Journal of Economic Growth, 8, 267–299, 2003

Inequality and Growth: What Can the Data Say?

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This paper describes the correlations between inequality and the growth rates in cross-country data. Using non-parametric methods, we show that the growth rate is an inverted U-shaped function of net changes in inequality: changes in inequality (in any direction) are associated with reduced growth in the next period. The estimated relationship is robust to variations in control variables and estimation methods. This inverted U-curve is consistent with a simple political economy model but it could also reflect the nature of measurement errors, and, in general, efforts to interpret this evidence causally run into difficult identification problems. We show that this non-linearity is sufficient to explain why previous estimates of the relationship between the level of inequality and growth are so different from one another.

Keywords: inequality, growth, cross-country regressions

JEL classification: O11, O15

1. Introduction

It is often that the most basic questions in economics turn out to be the hardest to answer and the most provocative answers end up being the bravest and the most suspect. Thus it is with the empirical literature on the effect of inequality on growth. Many have felt compelled to try to say something about this very important question, braving the lack of reliable data and the obvious problems with identification: Benabou (2000) lists 12 studies on this issue over the previous decade, based on cross-sectional ordinary least squares (OLS) analyses of cross-country data.

More recently, the literature received a substantial boost from the important work of Deininger and Squire (1996), who put together a much larger and more comprehensive cross-country data set on inequality than was hitherto available. Most importantly, their data set has a panel structure with several consecutive measures of income inequality for each country. This has made it possible to use somewhat more advanced techniques to investigate the effect of inequality on growth: Benhabib and Spiegel (1998), Forbes (2000), and Li and Zou (1998) all look at this relationship using fixed effects estimates, arguing that there are omitted country specific effects that bias the OLS estimates. In

We thank Kristin Forbes and Robert Barro for sharing their data, Alberto Alesina, Oriana Bandiera, Robert Barro, Roland Benabou, Olivier Blanchard, Michael Kremer, Debraj Ray, and Emmanuel Saez for useful conversations.

contrast, Barro (2000) uses a three-stage least squares (3SLS) estimator which treats the country-specific error terms as random, arguing that the differencing implicit in running fixed effects (or fixed effect-like) regressions exacerbates the biases due to measurement errors.

Somewhat surprisingly, both approaches yield new results. While the OLS regressions using one cross-section typically found a negative relationship between inequality and subsequent growth, the fixed effect approach yields a positive relationship between changes in inequality and changes in the growth rate, which has been interpreted as saying that as long as one looks within the same country, increases in inequality promote growth.[1] Barro, by contrast, finds no relationship between inequality and growth. However, he then breaks up his sample into poor and rich countries and finds a negative relationship between inequality and growth in the sample of poor countries and a positive relationship in the sample of rich countries.

It is not clear that it is possible to interpret any of this evidence causally. Variations in inequality are likely to be correlated with a range of unobservable factors associated with growth. Moreover, as we argue later, none of the underlying theories give strong reasons to believe that the omitted variable problem can be solved by including a country fixed effect in a linear specification (as in Forbes, 2000 and Li and Zou, 1998).

Indeed, when we examine the data without imposing a linear structure, it quickly becomes clear that the data does not support the linear structure that has routinely been imposed on it. In particular, we find that changes in inequality (in any direction) are associated with lower future growth rates. There is also a non-linear relationship between inequality and the magnitude of changes in inequality. Finally, there seems to be a negative relationship between growth rates and inequality lagged one period. These facts taken together, and in particular the non-linearities in those relationships (and not differences in the control variables, the sample, and the lag structure), explain why different variants of the basic linear model (OLS, fixed effects, random effects) have generated very different conclusions: In many cases, it turns out that the differences arise out of giving different structural interpretations to the same reduced-form evidence.

In the end, our paper is probably best seen as a cautionary tale: Imposing a linear structure where there is no theoretical support for it can lead to serious misinterpretations.

The remainder of this paper proceeds as follows. In Section 2, we review the existing empirical specifications of the relationship between inequality and growth in the literature. In Section 3, we discuss the different approaches to modelling the relationship between inequality and growth, and observe that there is little support for any of the specifications that have been used. In Section 4, we present our empirical results. In Section 5, we show that these results help us to understand why different methods of estimating the same relationship led to different results. We conclude in Section 6.

2. Specifications in the Literature

The standard procedure for estimating the relationship between inequality and growth in the literature is to assume a simple linear relationship between inequality and subsequent growth:

$$(y_{it+a} - y_{it})/a = \alpha y_{it} + X_{it}\beta + \gamma g_{it} + v_i + \varepsilon_{it}. \tag{1}$$

As we noted in the introduction, and will elaborate on later, OLS estimations of this equation are likely to be biased by a correlation between inequality and the error term. If this is indeed the real structure of the data, it is possible to solve some of these identification problems by exploiting the panel structure of the data. Essentially, taking out period averages of variables eliminates the (additive) country fixed effect, thus allowing the interpretation of the estimated coefficients as the causal effect of inequality on growth, under the assumption that innovations in the error term are not correlated with changes in inequality.

Alternatively, one could first difference equation (1):

$$\frac{(y_{it+a} - y_{it})}{a} - \frac{(y_{it} - y_{it-a})}{a} = \alpha(y_{it} - y_{it-a}) + (X_{it} - X_{it-a})\beta + \gamma(g_{it} - g_{it-a}) + \varepsilon_{it} - \varepsilon_{it-a}. \tag{2}$$

This is a relationship between changes in the gini coefficient and changes in the growth rate. As long as $\alpha = 0$, the OLS estimate of this relationship gives an unbiased measure of α and is statistically equivalent to the fixed effect estimate of equation (1).

One problem is that when α is not equal to zero, the presence of lagged dependent variables on the right-hand side biases the OLS estimate of the differenced equation (as well as the fixed effect estimate of equation (1)). The literature (notably Forbes, 2000; and Benhabib and Spiegel, 1998) has therefore followed the lead of Caselli, Esquivel and Lefort (1996) in using a GMM estimator developed by Arellano and Bond (1991). The idea is to multiply equation (1) by a, to put y_t on the right-hand side, and to take first differences of the resulting equation. This leads to the following equation:

$$y_{it+a} - y_{it} = (a\alpha + 1)(y_{it} - y_{it-a}) + a(X_{it} - X_{it-a})\beta + a\gamma(g_{it} - g_{it-a}) + a\varepsilon_{it} - a\varepsilon_{it-a}. \tag{3}$$

An unbiased estimate of γ can be generated if this equation is estimated using y_{it-a}, X_{it-a}, g_{it-a} and all earlier lags available as instruments for $(y_{it} - y_{it-a})$, $(X_{it} - X_{it-a})$ and $(g_{it} - g_{it-a})$.

Results of estimating equation (1) with random effects, fixed effects, first difference, and Arellano and Bond estimators are presented in Table 1, assuming that the length of a period is 5 years. We restrict the data set to the Deininger and Squire "high quality" sample.[2] Both the results for the set of control variables X_{it} used in Perotti (1996) (and used by Forbes, 2000), and the set of control variables used in Barro (2000), which is much larger, are presented. The results are very consistent. Random effects are insignificant. First differences, fixed effects, and Arellano and Bond coefficients are positive and significant in both specifications. This stands in sharp contrast with the results obtained when estimating the same effect in a long cross-section.[3] Forbes (2000) and Li and Zou (1998), who first made this observation, have shown that this result is robust to a wide variety of changes in specifications.[4] Li and Zou (1998) propose a theoretical explanation based on a political economy model. Forbes (2000) rightly notes that the estimated coefficient indicates a short-run positive relationship between growth and inequality, which might not directly contradict the long-run negative relationship, and concludes that

Table 1. Relationship between growth and changes in Gini, linear specifications.

	Dependent Variable: $(y(t+a)-y(t))/a$							
	Perotti Specification				Barro Specification			
	Random Effects (1)	First Difference (2)	Fixed Effect (3)	Arellano and Bond (4)	Random Effects (5)	First Difference (6)	Fixed Effect (7)	Arellano and Bond (8)
Gini(t)	0.021	0.298	0.297	0.56	−0.03	0.158	0.155	0.27
	(0.09)	(0.18)	(0.16)	(0.039)	(0.043)	(0.068)	(0.063)	(0.016)
N	128	128	128	128	98	98	98	98

Note: Standard errors in parentheses; a is equal to 5 (5-year periods). Control variables: Perotti specification: log(GDP(t)), PPP I (t), male education (t), female education (t). Barro's specification: log(GDP($t-1$)), log(GDP($t-1$)) squared, government consumption ($t-1$), secondary education (t), higher education (t), fertility (t), (term of trade ($t+1$) − terms of trade (t)), rule of law, democ (t), democt (t) squared, Spanish or Portuguese colony, other colony, investment share ($t-1$).

her results suggest that ''in the short and medium term, an increase in a country's level of income inequality has a significant and positive relationship with subsequent economic growth.''

Barro (2000) notes that taking out fixed effects exacerbates the measurement error problem, especially for a variable like the gini coefficient, for which the variation across countries is more important than the variation over time. Classical measurement errors alone cannot, however, explain why the coefficient of inequality should change signs, becoming positive and significant. Furthermore, the GMM estimator instruments first differences with lagged levels, which should, in principle, attenuate the classical measurement error problem. Therefore, there is probably more to this reversal in sign than simple measurement error. In the empirical section, we will investigate this result in more detail. We now turn to the theoretical foundation of equation (1).

3. The Inequality–Growth Relationship

Our goal in this section is to understand what alternative theories tell us about the appropriate choice of specifications to be used when describing the data on inequality and growth, and in particular whether the specifications in (1) and (3) can easily be generated. There are essentially two classes of arguments in the literature that suggest a causal relation between inequality and growth: Political economy arguments, and wealth effect arguments. Most empirical studies of the relationship between inequality and growth refer to these arguments, without always taking their precise implications seriously. To these we add a third argument which is essentially statistical and emphasizes the role of measurement error in generating a relation between inequality and growth.

