the oil price shocks (Brueckner et al., 2015) were also considered but they failed to pass the overidentifying restriction and/or the weak instrument tests. For system-GMM, estimations use instruments starting at t-2 and the variance covariance matrix is computed using the small sample correction of Windmeijer (2005). We exclude anomalous observations (i.e., showing residuals above four standard deviations), which are less than 1% of the sample in all cases. Robust t statistics in parentheses: *** denotes significance at 1%, ** at 5%, * at 10%.

Table 4. Growth, inequality and inequality of opportunity.
(IO proxy from the Demographic and Health Surveys (DHS) in Ferreira et al., 2018)

	Pooled-OLS				Instrumental Variable				System GMM			
log(y), lag	0.00190	0.00261	-0.00759	-0.00688	-0.0826***	-0.0761**			0.00567	0.00889**	-0.00188	0.00171
	(0.65)	(0.80)	(-1.44)	(-1.34)	(-2.69)	(-2.56)			(1.28)	(2.49)	(-0.18)	(0.19)
Gini	-0.0811**	-0.0752**			0.00194	0.00271	-0.00748	-0.00671	-0.114**	-0.0836**		
	(-2.57)	(-2.44)			(0.68)	(0.86)	(-1.47)	(-1.36)	(-2.51)	(-2.36)		
IO-proxy		-0.00693				-0.00753				-0.0116		
		(-1.14)				(-1.28)				(-1.25)		
Gini(1-p0)			-0.110**	-0.0852			-0.113**	-0.0862*			-0.184***	-0.0815
			(-2.01)	(-1.63)			(-2.15)	(-1.71)			(-3.22)	(-1.45)
IO-proxy(1-p0)				-0.0126*				-0.0137*				-0.0175*
				(-1.66)				(-1.88)				(-1.68)
P0			-0.0882***	-0.0842***			-0.0895***	-0.0851***			-0.131***	-0.0907*
			(-3.27)	(-3.29)			(-3.44)	(-3.46)			(-2.90)	(-1.88)
Num.Observations	114	114	114	114	114	114	114	114	114	114	114	114
R2-adj	0.161	0.169	0.186	0.198	0.206	0.220	0.237	0.254				
Kleibergen Paap F-stat					4683911.6	212703.6	799624.5	51860.4				
Underidentification F-stat					36.15	36.21	35.61	28.61				
(P-value)					0.000	0.000	0.000	0.000				
Hansen (pvalue)									0.0133	0.145	0.380	0.206
m2-pvalue									0.534	0.782	0.846	0.924
Num. Cross-sections									39	39	39	39
Num. Instruments									33	38	50	47

Note: See the note in Table 3. For the DHS sample we exclude the two GDP growth lags as instruments for per capita real GDP in the preliminary regression $x_{it} = a + b * \ln(y_{it}) + v_{it}$ because otherwise the estimation does not pass the overidentifying restriction test.

Table 5. Growth, inequality and inequality of opportunity.

(IO proxy from the Gini adjusted by institutions and social division)

