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Unfair inequality and growth*

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Abstract

Fighting against economic inequality is one fundamental social goal in the agendas of most governments. However, recent studies highlight that people actually prefer unequal societies, as they accept inequality generated by an individual's effort and wish to reduce only unfair inequality (generated by factors beyond an individual's control). This distinction might help to explain the fundamental unsolved question about whether inequality is good or bad for growth: unfair inequality (UI) could be growth-deterring, while fair inequality (FI) might be growth-enhancing. We derive a reduced-form growth equation from a stylized overlapping-generations model with human capital that includes FI, UI, and poverty. Then, using an instrumental variable approach, we show for alternative samples and inequality measures at the worldwide level that the estimated coefficient associated with UI is always negative, while the coefficient of total inequality increases when UI is included in the regression. Moreover, we find that poverty mediates this relationship because the higher the poverty rate, the smaller the impact of either type of inequality on growth.

Keywords: Unfair inequality; growth; poverty; human capital

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1. Introduction

A fundamental social goal at the center of the political agenda of most countries is to fight against inequality. However, despite this concern, recent

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studies highlight that when people are asked about the ideal distribution, they actually prefer unequal societies (Starmans et al., 2017). This preference is observed in a wide range of countries and across people with opposite political views (Norton and Ariely, 2011; Kiatpongsan and Norton, 2014). These two sets of findings seem to be contradictory, but they can be reconciled through an empirical fact: people are not concerned with economic inequality, but with economic unfairness. When studies distinguish carefully between fairness and equality, they find that people choose fairness over equality (Baumard et al., 2012; Sloane et al., 2012). This distinction is critical because these concepts may have different effects on growth: fair inequality could increase growth while unfair inequality could harm growth.

The recognition that fairness and equality are different concepts is important for two reasons. First, public policy should focus on the reduction of unfairness – not inequality – in society. Because the problem for people is economic unfairness, political action should frame the problem of relating the existing distribution of outcomes to factors such as merit and initial circumstances (Sugden and Wang, 2020). Second, inequality in the distribution of any economic outcome can be thought of as resulting from a combination of fair and unfair processes, which may have different effects on growth. Indeed, an important challenging question in economics – over which there is still no consensus – is whether inequality is good or bad for growth (Panizza, 2002; Banerjee and Duflo, 2011; Voitchovsky, 2011; Berg and Ostry, 2017; Milanovic and Van der Weide, 2018).[1]

In this paper, our central hypothesis is that the reason for this ambiguous result is that unfair inequality (UI) and fair inequality (FI) have opposite impacts on growth: UI is growth-deterring, while FI is growth-enhancing (World Bank, 2006; Marrero and Rodríguez, 2013; Ferreira et al., 2018; Aiyar and Ebeke, 2019).[2] Making this distinction helps to explain the ambiguous inequality–growth relationship (see footnote 1), as growth-enhancing channels can be associated with FI, while growth-deterring channels can be directly linked to UI. In addition, because inequality and poverty are different but related aspects of the income distribution, we must consider whether

[1]The lack of consensus is attributed to the coexistence of a variety of channels through which inequality is affecting growth. The positive channels are related to the incentives for saving and investing (Kaldor, 1956; Barro, 2000), asymmetric information (Mirrlees, 1971), and productivity premiums (Goldin and Katz, 2008; Mankiw, 2013). The negative channels are related to imperfect capital markets (Banerjee and Newman, 1993; Galor and Zeira, 1993), political economy issues (Alesina and Rodrik, 1994; Stiglitz, 2012), and the development process (Dasgupta and Ray, 1986). An additional complication is that estimated channels may change over time (Blotevogel et al., 2020).

[2]In the literature on inequality of opportunity, a similar hypothesis (in terms of inequality of opportunity and inequality of effort) has been named the "cholesterol hypothesis" (Ferreira, 2007).

poverty mediates in this relationship between FI, UI, and growth. Hence, our second main hypothesis is to analyze whether poverty affects the impact that both sources of inequality have on growth, and to test whether poverty is growth-deterring (Ravallion, 2012; Marrero and Servén, 2022).[3] We analyze these aspects from both a theoretical and an empirical perspective.

To reach our goals, we first need to conceptualize UI in an objective way. For this task, following Brock (2020), we use the concept of inequality of opportunity (Roemer, 1998), which says that inequality due to responsibility factors, such as effort, is fair, while inequality due to circumstances over which one has no control is not. Consequently, we use a measure of inequality that isolates the unfair portion of overall inequality by focusing on the inequality that can be attributed to factors beyond a person's control, such as race, place of birth, health endowments, and macroeconomic conditions (Rodríguez, 2008; Marrero and Rodríguez, 2012). In a fair society, factors at birth should not affect an individual's outcomes, although they have been shown to heavily influence outcomes for disadvantaged groups (Altonji and Blank, 1999; Bertrand and Mullainathan, 2004).

We first build a model that combines wage determination and human capital accumulation (Glomm and Ravikumar, 1992) with unfairness (Roemer, 1993; Fleurbaey, 2008) and poverty traps (Azariadis and Stachurski, 2005). The economy is populated by a continuum of dynasties, where effort is a non-monetary factor that generates disutility but is needed to accumulate human capital. A dynasty is defined as a common individual who lives for two periods (childhood and adulthood) and gives birth to another individual during adulthood, so the population remains constant over time. For tractability, parents care about the total amount of resources that they leave to their offspring (warm-glow preferences) and not about the offspring's utility. Each dynasty is characterized by an initial level of human capital, exogenous factors (beyond the individual's control such as race, place of birth, or macroeconomic conditions) that affect human capital productivity, and an idiosyncratic parameter of preference for effort, which is assumed to be uncorrelated with any other characteristic of the dynasty. We associate inequality of exogenous factors to UI, and inequality of preferences to exert effort to FI.

To consider the existence of a poverty trap, which is of especial relevance when modeling less-developed countries, the human capital accumulation process is assumed to be non-convex. In this setting, each dynasty faces two

[3]The literature has studied a variety of mechanisms through which poverty may harm growth, most of them based on the existence of poverty traps (for a survey, see Azariadis and Stachurski, 2005). The idea is that below a certain level of income or wealth, individuals are too poor to afford the investments in human or physical capital, or the technologies necessary to raise their future levels of human capital and income.

potential equilibria – a low equilibrium and a high equilibrium – and the poverty rate is defined as the percentage of dynasties in the low equilibrium. The solution for the aggregate economy leads us to a reduced-form growth equation that includes FI, UI, poverty, and their interactions. The prediction of this equation is that FI enhances growth, while UI and poverty are harmful for growth. This result does not rely on any channel. Specifically, unobservable effort, individual talent, market imperfections, and the functioning of the political economy are not modeled, so our setting provides a broad perspective to understand the relationship between FI and UI, and growth. Indeed, the inclusion of imperfect markets would reinforce the negative effect that UI has on growth.

The reduced-form growth equation is the basic element for the empirical analysis conducted in Section 3. However, although we can collect information on growth, poverty, total inequality, and even a lower-bound estimate of inequality of opportunity to proxy UI, we do not have good and homogeneous measures of FI at a worldwide level (see the discussion in Ferreira et al., 2018).[4] Hence, we cannot expect reliable results when testing directly whether UI and FI have opposite effects on growth. However, we show that this hypothesis is consistent with the following fact: the UI proxy is negatively correlated with growth, and the estimated coefficient of total inequality increases when the UI proxy is included in the regression.

To proxy UI we use the available estimates of inequality of opportunity at the worldwide level from (Ferreira et al., 2018). However, given the commented deficiencies of these measures (see footnote 4), and for robustness, we propose an alternative institutional-based proxy of UI. Our strategy is based on two ideas. First, macroeconomic factors, which are beyond the individual's control, are very important for global inequality of opportunity (Milanovic, 2015). Second, the institutional set-up and ethnic–linguistic and religious tensions may significantly influence the capacity of individuals to achieve a given socioeconomic status (Alesina et al., 2003; Acemoglu et al., 2015). Then, in the same spirit as Fatás and Mihov (2003), we estimate a political economy model by regressing overall inequality on the degree of democracy, the level of law enforcement, corruption, and the existing ethnic–linguistic and religious tensions, and we take the fitted value as our proxy of UI.

[4]Because the whole set of circumstances at birth is never fully observed, the resultant inequality of opportunity estimation is a lower bound (Ferreira and Gignoux, 2011). Moreover, databases containing information to estimate inequality of opportunity for many countries tend to be heterogeneous across countries, with different numbers and types of circumstances, dependent variables, and sources (Ferreira et al., 2018). In this situation, the resultant estimation of FI would be highly contaminated by the influence of other exogenous factors not observed and not considered in the measurement of UI.