3.1. *Political Economy Arguments*

Political economy models, in their simplest version, start with the premise that inequality leads to redistribution and then it is argued that redistribution hurts growth.[5] Since our goal is to illustrate what can happen in this class of models, we present a version of the argument that minimizes institutional detail.

3.1.1. *A Very Simple Model Based on ''Hold-up''*

Consider an economy constituted of two classes, A and B, which function as competing political groups. Assume that the economy at any point of time is characterized by a single number g which represents the sharing rule for the economy: Group A gets g percent of the output.

In each period, this economy is presented with an opportunity which, if availed of, can lead to growth. These opportunities could be a new technology, a trade agreement, an internal reform, or a major foreign investment. The potential growth generated by the opportunity will be denoted by Δy, which is a random variable that is independent over time and has the distribution $F(\Delta y)$.

The growth opportunity does not, however, automatically translate into growth. Some structural changes need to be implemented in order to benefit from the opportunity, and the political system allows for the possibility that these changes would be blocked by one of the groups. To keep matters simple, assume that in every period once the potential growth rate is known, one of the groups, chosen at random, gets to hold up the rest of the economy. More specifically, assume that this group has the option of either acquiescing immediately to the changes, in which case the changes are made and the full growth opportunity is realized, or demanding a transfer from the other group (i.e. an increase in its share) before the changes can be made. The other group, in turn, can agree to make the transfer or refuse. If it refuses to make the transfer, status quo is maintained and there is no growth. If it agrees, the changes are made and growth takes place, but by now a part of the growth opportunity has been lost and the economy only grows by $\alpha_I \Delta y (\alpha_I \leq 1)$ where $I = A, B$ is the identity of the group being held up. α_I is a random variable which is drawn independently from the distribution $G_I(\alpha_I)$ in every period, and is known to both groups at the beginning of the period (i.e. before the hold-up ''game'' is played).

The assumption that there is some efficiency loss in the process of bargaining (i.e. the fact that α_I may be less than 1) plays an important role in our analysis. Delay may be one reason for the loss: It is plausible that the process of getting all members of the losing group to agree to the transfer would take quite some time. Making a credible demand for a transfer typically takes time and resources—as we know, a group might have to resort to industrial action, street protests, and even civil war in order to establish their claim. On the other side, making a credible transfer may require involving third parties (such as the state) and/or changing the institutional framework,[6] which has potential costs of its own. Finally, there are the standard arguments explaining why transfers tend to be distortionary.[7]

To complete the description of the model, we assume that all agents are either shortlived or have short horizons. When they decide whether or not to resist, they ignore the effect it will have on output in future periods.

3.1.2. Results and Implications for Empirical Work

Let us assume, without loss of generality, that in a given period it is group B that has the chance to hold up the rest of the economy. Whether or not it does depends on how much it can extract from group A. To figure this out, we need to look at the decision of group A when faced with a demand for transfers worth Δg. If they acquiesce to the transfer their payoff will be $(g - \Delta g)(1 + \alpha_A \Delta y)$ (the growth rate is $\alpha_A \Delta y$ because group B has already demanded a transfer). If they do not acquiesce, their payoff will be g, as there will be no growth. Comparing the two, it is clear that the maximum transfer that can be extracted from group A is given by

$$\frac{\alpha_A \Delta y}{(1 + \alpha_A \Delta y)} = \frac{\Delta g}{g}, \tag{4}$$

which, reassuringly, tells us that $\Delta g < g$, so the transfer is always feasible. Group B makes its decision taking this as given—it never pays for them to demand more since group A will never acquiesce and there will be less growth in the bargain. They will demand a transfer of size Δg if and only if

$$(1 - g + \Delta g)(1 + \alpha_A \Delta y) \geq (1 - g)(1 + \Delta y),$$

which implies

$$(1 - g)\alpha_A \Delta y + \Delta g(1 + \alpha_A \Delta y) \geq (1 - g)\Delta y.$$

Using the expression for Δg from above, this reduces to:

$$\alpha_A \geq 1 - g.$$

Then, $\alpha_A \geq 1 - g$ is the condition under which group B always demands a transfer when it gets a chance. By a similar argument, the corresponding condition for group A is

$$\alpha_B \geq g.$$

These two conditions ought to be intuitive: They say that each group will hold up the rest of economy when its share of output is low, which is when they have the least stake in the growth of the overall economy. This is essentially the same reason why the poor in Alesina and Rodrik (1994), Persson and Tabellini (1991) and Benhabib and Rustichini (1998) choose high levels of redistribution even though it hurts growth.

Note also that both of these conditions make no mention of Δy. The potential growth rate for the economy does not influence the probability of growth-reducing bargaining/ conflict. The growth rate in our economy only depends on whether there is a hold-up: If there is no hold-up, the rate is Δy, while if there is a hold-up it is $\overline{\alpha_I}\Delta y$, where $\overline{\alpha_I}$ is the expectation of α_I. In the world of this model, hold-ups only happen when there are redistributive transfers that result from the hold-up. Therefore, we have the following result.

Result 1. As long as $\overline{\alpha_A}$ and $\overline{\alpha_B}$ are less than one, the expected growth rate in this economy in any period following a distributional change is lower than when there is no conflict.

In order to interpret the variable g as a measure of inequality, we need to assume that one of the groups (say group A) is substantially richer than the other in terms of per capita income (in other words, group B has a much larger share of the population than group A). In this case, an increase in g in our model would correspond to an increase in inequality.[8]

The relationship between distributional changes and expected growth implied by the above result is, however, highly discontinuous. This is because our model clearly makes an excessively strong distinction between the case where there are no distributional changes and the case where there are some distributional changes. A smoother relationship could be derived if we assumed instead that the hold-up problem only determines the planned transfer, whereas the actual transfer is determined ex post by adding a random shock to the planned transfer. This allows the possibility that there will be some small distributional changes even when there is no conflict. Combined with the assumption that growth is higher when the planned transfer is zero, this would give us *a smooth inverted U-shaped relation between expected growth and actual changes in inequality.*

If we were prepared to take this model literally, it would allow us to estimate a (non-linear) causal relationship between growth and changes in inequality. There are, however, many reasons why this model is special: Most importantly perhaps, growth here does not have any direct distributional effect. If more growth leads to more redistribution, then the anticipation of a large growth shock could raise the likelihood that there is a hold-up problem. More redistribution could then be associated with higher growth and the relationship would no longer be U-shaped. More importantly, there would be reverse causality—running from growth to anticipatory changes in the distribution—making it impossible to interpret the relationship between growth and distributional changes causally. A possible source of reverse causality comes from the idea that the lack of growth opportunities makes the environment more conflictual (say, because people feel frustrated), and conflicts lead to changes in inequality.[9] We therefore only offer this model as a possible way to interpret the data.

The discussion above suggests that, at least in terms of data description, if not causal interpretation, we should estimate a relationship of the form:

$$\frac{(y_{it+a} - y_{it})}{a} = \alpha y_{it} + X_{it}\beta + k(g_{it} - g_{it-a}) + v_i + \varepsilon_{it}, \tag{5}$$

where y_{it} represents the logarithm of GDP in country i at date t, a is the length of the time period we choose, 5 or 10 years in the examples we will consider ($(y_{it+a} - y_{it})/a$ is therefore the growth rate), X_{it} is a set of control variables, g_{it} is the gini coefficient in country i at date t, and $k(\cdot)$ is a generic function. At this point we do not impose any structure on the shape of the $k(\cdot)$ function. The error term is modelled as a country-specific time invariant effect (v_i) and a time varying error term (ε_{it}). y_{it} is included among the controls in order to capture convergence effects, and X_{it} controls for possible sources of spurious correlation.

However, the political economy literature has not taken this route. Instead, the approach has been to derive a relationship between the level of inequality and changes in inequality, which, combined with a relationship between growth and changes in inequality (such as the one just derived), generates a relation between growth and the level of inequality.[10] We could also take a similar approach here. To do this, observe that in our model changes in inequality are causally related to the level of inequality. The expected increase in the share of group A

$$\Delta g^e = \frac{1}{2}\left[\int_g^1 \frac{\alpha_B \Delta y}{(1+\alpha_B \Delta y)}(1-g)dG_B(\alpha_B) - \int_{1-g}^1 \frac{\alpha_A \Delta y}{(1+\alpha_A \Delta y)} g dG_A(\alpha_A)\right],$$

is obviously decreasing in g, which tells us the following result.

Result 2. The relation between the level of inequality and the expected change in inequality in our model is broadly negative.

This suggests estimating the following relationship:

$$g_{it+a} - g_{it} = \alpha y_{it} + X_{it}\beta + h_1(g_{it-a}) + v_i + \varepsilon_{it}. \tag{6}$$

What matters for growth in our model, however, is not the actual change in inequality but the absolute value of that change (as both positive and negative changes reduce growth), which is given by:

$$\frac{1}{2}\left[\int_g^1 \frac{\alpha_B \Delta y}{(1+\alpha_B \Delta y)}(1-g)dG_B(\alpha_B) - \int_{1-g}^1 \frac{\alpha_A \Delta y}{(1+\alpha_A \Delta y)} g dG_A(\alpha_A)\right].$$

As g goes up, the first term of this expression goes down but the second goes up, making it difficult to predict the sign of the relationship. However, as long as $\max\{\alpha_A\} + \max\{\alpha_B\} \leq 1$, there exist values of g satisfying $\max\{\alpha_B\} \leq g \leq 1 - \max\{\alpha_A\}$, and for such intermediate values of g, there are no planned changes in inequality. There are planned changes in inequality for $g \leq \alpha_B$, to the extent of

$$\frac{1}{2}\left[\int_g^1 \frac{\alpha_B \Delta y}{(1+\alpha_B \Delta y)}(1-g)dG_B(\alpha_B)\right],$$

and, as is apparent from this expression, these changes are bigger the closer g is to 0. Likewise, inequality falls when g is bigger than $1 - \max\{\alpha_A\}$, and it falls faster when g is closer to 1. We state these conclusions as the following result.

