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TRADE AND CLIMATE CHANGE: THE CHALLENGES AHEAD

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ABSTRACT

Inequality and Growth: The Neglected Time Dimension

The empirical literature on the relationship between inequality and growth offers a contradictory assessment: Estimators based on time-series (differences-based) variation indicate a strong positive link while estimators (also) exploiting the cross-sectional (level-based) variation suggest a negative relationship. Using an expanded dataset, the present paper confirms this conflicting pattern — and reconciles it on the basis of a simple model. We argue that the differences-based methods are prone to reflect the mostly positive short or medium-run implications of inequality while the level-based estimators also incorporate more negative long-term consequences. Thus, the latter estimates come close to reflecting the adverse overall impact of inequality in the long run.

JEL Classification: C23, O11, O15 and O43
Keywords: growth, inequality, long-run effects, medium-run effects

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1 Introduction

Over the past two decades, theoretical work has come up with a substantial number of channels through which inequality may influence economic growth, either in a *positive* or in a *negative* direction (see, e.g., Galor, 2009, for a recent and comprehensive overview). These theoretical contributions have made clear that the impact of inequality is quite complex and likely to depend on, among other things, the specifics of a country (e.g., the stage of economic development; the extent of market failures; the form of government) or the time horizon considered (e.g., medium run vs. long run). This theoretical ambiguity is mirrored in the empirical literature which – mainly based on broad panels of countries – finds both significantly positive and negative effects, and sometimes no effects at all.

Yet, a closer look at the empirical literature reveals an interesting pattern. Estimates based on time-series variation only (e.g., estimations relying on first-differences estimators such as those in Forbes, 2000; Li and Zou, 1998; Benhabib and Spiegel, 1997) find a strong positive impact of inequality. On the other hand, estimates which also exploit the cross-sectional variation in the data, such as the random-effects estimators in Barro (2000), find a negative relationship (and significantly so in samples that exclude rich countries). Such a negative link is also present in earlier studies based on simple cross-country OLS estimates (e.g., Alesina and Rodrik, 1994; Persson and Tabellini, 1994; Deiniger and Squire, 1998; Clarke, 1995).

These results in the literature can already be seen from a look at some crude data. Panel *a.* of Figure 1 is based on time-series variation only. Exploiting multiple observations within countries, it plots changes in the log GDP p.c. against changes in the lagged Gini coefficient and reveals a mildly positive relationship. Panel *b.* highlights the relationship in levels. It plots the log GDP p.c. against the lagged Gini coefficient and documents a clear negative link.[1]

Figure 1 here

This paper contributes to the literature in two ways. *First*, we show that the pattern of existing results is indeed driven by the choice of methods rather than idiosyncratic differences across studies (such as the selection of countries, time periods, or included control variables). We do so by taking advantage of an expanded and more comprehensive inequality data set. Also in this much larger data set, the first-differences GMM estimator consistently indicates a strong positive inequality-growth relation while the system GMM estimator (which also exploits the cross-sectional variation) indicates a negative link (and significantly so in all but the

[1] Figure 1 is about inequality and GDP p.c., both in terms of first differences (panel *a.*) and levels (panel *b.*). It is this variation that is exploited in the GMM estimation below (see equations 1 and 2 of Section 2.1).

richest countries). *Second,* we interpret these results through the lens of the recent theoretical literature on growth and development. We argue that the standard regression equation underlying most empirical estimates is (mis-)specified in a way that induces (i) the first-difference GMM estimators to systematically pick up the positive (short–run) effects; (ii) the system GMM estimator to reflect primarily the negative (long-run) consequences.

To convey our argument in a precise way, we introduce a simple model. This approach helps us to shed light on the associated biases involved in empirical estimates that rely on time-variation versus cross-sectional variation, respectively. The model mirrors that inequality has both positive and negative effects on growth and, importantly, that these different effects cluster in a specific way. On the one hand, inequality can *promote* growth by fostering aggregate savings (Kuznets, 1955; Kaldor, 1955); by promoting the realization of high-return projects (Rosenzweig and Binswanger, 1993); or by stimulating R&D (Foellmi and Zweimueller, 2006). On the other hand, inequality may *hamper* growth by promoting expensive fiscal policies (Perotti, 1993); by inducing an inefficient state bureaucracy (Acemoglu et al. 2008); by hampering human capital formation (Galor and Zeira, 1993; Galor and Moav, 2004); by leading to political instability (Bénabou, 1996); or by undermining the legal system (Glaeser et al., 2003). Most of the positive effects (e.g., those operating through convex savings functions, market imperfections or innovative incentives) rely on purely economic mechanisms. Arguably, these effects materialize relatively fast, in the *short* or *medium run.* Most of the negative effects, however, involve the political process, the change of institutions, the rise of socio-political movements, or they operate through changes in educational attainment of the population. Arguably, these effects take time and materialize primarily in the *long run.*

On the basis of these theoretical arguments, the seemingly contradictory evidence on the inequality-growth relationship can be reconciled in a quite natural way. Studies that exploit mainly the time-series dimension of the data, such as the first-differences GMM estimator, regress changes in (log) output on (slightly) lagged changes in inequality. When inequality goes up, the positive short- or medium-run effects are associated with positive changes in inequality while the subsequent negative changes (i.e., those coming from the long-run effects) are treated as noise. In other words, the first-differences estimator is biased in the sense that it only reflects the positive short- or medium-run effects while leaving out the potentially adverse long-run consequences of higher inequality (see Panel *a.* of Figure 1).

In contrast, the system GMM estimator is likely to find a negative relationship, in particular if (i) the negative long-run effects dominate the positive short- or medium-run effects and (ii) if inequality is highly persistent (which is actually true in the data). Under these circumstances, the majority of observations is either of the type “low level of inequality and high level of output” or “high level of inequality and low level of output.” Hence, the system GMM estimator (which also exploits the cross-country variation) tends to reflect a negative relationship (see Panel *b.* of Figure 1) – which corresponds to the true overall impact of inequality.

This paper is part of a small literature which is trying to get a better grasp of the empirical picture with respect to inequality and growth. Earlier contributions include Banerjee and Duflo (2003) and Voitchovsky (2005). The former paper presents evidence suggesting that changes in inequality (in any direction) are associated with reduced growth in the short run; as a result, the standard regression equation might be mis-specified in a way that – misleadingly – makes differences-based estimators indicate a positive relationship. Voitchovsky (2005), by contrast, argues that inequality coming from the top end of the distribution is indeed likely to promote growth while bottom-end inequality tends to be harmful. She thus suggests controlling separately for inequality coming from different parts of the distribution (and finds supportive evidence in a panel of rich countries). None of these papers, however, focuses specifically on the time dimension, and so we view our paper as complementary.

The remainder of this paper is organized as follows. Section 2 presents the empirical results and links them to the earlier literature. In Section 3, we interpret our findings through the lens of the existing theoretical literature. Section 4 introduces a simple model to make our reasoning more precise and to gain additional analytical insights. Section 5 concludes.