	Pooled-OLS				Instrumental Variable				System-GMM			
log(y), lag	-0.0807***	-0.0800***	-0.0849***	-0.0856***	-0.0766***	-0.0761***	-0.0822***	-0.0829***	-0.00569	-0.00992**	-0.0208***	-0.0290***
	(-10.38)	(-10.42)	(-11.73)	(-12.11)	(-11.06)	(-11.11)	(-13.02)	(-13.35)	(-1.39)	(-2.15)	(-4.88)	(-4.31)
Gini	0.00794	0.0122			-0.0772**	-0.0708**			-0.256***	-0.239***		
	(0.24)	(0.37)			(-2.50)	(-2.31)			(-5.48)	(-4.66)		
IO-proxy		-0.181***				-0.148***				-0.171		
		(-4.02)				(-3.73)				(-1.60)		
Gini(1-p0)			-0.0215	-0.0211			-0.134***	-0.129***			-0.204***	-0.167***
			(-0.47)	(-0.46)			(-3.22)	(-3.10)			(-4.59)	(-3.12)
IO-proxy(1-p0)				-0.198***				-0.166***				-0.284***
				(-3.96)				(-3.80)				(-2.62)
P0			-0.0757***	-0.248***			-0.121***	-0.264***			-0.171***	-0.421***
			(-3.21)	(-5.15)			(-5.39)	(-6.11)			(-5.53)	(-3.92)
Num.Observations	530	530	530	530	531	531	531	531	530	530	530	530
R2-adj	0.508	0.552	0.535	0.553	0.357	0.383	0.392	0.415				
Kleibergen Paap F-stat					26977.7	12845.2	8524.0	4384.9				
Underidentification F-stat					94.88	100.2	98.98	96.82				
(P-value)					0	0	0	0				
Hansen (pvalue)									0.0371	0.0240	0.198	0.149
m2-pvalue									0.107	0.188	0.170	0.667
Num. Cross-sections									111	111	111	111
Num. Instruments									79	88	95	107

Note: See the note in Table 3. In addition to time dummies, fixed effects are also included in pool-OLS and IV. The IO proxy used in the estimations is from the results in column 11, Table 2 (system-GMM controlling by income growth).

FIGURES

Figure 1. The dynamic of human capital in the basic model.

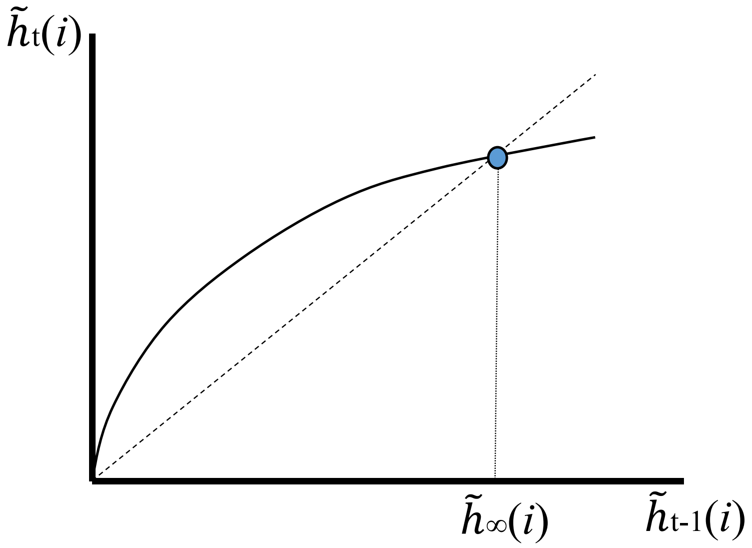


Figure 2. Effects of circumstances and pure effort on human capital.

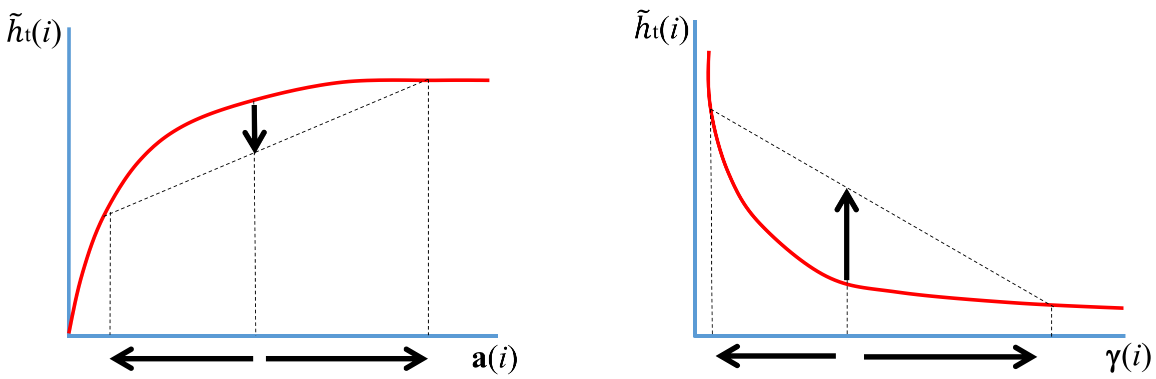


Figure 3. The dynamic of human capital with a poverty trap.