Finally, to estimate the inequality–growth models, we follow the instrumental variable (IV) approach in Brueckner et al. (2012). We use the lagged levels of the saving rate (Acemoglu et al., 2008) and of the growth rates (Fatás and Mihov, 2003) as instruments for real per capita GDP. Alternative instruments, such as the lagged trade-weighted world income (Acemoglu et al., 2008) and oil price shocks (Brueckner et al., 2012), were also considered, but they did not pass the corresponding tests. For robustness, we also estimated our models by system generalized methods of moments (GMM; Blundell and Bond, 1998; Roodman, 2009).

Our results fail to reject our main hypothesis at the worldwide level: the effect of the UI proxy on economic growth is significantly negative and the estimated coefficient of overall inequality becomes higher when the UI proxy is included in the growth regression. Moreover, these results are robust to the alternative sample used, the econometric techniques, and the model's specification. We further show that when the sample contains a large set of less-developed and developing countries, the growth equation needs to include poverty. For this case, poverty is found to be growth-deterring.

The rest of the paper is structured as follows. In Section 2, we solve a human capital model and derive a reduced-form growth equation. In Section 3, we present the empirical strategy. In Section 4, we explain the databases and alternative measures of UI used. In Section 5, we show the main results. Finally, we conclude in Section 6.

2. The theoretical framework

Our model is a stylized dynamic macroeconomic framework to help us to understand how different types of inequality (fair and unfair), interacted with poverty, may have different effects on economic growth. The economy is small and open, with perfect competitive markets, although we deviate from the assumption of perfect markets at the end of this section, arguing that the inclusion of imperfect markets in the model only reinforces our main conclusions. Thus, we show that even without this assumption about markets, it is possible to find a negative effect of inequality on growth when we focus on UI.

The economy is inhabited by a continuum of heterogeneous dynasties, each one indexed by $i \equiv [0, 1]$. 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. The accumulation of human capital is the unique driver of growth. Heterogeneity comes from differences in the initial parental human capital of the dynasty, in the preferences to exert effort (i.e., the source of fair inequality, FI), and in exogenous factors that are beyond the individual's control (i.e., the source of unfair inequality, UI), which affect the individual productivity to accumulate human capital.

2.1. Technology, preferences, circumstances, and human capital

A single homogeneous good, y_t, is produced every period t according to a neoclassical production function,

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

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 (Mincer, 1974; Bils and Klenow, 2000; Barro and Lee, 2013). 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. The Hicks-neutral technological term A is assumed to be constant.

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, $\bar{r}$.[5] Because producers operate in a perfectly competitive environment, $\bar{r}$ determines the $k_t/\tilde{h}_t$ constant ratio,

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

The real wage per unit of effective labor, w, is given by

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

which is constant and 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 equation (3) into equation (1)):

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

[5]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 Tsiddon, 1997).

The utility of the dynasty depends positively on consumption, c_t, and the bequests devoted to offspring, x_t (warm-glow preferences), and negatively on exerted effort, e_t:

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

Without loss of generality, $\eta \in (0, 1)$ 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. Labor is inelastically supplied. Effort e_t is a non-monetary factor that generates disutility but is needed to accumulate human capital (Roemer, 1998), and $\beta > 0$ so that the marginal disutility of effort is increasing, and the effort function is convex; this is a common assumption in the literature (see Roemer, 1993; Macho-Stadler and Pérez-Castrillo, 2001). Preferences for bundles of effort, and consumption and bequest are determined by the dynasty-specific parameter, $\gamma(i) \geq 0$. While $e_t(i)$ is a control variable, $\gamma(i)$ is an idiosyncratic parameter related to individual's preference to exert effort and independent of any other characteristic of the dynasty. As a result, we can distinguish the part of total effort that depends on the characteristics of the individual from the part of total effort that is independent of them (Roemer, 1993).[6]

When born, each individual inherits a set of circumstances, which are beyond the individual's control but affect their human capital accumulation process, as shown below. We assume the set of circumstances is a composite index,

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

where $x_{t-1}(i)$ is the bequest devoted to offspring (Card and Krueger, 1992; Glomm and Ravikumar, 1992), $\tilde{h}_{t-1}(i)$ represents home externalities generated by parental human capital (Galor and Tsiddon, 1997; Hanushek, 1996), and $a(i)$ collects exogenous factors to the individual, such as race, gender, health endowments, or macroeconomic factors.[7] In the model, UI is related to the heterogeneity of $a(i)$.

During childhood, individuals accumulate human capital, which is, as for the aggregate level, a one-to-one function of the years of schooling,

[6]The term $\gamma(i)$ corresponds to what Roemer (1993) called "pure effort" because it is the part of individual effort that is independent from circumstances (see equation (10)).

[7]Our model does not include several sources of inequality, which require a more complex framework beyond the scope of this paper. Specifically, we do not consider talent (Hassler and Rodríguez-Mora, 2000) and luck (Lefranc et al., 2009).

$\tilde{h}_t(i) = e^{\pi h_t(i)}$. During adulthood, individuals work (supplying one unit of labor inelastically) and earn labor income,

$$w_t(i) = w\tilde{h}_t(i), \tag{7}$$

where $w > 0$ (see equation (3)) represents a common wage in the economy for the individuals with zero years of schooling: if $h_t(i) = 0$, then $\tilde{h}_t(i) = 1$. We observe in equation (7) that wage inequality only comes from differences in the way individuals accumulate human capital.

Individuals accumulate human capital according to a process that depends on two non-purchasable but complementary factors: circumstances, $\theta_t(i)$, and effort, $e_t(i)$ (Roemer, 1993; Fleurbaey, 2008). Moreover, following the literature on poverty traps (Azariadis and Stachurski, 2005), which is of especial relevance when modeling less-developed and developing countries, we assume the following non-convex accumulation process of individual human capital:

$$\tilde{h}_t(i) = R[\theta_t(i), e_t(i)] = \begin{cases} \bar{h} & w\tilde{h}_{-1}(i) \le \bar{w} \\ \theta_t(i)^{\psi} e_t(i)^{1-\psi} & w\tilde{h}_{-1}(i) > \bar{w} \end{cases}, \tag{8}$$

where $R'_\theta \ge 0$ and $R'_e \ge 0$. The term $0 < \bar{h} < \min_i\{\theta(i)^{\psi} e(i)^{1-\psi}\}$ is a sufficiently small value of human capital, common to all dynasties and economies, $\tilde{h}_{-1}(i)$ is the initial human capital of the ith dynasty and $\bar{w}$ is an absolute poverty line.

In addition to the definition of poverty at the individual level (i.e., a poor person is an individual whose income is below $\bar{w}$), we also define a measure of poverty at the country level. In this respect, because the dynasty is trapped when its initial human capital is below $\bar{w}/w$, we can interpret

$$p = \Pr[w\tilde{h}_{-1}(i) \le \bar{w}] \tag{9}$$

as a headcount poverty rate (Ravallion, 2012). Finally, the parameter $\psi \in (0, 1)$ represents, for non-trapped dynasties, the relative importance of $\theta_t(i)$ with respect to $e_t(i)$ in the determination of human capital. Indeed, the parameter ψ can be related to the lack of meritocracy in the economy: $\psi = 1$ represents the extreme case of total nepotism, while $\psi = 0$ represents a fully meritocratic economy.

2.2. Human capital dynamics and the sources of inequality

For the competitive equilibrium, each individual belonging to the ith dynasty takes $\theta_t(i)$ as given and maximizes equation (5) subject to $c_t(i) + x_t(i) =$

$w_t(i)$.[8] When the dynasty is trapped, the solution is trivial (allocations are denoted with a 0 superscript) because $\tilde{h}^0(i) = \bar{h}$ and $e^0(i) = 0$. Otherwise, the individual decides to exert positive effort and accumulate human capital above $\bar{h}$:

$$e_t(i) = \left[\frac{(1-\psi)w}{\gamma(i)(1+\beta)}\right]^{1/(\beta+\psi)} \theta_t(i)^{\psi/(\beta+\psi)}; \tag{10}$$

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

According to equation (10), individual effort $e_t(i)$ depends on the aggregate economy, w, personal circumstances, $\theta_t(i)$, and individual preferences to exert effort, $\gamma(i)$. Because $\gamma(i)$ affects personal effort but is independent of $\theta_t(i)$ and w, we consider its heterogeneity to be related with FI in the model.