2 Empirical Analysis

We now apply the standard estimators to a common data set, relying on a common set of controls. We find the inequality-growth relationship to be consistently positive when we rely on time-series variation only (first-diffferences GMM estimator) and consistently negative when we also consider cross-sectional variation (system GMM estimator). This suggests that the pattern of existing results is driven by the choice of methods rather than idiosynchratic differences across studies (such as the selection of countries, time periods, or control variables).

2.1 Specification and Estimation

Specification and data. We rely on a standard 5-year panel data model which is similar to those used in several recent empirical studies on growth (e.g., Caselli et al., 1996; Barro, 2000; Forbes, 2000; Voitchovsky, 2005). Specifically, we estimate the linear regression equation

$$y_{it} - y_{it-1} = \gamma y_{it-1} + \mathbf{x}'_{it}\boldsymbol{\delta} + \zeta_t + \eta_i + v_{it}, \tag{1}$$

where $i = 1, \cdots, N$ denotes a particular country and $t = 1, \cdots, T$ is time (with t and $t-1$ five years apart). The variable y stands for the log of real GDP per capita so that the left-hand side of equation (1) approximately gives country i's five-year growth rate in the years between $t-1$ and t. On the right-hand side, we have y_{it-1} to control for convergence; a vector $\mathbf{x}_{it}$ consisting of variable (and observable) country characteristics; a period-specific effect ζ_t to capture productivity changes common to all countries; a country-specific effect η_i to capture time-invariant (and unobserved) country characteristics; an idiosyncratic error term v_{it}.

The vector $\mathbf{x}_{it}$ consists of the Gini index and three additional standard control variables. In line with the recent literature (e.g., Perotti, 1996; Forbes, 2000), these additional variables are the average years of secondary schooling in the population aged over 25 (separately for males and females) and the price level of investment (to control for market distortions). In general, the explanatory variables are measured at the beginning of each 5-year period. In case of inequality, this is not always possible because the Gini index is not usually available on an annual basis. In these cases, we take the last available value in the previous 5-year period.

The analysis includes up to 90 countries and covers the period from 1966 to 2005. The GDP per capita data comes from the World Development Indicators (WDI; World Bank, 2006) and is in constant 2000 US$. The Deininger and Squire (1996) data base serves as the primary source for the inequality data. However, in order to broaden our sample in the cross-sectional as well as the time-series dimension, we also rely on a subsidiary source, the UNU-WIDER (2008) data base.[2] Finally, the education data comes from Barro and Lee (2000) and the source for the price of investment is Heston et al. (2006; PWT 6.2). More detailed sources and definitions for these variables as well as some summary statistics are presented in Table 1.

Table 1 *here*

Estimation methods. It is well-known that the standard panel data methods (i.e., fixed-effects [FE] and random-effects [RE] estimations) are unlikely to provide consistent estimates of γ and $\boldsymbol{\delta}$ (see, e.g., Bond et al., 2001). Obviously, using the random-effects estimator is problematic because the unobserved country effect, η_i, is most likely correlated with the other explanatory variables. A second problem emerges when we rewrite model (1) as

$$y_{it} = (\gamma + 1)y_{it-1} + \mathbf{x}'_{it}\boldsymbol{\delta} + \zeta_t + \eta_i + v_{it}. \tag{2}$$

Equation (2) highlights that controlling for convergence in a panel data growth model actually introduces a lagged dependent variable. As a result, even if equations (1) and (2) gave an

[2] Some of the Gini coefficients are based on income and others on expenditures. To account for this, we follow Deininger and Squire's (1996) and Forbes' (2000) suggestion to add 6.6 points to expenditure-based coefficients.

accurate description of reality, both the RE estimator and the FE estimator would be very likely to give inconsistent estimates of the parameters γ and $\boldsymbol{\delta}$.

To deal with these problems, the literature has developed specific GMM estimation techniques, most notably the first-difference GMM estimator and the system GMM estimator. The first-difference GMM estimator was developed by Arellano and Bond (1991) and is similar to the FE estimator in the sense that it employs only *within-country* variation. The idea is to eliminate the country-specific effect by differencing model (2) and then to use sufficiently lagged values of y and $\mathbf{x}$ as instruments. However, although the first-difference GMM estimator "solves" the problems of unobserved heterogeneity and lagged dependent variables, it has been criticized for the fact that it does not exploit the variation in levels. The main concern is that the cross-sectional variation embodies a large part of the information since within-country inequality is quite persistent.[3] Thus, ignoring this cross-sectional variation may give rise to unnecessarily large biases and imprecision. One way to address these shortcomings is to use the system GMM estimator pioneered by Arellano and Bover (1995) and Blundell and Bond (1998). While requiring a slightly more stringent set of restrictions, the system GMM procedure does better in terms of efficiency since – like the RE estimator – it also exploits the *cross-country* variation in the data (see, e.g., Bond et al., 2001, for the details).

In what follows, we will apply both GMM estimation techniques to our expanded dataset and document that – consistent with the existing empirical picture – the two approaches lead to systematically different estimation results. Sections 3 and 4 are then devoted to explaining these differences across methods, also with the help of a simple model that incorporates both short-run and long-run effects of inequality on growth.

2.2 Results

Time-series variation only. We now go through the first-difference estimation results. To connect with the previous literature, we first present evidence based on a sample which is similar to that in Forbes (2000) in terms of countries included and periods covered. We then show that these results are quite robust to the inclusion of additional countries and more recent observations (from the WIDER data base) as well as to a number of other modifications.

The first column of Table 2 gives the results based on the Forbes sample (which includes 42 countries and covers the 1965-1995 period). Like Forbes, we find a significant positive impact of inequality on growth, and the magnitude of the effect is very similar: On an annualized

[3] This observation also applies to our dataset: The adjusted R^2 from a regression of the Gini coefficient on country dummies is 0.84 (and rises only to 0.85 if time dummies are also included).

basis, our estimates imply a coefficient of 0.0015 while Forbes (2000) reports one of 0.0013. As the second column shows, the coefficient on inequality remains significant and comparable in size after extending the sample by two additional 5-year periods (i.e., the 1996-2000 and 2001-2005 periods). Similarly, as documented in the third column, the inclusion of 28 additional countries does not change the basic empirical finding: Higher inequality has a significantly positive impact on (short-run) growth, albeit the effect is somewhat smaller in the broader country sample (which includes a larger fraction of less-advanced countries).[4]

Table 2 *here*

The remaining columns of Table 2 document the robustness of this empirical outcome to some natural variations. First, the estimates in columns (4) and (5) are based on subsets of the full sample. Specifically, column (4) shows the impact of inequality in countries which are classified as high income or upper-middle income (according to the 2009 World Bank definition); column (5) provides the corresponding results for the remaining countries (lower-middle income or low income). Apparently, although the two subsets contain very different economies, the estimated impact of inequality is still significantly positive in both cases and also of very similar size across the two country groups.