Result 3. The relation between the level of inequality and the expected value of the absolute changes in inequality for the economy in our model is U-shaped when $\max\{\alpha_A\} + \max\{\alpha_B\} \leq 1$. The (expected) absolute value of changes in inequality is first decreasing with inequality, then flat over a range and then increasing with inequality.

This tells us that planned changes in inequality, and therefore hold-ups, become more common as we move towards the two extremes of complete equality and maximum inequality. Moreover, the threshold level of α_I at which people are willing to hold the other side up, goes down as we approach either extreme, with the implication that as we approach either extreme, hold-ups become more costly (in terms of lost growth) on average. The net result is the following.

Result 4. The relation between the level of inequality and future growth for the economy in our model is inverted U-shaped when $\max\{\alpha_A\} + \max\{\alpha_B\} \leq 1$, i.e. there is less growth when inequality is either very high or very low.

What happens when $\max\{\alpha_A\} + \max\{\alpha_B\} > 1$ is less straightforward. However, one special case that is easily understood is where both α_A and α_B are constants, with $\alpha_A + \alpha_B > 1$. In this case, there is range of values of g between $1 - \alpha_A$ and α_B where both sides are going to try to hold the other side up. This has the consequence that there are more hold ups in the middle than at either extreme. Changes in inequality are more common in the middle and the growth rate is lowest for intermediate values of inequality, generating a U-shaped rather than an inverted U-shaped relation between inequality and growth.

Another interesting special case is where α_A and α_B are constants and $\alpha_A < \alpha_B = 1$. This is the case where the rich can costlessly hold up the poor, with the consequence that they do so whenever they are given a chance. However, since it is costly to hold up the rich, the poor only initiate a hold up when their share is low enough. Therefore, the frequency of hold-ups (and distributional changes) goes up as inequality rises, and the growth rate falls. This gives us a monotonic relationship between inequality and growth, which could justify estimating something like (1) or its differenced version, (3). This is consistent with the fact that estimating (1) is often justified in terms of a model where redistribution towards the rich takes place through a tax cut, and it is assumed that tax cuts create no upheavals and therefore have no efficiency costs (in fact they raise efficiency), which is very much in the spirit of our assumption that $\alpha_B = 1$.[11]

In general, however, there seems to be no grounds for the presumption that the right equation to estimate is linear. Taking our model seriously would suggest estimating equation (5) as well as the following flexible specifications that correspond broadly to our Results 3 and 4. The first relationship relates the square (or, alternatively, the absolute level) of changes in inequality to the level of inequality:

$$(g_{it+a} - g_{it})^2 = \alpha y_{it} + X_{it}\beta + h_2(g_{it-a}) + v_i + \varepsilon_{it}. \tag{7}$$

The second relationship is a "reduced-form relationship," which relates the level of inequality (lagged one period) to the growth rate:

$$(y_{it+a} - y_{it})/a = \alpha y_{it} + X_{it}\beta + h(g_{it-a}) + v_i + \varepsilon_{it}, \tag{8}$$

where once again $h(\cdot)$ may be non-monotonic.

It is worth noting that estimating these relationships using cross-country data introduces a number of additional problems. First, Δy and the distributions of α_A and α_B may be different for different countries and the initial level of inequality may be correlated with these (unobserved) differences in Δy, α_A and α_B. Second, the shape of the relationships may vary across countries: They may be U-shaped in some and the reverse in others. Finally, the value of measured inequality that corresponds to $g = \frac{1}{2}$ may vary from country to country, and therefore the relationship may peak (and bottom out) at different points in different countries. For all of these reasons, interpreting these relationships estimated from cross-country data is, at best, a perilous undertaking. It remains, however, that the correspondence between Results 3 and 4 should hold even when these countries are heterogenous. In other words, as long as our basic model is correct, it is always a prediction of our model that our estimates of the functions $h(\cdot)$ and $h_2(\cdot)$ in equations (8) and (7) should have the opposite shape.

The right structure of time lags for estimating this model is also an issue. For example, in our model high inequality is bad for growth because it creates incentives for hold ups, intended to reduce inequality. But the resulting reduction in inequality makes it less likely that in the subsequent period there will be a hold up and therefore the expected growth rate in that period will be higher than what it would have been, absent the costly change in inequality in the previous period. Averaged over the two periods, the net effect on growth coming from the initial reduction in inequality is obviously much smaller than the impact effect, and we can clearly have shocks to inequality that are costly in the short run but beneficial over a longer horizon.

3.2. Wealth Effect Arguments

3.2.1. A Model

Wealth effect arguments for why inequality should have an effect on growth start with the premise that there is some relation between wealth now (w_t) and future wealth $(w_{t+1}) : w_{t+1} = f(w_t, p)$, where p is a vector of market prices, which include the wage rate and the rate of interest.[12] It is reasonable to assume that f_w is positive, but to say anything robust about the effect of inequality we also need to know f_{ww}. If we assume $f_{ww} < 0$, it immediately follows (since f is concave in w) that if $G'_t(w)$ is a mean preserving spread of $G_t(w)$, the current distribution of wealth, aggregate future wealth under G_t, $\int f(w,p)dG_t(w)$, will be greater than aggregate future wealth under G'_t, $\int f(w,p)dG'_t(w)$. In other words, a more equal economy grows faster than a less equal one. The problem with this formulation is that the f function telescopes a number of separate economic decisions, including those about savings, investment and bequests. To understand what is reasonable to assume about the shape of the f function we need to ''unpack'' the f function.

One simple formulation is to consider a model where everyone is identical in all respects except possibly in wealth, and there is only intergenerational transmission of wealth. Let capital be the only marketed factor of production. Assume people live for one period. Assume in addition, that capital markets are imperfect and as a result individuals can only borrow up to λ times their wealth, where λ is a function of r_t, the current rate of interest $(\lambda' < 0)$.[13] Finally, assume that corresponding to each individual, there is a strictly concave production function $h(k)$, which tells us the amount of income he generates when his total investment is k.[14]

If we assume that each individual starts with a certain bequest from his parent, invests it during his lifetime and dies at the end of the period after consuming a fraction $1-\beta$ of his end-of-period wealth and bequeathing the rest to his child, this model turns out to give us a very simple f function. At the current rate of interest, people will want to invest an amount k^*, which is given by the usual marginal condition $h'(k^*) = r_t$. Therefore, those who start

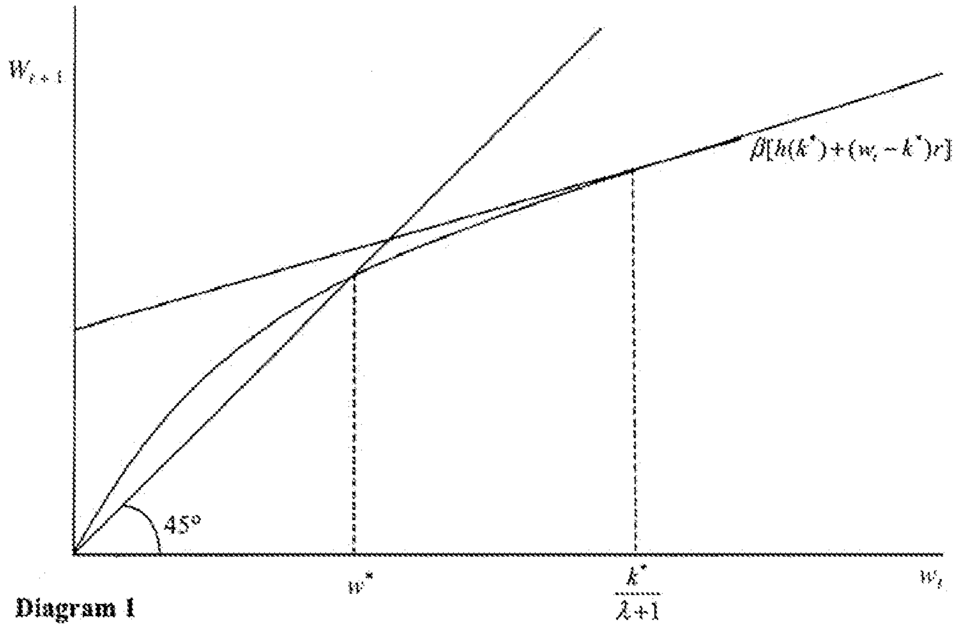

Diagram 1

with enough wealth, i.e. $(\lambda+1)w_t > k^*$, will invest k^*, while the rest will invest all that they can, i.e. $(\lambda+1)w_t$. They will earn a net income of:

$$\min\{h(k^*) + (w_t - k^*)r_t, h((\lambda+1)w_t) - \lambda w_t r^*\}.$$

Out of this income, a fraction β will be left to their children, which gives us w_{t+1}, the beginning of period wealth for the next period.

3.2.2. Results and Implications for Empirical Work

The map from current wealth to future wealth generated by this model is represented in Diagram 1 and is indeed concave. This immediately gives us the following result.

Result 5. An exogenous mean-preserving spread in the wealth distribution in this economy will reduce future wealth and by implication the growth rate.