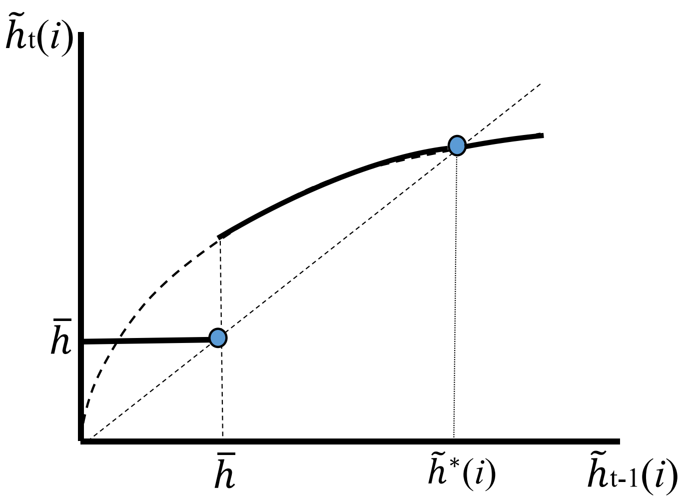


Figure 4. Inequality and Institutional-induced inequality (IO proxy).

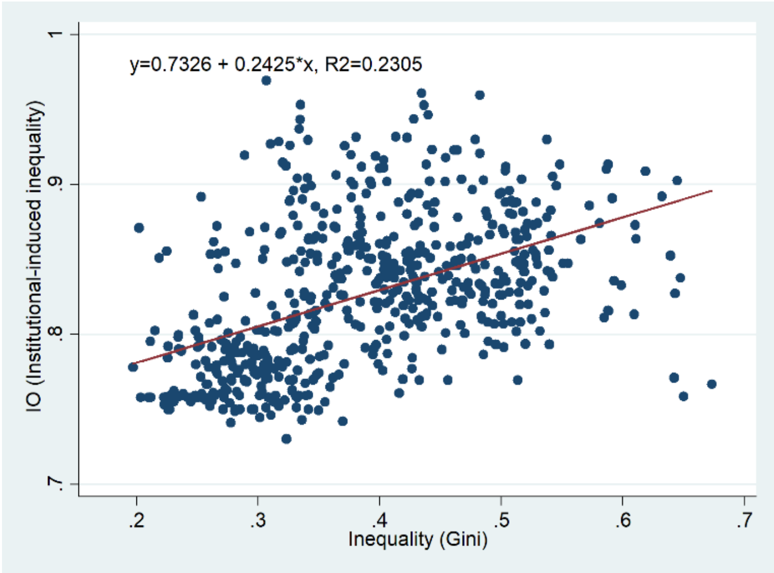
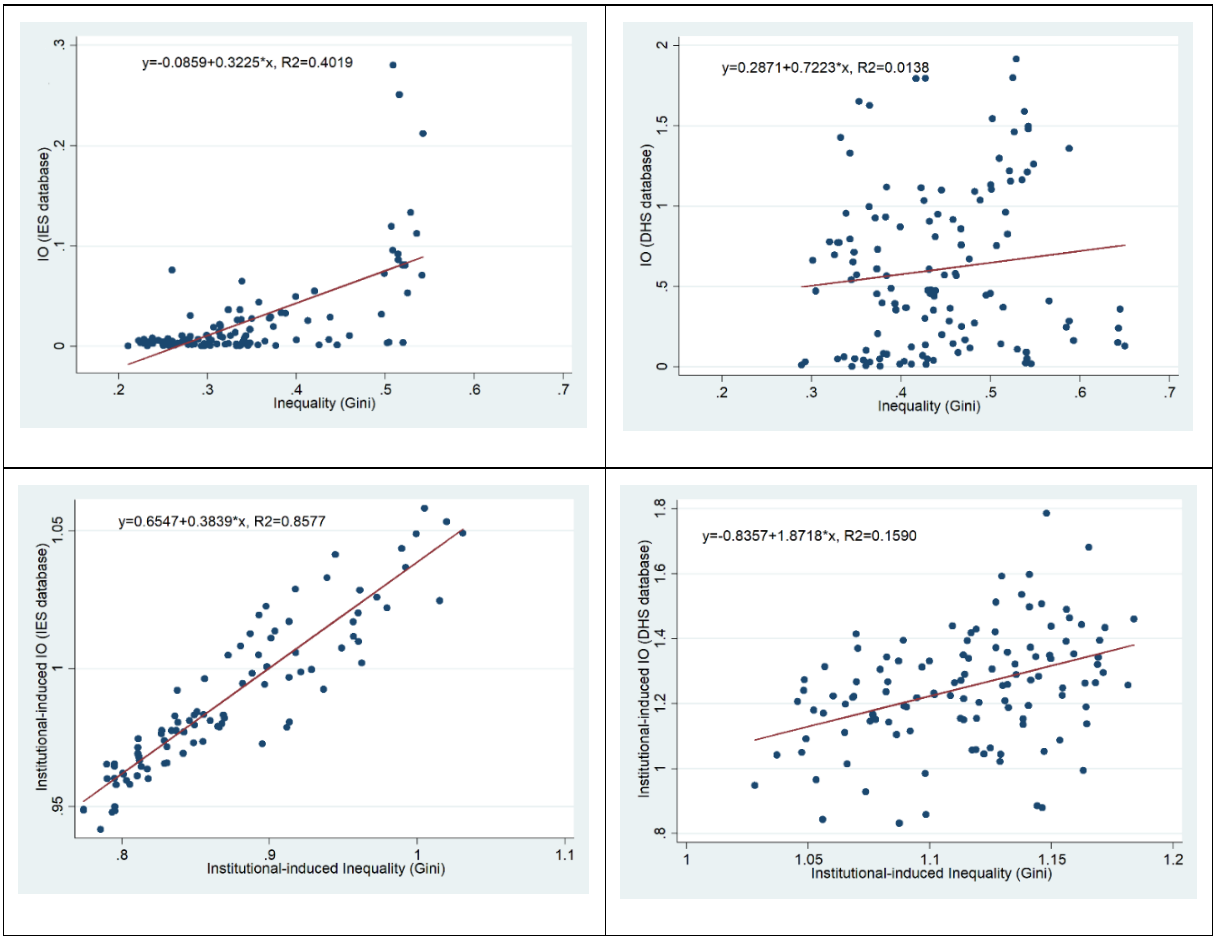


Figure 5. Inequality and institutional-induced measures (IES and DHS samples).



Appendix

A1. The growth equation for the non-convex model

From the main text, we know that $g_{y_t} = \pi(h_t - h_{t-1})$ so using (21) we have

$$g_{y_t} = pln\bar{h} + (1-p)\pi E\big[\xi\,[h_{t-1}(i)]/ln\tilde{h}_{-1}(i) > ln(\varpi/\omega)\big] - \pi h_{t-1}. \quad \text{(A1.1)}$$

Assume that the random variable $X = ln\tilde{h}_{-1}(i) - ln(\varpi/\omega)$ follows a normal distribution with mean $\mu_X = \left(ln\hat{h} - \frac{\Delta_{-1}^2}{2}\right) - ln\left(\frac{\varpi}{\omega}\right)$ and variance Δ_{-1}^2, and that $\big(\xi\big(h_{t-1}(i)\big), X\big)$ follows a bivariate normal distribution. Then, we can apply the following result for truncated bivariate normal distributions (Green, 2008, pp. 883):

$$E\big[\xi\,[h_{t-1}(i)]/ln\bar{h}_{-1}(i) > ln(\varpi/\omega)\big] = E\big[\xi\big(h_{t-1}(i)\big)\big]$$

$$+\frac{Cov\big(\xi\big(h_{t-1}(i)\big),X\big)}{\Delta_{-1}}\frac{\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)}{1-\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)}. \quad \text{(A1.2)}$$