The second modification concerns the time structure of the panel. In order to check whether the above results are not just an artifact of the 5-year structure, the estimates in columns (6) and (7) are based on four 10-year periods. The results suggest that higher inequality tends to foster growth also over this medium time horizon, and the size of the estimated impact is somewhat larger: For instance, on an annualized basis, the coefficient in the fourth column (5-year periods; high and up-mid countries) is 0.00082 while the corresponding coefficient for the 10-year structure is 0.00114. However, the estimates are less precise – which is not surprising given that we have a much smaller number of observations.

The validity of the first-difference estimator depends on the absence of serial correlation in the error terms, v_{it}. This means that the differenced error terms should not show second-order serial correlation (though they have a first-order correlation by construction). The statistics $M1$ and $M2$ in Table 2 give the t-values associated with the tests for, respectively, first-order and second-order correlation in the $\triangle v_{it}-$series. As the numbers show, serial correlation may only be an issue in the first regression (Forbes replication) but not in columns (2) – (7).

[4] Note that 20 of these 28 additional countries are low income countries or lower-middle income countries according to the classification by the World Bank (2006). As a result, in the full sample, 47% of the countries fall into these two categories (while the rest belong to the categories upper-middle income or high income).

Time-series and cross-sectional variation. Table 3 presents the results based on the system GMM estimator. The first column presents the estimates based on the full sample. Unlike in all the regressions shown in the previous table, the estimated impact of inequality on growth is now negative, yet not significantly so.[5] More precise results can be gained by splitting the country sample along income classes (columns 2 – 4). It turns out that, as shown in the second column, the system GMM estimates also indicate a positive impact of inequality among the small group of high-income countries. However, there is no significant relationship among upper-middle-income countries (third column),[6] and – most importantly – the system GMM estimates indicate a negative impact in the large group of countries with lower-middle income or low income (fourth column). Note further that switching to a 10-year structure again confirms the results obtained under the 5-year structure (columns 6 and 7 of Table 3).

Table 3 *here*

So, even though the test statistics at the bottom of Table 3 support the validity of the instruments with this estimation strategy too, the system GMM approach paints a decidedly different picture than the first-difference estimator: While the latter uniformly points to a positive relationship (and thus confirms the results of, e.g., Li and Zou, 1998; Forbes, 2000), the findings here suggest that the impact of inequality on growth is negative (or at least non-positive) in countries which are not among the richest. Note that this result is perfectly in line with Barro's (2000) random-effects analysis (which also exploits cross-sectional as well as time-series variation) and also matches the results in earlier OLS-based studies such as those of Alesina and Rodrik (1994) or Persson and Tabellini (1994).

3 Interpreting the Empirical Results

The present section looks at how these seemingly contradictory estimation results can be interpreted and reconciled. We proceed in two steps. The first step is to stress that, in fact, the existing literature suggests that both relationships should be present in reality (Subsection 3.1). In the second step, we argue that regression equation (1) is mis-specified so that the two different GMM estimators are prone to systematically reflect just one of the two relationships,

[5] The number of countries included in the sample rises to 90 since the system GMM estimator also includes moment conditions on the basis of the level form of the regression equation (and hence – in contrast to the first-difference estimator – does not strictly require two consecutive observations).

[6] If we combine – as in Table 2 – high-income countries and upper-middle income countries in one sample, the estimated coefficient on inequality is insignificant (result not reported in the table).

namely the positive one in the case of the differences-based approach and the negative one if the estimator also exploits cross-sectional variation (Subsection 3.2).

3.1 Short-run and Medium-run Effects vs. Long-run Effects

Inequality affects economic performance through many channels, and the theoretical literature prominently discusses both negative and positive effects. As for the positive channels, the literature has long argued that savings functions tend to be convex in wealth (see, e.g., Kuznets, 1955; Kaldor, 1955). So, other things equal, higher inequality is associated with higher aggregate savings and thus faster convergence to the balanced growth path. More recently, the focus has been on the impact of inequality on the selection of physical investment projects (see, e.g., Matsuyama, 2000, in particular Section 4). The main argument here is that, if the financial system is imperfect, access to external finance depends on personal wealth. As a result, if wealth is widely spread among the population, nobody may be able to raise sufficient funds to realize high-return projects which require large minimum investments. In this case, a more concentrated distribution of productive assets may put at least a limited number of entrepreneurs into a position to realize such projects – and thus boosts growth.[7] This effect is reinforced by the fact that the high-return projects are often the more risky ones (see, e.g., Rosenzweig and Binswanger, 1993). As a result, with a relatively equal wealth distribution, the number of entrepreneurs who are sufficiently rich to absorb significant risks may be very small. So, once again, a more concentrated distribution of wealth may multiply the number of high-return projects realized. Finally, the literature also discusses positive demand-side effects. With a more unequal distribution, a larger fraction of total demand falls on "high-end" products (as opposed to goods satisfying basic needs). Thus, potential innovators benefit from larger home markets which more easily support the investments required to develop novel or better varieties (see, e.g., Foellmi and Zweimueller, 2006). Clearly, this positive demand-side effect is more relevant in advanced economies where R&D is the main driver of growth.

While all these positive effects work through different channels, they have one thing in common: They all emphasize purely economic mechanisms. As a result, we should expect these effects to materialize relatively fast. This, however, is clearly different in the case of the negative channels. Some of the most prominent negative links rely on political-economy arguments. For instance, it has been pointed out that more unequal societies tend to have

[7] It has also been argued that, with convex technologies and financial markets imperfections, higher inequality deteriorates economic performance because investment returns are more heterogeneous. However, as shown by Foellmi and Oechslin (2008), this is by no means a robust theoretical prediction.

higher levels of redistribution and hence higher levels of taxation – which weakens the incentives to save and invest (see, e.g., Perotti, 1993). A related argument focuses on the composition of government expenditures. With higher inequality, the decisive voter tends to supply fewer production factors (i.e., physical or human capital). As a result, he may strongly prefer direct transfers ("handouts") over productivity-enhancing investments in public goods. Finally, even if political power rests with the rich, inequality may still have a negative impact via the fiscal policy channel. As highlighted by Acemoglu et al. (2008), if inequality is high, an oligarchic government has incentives to set up an inefficient bureaucracy in order to avoid high taxation once the country is transformed into a democracy.[8] Yet, at least via these channels, changes in inequality cannot be expected to have an immediate effect on economic performance. It certainly takes time for shifts in the population's policy preferences to be reflected in similar changes within the legislative body. Moreover, even with a fresh legislature in place, altering tax laws (or even changing the bureaucracy) is a time-consuming process.

Note further that the remaining negative effects are also unlikely to materialize quickly. If higher inequality reduces aggregate spending on human capital formation (see, e.g., Galor and Zeira, 1993; Galor and Moav, 2004), it arguably takes a decade or more for the effects to be felt. Similarly, it may be a long time before disaffection caused by higher inequality is bundled in social movements which then may threaten political stability (see, e.g., Bénabou, 1996) or before higher inequality has undermined the reliability of the judicial system and the security of property rights (see, e.g., Glaeser et al., 2003).