The extent to which inequality is costly will depend, however, on the mean wealth in this economy: The map in Diagram 1 is linear for wealth levels above $k^*/(\lambda+1)$ and therefore inequality will have no effect as long as no one has wealth less than $k^*/(\lambda+1)$. More intuitively, once the economy is rich enough that everyone can afford the optimal level of investment, inequality should not matter. The estimated relationship between inequality and growth should therefore allow for an interaction term between inequality and mean income.

Note that the same diagram also tells us something about the dynamics of this economy. On the assumption that the rate of interest does not vary over time, the diagram summarizes the process of evolution of the wealth of a dynasty. As is evident, this economy embodies a very strong convergence property: Everyone's wealth eventually converges to a steady state at the point marked w^* by implying that the long-run average wealth is independent of initial conditions. We state this as the following result.

Result 6. Starting with any initial distribution of wealth, both inequality and the growth rate must, on average, go down over time, with the consequence that in the long run there is no inequality and no growth.

This has two implications for the estimation of the inequality–growth relationship. First, the fact that the economy becomes more equal as it grows tends to generate a mechanical positive relation between growth and inequality, both in the cross-section and in the time series. As a result, both the cross-sectional and the first differenced (or fixed effects) estimates of the effect of inequality on growth run the risk of being biased upwards, compared to the true negative relation that we might have found if we had compared economies at the same mean wealth levels. Moreover, consider a variant of the model where there are occasional shocks that increase inequality. Since the natural tendency of the economy is towards convergence, we should expect to see two types of changes in inequality: Exogenous shocks that increase inequality and therefore reduce growth, and endogenous reductions in inequality that *are also associated with a fall in the growth rate. In other words, measured changes in inequality in either direction will be associated with a fall in growth,* suggesting that the right equation to estimate is the one in (5), or the following more general specification that nests both a direct effect of the level of inequality and an effect of changes in inequality:

$$\frac{(y_{it+a} - y_{it})}{a} = \alpha y_{it} + X_{it}\beta + k(g_{it} - g_{it-a}) + h(g_{it}) + v_i + \varepsilon_{it}. \tag{9}$$

This of course assumes that we have not eliminated the convergence effect by adequately controlling for mean wealth (or mean income). In fact most specifications that are estimated do try to control for the convergence effect, as is standard in growth regressions, by including a linear function of the mean level of income at the beginning of the period (as in equations (1) and (9)). In first differences, one controls for past growth (as in equation (3)). For most functions $f(w_t, p)$ however, the convergence term does not enter linearly. Moreover, it seems plausible that different economies will have different λs and therefore will converge at different rates. Therefore, controlling linearly for past level (in the level equation) or past growth (in the first differences equation) will not necessarily help in solving the non-monotonicity of the relationship between growth and changes in inequality.

The model also tells us that while initial distribution matters for the growth rate, it only matters in the short run. Over a long enough period, two economies starting at the same mean wealth level will exhibit the same average growth rate, since they both would have gone from the initial mean wealth to a mean wealth of w^*. In other words, the length of the time period over which growth is measured will affect the strength of the relationship between inequality and growth.[15]

Note that all this is still in the context of what is, more or less, the best-behaved model we could come up with. There is, for example, no very good reason to assume that $h(k)$, the production function in the above example, is globally concave—most machines, for one, come in a few discrete sizes.[16] Consider a simple variant of the model above where there is

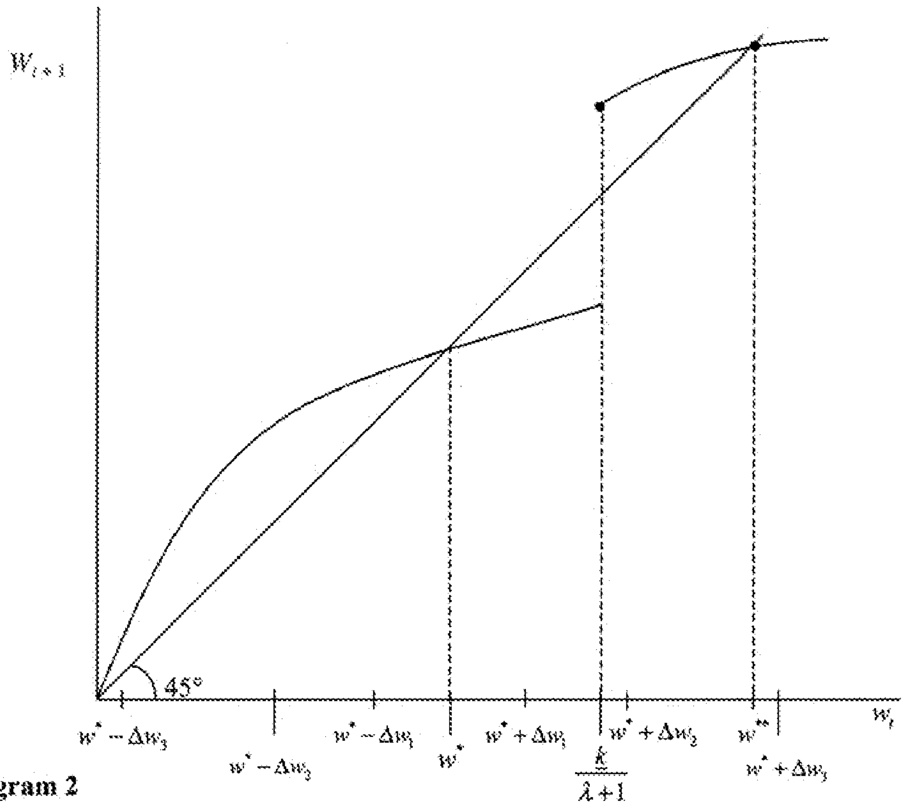

Diagram 2

a second technology requiring a minimum investment of $\underline{k} > (\lambda + 1)w^*$ but yielding a far higher return than the $h(\cdot)$ technology.

Assuming the yields from this new technology are sufficiently high that those who can afford it want to invest in it, the resulting map from w_t to w_{t+1} is represented in Diagram 2. It is clear that the map is no longer concave, and while it is not convex it behaves like a convex function over certain ranges (and like a concave function over others).[17] In particular, starting with an economy where everyone is at w^*, a small increase in inequality, shown in Diagram 2 by $[-\Delta w_1, \Delta w_1]$, leads to a fall in the growth rate (i.e. the mean wealth shrinks).[18] But a larger increase, shown by $[-\Delta w_2, \Delta w_2]$, will actually increase the growth rate, because those who gain from the increase in inequality will be able to take advantage of the very rewarding second technology. Even larger increases in inequality, shown by $[-\Delta w_3, \Delta w_3]$, may, however, be counterproductive.

The relation between inequality and growth delivered by this model is clearly non-monotonic. Moreover, the strong convergence property that holds in the simpler model is now only true if everyone starts with a wealth less than $\underline{k}/(\lambda + 1)$. Anyone who starts with more wealth than $\underline{k}/(\lambda + 1)$, that is, more wealth than he needs to be able to invest an amount $\underline{k}$, will converge to a different steady state, represented by w^{**} in Diagram 2.[19] In other words, the growth rate of wealth will *jump up at* $w_t = \underline{k}/(\lambda + 1)$, with the obvious implication that economies with higher mean wealth will not necessarily grow more slowly. In other words, the effect of mean wealth, that is the so-called convergence effect, may not be monotonic in this economy. Linearly controlling for mean wealth therefore does not guarantee that we will get the correct estimate of the effect of inequality.[20] It is worth noting that this economy will have a connected continuum of steady states. This means that after a shock the economy will not typically return to the same steady state. However, since it does converge to a nearby steady state this is not an additional source of non-linearity.

So far, we have assumed that the evolution of the economy leaves the interest rate unchanged. Making the interest rate endogenous complicates matters substantially: Variants of the simple concave economy may no longer converge, even in the weaker sense of the long-run mean wealth being independent of the initial distribution of wealth. Intuitively, poor economies will tend to have high interest rates, and this in turn will make capital accumulation difficult (note that $\lambda' < 0$) and tend to keep the economy poor.[21] This effect reinforces the claim made above that inequality matters most in the poorest economies.[22] This economy can have a number of distinct steady states that are each locally isolated. This means that small changes in inequality can cause the economy to move towards a different and further away steady state, making it more likely that the relationship will be non-linear.

Even if we could agree on a specification that is worth estimating, it is not clear how we can use cross-country data to estimate it. Countries, like individuals, are different from each other. Even in a world of perfect capital markets, countries can have very different distributions of wealth because, for example, they have different institutions or distributions of ability. In this case, we run the risk of misinterpreting a purely non-causal association between inequality and growth as a causal relationship: For example, cultural structures (such as a caste system) may restrict occupational choices and therefore may not allow individuals to make proper use of their talents, causing both higher inequality and lower growth. Conversely, if countries use technologies that are differently intensive in skilled labor, those countries using the more skill-intensive technology can have both more inequality and faster growth.

Countries may also have different kinds of financial institutions, implying differences in the λ's in our model. Our basic model would predict that the country with the better capital markets is likely both to be more equal and to grow faster (at least once we control for the mean level of income). The correlation between inequality and growth will therefore be a downwards biased estimate of the causal parameter, if the quality of financial institutions differs across countries.[23] Changes in inequality may also be systematically related to changes in growth rates: For example, skill-biased technological progress will lead both to a change in inequality and a change in growth rates, causing a spurious positive correlation between the two. To make matters worse, we have to recognize the fact that λ itself (and therefore the effect of inequality on growth at a given point in time) may be varying over time as a result of monetary policies or financial development, and may itself be endogenous to the growth process.[24]

The more general point that comes out of the discussion above is that unless we assume capital markets are extremely efficient (which, in any case, removes one of the important sources of the effect of inequality), changes in inequality will be partly endogenous and related to country characteristics which are themselves related to changes in the growth rate. Even in the simplest model, controlling for convergence effects linearly is not adequate, and relationships such as equations (1) and (3) cannot be derived from the model. In particular, one would expect strong non-monotonicity in the observed relationship between inequality (and changes in inequality) and growth even if the underlying mechanism implies a negative relationship between inequality and growth.