To obtain the individual human capital dynamics, we use $x_t(i) = (1-\eta) w\tilde{h}_t(i)$ to rewrite $\theta_t(i)$ in terms of $\tilde{h}_{t-1}(i)$ and then substitute it into equations (8) and (11):

$$\tilde{h}_t(i) = \Omega[\tilde{h}_{t-1}(i)] = \begin{cases} \bar{h} & w\tilde{h}_{-1}(i) \leq \bar{w} \\ \zeta[\tilde{h}_{t-1}(i)] & w\tilde{h}_{-1}(i) > \bar{w} \end{cases}. \tag{12}$$

Here,

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

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

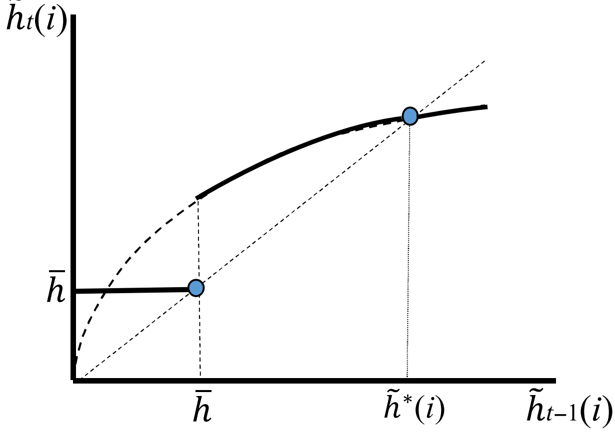
and $\Omega[0] = \bar{h}$. Because

$$0 < \frac{\psi(1+\beta)(\alpha+\varphi)}{\beta+\psi} < 1,$$

$\zeta[\cdot]$ is strictly increasing and strictly concave in $\tilde{h}_{t-1}(i)$. Moreover, because $\bar{h}$ is sufficiently small, it is true that $\zeta[\bar{h}] > \bar{h}$ so that $\Omega[\cdot]$ is increasing and concave in $\tilde{h}_{t-1}(i)$ (see Figure 1).

[8]The problem is solved in two steps. First, taking $\tilde{h}_t(i)$ as given, utility is maximized subject to the previous restriction and equation (7), obtaining $c_t(i) = \eta w\tilde{h}_t(i)$ and $x_t(i) = (1-\eta)w\tilde{h}_i(i)$. These expressions are then substituted into equation (5) to obtain the indirect utility function, which, in a second step, is maximized with respect $e_t(i)$ subject to equation (8).

Figure 1. The dynamics of human capital and a poverty trap



A direct implication of the non-convexity of $\Omega[\tilde{h}_{t-1}(i)]$ in equation (12) is the multiplicity of steady states: one low, common to all dynasties and given by $\bar{h}$, and another high, dynasty-specific, given by the solution of $\tilde{h}_\infty(i) = \zeta[\tilde{h}_\infty(i)]$,

$$\tilde{h}_\infty(i) = \left[e^S \frac{a(i)^{(1+\beta)\psi(1-\alpha-\varphi)}}{\gamma(i)^{1-\psi}} \right]^{1/\{\beta+\psi[1-(1+\beta)(\alpha+\varphi)]\}}, \tag{13}$$

which is locally stable. Hence, 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.[9]

The ultimate sources of heterogeneity in the aggregate economy come from differences in $\gamma(i)$, $a(i)$, and $\tilde{h}_{-1}(i)$. Following Bénabou (2000), we assume that γ, a, and $\tilde{h}_{-1}$ follow mean-invariant log-normal independent distributions, that is,[10]

[9]Despite the simplicity of our model, intergenerational mobility is possible: dynasties with good exogenous circumstances can be overtaken by dynasties with bad exogenous circumstances but high willingness to exert effort.

[10]The log-normal distribution captures the negative skewness of income distributions in practice reasonably well. Moreover, the product of independent normal distributions converges to a log-normal so we can view income as the product of multiple factors (Gibrat, 1957).

$$\ln \gamma \sim N\left(\ln \hat{\gamma} - \frac{\Delta_{\gamma}^{2}}{2}, \Delta_{\gamma}^{2}\right),$$

$$\ln a \sim N\left(\ln \hat{a} - \frac{\Delta_{a}^{2}}{2}, \Delta_{a}^{2}\right),$$

$$\ln \tilde{h}_{-1} \sim N\left(\ln \hat{h} - \frac{\Delta_{-1}^{2}}{2}, \Delta_{-1}^{2}\right).$$

Random variables γ, a, and $\tilde{h}_{-1}$ have constant means equal to $\hat{\gamma}$, $\hat{a}$, and $\hat{h}$, respectively, and their variances are closely related to the class of relative inequality indices consistent with the Lorenz curve, 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., $T_0(a) = \Delta_a^2/2$, $T_0(\gamma) = \Delta_\gamma^2/2$, $T_0(\tilde{h}_{-1}) = \Delta_{-1}^2/2$. As said, we take $T_0(a)$ as a proxy of UI, and $T_0(\gamma)$ as a proxy of FI.[11]

At this point, it is important to note that the literature has traditionally viewed parental education as a factor beyond the individual's control (Roemer, 1993; Roemer, 1998). However, the human capital of parents differs in an important way from other factors included in $a(i)$, such as race or gender: parental human capital includes parental effort.[12] As a result, when we consider the young generation as part of an infinite set of generations (given an infinite time horizon), the initial inequality of human capital, $T_0(\tilde{h}_{-1})$, would mix both unfair and fair inequality processes (more on this below) and, for this reason, we take only $T_0(a)$ to proxy UI in the model.

2.3. The aggregate economy: the growth equation with FI and UI

Let $g_{y_t} = \ln y_t - \ln y_{t-1}$ be the growth rate of income per capita in period t. Because A is assumed to be constant, g_y is equal to the growth rate of human

[11]The connection between the Gini coefficient and the variance for any log-normal variable x is $G(x) = 2\Phi(\Delta_x/\sqrt{2}) - 1$, 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 the theoretical model. However, we will consider alternative measures of inequality in our empirical exercise, depending on the sample and UI measure used (see Section 4).

[12]In this respect, some authors have stressed that the effort of parents should be respected whatever its consequences to the next generation. This position corresponds to Swift's point of view (Swift, 2005; Brighouse and Swift, 2009), which argues that "[to] the extent that the reproduction of inequality across generations occurs through the transmission of cultural traits, it does so substantially (though not exclusively) through intimate familial interactions that we have reason to value and protect" (Swift, 2005, p. 271).

capital, which is a function of the change in the average years of schooling, $\pi(h_t - h_{t-1})$. The aggregate growth equation in our economy is (see Online Appendix A1 for details):

$$g_{y_t} = b_0 - [1 - (1-p)b_h]\ln(y_{t-1}) - b_p p - b_a(1-p)T_0(a) + b_\gamma(1-p)T_0(\gamma) + b_h^{t-1}\phi\left(\frac{-\mu_X}{\Delta_{-1}}\right)[2T_0(\tilde{h}_{-1})]^{1/2}, \tag{14}$$

where[13]

$$b_h = \frac{(1+\beta)\psi(\alpha+\varphi)}{\beta+\psi},$$
$$b_a = \frac{(1+\beta)\psi(1-\alpha-\varphi)}{\beta+\psi},$$
$$b_\gamma = \frac{1-\psi}{\beta+\psi};$$
$$b_0 = \frac{S}{(\beta+\psi)} + b_a \ln\hat{a} - b_\gamma \ln\hat{\gamma} + \frac{(1-b_h)[\lambda\ln(\lambda/\bar{r}) + \ln A]}{1-\lambda},$$
$$b_p = b_0 - \frac{\lambda\ln(\lambda/\bar{r}) + \ln A}{1-\lambda} - \ln\bar{h}.$$

The model predicts conditional convergence because b_h is between zero and one. It also predicts that poverty is harmful for growth (see Online Appendix A2), which is consistent with the empirical evidence found by Ravallion (2012) and Marrero and Servén (2022).

However, our main finding is the following: for economies with $p < 1$, $T_0(a)$ (our measure of UI) has a negative effect on growth, while the impact of $T_0(\gamma)$ (the fair component of inequality) is positive.[14] Their short-run elasticities are $-b_a(1-p)$ and $b_\gamma(1-p)$, respectively, and their long-run elasticities are equal to these terms divided by $1-(1-p)b_h$. However, the effect of our third source of inequality, $T_0(\tilde{h}_{-1})$, on growth

[13] In the last term of equation (14), $\phi(\cdot)$ is the standard normal density function of the random variable $X = \ln\tilde{h}_{-1}(i) - \ln(\bar{w}/w)$ with mean $\mu_X = \ln\hat{h} - (\Delta_{-1}^2/2) - \ln(\bar{w}/w)$ and variance Δ_{-1}^2.

[14] The negative effect of UI on growth implies that $b_a = [(1+\beta)\psi(1-\alpha-\varphi)]/(\beta+\psi) > 0$. Because $(\alpha+\varphi) < 1$, $\beta > -\psi$ is needed, which is always true as far as $\beta > 0$. The positive effect of FI on growth implies that $b_\gamma = (1-\psi)/(\beta+\psi) > 0$. Because $\psi \in (0,1)$, we only need that $\beta > -\psi$. Hence, $\beta > -\psi$ is a necessary condition to achieve our main results, while the convexity assumption of the effort function ($\beta > 0$) is sufficient.