3.2 Differences vs. Levels

Our brief literature survey clearly suggests that the positive and negative effects of inequality cluster in a very specific way: The positive effects tend to materialize quickly while the negative effects need more time to emerge. The present subsection argues that it is exactly this pattern which is responsible for the different estimation results obtained above. To see this, it is convenient to look first at the differences-based methods (e.g., the first-difference GMM estimator). Clearly, since these methods regress changes in output on moderately lagged changes in inequality, they are likely to pick up the short-run or medium-run effects – and thus to find a positive relationship. To give an example, if inequality goes up, aggregate output tends to respond positively in the short or medium run because, for instance, a higher wealth concentra-

[8] More generally, based on the experience of the colonization of the New World, Sokoloff and Engerman (2000) argue that huge wealth inequalities may promote institutions that protect the privileges of the elites and restrict opportunities for the broad masses – with adverse consequences for economic development.

tion supports a larger number of high-return investments while the supply of the public good or the quality of the institutions have yet to deteriorate. As a result, differences-based methods associate a positive change in inequality with a positive change in output but – due to the specific time structure of the panel – fail to systematically attribute the subsequent negative changes (i.e., those changes coming from the long-run effects) to the initial increase in inequality. Put differently, the negative changes are just treated as noise, and so the differences-based methods are set to find a positive effect.[9]

However, methods also exploiting the variation in the levels (e.g., the system GMM estimator) are nonetheless likely to find a negative link, in particular if two conditions are satisfied. First, the long-run effects must dominate the short-run or medium-run effects and, second, within-country inequality has to be a rather persistent phenomenon. Note, however, that there are indeed good reasons to assume that these conditions hold. As for the relative strength of the different effects, a broad empirical literature suggests that institutional quality has a dominant impact on economic performance (see, e.g., Acemoglu et al., 2001). Regarding persistence, our data as well as an elaborate literature support the notion that countries do not frequently undergo significant changes in inequality. To see now why under these circumstances the cross-sectional methods find a negative link, consider two countries which have had different degrees of inequality for a while. Then, other things equal, the low-inequality country (i.e., the country with the good institutional quality) would have a higher GDP than the high-inequality country (i.e., the country with the bad institutional quality). Hence, if within-country inequality was perfectly persistent over time, the level-based methods would find a clear-cut negative link between inequality and economic performance – which is driven by the comparatively strong long-run effects. Yet, inequality is not completely persistent, and so the data-generating process creates observations which potentially "mire" the picture. For instance, following a switch from low to high inequality, we may have a number of observations with both high inequality and high output because the positive effects have already set in but the negative long-run effects are still to come. However, if within-country inequality is persistent, such transition periods are relatively rare and a large fraction of the observations is either of the type "high inequality and low output" or "low inequality and high output." Accordingly, the data points that do not fit into this latter pattern are treated as noise (i.e., driven by exogenous shocks), and the regression analysis points towards a negative relationship

[9] The argument is completely symmetric for negative changes in inequality. The time-series methods link negative changes in inequality to contemporaneous negative changes in output but fail to attribute subsequent improvements to the initial decline in inequality. Again, the long-run effect is just regarded as noise.

– which can be interpreted as the overall relationship in the long run.

4 A Formal Approach

We now introduce a parsimonious model to make the above reasoning precise. Doing so also helps us to go one step further by exploring how closely differences-based methods come in estimating the true short-run effect and similarly level-based methods in estimating the true overall effect. In particular, the model shows that the associated biases depend on three crucial magnitudes, the short-run effect, the long-run effect, and the persistence of inequality.

Assumptions. We focus on an infinite-horizon economy which is populated by a continuum of individuals of measure 1. All agents derive utility from consumption of a single (non-storable) output good, and preferences are represented by the inter-temporal utility function

$$U_t = E_t \left\{ \sum_{s=0}^{\infty} \beta^s c_{t+s} \right\}, \tag{3}$$

whereas c_t denotes consumption in period t. Individuals differ regarding their endowment with the productive asset (which we may interpret as "skills," for instance). A fraction $\alpha > 1/2$ of the population (the "poor", P) is endowed with $\omega^P(D_t) < 1$ units of this asset, whereas 1 is the average endowment in the economy. The endowment of the remaining agents (the "rich", R) is then given by $\omega^R(D_t) = (1 - \alpha\omega^P(D_t))/(1-\alpha) > 1$. The state variable $D_t \in \{L, H\}$ represents the degree of inequality, whereas L stands for low inequality so that $\omega^P(L) > \omega^P(H)$. Note further that, at the beginning of each period, inequality may change exogenously. In particular, we have $D_t = D_{t-1}$ with probability π and $D_t \neq D_{t-1}$ with probability $1 - \pi$. Thus, a high value of π mirrors strong *persistence* in inequality. In practice, a change in the distribution of skills may be due to a shock to the educational system which improves the quality of primary education relative to that of university education, for instance.

Suppose further that the individuals have access to a simple linear technology of the form

$$y^i(D_t, G_t) = a^i \omega^i(D_t) X(G_t), \tag{4}$$

with $i \in \{P, R\}$, whereas a^i is a group-specific productivity parameter and $X(G_t)$ denotes the level of the public good provided by the government. Rich agents are assumed to be *more productive* than the poor: $a^R > a^P$. A natural way to think of this assumption is that the more productive technology requires a certain skill level which cannot be achieved by the poor.[10]

[10] More generally, this assumption can be seen as a reduced-form representation of the notion that only

The state variable $G_t \in \{0,1\}$ reflects whether – in the previous period – the government has invested in the public good, with 1 indicating investment. Hence, $X(1) - X(0) \equiv \triangle X > 0$.

On the aggregate level, we can now easily infer that (private-sector) output is given by

$$Y(D_t, G_t) = \left(a^R - \alpha(a^R - a^P)\omega^P(D_t)\right) X(G_t). \tag{5}$$

Other things equal, Y is higher in the high-inequality state ($D_t = H$) since a larger fraction of the productive asset is allocated to the high-return technology; similarly, output is higher if the level of the public good is high ($G_t = 1$). In what follows, we impose

$$\frac{X(1) - X(0)}{X(1)\omega^P(L) - X(0)\omega^P(H)} > \alpha \frac{a^R - a^P}{a^R}, \tag{6}$$

so that $Y(L,1) > Y(H,0)$. As we will see below, this condition ensures that – in the interesting equilibrium – the long-run effect of inequality dominates the short-run effect.

Turning to the public sector, suppose that the government has access to an income stream of Z units of the final good. We can think of this income as arising from a publicly owned enterprise, the natural resource sector, etc. Regarding public spending, the government has to decide on G_{t+1} in each period t. A decision to invest is associated with a contemporaneous cost of $F < Z$ units of the final good. The budget surplus is distributed to the population in a lump-sum manner. Finally, when deciding on G_{t+1}, we assume that the government has no choice but to implement the variant preferred by the majority of the population, i.e., the poor.