3.3. Measurement Error Arguments

Inequality is not easy to measure, and while the Deininger and Squire (1996) high quality data set is a considerable improvement over the data that was previously available, substantial scope for error remains. Atkinson and Brandolini (2001) carefully discuss the Deininger and Squire data for the OECD countries, and find that it has important problems. Most worrisome is the fact the data may be especially ill-suited for comparison over time and within countries. For example, the Deininger and Squire data for France shows a sharp drop in inequality from 1975 to 1980. As Atkinson and Brandolini (2001) show, this is due to a rupture in the series rather than to a genuine change in the underlying inequality. As shown in Table 2, several countries where the Deininger and Squire high quality data set show a large increase in inequality over a 5-year period seem to also have a large decrease in inequality over the following or the previous 5-year period, which seems unlikely in the absence of measurement error.[25]

To see why this matters, assume that all apparent changes in inequality arise out of mis-measurement by the statistical agency. Assume also that the statistical agency is more likely to mis-measure when the society as a whole is under stress, because of an economic or a political crisis, or a war. These are also times when the growth rate is likely to fall. We will therefore expect an inverted U-shaped relation between measured changes in inequality and changes in the growth rate—measured changes in inequality in any direction will be associated with a subsequent fall in the growth rate.

3.4. Summary

This section makes the case that there is no reason to expect that we can learn about the relationship between inequality and growth by running linear cross-country regressions. There are no strong grounds for thinking that the right specification would be monotonic, let alone linear. Finally, none of the theories give us any confidence that the effect will be properly identified. In the remainder of this paper, we focus on the functional form issue, to show that this issue enough is sufficient to cast doubt on the validity of the results in the previous literature, as well as to reconcile the different results that have been obtained with different specifications.

Table 2. Countries with large changes in gini coefficients.

Decrease in gini coefficient larger than 3 percentage points				Increase in gini coefficient larger than 3 percentage points			
Country (1)	Period (2)	Beginning of Period Gini (in %) (3)	Change in Gini (Percentage Points) (4)	Country (5)	Period (6)	Beginning of Period Gini (in %) (7)	Change in Gini (Percentage Points) (8)
Bangladesh	65–70	37.3	– 3.1	Australia	85–90	37.6	4.1
Bulgaria	70–75	21.5	– 3.7	Bulgaria	75–80	17.8	7.2
Brazil	75–80	61.9	– 4.2	Brazil	80–85	57.8	4.0
Canada	85–90	32.8	– 5.3	Brazil	70–75	57.6	4.3
Colombia	70–75	52.0	– 6.0	Chile	75–80	46.0	7.2
Spain	75–80	37.1	– 3.7	China	85–90	31.4	3.2
Finland	70–75	31.8	– 4.8	Colombia	75–80	46.0	8.5
Finland	85–90	30.8	– 4.7	Germany	65–70	28.1	5.4
France	75–80	43.0	– 8.1	Dominican Republic	85–90	43.3	7.2
Hong Kong	85–90	45.2	– 3.2	Finland	75–80	27.0	3.9
Hungary	65–70	25.9	– 3.0	United Kingdom	85–90	27.1	5.2
Indonesia	80–85	42.2	– 3.2	Hong Kong	80–85	37.3	7.9
Ireland	75–80	38.7	– 3.0	Sri Lanka	75–80	35.3	6.7
Italy	75–80	39.0	– 4.7	Sri Lanka	80–85	42.0	3.3
Korea, Republic	80–85	38.6	– 4.1	Mexico	85–90	50.6	4.4
Sri Lanka	85–90	45.3	– 8.6	New Zealand	85–90	35.8	4.4
Sri Lanka	65–70	47.0	– 9.3	New Zealand	75–80	30.0	4.8
Mexico	75–80	57.9	– 7.9	Sweden	75–80	27.3	5.1
Norway	75–80	37.5	– 6.3	Thailand	85–90	43.1	5.7
Portugal	75–80	40.6	– 3.8	Venezuela	80–85	39.4	3.4
Sweden	70–75	0.4	– 6.1	Venezuela	85–90	42.8	11.0
Trinidad and Tobago	75–80	51.0	– 4.9				
Trinidad and Tobago	80–85	46.1	– 4.4				
Turkey	70–75	56.0	– 5.0				
Venezuela	75–80	47.7	– 8.2				

Source: Deininger and Squire (high quality sample).

4. Estimation and Results

In this section, we start by presenting estimates of equations (5)–(9). After having established the importance of non-linearities, we turn to their consequences for the interpretation of equations (1) and (3).

4.1. Data and Variables

Our main focus in this paper is on the potentially non-linear effects of distributional changes, and therefore we have chosen to sidestep a number of important and natural questions. First, the question of what should be the right set of control variables. The choice of these variables is clearly critical, since a central concern for the empirical literature is that the gini coefficient could proxy for omitted variables. For example, Barro (2000) criticizes earlier studies on their choice of control variables and shows, in particular, that their results are sensitive to the inclusion of fertility in the regression. But the choice of the variables entails making judgements about causality that are not easy to defend. We therefore avoid taking a position on this subject. Instead, we present all the results for the set of control variables X_{it} used in Perotti (1996) and the set of control variables used in Barro (2000). These specifications are useful benchmarks for two reasons. First, the Perotti specification has been used by most subsequent studies. Second, they represent two extremes: The Perotti specification uses the smallest number of control variables and the Barro specification the largest. The list of variables included in both specifications is included as a note to Table 1. The Perotti specification excludes most variables (in particular, investment and government spending) through which the influence of inequality could be channelled. The only variables included are male and female education and the purchasing power parity of investment goods, a measure of distortion. Barro, on the other hand, includes investment share of GDP, fertility, education, and government spending, which are plausible channels through which inequality could affect growth.[26] The interpretation of the coefficient of inequality in the two regressions is therefore different.

Second, the question of what the right definition of inequality (interquartile range, measure of poverty, etc.) ought to be. There are reasons to doubt that the gini coefficient is the appropriate measure of inequality from the point of view of growth regressions. However, most empirical work on growth and inequality focuses on the gini coefficient. Therefore, our focus in this paper is also on the relationship between the gini coefficient and economic growth.

A distinct but related question concerns the reliability of the measure of the gini coefficient. A new data set, compiled by Deininger and Squire (1996), has substantially improved the reliability and the comparability of available measures of inequality. They have compiled an extensive data set for a large panel of countries. They also identify a sub-set of their data as a ''high quality'' data set.[27] Most recent studies have used this new high quality data set (or its extended version). Therefore, despite the problems we noted above with this data set, we will present most results in the Deininger and Squire high quality data set restricted to countries with at least two consecutive observations.[28]

It should be noted that, depending on the data source, the data refers either to ex post inequality (i.e. to income measured net of redistribution, or to expenditure inequality) or to gross inequality. The distinction is less strong than it appears, however, since a substantial fraction of the redistribution does not occur through the tax system but through other mechanisms (minimum wages, labor laws, inflation, etc.). An additional drawback is that the "high quality" data set is small, and includes very few poor countries, especially when it is limited to countries where at least two observations are available.[29]

Finally there is the question of the relevant time period (the choice of a). As we emphasized in the previous section, the theory predicts different effects over different lags. The first set of empirical papers studied growth over a long time period (25–30 years). Subsequent papers have exploited the richness of the Deininger and Squire data set and have chosen shorter lags (5 or 10 years) in an attempt to increase the number of available observations. Since using longer lags substantially reduces the number of changes in inequality in our data set, we will focus on 5-year lag periods.

4.2. Basic Results

Table 3 presents the results from estimating various versions of equations (5) and (9).[30] In columns (1) and (5), we regress growth on the change in inequality and the change in inequality squared. Past variation in inequality is related to subsequent growth, in a very non-linear way: While the linear term is insignificant, the quadratic term is negative and significant with both sets of control variables.

We then introduce the level of the gini coefficient into the regression (columns (2) and (6)). The coefficients of $(g_{it} - g_{it-a})$ and $(g_{it} - g_{it-a})^2$ are not affected by the introduction of the gini coefficient.[31] To explore the non-linearity further, we use a kernel regression, and we "partial out" the linear part of the model (i.e., y_{it}, g_{it} and X_{it}) using a method analogous to that developed by Robinson (1988) and applied in Hausman and Newey (1995).[32] The results are shown in Figures 1 (with Perotti variables) and 2 (with Barro variables). The kernel regression line is shown as a solid line. This relationship has the shape of an inverted U, with a maximum around 0 and a relatively flat section at the top. Changes in inequality, in any direction, are associated with reduced growth in inequality, and larger changes are associated with larger decline in growth.

This result is striking, and we investigated its significance using a variety of methods. First, we estimated the relationship using series estimation. In Figure 1, we show the predicted value using a quartic specification for the function $h(\cdot)$. This polynomial is maximized when the value of lagged change in inequality is 0.012 (using Perotti variables), which is very close to 0. To test whether the non-linearity is statistically significant, we present in columns (4) and (8) the F-test for the joint significance of the non-linear terms in the partially linear model. Linearity is rejected in both cases, at 3 percent in the Perotti specification and 12 percent in the Barro specification. Given the limited amount of data (128 and 98 observations, respectively) and the fact that it is very noisy, this result is a surprisingly strong rejection of linearity. Finally, we estimate a piece-wise linear specification for $h(\cdot)$ (columns (3) and (7)), where we treat the effects of

Table 3. Relationship between inequality and changes in inequality and growth.