Using (15) and noting that p is equivalent to $\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)$, we can rewrite (A1.2) as

$$E\big[\xi\,[h_{t-1}(i)]/ln\tilde{h}_{-1}(i) > ln(\varpi/\omega)\big] = \frac{S}{(\beta+\psi)\pi} + b_h h_{t-1}$$

$$+\frac{b_a}{\pi}E\,lna - \frac{b_\gamma}{\pi}E\,ln\gamma$$

$$+\frac{\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)Cov\big(\xi\big(h_{t-1}(i)\big),X\big)}{(1-p)\Delta_{-1}}. \quad \text{(A1.3)}$$

Next, we calculate the term $Cov\big(\xi\big(h_{t-1}(i)\big),X\big)$. From the definitions of $\xi\big(h_{t-1}(i)\big)$ and X, it can be shown that $Cov\big(\xi\big(h_{t-1}(i)\big),X\big) = b_h Cov\left(h_{t-1}(i), ln\tilde{h}_{-1}(i)\right)$. Moreover, we know that $h_t = \xi\big(h_{t-1}(i)\big)$ for all t if $ln\tilde{h}_{-1}(i) > ln(\varpi/\omega)$. Consequently, $Cov\left(h_{t-1}(i), ln\tilde{h}_{-1}(i)\right)$=$Cov\left(\xi\big(h_{t-2}(i)\big), ln\tilde{h}_{-1}(i)\right)$, which in turn is equal to $b_h Cov\left(h_{t-2}(i), ln\tilde{h}_{-1}(i)\right)$. Iterating backward, we obtain $Cov\big(\xi\big(h_{t-1}(i)\big),X\big) = b_h^{t+1}\,Cov\left(h_{-1}(i), ln\tilde{h}_{-1}(i)\right)$ and then, using the definition $h_{-1}(i) = \frac{1}{\pi}ln\tilde{h}_{-1}(i)$, we find:

$$Cov\big(\xi\big(h_{t-1}(i)\big),X\big) = \frac{b_h^{t+1}}{\pi}\Delta_{-1}^2. \quad \text{(A1.4)}$$

Introducing the last expression into A1.3, we have,

$$E\left[\xi\ [h_{t-1}(i)]/ln\tilde{h}_{-1}(i) > ln(\bar{\omega}/\omega)\right] = \frac{S}{(\beta+\psi)\pi} + b_h h_{t-1}$$

$$+\frac{b_a}{\pi}E\ lna - \frac{b_\gamma}{\pi}E\ ln\gamma$$

$$+\frac{b_h^{t+1}\phi\left(\frac{\mu_X}{\Delta_{-1}}\right)}{\pi(1-p)}\Delta_{-1}. \quad \text{(A1.5)}$$

Substituting (A1.5) into (A1.1), we obtain:

$$g_{y_t} = pln\bar{h} + (1-p)\left[\frac{S}{\beta+\psi} + \pi b_h b_{t-1} + b_a E\ lna - b_\gamma E\ ln\gamma\right]$$

$$+b_h^{t+1}\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)\Delta_{-1} - \pi h_{t-1}, \quad \text{(A1.6)}$$

and using the definitions $E\ lna = ln\hat{a} - T_0(a), E\ ln\gamma = ln\hat{\gamma} - T_0(\gamma)$ and $T_0(\tilde{h}_{-1}) = \frac{\Delta_{-1}^2}{2}$, we have:

$$g_{y_t} = \left[\frac{S}{\beta+\psi} + b_a ln\hat{a} - b_\gamma\ ln\hat{\gamma}\right] - [1-(1-p)b_h]ln\tilde{h}_{t-1}$$

$$-(1-p)b_a T_0(a) + (1-p)b_\gamma T_0(\gamma)$$

$$-\left[\frac{G}{\beta+\psi} + b_a ln\hat{a} - b_\gamma E\ ln\hat{\gamma} - ln\bar{h}\right]p$$

$$+b_h^{t+1}\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)\left[2T_0(\tilde{h}_{-1})\right]^{\frac{1}{2}}. \quad \text{(A1.7)}$$