An interesting equilibrium. We now show that our model is able to generate equilibrium patterns that are consistent with the estimation results outlined in Section 2. The first step is to establish that the level of the public good may fluctuate over time:

Proposition 1 *Suppose that the following condition holds:*

$$\frac{\triangle X}{F} a^P \left(\pi\omega^P(L) + (1-\pi)\omega^P(H)\right) \geq \frac{1}{\beta} > \frac{\triangle X}{F} a^P \left(\pi\omega^P(H) + (1-\pi)\omega^P(L)\right). \tag{7}$$

Then, the equilibrium shows fluctuations in the provision of the public good, with a positive level of investment in times of low inequality (i.e., $G_{t+1} = 1$ if $D_t = L$) and no investment in times of high inequality (i.e., $G_{t+1} = 0$ if $D_t = H$).

Proof. See Appendix. ■

Intuitively, when condition (7) holds, the poor prefer direct transfers over investment in the public good if inequality is high. This is because if $D_t = H$ they can gain little from productive

relatively rich people can rely on high-return technologies because – as discussed in Subsection 3.1 – the financing of such technologies requires good access to the financial system (which the poor lack).

public investment. However, in the case of low inequality, this gain is sufficiently strong to make the poor prefer productive investment over higher lump-sum transfers.

Note that the model predicts that an increase in inequality generates both a short-run increase and a long-run reduction in output. Corollary 1 discusses the associated co-movements of inequality and output in terms of changes (as captured by differences-based estimators). Corollary 2 looks at the relationship in levels (as captured by the level-based methods).

Corollary 1 *Suppose that conditions (6) and (7) hold. Moreover, assume that inequality has been unchanged between* $t-2$ *and* $t-1$*. Then,*

(i) an increase in inequality in period t *(i.e.,* $D_{t-1} = L \rightarrow D_t = H$*) leads to a contemporaneous increase in output* ($Y_{t-1} = Y(L,1) < Y_t = Y(H,1)$)*; however, in* $t+1$*, output declines sharply, with inequality either unchanged or decreasing.*

(ii) a decrease in inequality in period t *(i.e.,* $D_{t-1} = H \rightarrow D_t = L$*) leads to a contemporaneous decrease in output* ($Y_{t-1} = Y(H,0) > Y_t = Y(L,0)$)*; however, in* $t+1$*, output rises sharply, with inequality either unchanged or increasing.*

The intuition behind Corollary 1 is that the level of the public good is a state variable and thus cannot change quickly. So an increase in inequality must lead to a positive effect on output in the short run (i.e., with X still at the high level) but to a negative one in the long run (i.e., when the increase in inequality has undermined to provision of the public good).

Corollary 2 *Suppose that the conditions (6) and (7) hold. Moreover, assume that inequality is persistent (i.e., that* π *is "high"). Then, over time,*

(i) a large fraction of the observations (D_t, Y_t) *will either be "low" inequality and "high" output,* $(L,\, Y(L,1))$*, or "high" inequality and "low" output* $(H, Y(H,0))$.

(ii) very few observations (D_t, Y_t) *will either be "low" inequality and "(very) low" output,* $(L, Y(L,0))$*, or "high" inequality and "(very) high" output,* $(H, Y(H,1))$.

The central point behind Corollary 2 is *persistence* in inequality. Persistence means that periods with changes in inequality – which generate observations of the type ("high" inequality/"high" output) or ("low" inequality/"low" output) – are relatively infrequent.

Estimating the relationship. We now discuss how the different estimation methods reflect the inequality-output relationship that is implied by data generated from the present model. An illustrative way to do so is to give a graphical representation of the two corollaries in a single picture – which is done in Figure 2. To see how the figure is constructed, consider the case of an *increase* in inequality in period t. If the focus is on changes (Panel a.), the following observations are generated: Observation -1^{in} in period $t-1$, observation 0^{in} in period t (when the short-run effect materializes), and – in period $t+1$ – observation 1_a^{in} (if D is unchanged in $t+1$ so that only the long-run effect materializes) or observation 1_b^{in} (if D decreases in $t+1$ so that the long-run effect materializes together with a negative short-run effect). The remaining observations in Panel a. can be generated by going through the opposite case, i.e., by considering a *decrease* in inequality in period t. Note that the numbers in Panel b. refer to the same thought experiments, but from the perspective of the levels. The two panels further indicate the theoretical frequencies with which the different types of observations occur.

Figure 2 here

Figure 2 illustrates that the different aspects of the relationship between inequality and output are picked up by different estimation methods. If the relationship is assessed on the basis of changes (Panel a.), we can see that estimating a linear regression would give us a clear positive relationship. On the other hand, if levels are considered (Panel b.), fitting a linear trend line would arguably point to a significant negative impact of inequality (since the observations marked by a bigger dot are much more numerous than the remaining observations).

It might also be interesting to look at the different estimation methods from a more formal perspective. We start by deriving the formal relationship between output and inequality, given that conditions (6) and (7) hold. Taking logs on both side of equation (5) gives us

$$y_t \equiv \ln Y_t = \ln\left(1 - \alpha \frac{a^R - a^P}{a^R}\omega^P(D_t)\right) + \ln\left(1 + \frac{\triangle X}{X(0)}\frac{H - D_{t-1}}{H - L}\right) + \ln a^R + \ln X(0),$$

whereas the second term on the right-hand side represents the equilibrium expression for $X(G_t(D_{t-1}))$. Assume now further that $\omega^P(D_t) = 1 - D_t$. Then, the above expression can be approximated by the linear regression equation

$$y_{it} = \delta_1 D_{it} + \delta_2 D_{it-1} + \eta_i + v_{it}, \tag{8}$$

whereas $\delta_1 \equiv \alpha(a^R - a^P)/a^R$, $\delta_2 \equiv -\triangle X/(X(0)(H-L))$, and $\delta_1 + \delta_2 < 0$ due to condition (6). The sum of the constant terms is represented by η (which we allow to vary across countries) and – as in equation (2) – v_{it} denotes an idiosyncratic error term which reflects exogenous influences on private-sector output.[11] Obviously, the key difference between the theory-based equation (8) and the standard equation (2) is that the former also includes lagged inequality, D_{t-1}, while the latter just ignores earlier levels of inequality.

[11] The constant η_i may be country-specific due to, for instance, cross-country differences in the levels of firm productivity (even though $(a^R - a^P)/a^R$ is constant across countries).