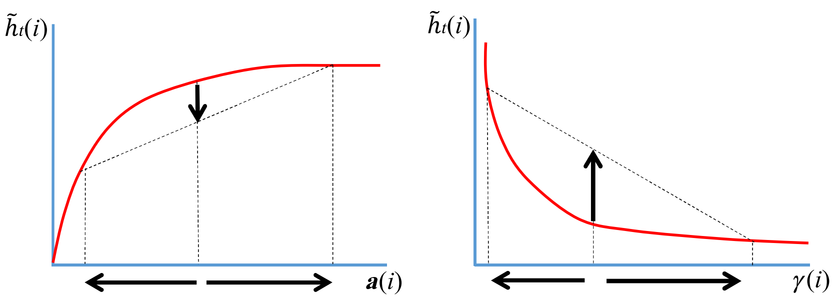
is ambiguous, as it is proved in Online Appendix A3. This finding connects with our discussion at the end of Section 2.2 regarding the interpretation of $T_0(\tilde{h}_{-1})$.

The explanation of our main result lies in the human capital accumulation process in equation (12) (see Figure 2). On the one hand (left panel of Figure 2), $\tilde{h}_t(i)$ is increasing and concave with respect to $a(i)$ and, therefore, compensating for bad circumstances is growth-enhancing as marginal returns to human capital are higher for those individuals who have less favorable circumstances. On the other hand (right panel of Figure 2), $\tilde{h}(i)$ is decreasing and convex with respect to $\gamma(i)$, and hence economies with higher heterogeneity in preferences to exert effort are growing faster, because marginal returns to human capital are higher for individuals with lower aversion to effort.

Notice that the magnitudes of the effects of UI and FI on human capital and growth depend greatly on the parameter ψ: if $\psi = 0$ (full meritocratic society), UI does not affect growth ($b_a = 0$), and the impact of FI on growth is maximum ($b_\gamma = 1/\beta$); if $\psi = 1$ (total nepotism), we find the opposite result, with b_a at its maximum and $b_\gamma = 0$.

A close examination of equation (14) shows that, for extremely poor economies, where p is close to one, the impact of $T_0(a)$ and $T_0(\gamma)$ on growth tends to disappear. The reason lies in the fact that UI and FI only affect the human capital accumulation process of the individuals that are not trapped (non-poor). Thus, if everybody is trapped ($p = 1$), they accumulate $\bar{h}$ so any marginal change of UI or FI does not modify the individual status, and human capital remains $\bar{h}$ for everyone. On the contrary, if $p < 1$, then UI reduces the average accumulated human capital of non-poor people, while FI increases their average level of human capital. Consequently, the higher the fraction of non-poor people, the greater the impacts of UI and FI on growth.

Figure 2. Effects of changes in circumstances and the idiosyncratic effort parameter on human capital accumulation



In the limit, when p is close to zero (rich countries), the growth equation simplifies to[15]

$$g_{y_t} = b_0 - [1 - b_h] \ln(y_{t-1}) - b_a T_0(a) + b_\gamma T_0(\gamma), \tag{15}$$

which is transparent in showing that UI is bad for growth while FI is good for growth.

2.4. Final caveats and imperfect markets

Our main result that FI and UI have opposite effects on growth does not depend on the log-normality assumption for $a(i)$, $\gamma(i)$, and $\tilde{h}_{-1}(i)$.[16] Moreover, it does not rely on any particular channel. Assumptions about market imperfections, rent-seeking, political economy functioning, unobservable effort, or individual talent have not been explicitly modeled. Hence, our baseline setting provides a broader perspective to understand the existing relationship between FI, UI, and growth.

Our argument in Online Appendix A4 is that the inclusion of imperfect markets would only reinforce the negative effect of UI on growth. In the same spirit as Galor and Zeira (1993) and Banerjee and Newman (1993), we introduce a borrowing constraint that affects human capital accumulation. The main implication is that a share of population is not able to borrow or to access high-quality education – these being people those who have bad circumstances and not necessarily those who make the least effort. In this framework, reducing UI is an extra benefit for growth because fewer people are affected by the borrowing constraint, so it increases the human capital level of the economy. In Section 4, we will connect the quality of institutions in a country with this extension.

3. Empirical approach

The usual reduced form used in the literature to test the impact of inequality on growth is the following (Berg et al., 2018; Brueckner and Lederman, 2018):

$$g_{it} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \varphi I_{it} + \varepsilon_{it}. \tag{16}$$

[15] Note that $\phi[(-\mu_X)/\Delta_{-1}] = 0$ when $p = 0$ because p is equivalent to the standard normal cumulative distribution function of X, i.e., $p = \Phi[(-\mu_X)/\Delta_{-1}]$, by definition. In this case, there is only one steady state of $\tilde{h}$, given by $\tilde{h}_\infty(i)$, which is dynasty-specific and globally stable. As a result, $T_0(\tilde{h}_{-1})$ does not have a direct impact on the long-run equilibrium and affects transitory growth only through its correlation with lagged income.

[16] This assumption allows us to write our results in terms of the MLD, which is an inequality index that fulfills the basic principles found in the literature on inequality (progressive transfers, symmetry, scale invariance, and replication of the population). Otherwise, our results would be written in terms of the variance, which is an inequality index that does not verify the principle of scale invariance.

Here, g_{it} denotes the growth rate in per capita income for country i between the periods $t-1$ and t (usually five or ten years), α_i and δ_t denote country- and time-specific effects, $\ln y_{it-1}$ 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 independent and identically distributed error term.[17] However, our framework from Section 2 suggests that we should estimate a different growth equation. For expository reasons, we start with the case where the sample contains only rich countries (i.e., $p = 0$). Based on equation (15), we should estimate the following equation,

$$g_{it} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \varphi_U \mathrm{UI}_{it} + \varphi_F \mathrm{FI}_{it} + \eta_{it}, \tag{17}$$

where UI and FI are unfair and fair inequality, respectively.

In the empirical implementation, if the measures of UI and FI are accurate, the coefficients φ_U and φ_F will be comparable with $-b_a$ and b_γ in equation (15). Consequently, we must check whether $\varphi_U < 0$ and $\varphi_F > 0$.[18] However, obtaining accurate estimations of UI and FI is very difficult in practice, especially for a large set of heterogeneous countries. On the one hand, objectively we need to capture UI empirically. For this task, we follow Brock (2020) and use a measure based on the concept of inequality of opportunity (Roemer, 1998). This class of estimator tries to isolate the unfair portion of overall inequality by focusing on individuals' circumstances beyond a person's control, such as race and gender (Marrero and Rodríguez, 2011). However, the set of relevant circumstances is never fully observed so that the estimators of UI are actually a lower bound (Ferreira and Gignoux, 2011).[19]

On the other hand, obtaining an empirical measure of FI is even more challenging as pure effort (the part of total effort not influenced by individual circumstances) is never observed. In principle, we could rely on the residual inequality (i.e., total inequality minus the estimated UI). Unfortunately, this strategy is not accurate for two reasons. First, as said, the set of relevant circumstances is never fully observed; consequently, the residual

[17] 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 (14) and (15).

[18] An empirical result in this vein was found for a panel of 26 US states and three decades (1970–2000) in Marrero and Rodríguez (2013).

[19] Databases with large number of circumstances are typically available only for developed countries (Marrero and Rodríguez, 2012; Palomino et al., 2019).

inequality is contaminated with unobserved circumstances and not all FI is fair by construction. Second, there are other sources of inequality such as luck and individual talent that cannot be straightforwardly assigned to FI but, because they are difficult to estimate, are included in the residual inequality.

Therefore, in the empirical implementation, we face the following dilemma: we usually estimate equation (16), but we must estimate equation (17), although we cannot properly estimate it. Our greatest aspiration is to have accurate measures of total inequality and a proxy of UI (the mentioned lower bound). Is this information enough to prove that $\varphi_U < 0$ and $\varphi_F > 0$ in equation (17)? Under certain basic assumptions, our answer is affirmative. For illustrative purposes and without loss of generality, we keep with the model excluding poverty.

Assume that total inequality is additively decomposable in three components: FI, UI, and residual inequality (RI), i.e., $I_{it} = \mathrm{FI}_{it} + \mathrm{UI}_{it} + \mathrm{RI}_{it}$. Moreover, suppose that $\mathrm{UI}_{it} = Q_{it} + V_{it}$, where Q_{it} is the part of UI that is observable for country i at time t, and V_{it} is the part of UI that cannot be measured. Both terms 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, using these definitions in equation (17) gives

$$g_{it} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \varphi_{I1t} I_{it} + \varepsilon_{it}, \tag{18}$$

where $\varphi_{I1t} = [\varphi_F + (\varphi_U - \varphi_F)(q_{it} + v_{it})]$ and $\varepsilon_{it} = \eta_{it} - \varphi_F \mathrm{RI}_{it}$. Notice that we can establish an exact equivalence between equations (18) and (16). Thus, under $\varphi_U < 0$ and $\varphi_F > 0$ in equation (17), the coefficient of overall inequality can be positive, negative, or null, depending on the relative strength of the UI and FI components. This result can explain the existing controversy in the literature about the sign of inequality in a growth model such as equation (16) (recall from footnote 1).