Finally, noting from (4) that $ln\tilde{h}_{t-1} = lny_{t-1} - \frac{\lambda ln\left(\frac{\lambda}{\bar{r}}\right)+lnA}{1-\lambda}$, the result in (22) is obtained.

A2. Poverty is harmful to economic growth

Taking first derivatives in (22), we have:

$$\frac{\partial g_{y_t}}{\partial p} = \frac{\lambda ln\left(\frac{\lambda}{\bar{r}}\right)+lnA}{1-\lambda} - b_h lny_{t-1} + b_a T_0(a) - b_\gamma T_0(\gamma) - \left(b_0 - ln\bar{h}\right). \quad \text{(A2.1)}$$

In addition, we know from (4) that $ln\tilde{h}_{t-1} = lny_{t-1} - \frac{\lambda ln\left(\frac{\lambda}{\bar{r}}\right)+lnA}{1-\lambda}$, hence we have,

$$\frac{\partial g_{y_t}}{\partial p} = -\left[\frac{S}{\beta+\psi} + b_a ln\hat{a} - b_\gamma \, ln\hat{\gamma}\right] - b_h ln\tilde{h}_{t-1} + b_a T_0(a) - b_\gamma T_0(\gamma) + ln\bar{h}. \qquad \text{(A2.2)}$$

From the main text (page 15) we know that,

$$E\xi[h_{t-1}(i)] = \frac{1}{\pi}\left[\frac{S}{\beta+\psi} + b_a ln\hat{a} - b_\gamma \, ln\hat{\gamma} + b_h ln\tilde{h}_{t-1} - b_a T_0(a) + b_\gamma T_0(\gamma)\right]. \qquad \text{(A2.3)}$$

Hence, $\frac{\partial g_{y_t}}{\partial p} < 0$ if and only if $E\xi[h_{t-1}(i)] > \frac{1}{\pi} ln\bar{h}$. By taking logs in (20), we have

$$h_t(i) \begin{cases} \frac{1}{\pi} ln\bar{h} & \tilde{h}_{-1}(i) \leq \bar{\omega}/\omega \\ \xi[h_{t-1}(i)] & \tilde{h}_{-1}(i) > \bar{\omega}/\omega \end{cases}, \qquad \text{(A2.4)}$$

where $\xi[h_{t-1}(i)] = \frac{S}{(\beta+\psi)\pi} + b_h h_{t-1}(i) + \frac{b_a}{\pi} lna(i) - \frac{b_\gamma}{\pi} ln\gamma(i)$. Therefore, it is always true that $E\xi[h_{t-1}(i)] > \frac{1}{\pi} ln\bar{h}$.

A3. The effect of $T_0(\tilde{h}_{-1})$ on growth through poverty

The indirect effect of $T_0(\bar{h}_{-1})$ on growth through p is given by $\frac{\partial g_y}{\partial p}\frac{\partial p}{\partial T_0(\tilde{h}_{-1})}$, where $\frac{\partial g_y}{\partial p} < 0$ (see A2). Consequently, we need only to calculate the sign of $\frac{\partial p}{\partial T_0(\tilde{h}_{-1})}$. We know that $p = \Phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)$, where $\mu_X = \left(ln\hat{h} - T_0(\tilde{h}_{-1})\right) - ln\left(\frac{\bar{\omega}}{\omega}\right)$ and $\Delta_{-1} = \left[2T_0(\tilde{h}_{-1})\right]^{\frac{1}{2}}$. Therefore, we have:

$$\frac{\partial p}{\partial T_0(\tilde{h}_{-1})} = \phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)\frac{\partial\left(\frac{-\mu_X}{\Delta_{-1}}\right)}{\partial T_0(\tilde{h}_{-1})}, \qquad \text{(A3.1)}$$

which, after some operations, is reduced to,

$$\frac{\partial p}{\partial T_0(\tilde{h}_{-1})} = \frac{\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)}{\Delta_{-1}}\left[1 + \frac{\mu_X}{\Delta_{-1}^2}\right]. \qquad \text{(A3.2)}$$

Thus, it is straightforward to see that $\frac{\partial p}{\partial T_0(\tilde{h}_{-1})} > 0$, and therefore $\frac{\partial g_y}{\partial p}\frac{\partial p}{\partial T_0(\tilde{h}_{-1})} < 0$ if and only if $-\mu_X < \Delta_{-1}^2$ which is equivalent to $p < \Phi(\Delta_{-1})$.

Appendix A4. Estimation results using alternative specifications and methods for the IO proxy

Table A4.1. Growth, inequality and inequality of opportunity

(IO proxy from the results in column 8, Table 2: pooled-OLS not controlling by income growth)

	Pooled-OLS				Instrumental Variable				System-GMM			
log(y), lag	-0.0807***	-0.0811***	-0.0849***	-0.0858***	-0.0766***	-0.0770***	-0.0822***	-0.0832***	-0.00569	-0.00841**	-0.0208***	-0.0254***
	(-10.38)	(-10.48)	(-11.73)	(-11.99)	(-11.06)	(-11.19)	(-13.02)	(-13.29)	(-1.39)	(-2.09)	(-4.88)	(-3.88)
Gini	0.00794	0.0114			-0.0772**	-0.0721**			-0.256***	-0.247***		
	(0.24)	(0.34)			(-2.50)	(-2.35)			(-5.48)	(-4.74)		
IO-proxy		-0.106***				-0.100***				-0.0910		
		(-2.93)				(-3.16)				(-1.15)		
Gini(1-p0)			-0.0215	-0.0187			-0.134***	-0.131***			-0.204***	-0.175***
			(-0.47)	(-0.41)			(-3.22)	(-3.18)			(-4.59)	(-3.07)
IO-proxy(1-p0)				-0.0982**				-0.0928**				-0.178*
				(-2.30)				(-2.50)				(-1.77)
P0			-0.0757***	-0.163***			-0.121***	-0.204***			-0.171***	-0.329***
			(-3.21)	(-3.81)			(-5.39)	(-5.28)			(-5.53)	(-3.18)
Num.Observations	530	530	530	530	531	531	531	531	530	530	530	530
R2-adj	0.508	0.542	0.535	0.541	0.357	0.372	0.392	0.401				
Kleibergen Paap F-stat					26977.7	13558.2	8524.0	4421.0				
Underidentification F-stat					94.88	95.65	98.98	97.95				
(P-value)					0.000	0.000	0.000	0.000				
Hansen (pvalue)									0.0371	0.0730	0.198	0.162
m2-pvalue									0.107	0.194	0.170	0.517
Num. Cross-sections									111	111	111	111
Num. Instruments									79	88	95	107

Note: See the note in Table 3. In addition to time dummies, fixed effects are also included in pool-OLS and IV.