We are now able to analytically determine the biases if model (8) were true but the impact of inequality was estimated based on the mis-specified regression equation

$$y_{it} = \delta_1 D_{it} + \eta_i + w_{it}, \tag{8'}$$

with $w_{it} \equiv v_{it} + \delta_2 D_{it-1}$ representing the "error term". If we fit a regression line like the one in Figure 2*a*. (i.e., OLS based on differences), the estimated coefficient converges to $\delta_1 - \delta_2(1-\pi)$ as the number of observations goes to infinity; on the other hand, if we consider a regression similar to that in Figure 2*b*. (i.e., OLS based on levels), the estimator of δ_1 converges to $\delta_1 + \delta_2(2\pi - 1)$. Note that these limits become arbitrarily close to δ_1 and $\delta_1 + \delta_2$, respectively, as π approaches 1. Thus, as already informally argued above, the estimated coefficient approximates (but overstates) the positive short-run relationship when we rely on first differences while the level-based estimator approximates (but understates) the negative overall consequences which materialize only in the long run. Note that this pattern is robust to the application of more advanced estimation techniques. In particular, when we estimate the mis-specified model (8') by applying the first-difference and system GMM estimators to data generated by the model, we consistently find that the former estimator comes close to reflecting the short-run effect while the latter approximates the negative overall effect.[12]

5 Conclusions

This paper reconciles seemingly contradictory results in the empirical literature on the inequality-growth relationship. Empirical studies that exploit time-series variation only (differences-based studies) find a positive relationship between inequality and growth, whereas studies that also exploit cross-sectional variation (level-based studies) suggest a negative link. We argue that these findings can be reconciled using early and more recent arguments put forward in the theoretical literature on the relationship between inequality and economic development.

The theoretical literature suggests that the growth-promoting effects arise from purely economic mechanisms (convex savings, capital market imperfections, innovation incentives). These mechanisms tend to set in relatively quickly, i.e., in the short or medium run. In contrast, growth-reducing effects arise from politico-economic considerations and/or arguments that involve educational attainment. These mechanisms take more time and materialize only

[12] Details can be obtained from the authors upon request. In brief, we used the model to generate panel data sets consisting of observations of the type (y_{it}, D_{it}), with $i = 1, \cdots, 50$ and $t = 1, \cdots, 20$. These data sets were then used to estimate (8') with the first-differences and system GMM estimators. The exact Stata commands were, respectively, *xtabond2 y D, gmmstzle(D) robust nolevelequ* and *xtabond2 y D, gmmstzle(D) robust.*

in the long-run. This observation is important in at least two different dimensions. *First*, with this specific time pattern in mind, we can interpret the existing – and seemingly conflicting – empirical results in a natural way: The differences-based estimation methods (i.e., the FE or first-difference GMM approaches) are likely to systematically pick up the beneficial short- or medium-run implications – and thus tend to indicate a positive relationship. The level-based methods, on the other hand, also reflect the slowly materializing (but more powerful) adverse consequences of inequality; thus, the mostly negative results associated with RE or system GMM estimators should be interpreted as the overall effect of inequality in the long run. *Second*, the observation that the positive and the negative consequences of inequality manifest themselves at different points in time has implications for future empirical research: Regression equations including just one (linear) inequality term are likely to be mis-specified. According to our model, an appropriate equation should include several Gini coefficients which control for inequality at different points in the past. Clearly, the successful estimation of such equations requires long time series – and thus may become feasible only in the future.

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Appendix

Proof of Proposition 1. The first step is to introduce some notation. The value function of a representative member of group $i \in \{P, R\}$ is denoted by $V^i(D_t, G_t)$, whereas D_t and G_t are the two state variables. Thus, when thinking about the preferred level of the public good tomorrow, the poor individuals (i.e., the decisive agents) have to solve the recursive problem

$$V^P(D_t, G_t) = \max_{G_{t+1} \in \{0,1\}} \left\{ a^P \omega^P(D_t) X(G_t) + Z - G_{t+1} F + \beta E \left\{ V^P(D_{t+1}, G_{t+1}) \right\} \right\}.$$

A solution to this problem is a policy function $G_{t+1} = G^P(D_t, G_t)$ which gives tomorrow's level of the public good, G_{t+1}, as a function of the two state variables.

We now prove that if condition (7) holds, the proposed policy function is in fact a solution to the recursive problem stated above. To do so, we have to establish that in any given period t it is indeed optimal to stick to the policy function stated in the proposition – provided that this policy function is applied in all future periods $t+1$, $t+2$, $\cdots$. More precisely, we have to establish that – irrespective of the value of G_t – the representative poor agent finds it optimal to choose (i) $G_{t+1} = 1$ if $D_t = L$ and (ii) $G_{t+1} = 0$ if $D_t = H$ (again, provided that this rule is invariably applied in the future). The formal condition for point (i) to hold is

$$\begin{aligned} V^P(L, G_t) &= a^P \omega^P(L) X(G_t) + Z - F + \beta \left(\pi V^P(L, 1) + (1-\pi) V^P(H, 1) \right) \\ &\geq a^P \omega^P(L) X(G_t) + Z + \beta \left(\pi V^P(L, 0) + (1-\pi) V^P(H, 0) \right), \end{aligned}$$

whereas the second line in the above expression gives the value if the decision is in favor of the alternative choice, $G_{t+1} = 0$. Rearranging terms yields the much simpler restriction

$$\pi \left(V^P(L,1) - V^P(L,0) \right) + (1-\pi) \left(V^P(H,1) - V^P(H,0) \right) \geq F/\beta, \tag{A-1}$$

which is indeed independent of G_t. Similarly, for point (ii) to be true, we must have

$$\pi \left(V^P(H,1) - V^P(H,0) \right) + (1-\pi) \left(V^P(L,1) - V^P(L,0) \right) < F/\beta, \tag{A-2}$$

which is again independent of the current level of the public good, G_t.

To proceed, we now have to find explicit expressions for the value differentials $V^P(L,1) - V^P(L,0)$ and $V^P(L,1) - V^P(L,0)$ which show up in (A-1) and (A-2). Assuming that the proposed policy function is applied in all (future) periods, the two differences are given by

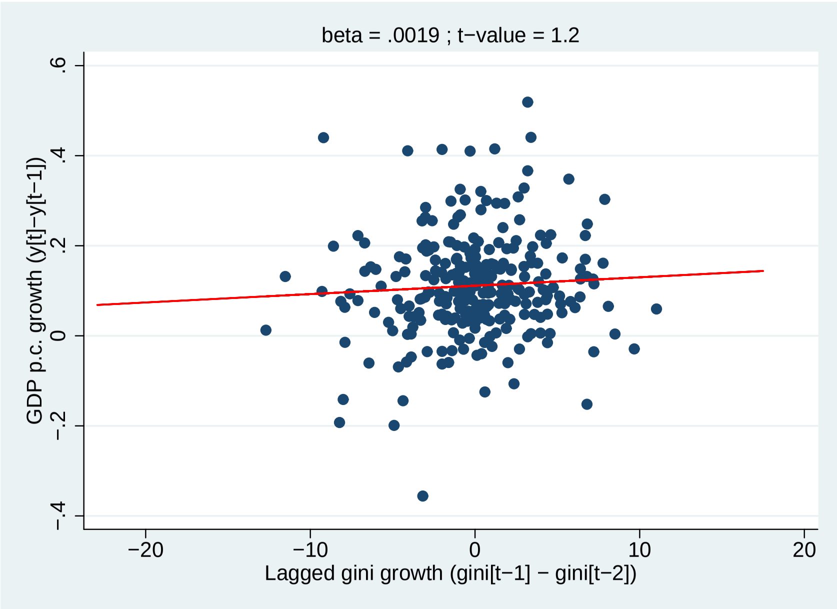
$$V^P(D,1) - V^P(D,0) = a^P \omega^P(D) \left[X(1) - X(0) \right],$$

with $D \in \{L, H\}$. Using this last expression in (A-1) and (A-2) completes the proof.