Next, using $Q_{it} = q_{it} I_{it}$ (the proxy of UI) in equation (18), we obtain the following growth equation,

$$g_{it} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \varphi_{I2t} I_{it} + \varphi_Q Q_{it} + \varepsilon_{it}, \tag{19}$$

where $\varphi_{I2t} = \varphi_F + (\varphi_U - \varphi_F) v_{it}$ and $\varphi_Q = \varphi_U - \varphi_F$.

From these expressions, we extract two necessary conditions for our main hypothesis to be satisfied [$\varphi_U < 0$ and $\varphi_F > 0$ in equation (17)]: first, φ_{I2t} can be positive, negative, or zero, although it must be higher than φ_{I1t}; second, φ_Q must be negative. In the empirical application, assuming that φ_{I1t} and φ_{I2t} are time-invariant, we can characterize these two conditions with available information on growth, total inequality, and a proxy of UI.

We can easily extend this result for the case where the sample contains countries with high poverty rates. In this situation, we start from equation (14).[20] The equivalent equations to equations (17), (18), and (19) are, respectively,

$$g_{y_{it}} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \vartheta p_{it} + \varphi_U \mathrm{UI}_{it}(1 - p_{it}) + \varphi_F \mathrm{FI}_{it}(1 - p_{it}) + \upsilon_{it}, \tag{20}$$

$$g_{it} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \vartheta p_{it} + \varphi_{I1}(1 - p_{it}) I_{it} + \varepsilon_{it}, \tag{21}$$

$$g_{it} = \alpha_i + \delta_t + \varrho \ln y_{it-1} + \vartheta p_{it} + \varphi_{I2}(1 - p_{it}) I_{it} + \varphi_Q (1 - p_{it}) Q_{it} + \varepsilon_{it}. \tag{22}$$

In these equations, we include the effect of poverty and its interaction with the different components of inequality. Now, we can analyze whether estimated φ_{I2} in equation (22) is higher than estimated φ_{I1} in equation (21), and whether estimated φ_Q in equation (22) is negative; we can also test whether poverty is growth-deterrent, i.e., $\vartheta < 0$ in equation (22) (Ravallion, 2012; Marrero and Servén, 2022).

4. Data: growth, inequality, unfair inequality, and poverty

In this section, we describe our measures for income growth, inequality, UI, and poverty, which are the data needed to estimate the growth equations described above. For income growth and overall inequality, we take data from Berg et al. (2018): per capita real GDP from the Penn World Table 7.1 and the net income Gini coefficient from the Standardized World Income Inequality Database 3.1 (Solt, 2016). For poverty (absolute headcount ratio with 1.90 US$ poverty line), we take data from POVCALNet (Ferreira et al., 2016).[21] By using data for these three variables every five years between 1960 and 2010, we construct a strongly balanced panel with 688 observations, for a total of 140 countries and 10 periods. With all this information, we only need a measure of UI to estimate equations (19) and (22). As said in

[20] As noted in Online Appendix A3, the last term in equation (14) is only transitory because $b_h < 1$ by definition. Moreover, it is very difficult in practice to compute it for a large number of countries and years. Consequently, for simplicity, we assume that this element is composed by a fixed term that is time-invariant and country-specific and by a random term that is time-variant but follows a random walk process. In this manner, its effect is captured by the fixed effects term and the error term.

[21] If there is no information about poverty in a given year, we use the nearest available year.

Table 1. Descriptive statistics of the three samples

	IES sample	DHS sample	Institutional sample
Sample size	115	114	533
Number of countries	42	39	111
Growth rate (average)	0.022	0.016	0.018
	(0.022)	(0.027)	(0.029)
Poverty rate (average)	0.079	0.408	0.173
	(0.144)	(0.231)	(0.236)
Inequality (Gini) (average)	0.344	0.447	0.388
	(0.091)	(0.081)	(0.102)
UI proxy (average)	0.025	0.599	0.845
	(0.046)	(0.495)	(0.051)
Std within/between	20.00%	16.50%	51.72%

Note: Standard deviations are given in parentheses.

Section 1, we follow Brock (2020) and use a measure based on the concept of inequality of opportunity. In this respect, we adopt two complementary strategies.

First, we use the largest set of available inequality of opportunity indices across countries obtained by Ferreira et al. (2018) from two different microeconomic panel data sets: the Income and Expenditure Survey (IES) and the Demographic and Health Survey (DHS). Second, to have a larger set of countries and years, we propose a strategy to construct an alternative measure of UI as described in Section 4.1. Then, the information of UI is merged with the income growth, inequality, and poverty data.

For each sample, Table 1 shows the descriptive statistics of the key variables (growth, poverty, inequality, and the UI measure). While descriptive statistics for growth, poverty (the headcount rate), and inequality (the Gini index) are directly comparable for the three samples, the metrics for the alternative UI measures are totally different because they are constructed using different sources, samples, methodologies, and indices, as discussed shortly. Far from being a problem, this fact allows us to develop a large robustness analysis for our results.

4.1. The IES and DHS samples

The first sample (IES) contains 42 countries – both developed and developing – for a total number of 115 observations.[22] The variable used

[22]The authors used three harmonized meta-databases: 23 (mostly developed) countries from the Luxembourg Income Study (LIS), six Latin American countries from the Socioeconomic

to calculate inequality of opportunity was net household income per capita for 32 countries and household expenditure per capita for the other 10 countries. The inequality index used to compute inequality of opportunity was the MLD, and the set of circumstances was gender, race, or ethnicity, the language spoken at home, religion, caste, nationality of origin, immigration status, and region of birth.[23]

The second sample (DHS) contains 39 developing countries from Africa, Asia, and Latin America for a total number of 114 observations. Because the DHS does not contain information of household income or expenditure, Ferreira et al. (2018) 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 inequality index used to calculate inequality of opportunity was the variance, and the set of circumstances was region of birth, number of siblings, religion, ethnicity, and mother tongue. Again, the list of circumstances varies from country to country (see Ferreira et al., 2018).

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 percent (with a standard deviation of 14 percent); 55 percent of the country–year observations showing a poverty rate equal to zero and 75 percent below 12 percent. However, for the DHS sample, the average poverty rate is above 40 percent (with a standard deviation of 23.1 percent); all observations show positive poverty rates and 25 percent of the observations show a rate above 60 percent. The average levels of the Gini coefficient are also quite different: 34.4 percent for the IES and 44.7 percent for the DHS, 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 percent for the IES sample and 1.6 percent for the DHS.

These notorious differences put forth that, while it would be reasonable to use the model specification without poverty (equations (18) and (19)) for the IES sample, we must focus on the specification with poverty (equations (21) and (22)) for the DHS sample. However, these two samples have three important limitations: a reduced coverage of countries for a worldwide analysis; lack of homogeneity in the set of circumstances across countries;

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.

[23]The authors used the current region of residence for those countries where the birth region was unavailable. However, the number and kind of circumstances differed across countries (for details, see Ferreira et al., 2018).

and a small within-group variability of the inequality of opportunity measure (see Table 1), which makes it difficult to exploit the time dimension of the panel dataset.

For all these reasons, we propose an alternative measure of UI, which allows us to more than triple the sample size and to increase the within-group variability of the sample (see the final column in Table 1). As expected, because this new sample contains countries belonging to both the IES and DHS sample, its statistics are between them.

4.2. An alternative institutional-based sample

We propose an alternative approach to proxy UI by combining macroeconomic information on inequality with institutional variables. With respect to the IES and DHS samples to have a proxy for UI, our alternative has several advantages: a larger sample size, homogeneity, and a higher within-country variability (see the final column of Table 1).

Our proposal is supported by two results from the inequality and growth literature. First, macroeconomic factors, which are beyond an individual's control, are important determinants of the global inequality of opportunity (Milanovic, 2015).[24] Second, 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 socio-economic status (Alesina et al., 2003; Stiglitz, 2012; Acemoglu et al., 2015).

Two additional arguments reinforce the use of institutional variables to proxy UI at the country level. First, as Brock (2020, p. 658) has shown, the amount of UI in a society depends on "whether people believe the system is unfair, and how well governing institutions safeguard fair-play". Second, institutions are key to reduce the effect of market imperfections in the economy and to assure a fair access to the labor and capital markets. The last idea connects with the extension of the model discussed at the end of Section 2 and developed in Online Appendix A4.