Table A4.2. Growth, inequality and inequality of opportunity

(IO proxy from the results in column 9, Table 2: pooled-OLS controlling by income growth)

	Pooled-OLS				Instrumental Variable				System-GMM			
log(y), lag	-0.0811***	-0.0813***	-0.0853***	-0.0860***	-0.0766***	-0.0769***	-0.0822***	-0.0830***	-0.00630	-0.00842**	-0.0203***	-0.0246***
	(-10.44)	(-10.52)	(-11.85)	(-12.10)	(-11.06)	(-11.16)	(-13.02)	(-13.25)	(-1.54)	(-2.07)	(-4.81)	(-3.81)
Gini	0.00639	0.00948			-0.0772**	-0.0725**			-0.257***	-0.255***		
	(0.19)	(0.29)			(-2.50)	(-2.36)			(-5.53)	(-5.03)		
IO-proxy		-0.0965***				-0.0996***				-0.0641		
		(-2.67)				(-3.03)				(-0.81)		
Gini(1-p0)			-0.0241	-0.0216			-0.134***	-0.132***			-0.207***	-0.190***
			(-0.53)	(-0.48)			(-3.22)	(-3.19)			(-4.69)	(-3.50)
IO-proxy(1-p0)				-0.0888**				-0.0886**				-0.150
				(-2.04)				(-2.31)				(-1.47)
P0			-0.0760***	-0.155***			-0.121***	-0.200***			-0.167***	-0.306***
			(-3.21)	(-3.57)			(-5.39)				(-5.37)	(-2.91)
Num.Observations	529	529	529	529	531	531	531	531	529	529	529	529
R2-adj	0.516	0.548	0.544	0.547	0.357	0.370	0.392	0.399				
Kleibergen Paap F-stat					26977.7	13549.7	8524.0	4403.9				
Underidentification F-stat					94.88	95.51	98.98	97.99				
(P-value)					0.000	0.000	0.000	0.000				
Hansen (pvalue)									0.0368	0.0958	0.245	0.148
m2-pvalue									0.125	0.200	0.186	0.492
Num. Cross-sections									111	111	111	111
Num. Instruments									79	88	95	107

Note: See the note in Table 3. In addition to time dummies, fixed effects are also included in pool-OLS and IV.

Table A4.3. Growth, inequality and inequality of opportunity

(IO proxy from the results in column 10, Table 2: system-GMM not controlling by income growth)

	Pooled-OLS				Instrumental Variable				System-GMM			
log(y), lag	-0.0807***	-0.0804***	-0.0849***	-0.0864***	-0.0766***	-0.0764***	-0.0822***	-0.0839***	-0.00569	-0.0120***	-0.0208***	-0.0294***
	(-10.38)	(-10.56)	(-11.73)	(-12.28)	(-11.06)	(-11.24)	(-13.02)	(-13.59)	(-1.39)	(-2.72)	(-4.88)	(-4.94)
Gini	0.00794	0.0154			-0.0772**	-0.0647**			-0.256***	-0.229***		
	(0.24)	(0.47)			(-2.50)	(-2.14)			(-5.48)	(-4.36)		
IO-proxy		-0.191***				-0.198***				-0.228**		
		(-4.59)				(-5.35)				(-2.32)		
Gini(1-p0)			-0.0215	-0.0206			-0.134***	-0.123***			-0.204***	-0.168***
			(-0.47)	(-0.46)			(-3.22)	(-3.00)			(-4.59)	(-3.19)
IO-proxy(1-p0)				-0.221***				-0.230***				-0.322***
				(-4.66)				(-5.44)				(-3.24)
P0			-0.0757***	-0.263***			-0.121***	-0.312***			-0.171***	-0.442***
			(-3.21)	(-5.71)			(-5.39)	(-7.31)			(-5.53)	(-4.89)
Num.Observations	530	530	530	530	531	531	531	531	530	530	530	530
R2-adj	0.508	0.557	0.535	0.561	0.357	0.391	0.392	0.426				
Kleibergen Paap F-stat					26977.7	13779.3	8524.0	4192.6				
Underidentification F-stat					94.88	95.56	98.98	99.65				
(P-value)					0.000	0.000	0.000	0.000				
Hansen (pvalue)									0.0371	0.0212	0.198	0.188
m2-pvalue									0.107	0.190	0.170	0.626
Num. Cross-sections									111	111	111	111
Num. Instruments									79	88	95	107

Note: See the note in Table 3. In addition to time dummies, fixed effects are also included in pool-OLS and IV.