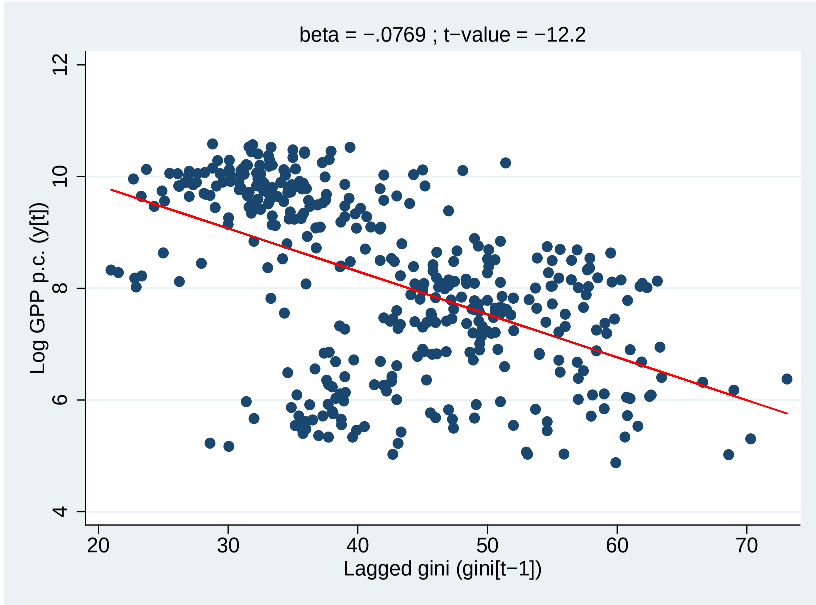
Figures

***Figure* 1 –** Inequality and output: the data

a. The relationship in changes



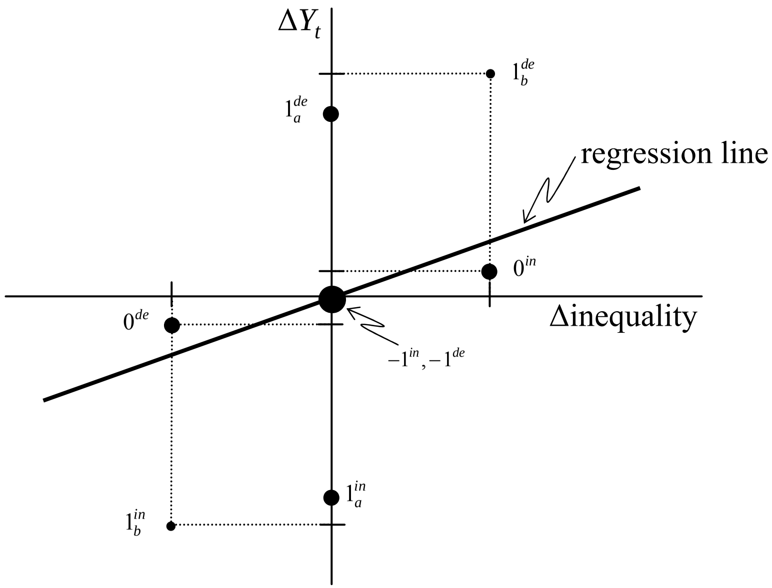
b. The relationship in levels



Sources: See Table 1

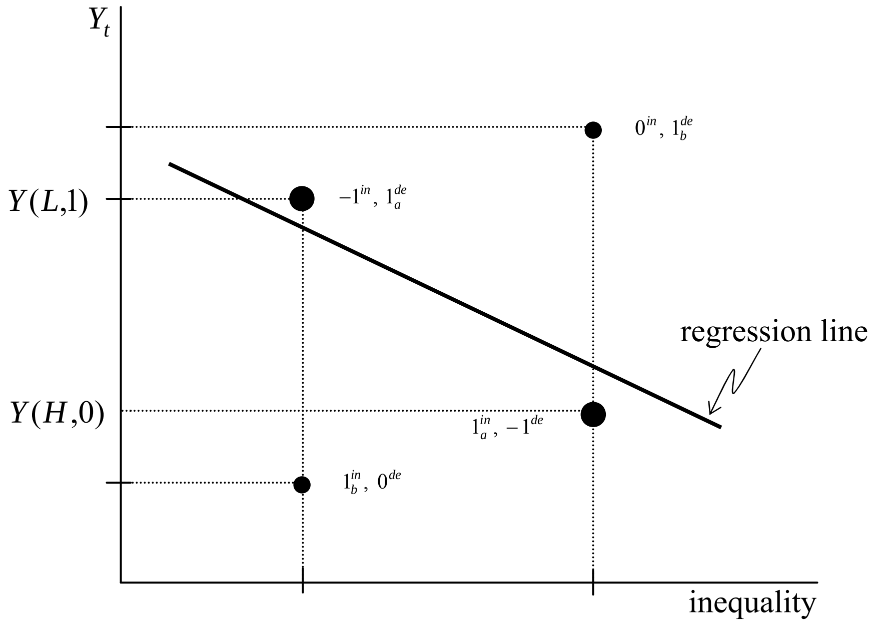
***Figure* 2 –** Inequality and output: the theory

a. The relationship in changes



Frequencies: • $(1-\pi)^2/2$; ● $\pi(1-\pi)/2$; ⬤ π^2

b. The relationship in levels



Frequencies: ● $(1-\pi)/2$; ⬤: $\pi/2$

Tables

***Table* 1 –** Summary statistics

Variable	Definition	Source	Year	Mean	Standard deviation	Minimum	Maximum
Inequality	Gini coefficient of the income distribution (in the case of expenditure based Ginis, we follow the convention and add 6.6 points); see also notes at the end of the table	Deininger and Squire (1996); UNU-WIDER (2008; WIID2c)	1965	42.22	8.93	24.30	55.50
			1970	42.14	10.76	22.91	61.88
			1975	41.22	9.37	22.80	67.94
			1980	41.15	8.84	21.54	57.78
			1985	39.95	9.24	20.97	61.76
			1990	42.75	10.74	22.70	70.30
			1995	44.51	11.65	26.11	73.10
			2000	44.52	11.64	23.70	66.60
Log of GDP	*ln* of the real GDP per capita (in 2000 USD)	World Bank (2006, WDI)	1965	7.72	1.54	5.23	9.71
			1970	7.86	1.53	5.34	9.81
			1975	7.98	1.40	4.98	9.91
			1980	8.01	1.54	4.94	10.09
			1985	8.15	1.61	5.03	10.30
			1990	8.02	1.53	5.16	10.42
			1995	7.96	1.61	4.96	10.48
			2000	8.07	1.62	5.02	10.53
Male schooling	Average years of secondary schooling in the male population aged over 25 years	Barro and Lee (2000)	1965	1.05	0.81	0.18	2.94
			1970	1.35	0.94	0.12	3.27
			1975	1.35	0.88	2.15	3.55
			1980	1.66	1.11	0.23	5.07
			1985	1.93	1.18	0.13	4.81
			1990	1.99	1.22	0.19	5.18
			1995	2.08	1.31	0.18	5.15
			2000	2.18	1.32	0.16	5.31