	Dependent Variable: $(y(t)-y(t-a))/a$							
	Perotti Specification				Barro Specification			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
gini(t)		0.05 (0.10)	0.064 (0.099)	0.094 (0.11)		− 0.042 (0.045)		− 0.039 (0.043)
gini(t) − gini($t-a$)	0.065 (0.16)	0.36 (0.17)			0.053 (0.063)	0.073 (0.066)		
(gini(t) − gini($t-a$))2	− 5.09 (2.95)	− 5.37 (3.06)			− 2.47 (1.16)	− 2.33 (1.17)		
gini(t) − gini($t-a$)* 1(gini(t) − gini($t-a$)) ≤ 0			0.63 (0.30)				0.27 (0.10)	
gini(t) − gini($t-a$)* 1(gini(t) − gini($t-a$)) ≥ 0			− 0.59 (0.33)				− 0.11 (0.13)	
F-test for (gini(t) − gini($t-a$))2, (gini(t) − gini($t-a$))3, (gini(t) − gini($t-a$))4				9.02 (0.029)				5.72 (0.12)
(p value in parentheses)								
Number of observations	128	128	128	128	98	98	98	98

Note: Coefficient obtained using random effect specifications.
Standard errors in parentheses; a is equal to 5 (5-year periods).
Control variables: see note to Table 1.

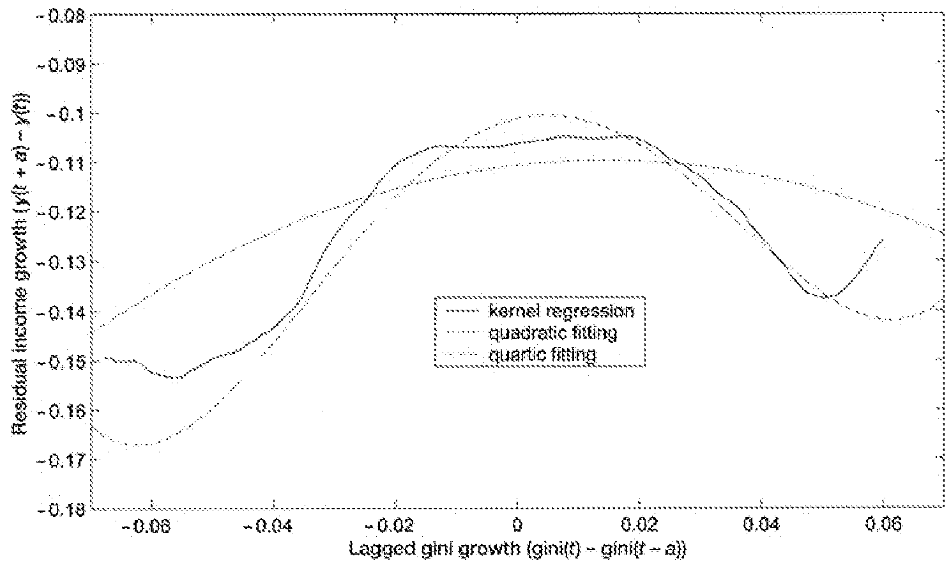

Figure 1. Relationship between income growth and lagged gini growth: partially linear model (Perotti variables).

increases and decreases in inequality separately. The coefficients of decreases and increases in inequality are positive and negative, respectively. The positive coefficient in the decreasing range is significant in both specifications. The negative coefficient in the increasing range is significant (at the 10 percent level) only in Perotti's specification. We

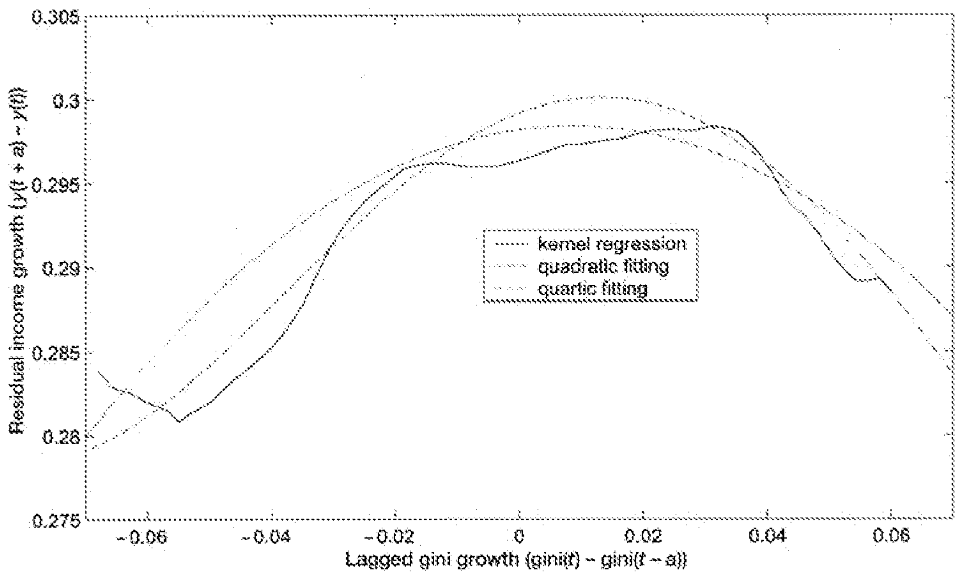

Figure 2. Relationship between income growth and lagged gini growth: partially linear model (Barro variables).

also ran these specifications using the Barro expanded data set, and 10-year lags instead of 5-year lags, and we find the same inverted U-shaped relationship between changes in inequality and growth, albeit estimated with less precision, which is not surprising given that we are left with only 78 observations (results not reported).

On balance, there is no strong evidence of a direct correlation of inequality on growth in the short run (over a 5-year lag period), but there seems to be an association between changes in inequality and growth. Changes in inequality, *whatever their direction*, are associated with lower growth in the next period. We discuss at the end of this section whether any causal interpretation can be given to this result, but before that we report the results from our reduced form estimates.

4.3. The Effect of Lagged Inequality

In Table 4 (columns (1)–(6)), we present the results of the estimation of equation (8). The difference between the specifications estimated in this table and the first column in the previous table is that the independent variable is not the beginning-of-period level of inequality $(g(t))$ but the *lagged* level of inequality $(g(t-a))$.

The coefficient of $g(t-a)$ entered linearly is now negative (around -4 percent), but still insignificant in both Perotti's and Barro's specifications (Table 4, columns (1) and (4)). Columns (3) and (6) show the results obtained when we lag the other regressors by one period as well, which, as we show below, is similar to the reduced form of the models of Barro (2000) and Forbes (2000). The coefficient of lagged inequality is similar in these specifications. It is significant with the Barro control variables. In the quadratic specification, the squared term is negative, though non-significant (Table 4, columns (2) and (5)). The corresponding Kernel regression (shown in Figure 4) is indeed a U-shaped relationship, with the correlation between lagged inequality on growth turning positive when the gini coefficient is larger than 0.45.

In columns (7)–(10) of Table 4, we estimate the relationship between changes in inequality and past inequality described by equations (6) and (7). In both the Perotti and Barro specifications, changes in inequality are strongly negatively correlated with past inequality, while the square of the change in inequality is positively related to inequality.

The kernel regression corresponding to equation (7) is shown in Figure 3. The relationship between inequality and squared changes in inequality is non-linear with a peak around 0.45. The shape is very similar if we replace the square of the change with its absolute value.

Interestingly, the non-parametric partial relationships between growth and inequality, on the one hand, and change in inequality and growth, on the other hand, do appear to be mirror images of each other, with a peak at about the same level. This corresponds fairly closely to the prediction of the political economy model, although given the identification problems we discussed, we stop short of committing to this explanation of the results.

Table 4. Estimation of the reduced form model.

	Dependent Variable: $(y(t+a)-y(t))/a$					
	Perotti			Barro		
	(1)	(2)	(3)	(4)	(5)	(6)
$g(t-a)$	-0.047	0.77	-0.033	-0.043	-0.21	-0.10
	(0.076)	(0.66)	(0.082)	(0.039)	(0.21)	(0.043)
$g(t-a)^2$		-0.94			0.26	
		(0.81)			(0.27)	
Control variables	$X(t)$	$X(t)$	$X(t-a)$	$X(t)$	$X(t)$	$X(t-a)$

	Dependent Variable: Change in Gini Coefficient			
	Perotti		Barro	
	$g(t)-g(t-a)$	$(g(t)-g(t-a))^2$	$g(t)-g(t-a)$	$(g(t)-g(t-a))^2$
	(7)	(8)	(9)	(10)
$g(t-a)$	-0.087	0.0067	-0.25	0.0076
	(0.038)	(0.0025)	(0.066)	(0.0038)
Control variables	$X(t-a)$	$X(t-a)$	$X(t-a)$	$X(t-a)$

Note: Coefficient obtained using random effect specifications.
Standard errors in parentheses; a is equal to 5 (5-year periods).
Control variables: $X(t)$ stands for control variable not lagged.
$X(t-a)$ stands for control variables lagged one period (5 years).
For a list of control variables see note to Table 1.