Consequently, bad institutions, as reflected by deficient levels of democracy, excessive levels of corruption, and large ethnic–linguistic and religious divisions, could explain a significant proportion of the UI observed in a particular country. How do we exactly construct this alternative UI

[24]Global inequality of opportunity measures inequality of opportunity at the global level by considering differences in opportunity across the world's population (regardless of the country of origin). The macro variables used by Milanovic were the country's own GDP per capita and the Gini coefficient.

measure? Following previous ideas, and in the same spirit as Fatás and Mihov (2003), our procedure is based on the following chain:

$$\begin{gathered}\text{Institutional set-up and social division}\\ \Downarrow\\ \text{Unfair inequality}\\ \Downarrow\\ \text{Overall inequality}\\ \Downarrow\\ \text{Growth}\end{gathered}$$

Differences in the institutional set-up and social (ethnic–linguistic and religious) division generate differences in the amount of UI and, therefore, in overall inequality. Then, this institutional-induced UI affects income growth through overall inequality. Because UI is not directly observed, we use the following political economy regression with fixed effects to proxy UI (Fatás and Mihov, 2003):

$$I_{it} = \alpha_i + \delta_t + \sum_{k=1}^{K} \tau_k X_{kit} + \pi g_{it} + w_{it}, \tag{23}$$

where I_{it} corresponds to the net income Gini index for each country–year, and X_{kit} represents each of the following institutional variables: democratic accountability (how responsive the government is to its people); law and order; corruption; religious division; and ethnic–linguistic division.[25] Note that, to isolate the UI channel (our interest) from other possible effects channeled through growth, we control the inequality–institutional relationship by the growth rate of real per capita GDP in equation (16). Thus, the UI institutional measure is the fitted part of inequality:

$$\hat{I}_{it} = \sum_{k=1}^{K} \hat{\tau}_k X_{kit}. \tag{24}$$

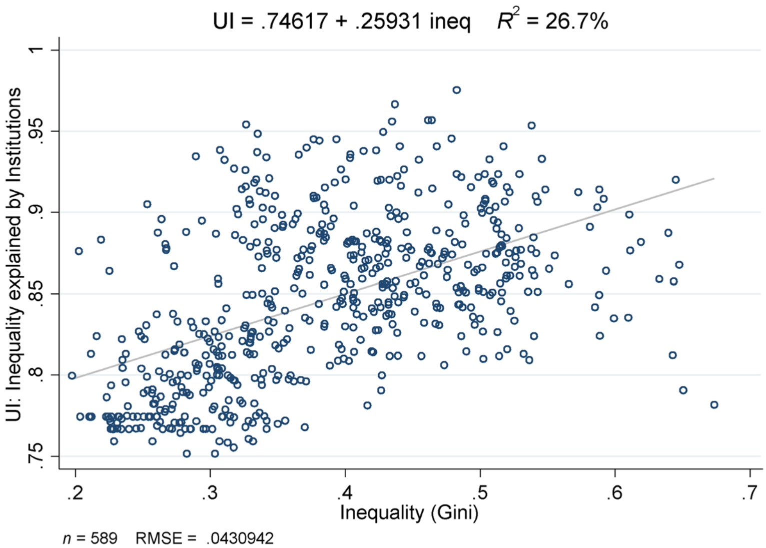
Because inequality and institutions can be determined simultaneously, we estimate expression (23) by system GMM, although the results are similar to when we use pooled ordinary least squares (OLS) with fixed effects. Table A5.1 in Online Appendix A5 shows the estimated results for alternative political economy models.

[25]These political economy variables – considered at five-year intervals from 1985 to 2015 – come from the Political Risk Module of the International Country Risk Database (ICRD), which is available from 1985 onwards.

For our entire sample, we calculated the correlation between the institutional-adjusted Gini coefficient (the fitted Gini of equation (23)) and total inequality (Gini). The coefficient of determination (R^2) was 0.231 (Figure 3), which is slightly lower than the correlations found in the literature (using other databases and measures) for developed economies (Marrero and Rodríguez, 2012, 2013; Brunori et al., 2013).

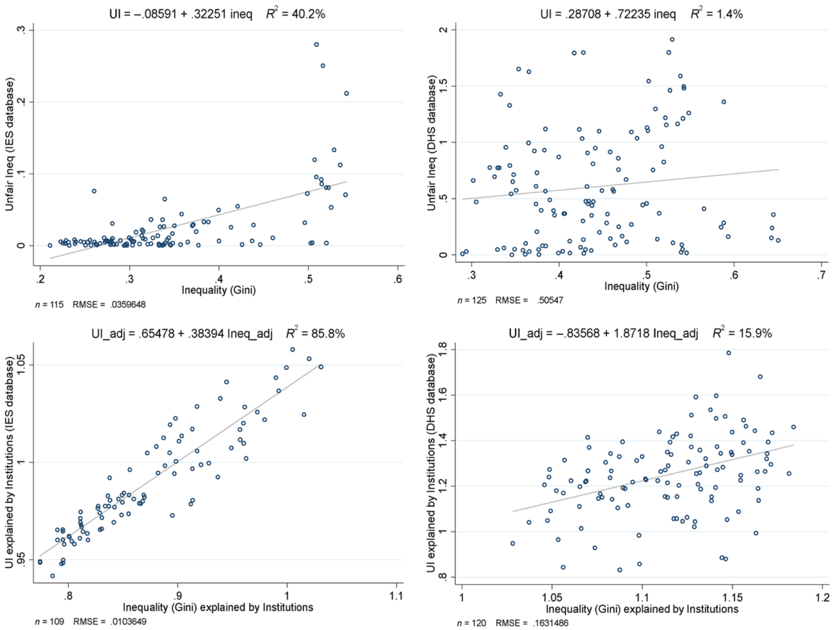
To illustrate the potentiality and validity of our approach for the construction of an alternative measure of UI, we carry out the following simple exercise. We compare the Gini coefficient and the institutional-adjusted Gini index with the inequality of opportunity measures in the IES and the DHS samples. When we compare the latter with the Gini index, the correlations are positive but modest, with R^2 equal to 0.402 (significant) for the IES and 0.014 (non-significant) for the DHS (see Figure 4, top panels). However, when the Gini coefficient and the measures from the IES and DHS samples are adjusted by the institutional set-up and social division, we find much higher correlations: 0.858 (strongly significant) for the IES sample and 0.159 (significant) for the DHS sample (Figure 4, bottom panels). Therefore, while overall inequality is a poor predictor of UI, its capacity to predict UI greatly increases when it is conditioned to the aforementioned macroeconomic institutional channels.

Figure 3. Inequality and UI (proxied by the Gini explained by institutional factors)



Notes: This figure represents the scatter plot (for the institutional sample) for the UI measure using the institutional approach (i.e., the inequality adjusted by the institutional characteristics according to equation 23) versus total inequality (Gini index).

Figure 4. Inequality, UI and measures adjusted by institutional factors (IES and DHS samples)



Notes: The top panels show the scatter plots between the different measures of UI, for the IES sample (left panel) and the DHS sample (right panel). The bottom panels show the scatter plots between the UI and inequality measures for these two samples but when these series are adjusted by institutional factors.

To end this section, it is worth mentioning that the institutional UI measure captures a different feature of UI than the measures based on the IES and DHS samples. It likely captures differences in class more than differences across demographic groups that occur in all classes, such as gender. This said, the institutional UI can do well capturing race/ethnicity differences as these are often correlated with class divisions.

5. Estimation results

In this section, we estimate equations (18)–(19) and (21)–(22) to analyze whether $\varphi_{I2} > \varphi_{I1}$ and $\varphi_Q < 0$ for a set of alternative UI measures, samples, and econometric techniques.

Our preferred econometric approach is the IV procedure used in Brueckner et al. (2012) and Brueckner and Lederman (2018) to control for potential reverse causality between inequality and growth (see Online Appendix A6).

For robustness, we also use pooled OLS and system GMM.[26] We include time-fixed effects in all models, but do not consider country-fixed effects when using the IES and DHS samples because of their small within-country variability, as commented above (Table 1).[27] For the institutional sample, which possesses a much higher within-country variability, we consider both time- and country-fixed effects.

5.1. Main results

We present the estimation results for the three alternative samples and UI measures, and two alternative econometric methods (IV and system GMM) in Tables 2, 3, and 4.[28] For each table, the first two columns correspond to the reduced forms without poverty. In the first column, we only include overall inequality, while in the second column we also consider the corresponding measure of UI. The next two columns show the results for the reduced forms in equations (21) and (22) which include poverty. Overall inequality interacts with poverty in the third column, while the interaction between UI and poverty is also included in the fourth column.

Table 2 shows the results for the IES sample. Recall that this sample includes developed countries and developing countries with small poverty rates. Hence, the relevant equations in this case are those without poverty (equations (18) and (19)). Table 3 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 equations are equations (21) and (22). Finally, Table 4 shows the results for the institutional 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 equations (21) and (22).