— table continues on the next page

***Table* 1,** continued

Variable	Definition	Source	Year	Mean	Standard deviation	Minimum	Maximum
Female schooling	Average years of secondary schooling in the female population aged over 25 years	Barro and Lee (2000)	1965	0.78	0.83	0.04	3.10
			1970	1.03	0.92	0.02	3.36
			1975	1.01	0.89	0.05	3.61
			1980	1.27	1.11	0.03	5.11
			1985	1.50	1.15	0.05	4.84
			1990	1.59	1.12	0.06	4.70
			1995	1.74	1.22	0.06	5.02
			2000	1.86	1.23	0.09	5.07
Price level of investment	PPP of investment (= national currency value of investments divided by the real value of investment in international dollars) / exchange rate relative to the USD	Heston et al. (2006; PWT 6.2)	1965	64.49	24.98	21.82	118.69
			1970	68.29	26.61	31.07	161.90
			1975	78.64	25.61	34.03	128.29
			1980	87.30	30.04	28.14	174.22
			1985	65.12	32.06	24.35	210.17
			1990	78.32	29.81	29.78	150.98
			1995	81.08	28.27	30.85	171.16
			2000	72.69	26.06	20.38	139.43

The inequality data is put together in the following way: If available, we take the "accept"-quality values from Deininger & Squire (1996); then we fill up with values from WIID2c using preferably good quality (according to the WIID-rating), net income values but also allow for other values if no such values are available (excluding bad quality). Consumption based values are corrected by adding 6.6 (both D&S and WIID2c values) as suggested by Deininger and Squire (1996). If no value is available for a certain year (e.g. 1965) the last available value in the previous period (e.g. 1961-65) is used.

Table 2 – First-difference GMM estimation results

	5-year growth rate of the real GDP p.c. (5-year periods)					10-year growth rate of the real GDP p.c. (10-year periods)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Forbes countries / periods	Forbes countries / more periods	Full sample	Full sample / high and up-mid	Full sample / low-mid and low	Full sample / high and up-mid	Full sample / low-mid and low
$\log(\text{GDP})_{t-1}$	-0.1236 *(0.09)	-0.1758 ***(0.002)	-0.1726 ***(0.005)	-0.1952 ***(0)	-0.1756 **(0.014)	-0.1988 (0.103)	-0.3879 *(0.001)
Gini coefficient	0.0075 ***(0.009)	0.0055 **(0.033)	0.0036 *(0.088)	0.0041 *(0.089)	0.0034 **(0.047)	0.0114 *(0.084)	0.128 (0.127)
Male schooling (yrs.)	-0.023 (0.787)	-0.0496 (0.54)	-0.036 (0.674)	-0.0905 (0.121)	0.1336 (0.159)	-0.0876 (0.542)	-0.0052 (0.969)
Female schooling (yrs.)	0.0766 (0.346)	0.027 (0.697)	0.028 (0.729)	0.0848 **(0.031)	-0.0265 (0.646)	0.016 (0.861)	-0.0099 (0.942)
Price level of investment	-0.0013 **(0.011)	-0.0008 (0.151)	-0.0005 (0.317)	-0.006 (0.113)	-0.0011 **(0.082)	0.0001 (0.938)	-0.0021 (0.236)
Number of countries	42	42	70	37	33	30	14
Number of observations	131	225	273	180	93	68	28
Number of instruments	75	140	140	140	93	30	26
M1	-1.96	-3.38	-3.44	-2.72	-2.14	-2.98	-1.67
M2	1.67	-0.89	-0.73	-1.41	-1.22	-0.025	-1.45
Hansen	1	1	1	1	1	0.289	0.943

All regressions include period dummies; ***, **, * denote significance at the 1, 5, 10% levels, respectively; *p*-values in parentheses; M1 and M2 are the *t*-values of the tests for, respectively, first-order and second-order serial correlation in the differenced error terms; Hansen denotes the *p*-value of the Hansen test of over identifying restrictions.

***Table* 3 –** System GMM estimation results

	5-year growth rate of the real GDP p.c. (5-year periods)				10-year growth rate of the real GDP p.c. (10-year periods)	
	(1)	(2)	(3)	(4)	(6)	(7)
	Full sample	Full sample / high	Full sample / up-mid	Full sample / low-mid and low	Full sample / high	Full sample / low-mid and low
$\log(\mathrm{GDP})_{t-1}$	-0.0047 (0.691)	-0.0346 (0.281)	-0.1474 ***(0.000)	-0.037 *(0.099)	-0.1648 ***(0.002)	-0.0488 (0.283)
Gini coefficient	-0.0013 (0.191)	0.0021 **(0.011)	0.0006 (0.55)	-0.0049 **(0.02)	0.0058 **(0.014)	-0.0103 **(0.028)
Male schooling (yrs.)	0.0907 ***(0.007)	0.0299 (0.121)	0.0218 (0.553)	0.0029 (0.946)	0.0761 *(0.1)	-0.0409 (0.746)
Female schooling (yrs.)	-0.0782 **(0.034)	-0.0151 (0.437)	-0.028 (0.407)	0.0481 (0.345)	-0.0467 (0.32)	0.1156 (0.275)
Price level of investment	-0.0014 ***(0.002)	-0.0013 ***(0.004)	-0.0016 *** (0.001)	-0.0006 (0.372)	-0.0019 **(0.044)	-0.0022 (0.218)
Number of countries	90	26	14	50	24	42
Number of observations	404	154	79	171	71	76
Number of instruments	176	150	77	129	46	42
M1	-4.08	-2.53	-2.16	-2.56	-2.53	-1.1
M2	-1.27	-0.08	-1.55	-0.94	-1.01	-1.57
Hansen	1	1	1	1	0.994	0.952

All regressions include period dummies; ***, **, * denote significance at the 1, 5, 10% levels, respectively; *p*-values in parentheses; M1 and M2 are the *t*-values of the tests for, respectively, first-order and second-order serial correlation in the differenced error terms; Hansen denotes the *p*-value of the Hansen test of over identifying restrictions.