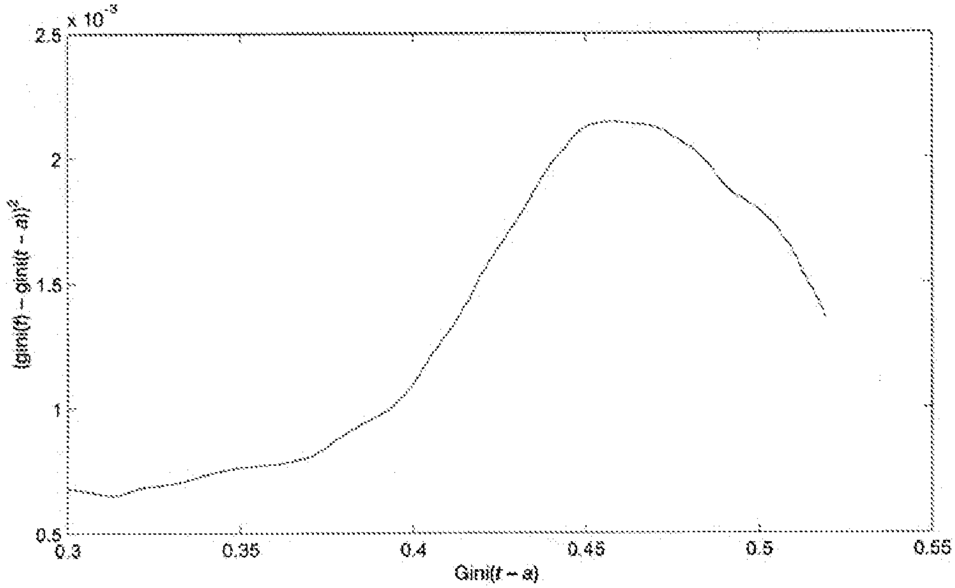

Figure 3. Relationship between gini and square of gini changes.

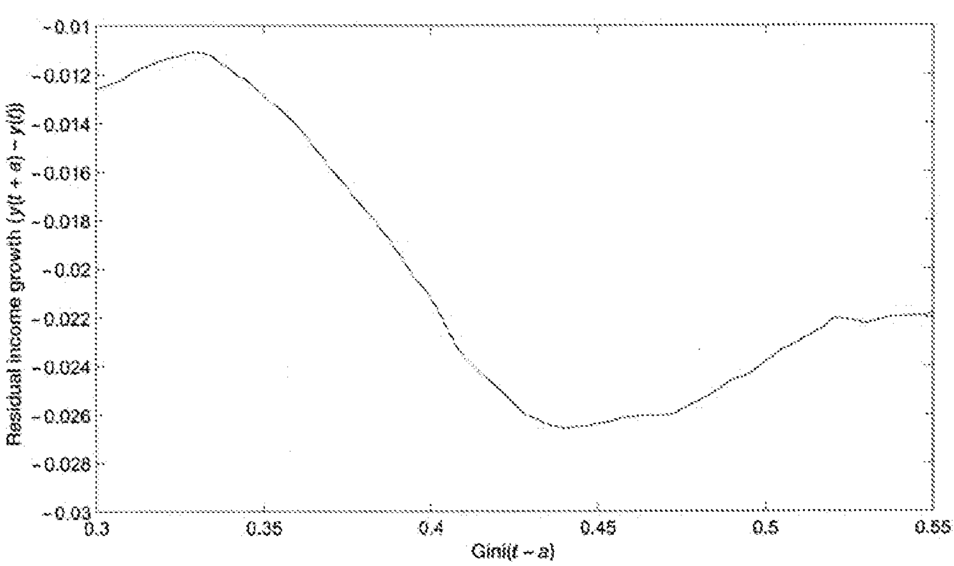

Figure 4. Reduced form, with Perotti variables.

5. Relationship with the Literature

Regardless of how we interpret these results, it is clear that they have important implications for how we read the existing results in the literature. In particular, we will show that the striking results obtained by those who have estimated the growth–inequality relationship with fixed effects arise from giving a different and misleading interpretation to the same reduced-form evidence that is presented here.

5.1. Non-linearity

As we noted in Section 2, all the approaches based on differencing the data rely heavily on the linearity of equation (1) and the exclusion of the differenced term. If either of these conditions are violated, the fixed effect and first difference estimates of γ will not be identical, and both will be different from the OLS estimate of equation (1) even if all the other conditions for the validity of the OLS estimate are satisfied. It will then be important to be very careful in interpreting each of these coefficients.

The results in the previous section suggest that changes in inequality were negatively correlated with subsequent growth. Assuming the relationship between *the level of inequality and growth* is indeed linear $(h(g) = \gamma g)$, and differencing equation (9), one obtains:

$$
\begin{aligned}
y_{it+a} - y_{it} = {} & (a\alpha + 1)(y_{it} - y_{it-a}) + a(X_{it} - X_{it-a})\beta \\
& + a\gamma(g_{it} - g_{it-a}) + ak(g_{it} - g_{it-a})) + ak(g_{it-a} - g_{it-2a})) \\
& + a\varepsilon_{it} - a\varepsilon_{it-a},
\end{aligned}
$$

or

$$
\begin{aligned}
y_{it+a} - y_{it} = {} & (a\alpha + 1)(y_{it} - y_{it-a}) + a(X_{it} - X_{it-a})\beta \\
& + a\phi(g_{it} - g_{it-a})) + k(g_{it-a} - g_{it-2a})) + a\varepsilon_{it} - a\varepsilon_{it-a},
\end{aligned}
\tag{10}
$$

where $\phi(x) = k(x) + \gamma x$.

In principle, this equation could be estimated. Using methods similar to those derived in Porter (1996), one could also recover $k(\cdot)$ and γ, but the data requirement would make the exercise senseless in the present context (there are too few countries with three successive measures of inequality).

However, if equation (10) is indeed the correct way to represent the relationship between changes in inequality and growth in the first differenced equation, it suggests that the interpretation of the fixed effects, first difference and GMM estimates of equation (1) could be very misleading. In order to investigate this point without relying on our (potentially biased) estimates of equation (9), we estimate a modified version of equation (3), which does not restrict the coefficient of the difference $g_{it} - g_{it-a}$ to be linear. In other words, we estimate the relationship

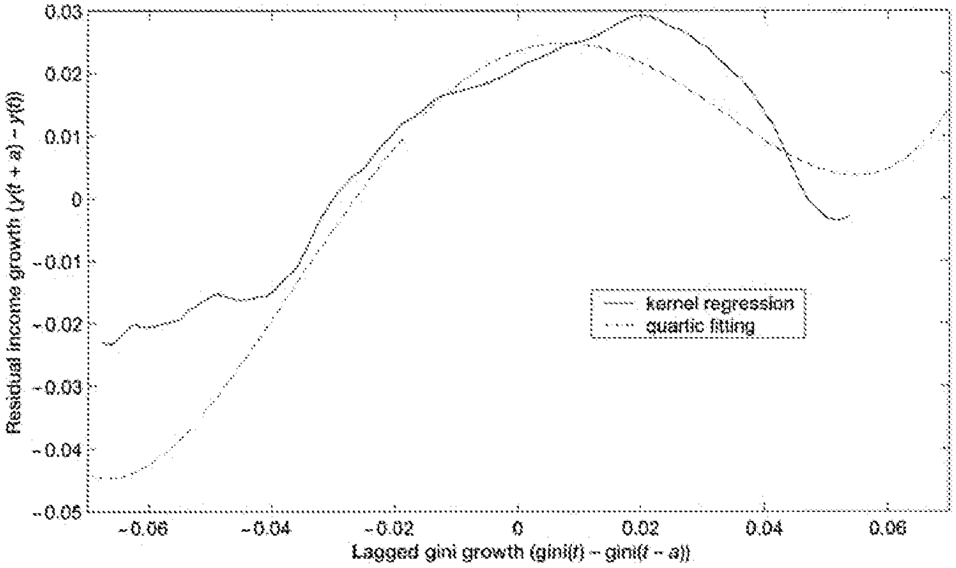

Figure 5. Relationship between income growth and lagged Gini growth: partially linear model.

$$y_{it+a} - y_{it} = (a\alpha + 1)(y_{it} - y_{it-a}) + a(X_{it} - X_{it-a})\beta + a\phi(g_{it} - g_{it-a}) + a\varepsilon_{it} - a\varepsilon_{it-a}, \qquad (11)$$

where $\phi(\cdot)$ is a function that we want to estimate flexibly. Under the hypothesis that the model in equation (1) is the correct model, we should not be able to reject the linearity of $\phi(\cdot)$.

We use kernel regression, and we ''partial out'' the linear part of the model using the same methodology we used before. The results are presented in Figure 5 for the Perotti variables (we obtain a very similar graphs when we use the Barro variables). The linearity seems, once again, to be rejected. To further explore this, we used the same specifications as in Section 3. We present them in Table 5. To test whether the non-linearity is statistically significant, we present in panel C of Table 5 the F-test for the joint significance of the non-linear terms in the partially linear model (columns (1) and (2)). Linearity is rejected in both cases, at the 9 percent and 3 percent levels of confidence, respectively. Panel D presents the results of estimating a quadratic specification for $\phi(\cdot)$. Finally, we estimate a piece-wise linear specification for $\phi(\cdot)$ (in panel B). The coefficients of decreases and increases in inequality are positive and negative, respectively. The positive coefficient in the decreasing range is significant. The negative coefficient in the increasing range is smaller in absolute value and insignificant.

To ensure that the non-linearity of the relationship between inequality and growth that we are finding here is not driven by some mis-specification in our estimation of the partially linear model,[33] we then test for linearity *under the assumption that the model in the literature we are critiquing was actually correctly estimated.*

Table 5. Non-linearity of the relationship between change in gini and growth in models based on first differences.