For the IES sample (Table 2), the coefficient of UI is always negative and significant at the 5 percent level of significance. Moreover, the coefficient of overall inequality, which is negative when the measure of UI is not included in the regression, turns positive (and even significant under system GMM)

[26]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 might 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).

[27]For these two samples, country-fixed effects would capture almost 100 percent of the conditional relationship between growth, inequality, and unfair inequality.

[28]Our main results – available upon request – are also robust to pooled OLS.

Table 2. Growth, inequality, and unfair inequality: UI proxy from the IES (Ferreira et al., 2018)

	Instrumental variable				System GMM			
log(income), lag	−0.003*	−0.002	−0.004	−0.004	−0.006	−0.003	−0.007	−0.006
	(−1.91)	(−1.45)	(−1.19)	(−1.08)	(−1.28)	(−0.69)	(−1.20)	(−0.62)
Gini index	−0.025	0.027			−0.081	0.114		
	(−1.12)	(1.01)			(−1.06)	(1.23)		
UI proxy		−0.147***				−0.546**		
		(−2.64)				(−2.14)		
Gini index (1 − poverty)			−0.021	0.034			−0.059	0.164*
			(−0.83)	(1.14)			(−0.98)	(1.84)
UI proxy (1 − poverty)				−0.177***				−0.655***
				(−2.63)				(−2.65)
Poverty			−0.021	−0.004			−0.026	0.021
			(−0.63)	(−0.11)			(−0.38)	(0.21)
Number of observations	114	114	114	114	114	114	114	114
R^2 adj.	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 (p-value)					0.275	0.331	0.233	0.362
m2 p-value					0.270	0.160	0.250	0.109
Number of cross-sections					42	42	42	42
Number of instruments					33	36	48	43

Notes: Constant term and time dummies are included in all models. For the IV approach, the instrument Z_x for the variable x (the Gini coefficient or the UI 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 (Fatás 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., 2012) 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 percent of the sample in all cases. Robust t-statistics are given in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

Table 3. Growth, inequality, and unfair inequality: UI proxy from the DHS (Ferreira et al., 2018)

	Instrumental variable				System GMM			
log(income), lag	−0.083***	−0.076**			0.006	0.009**	−0.002	0.002
	(−2.69)	(−2.56)			(1.28)	(2.49)	(−0.18)	(0.19)
Gini index	0.002	0.003	−0.007	−0.007	−0.114**	−0.084**		
	(0.68)	(0.86)	(−1.47)	(−1.36)	(−2.51)	(−2.36)		
UI proxy		−0.007				−0.012		
		(−1.28)				(−1.25)		
Gini index (1 − poverty)			0.113**	−0.086*			−0.184***	−0.082
			(−2.15)	(−1.71)			(−3.22)	(−1.45)
UI proxy (1 − poverty)				−0.0137*				−0.017*
				(−1.88)				(−1.68)
Poverty			0.089***	−0.085***			−0.131***	−0.091*
			(−3.44)	(−3.46)			(−2.90)	(−1.88)
Number of observations	114	114	114	114	114	114	114	114
R^2 adj.	0.206	0.220	0.237	0.254				
Kleibergen–Paap F-stat	4683911.6	212703.6	799624.5	51860.4				
Underidentification F-stat	436.15	36.21	35.61	28.61				
(p-value)	0.000	0.000	0.000	0.000				
Hansen (p-value)					0.0133	0.145	0.380	0.206
m2 p-value					0.534	0.782	0.846	0.924
Number of cross-sections					39	39	39	39
Number of instruments					33	38	50	47

Notes: See the note to Table 2. 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 4. Growth, inequality, and unfair inequality: UI proxy from the Gini adjusted by institutions and social division

	Instrumental variable				System GMM			
log(income), lag	−0.077***	−0.076***	−0.082***	−0.083***	−0.006	−0.010**	−0.021***	−0.029***
	(−11.06)	(−11.11)	(−13.02)	(−13.35)	(−1.39)	(−2.15)	(−4.88)	(−4.31)
Gini index	−0.077***	−0.071**			−0.256***	−0.239***		
	(−2.50)	(−2.31)			(−5.48)	(−4.66)		
UI proxy		−0.148***				−0.171		
		(−3.73)				(−1.60)		
Gini index (1 − poverty)			−0.134***	−0.129***			−0.204***	−0.167***
			(−3.22)	(−3.10)			(−4.59)	(−3.12)
UI proxy (1 − poverty)				−0.166***				−0.284***
				(−3.80)				(−2.62)
Poverty			−0.121***	−0.264***			−0.171***	−0.421***
			(−5.39)	(−6.11)			(−5.53)	(−3.92)
Number of observations	531	531	531	531	530	530	530	530
R^2 adj.	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)	0.000	0.000	0.000	0.000				
Hansen (p-value)					0.0371	0.0240	0.198	0.149
m2 p-value					0.107	0.188	0.170	0.667
Number of cross-sections					111	111	111	111
Number of instruments					79	88	95	107

Notes: See the note to Table 2. In addition to time dummies, fixed effects are also included in IV. The unfair inequality proxy used in the estimations is from the results in Column 11 of Table A5.1 (system GMM controlling by income growth).

when UI is considered. In accordance with the empirical strategy described in Section 3, these results are consistent with our main hypothesis that $\varphi_U < 0$ and $\varphi_F > 0$. Quantitatively, a decrease in one standard deviation of the UI (0.0463; see Table 1) – that is, moving levels of UI similar to the one in Peru or Brazil to levels related to countries such as the US or Italy – is associated with an increase in per capita annual GDP of 0.68 percentage points (0.0463×-0.147), which would imply, for example, a change from the sample average 0.0220 to an annual growth rate of about 0.0288.[29] In addition, it is worth mentioning that, for this sample, poverty is not significant in any specification. As in Marrero and Servén (2022), the negative effect of poverty on growth is restricted to samples with sufficiently high poverty rates.

For the DHS sample, when poverty is not included in the model, the coefficient of overall inequality is negative and significant for system GMM (non-significant for IV) and it changes little when the UI measure is included; the estimated coefficient of UI is non-significant in this case. However, when the model includes poverty and the cross term, these results become like those obtained for the IES sample. 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. Now, the coefficients of UI are negative and significant in all cases, while the coefficients of overall inequality increase when UI is included in the model.

The estimated results suggest that a decrease in one standard deviation of the corresponding measure of UI (0.4949; see Table 1) – that is, moving from an average level such as 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 real per capita GDP of 0.68 percentage points (0.4949×-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 our estimations is lower for the DHS sample, the impact is similar to the one obtained for the IES sample.[30] In any case, these results

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

[30] The results in Ferreira et al. (2018) using the IES and DHS samples differ from ours (they did not find any effect of inequality of opportunity on growth) most likely for three important reasons. First, we use different data sources as, following Acemoglu et al. (2008) and Berg et al. (2018), our inequality indices are from the SWIID 3.1 in Solt (2016) and per capita real output is from the PWT 7.1. Second, our econometric specification is the one suggested by the theoretical model developed in Section 2, which includes the interaction between poverty and inequality. Moreover, the controls are not lagged, following Berg et al. (2018) and Brueckner and Lederman (2018). Third, we use an IV approach (Brueckner et al., 2012) to control for a potential reverse causality problem in the inequality–growth relationship.

show the importance of using the correct reduced-form equation; that is, the correct reduced form must contain poverty and its interaction with inequality if the sample considered contains a large share of countries with high poverty rates.

Finally, we discuss the results for the institutional sample (Table 4). Again, UI is found to be harmful for growth, while the coefficient of overall inequality tends to increase when the measure of UI is included in the regression (for robustness, see also the results in Online Appendix A7, Tables A7.1–A7.3, for this sample). The coefficient of poverty in Table 4 is always negative and significant, and the differences between the estimated coefficients of UI are small when including poverty (and cross-effects) or not.

Quantitatively, the results are like those obtained for the IES and DHS samples. For instance, looking at the model with poverty for the IV approach, we obtain that a decrease in one standard deviation of the UI measure (0.0511; Table 1) – that is, moving from an average level similar to the one observed in countries such as Mali, Vietnam, or Nigeria to a level observed in Italy or Lithuania – is associated with an increase in real per capita GDP of 0.85 percentage points (0.0511×-0.166). For example, this change would imply moving from the observed average annual growth rate of 0.0185 to an annual growth level of, for example, 0.0270.

In comparison with the results for the DHS sample, the inclusion of poverty seems not to be important for UI. There are two possible explanations for this empirical fact. First, our institution-based sample is a mix of the countries in the DHS and IES samples. Second, the institutional proxy of UI includes indicators that reflect somehow the poverty of a country. In this respect, we find that the correlation between our institutional proxy of UI and poverty is 0.5177, while the correlation between the UI proxy from the IES and DHS samples and poverty is 0.1566 and −0.1462, respectively. Therefore, we cannot rule out either of these two possibilities.

Our empirical results therefore seem to support the two main hypotheses of the model. On the one hand, marginal returns to human capital are higher for those individuals who have less favorable initial conditions, so compensating for bad circumstances (reducing UI) is growth-enhancing. On the other hand, marginal returns to human capital are higher for individuals with lower aversion to effort, so increasing inequalities due to effort (FI) also helps to boost growth.

5.2. Further robustness analysis

In addition to all the robustness checks already performed, we develop three additional sensitivity analyses for our main results. To simplify the exposition and tables, we show the results for the three samples considered (IES, DHS, and institutional sample) only for our preferred IV approach.

The negative effect of UI on growth could be capturing possible nonlinearities in the relationship between poverty and growth. To control for this, we perform two alternative exercises. First, we estimate a modified version of the basic empirical equation that includes a quadratic poverty term (see Table A8.1 in Online Appendix A8). The inclusion of a poverty quadratic term introduces some collinearity in the regression, so estimations become less precise, especially for the IES and DHS samples. However, we observe that our main results are robust to this extension: the effect of UI remains negative and significant, while the estimated coefficient of inequality increases when the UI proxy is included in the equation. In addition, poverty is a growth deterrent in the DHS and institutional samples, but not in the IES sample. As for the quadratic term of poverty, it is also not significant in the IES sample, while it is significant (and positive) in the other two samples. For the latter two cases, the relationship between poverty and growth is decreasing and convex, although it is never upward (i.e., the value of the quadratic function is always negative for p between 0 and 1, because the magnitude of the linear coefficient is always higher than that of the quadratic term).

Second, we know from Marrero and Servén (2022) that the correlation between growth and poverty is systematically negative, but it is mainly driven by sample observations with high poverty rates. Accordingly, poverty should not have a significant effect on growth if the percentage of poor people is low (i.e., the negative association between poverty and growth is especially concentrated for the countries with high poverty rates). This non-linearity of poverty can be tested by a non-parametric approach for poverty. We use the semi-parametric approach in Robinson (1988) for the IES and DHS samples as we do not include fixed effects for them, and the one in Baltagi and Li (2002) for the institutional sample for which we include fixed effects.

For the different samples considered, the semi-parametric adjustments between growth and poverty, given the linear relationship of the other variables in the model (inequality and UI, crossed or not with poverty), are shown in Figure A8.1 (Online Appendix A8). For the IES sample, the relationship is unclear and highly volatile, mainly because there are few observations with large poverty rates. Conversely, for the other two samples, where the share of countries with high poverty rates is significantly larger, the relationship is clearly negative. More importantly, the fact that UI is growth-deterring does not change when we consider this potential non-linearity between growth and poverty (see Table A8.2).

Our last exercise considers simultaneously the two types of inequality, poverty, and the interactions of both types of inequality with poverty (see Table A8.3). This regression is not indicated by our model, but it helps to check the robustness of our results.

For the IES and DHS samples, UI and $(1-p)\cdot\text{UI}$ are almost perfectly correlated (0.996 for the IES sample and 0.868 for the DHS sample). The reason for this is that there is little within-country variability of UI and poverty in these two samples (recall the discussion in Section 4). Meanwhile, for the institutional sample, the correlation of the same two variables is −0.3188, probably because the sample size and the within-country variability are large.

For the IES sample, the estimates are negative, significant, and very similar for the UI variable when we include only UI or $(1-p)\cdot\text{UI}$ in the regression. For the DHS sample, the estimated results for the UI proxy are negative and significant only when UI is crossed with poverty alone, as in Table 3. For both samples, if we include both terms, UI and $(1-p)\cdot\text{UI}$, together they are not significant because of the high collinearity problem commented before.

For the institutional sample, the inclusion of both variables is not problematic. In this case, the linear term is positive but not significant, while the crossed term is negative and significant. Hence, our qualitative conclusions for UI remain the same. Moreover, the estimated coefficients for UI in Table A8.3 are consistent with our previous estimates in Table 4.

For inequality, both the linear and the cross terms are significant, but with opposite signs (see Column 7 in Table A8.3). Thus, the estimated coefficient, which is now $0.199-0.359(1-p)$, changes its sign depending on the level of poverty. For high levels of poverty, the sign is dominated by the linear term and its estimation is close to 0.199. However, the estimated relationship turns negative when poverty is approximately lower than 0.44, being −0.16 when poverty is equal to zero. Note that this range of values is consistent with our estimates in Table 4.

6. Conclusions

The way overall income inequality affects economic growth is more complex than what the literature has commonly considered. 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 growth. Instead, we have argued here that the difference between fair and unfair inequality is the main reason for this lack of robustness: the part of total inequality generated by factors beyond the individuals' control (UI) is growth-deterring, while the type of inequality that is generated by the difference in the willingness to exert effort (FI) is growth-enhancing. This is the hypothesis we have analyzed in the paper, theoretically and empirically.

From a theoretical point of view, we propose a human capital model that explicitly highlights the different effects of alternative types of inequality

(UI and FI) on growth without relying on any particular channel. Indeed, considering imperfect markets only reinforces our results. Moreover, by including a poverty trap framework, we analyze the consequences of the interaction between the different sources of inequality and poverty.

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. As 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, UI or FI, dominates in the overall change. Moreover, poverty is found to be harmful for growth and the effect of UI and FI on growth tends to decrease with poverty. However, the latter deserves further analysis, as it could be the case that poverty and UI are mutually reinforcing in reality.

From an empirical perspective, we have emphasized that testing our hypothesis directly is not reliable because the decomposition of overall inequality into UI and FI is difficult in reality. Instead, we propose an alternative empirical strategy to analyze our hypothesis.

We show that our hypotheses are consistent with the following results: the UI proxy has a negative effect on growth and the estimated coefficient of overall inequality increases when the standard inequality–growth equation is extended with the UI proxy. We find that these results are valid and robust to a variety of samples, UI proxies, econometric techniques (instrumental variables, system GMM, pooled OLS) and model specifications.

Our results help to explain some facts in the growth literature. On the one hand, some growth-enhancing and growth-deterring channels proposed in the literature can be directly linked to the fair and unfair inequality components discussed here. For example, the growth-enhancing channels, "accumulation of savings" (Kaldor, 1956) and "unobservable effort" (Mirrlees, 1971), are related to individual effort and, therefore, to the fair component of total inequality. On the contrary, the growth-deterring channels, "capital market imperfections" (Banerjee and Newman, 1993; Galor and Zeira, 1993), "fertility" (Galor and Zang, 1997), and "political instability" (Alesina and Perotti, 1996), can be related to factors beyond individual's responsibility (unfair inequality).

On the other hand, our distinction between FI and UI throws some light upon some intriguing results found in the literature. For example, Barro (2000) shows a negative relationship between growth and inequality within the poorest countries, while this relationship is positive when looking at the most-developed countries. An explanation that arises from our proposal is that unfair inequality is more important within less-developed countries, which is exactly what the literature has found (Cogneau and Mesplé-Somps, 2009; Ferreira and Gignoux, 2011). Similarly, some empirical studies have found that the effect of income inequality on growth is sensitive to the inclusion of some variables such as regional dummy variables (Birdsall et al., 1995). Our proposal offers an easy explanation for this result: the effect of income inequality upon growth has a different sign depending on the type of control (more related to FI or UI) that is introduced in the regression.

In addition, our results can provide policy implications. For very poor countries, the effect of any type of inequality on growth is weak, and fighting poverty is probably the most effective way not only to save lives but also to promote growth. Indeed, pro-poor policies, which have been shown to be highly effective to reduce poverty in developing countries (Dollar and Kraay, 2002; Dollar et al., 2016), could generate a virtuous cycle: a reduction of poverty would increase growth (for example, by augmenting savings, investment, and human capital) which, in turn, would reduce poverty. Moreover, because most of the sources of extreme poverty are associated with unfair situations (Banerjee and Duflo, 2011), such as the lack of access to credit for fertilizers or insecticides and to medicines against HIV or malaria, the low quality of education, and poor infrastructures such as running water or electricity in rural areas, reducing poverty would also help to reduce UI. Later, when the economy develops and shows low levels of poverty, anti-poverty measures would become less effective in promoting growth, with the fight against UI being a more important measure to enhance growth.

This is not, however, the whole story extracted from this paper. To overcome the limitations of the existing UI indices at worldwide level, we have constructed an alternative proxy of UI by considering that the quality of institutions and ethnic–linguistic and religious division are relevant macroeconomic drivers of UI. We have found that these are relevant drivers, and that the resultant UI 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 can have a double benefit effect on the economy. On the one hand, it can reduce overall inequality (in particular, the bad part of inequality) and, on the other hand, it can enhance economic growth by reducing UI. A detailed empirical analysis of this possibility at a more disaggregate level is a promising avenue that future research should take.

Supporting information

Additional supporting information can be found online in the supporting information section at the end of the article.

Online appendix
Replication files

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