	Dependent Variable			
	$(y(t+a)-y(t))/a$		$(1/a^*[y(t+a)-y(\mathrm{GDP}(t)]^*)$	
Control Variables	Perotti (1)	Barro (2)	Perotti (3)	Barro (4)
A. Linear assumption: OLS coefficient of (gini(t) − gini($t-a$))				
gini(t) − gini($t-a$)	0.298	0.158	0.36	0.17
	(0.18)	(0.068)	(0.18)	(0.07)
B. Piecewise linear assumption: OLS coefficients of (gini(t) − gini($t-a$))				
if gini(t) − gini($t-a$) <0	0.79	0.39	0.69	0.4
	(0.30)	(0.13)	(0.38)	(0.13)
if (gini(t) − gini($t-a$)) ≥ 0	−0.3	−0.13	−0.49	−0.11
	(0.35)	(0.11)	(0.38)	(0.14)
C. Quartic specification				
F-test for non-linear terms jointly significant	2.21	3.37	2.55	3.3
	(0.09)	(0.02)	(0.059)	(0.02)
D. Quadratic specification				
gini(t) − gini($t-a$)	0.23	0.13	0.311	0.15
	(0.18)	(0.067)	(0.19)	(0.66)
(gini(t) − gini($t-a$))^2	−5.88	−3.24	−5.94	−3.28
	(3.39)	(1.26)	(3.43)	(1.23)
Number of observations	128	98	128	98

Note: Standard errors in parentheses; a is equal to 5 (5-year periods). For a list of control variables see note to Table 1. For a definition of residual growth, see the text.

To do so, we estimate the main equation (1) using the Arellano and Bond method, and then compute:

$$(y_{it+a}-y_{it})^* = y_{it+a}-y_{it}-(a\hat{\alpha}+1)(y_{it}-y_{it-a})-a(X_{it}-X_{it-a})\hat{\beta}, \qquad (12)$$

where $\hat{\alpha}$ and $\hat{\beta}$ are the values of α and β obtained by estimating equation (1) using the Arellano and Bond estimator. If the assumptions necessary for the validity of each method are satisfied, α and β will be estimated consistently. Then, according to equation (3), the relationship between $(y_{it+a}-y_{it})^*$ and $g_{it}-g_{it-a}$ should be linear.

The next step is to make sure that the estimates of γ obtained if we regress $(y_{it+a}-y_{it})^*/a$ linearly on the difference $g_{it}-g_{it-a}$ are similar to those obtained using a fixed-effects type estimator. OLS estimates are presented in panel A of Table 5. They are alternative estimates of γ, consistent if equation (3) is correctly specified and if the innovation in inequality is not correlated with the innovation in the error term. They are not identical to the estimate of γ reported in Table 1, since they use different estimation methods. However, they are also positive and significant, and their magnitude is similar to that of the fixed effect and Arellano and Bond estimates. In other words, as long as we impose linearity, the results are very similar to what the literature finds.

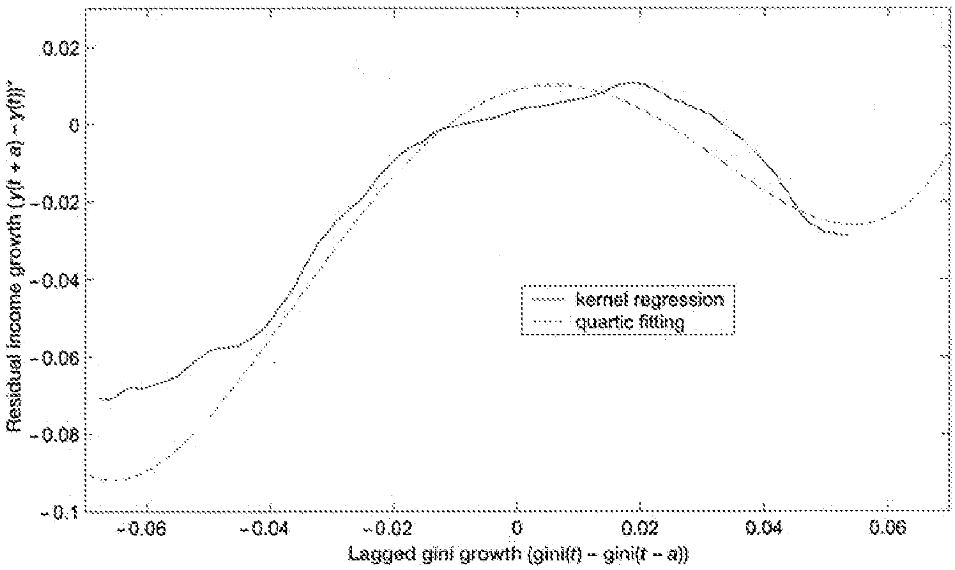

Figure 6. Relationship between income growth and lagged Gini growth: using Arellano and Bond coefficients.

Finally, we test the linearity assumption. We start by allowing the coefficient to vary with the sign of the difference $g_{it} - g_{it-a}$. The results indicate that there is a sharp non-linearity. As before, we find that both increases and decreases in inequality are associated with lower subsequent growth (panel B). This suggests that the conclusions of Forbes (2000), and Li and Zou (1998) are not warranted: There is no evidence in the data that increases in inequality are good for growth. In fact, the bulk of the evidence goes in the opposite direction.

In Figure 6, we present a kernel regression of $1/a^*(y_{it+a} - y_{it})^*$ on the difference $g_{it} - g_{it-a}$ for the Perotti control variables. The shape of the curve is similar across specifications, and similar to what we had found when we estimated the partially linear model. We have experimented with a variety of other specifications which we do not report here (Barro control variables, different lags, different way to estimate the other coefficients in the regression, etc.). The results are always similar. In panel C of Table 5, we report the F-statistic of the significance of the non-linear terms in a quartic regression of $1/a^*(y_{it+a} - y_{it})^*$ on $g_{it} - g_{it-a}$. Here also, the data clearly rejects linearity in almost all specifications.

5.2. *Consequences for Estimated Coefficients*

5.2.1. *Random Effects and Fixed Effects*

The results suggest that equation (1) is mis-specified. Non-linear terms in past changes are omitted in the regression. Since current levels and past changes are correlated, this introduces a bias in the coefficient of inequality when equation (1) is estimated using random effects.

This mis-specification is accentuated when the equation is estimated in first differences or using fixed effects. The fixed effect estimation imposes a linear structure on the relationship between the deviation of the growth rate from its average across all the periods and the deviation of the gini coefficient from its average. Since the relationship between growth and inequality is not monotonic in first differences, it is also not monotonic when period averages are taken out. The fixed effect estimator is, in effect, a weighted average of negative and positive coefficients, which can be positive if the weight given to positive coefficients is larger. As it turns out, there are more decreases than increases of inequality in the data. The majority of the data points are therefore in the region where changes are positively correlated with growth, which means that the positive coefficient gets more weight.

5.2.2. Estimation Using the Arellano and Bond Technique

The Arellano and Bond estimator uses lagged levels of inequality to instrument for changes in inequality with lags. Ignoring longer lags, the reduced form equation implicitly estimated when using the Arellano and Bond technique has the form:

$$(y_{it+a} - y_{it})/a = \lambda y_{it-a} + x_{it-a}\kappa + \delta g_{it-a} + v_i + \xi_{it}. \tag{13}$$

This reduced form is very similar to the equation we had estimated in Section 3. The only difference is that income levels and the control variables are lagged one period. In columns (3) and (6) of Table 4, we present the coefficient of g_{it-a} in this specification. As before, we find a negative, but insignificant, coefficient.

The Arellano and Bond GMM estimator in effect takes the ratio of this negative reduced form coefficient and the negative coefficient from estimating the effect of the level of inequality on changes in inequality. This naturally leads to the positive coefficient in the "structural" equation. For example, dividing -0.033 (column (3), Table 4) by -0.087 (column (7), Table 4) leads to 0.38, close to the Arellano and Bond coefficient of 0.58 reported in column (4) in Table 1. Therefore, the seemingly dramatic difference in results obtained when we use the Arellano and Bond method are in fact a different interpretation of the same reduced form evidence presented in this paper or in, for example, Barro (2000).

This interpretation of the reduced form is clearly misleading, because equation (3) is mis-specified. The effect of changes in inequality is not constant. There is also an asymmetry between increases in inequality and decreases in inequality: When we regress reductions in inequality on lagged inequality, the coefficient is negative (-0.083) and very significant, indicating that higher inequality is associated with larger declines in inequality. However, when we repeat this exercise with increases in inequality, the contrast is striking: Increases in inequality are not correlated with lagged levels (the coefficient is -0.011 and is insignificant). As a result, the Arellano and Bond estimator gives more weight to the effect of decreases in inequality, which are positively related to growth, and therefore finds a positive effect on average.

Appendix

Table A1. Descriptive statistics and countries in the sample.

Countries in the Sample	
Australia	Japan
Bangladesh	Korea, Republic of
Belgium	Malaysia
Brazil	Mexico
Bulgaria	Netherlands
Canada	New Zealand
Chile	Norway
China	Pakistan
Colombia	Peru
Costa Rica	Philippines
Denmark	Poland
Dominican Republic	Portugal
Finland	Singapore
France	Spain
Germany	Sri Lanka
Greece	Sweden
Hong Kong	Thailand
Hungary	Trinidad and Tobago
India	Tunisia
Indonesia	Turkey
Ireland	United Kingdom
Italy	United States
	Venezuela
Means (standard deviation)	
Log(GDP per capita) in 1980 dollars (Summers and Heston)	
1965	8.03 (0.86)
1975	8.37 (0.85)
1985	8.58 (0.82)
1995	8.82 (0.79)
Gini coefficient	
1965	0.38
1970	0.4
1975	0.4
1980	0.38
1985	0.37
1990	0.38

Source: Deininger and Squire ''high quality sample.'' For the construction of the sample and variable, see text.

6. Conclusion

The main goal of this paper is to investigate the pertinence of the linear relationships that have been used in the literature to investigate the effect of inequality on growth. We find that there are strong *a priori* reasons to doubt their validity, and that the data does seem inconsistent with a linear structure.

This paper is primarily an attempt to forestall a potentially influential misinterpretation of the data on inequality and growth. If it serves any purpose beyond that, it is to serve as a broader warning against the automatic use of linear models in settings where the theory does not necessarily predict a linear or even a monotonic relationship.

On the more fundamental question of whether inequality is bad for growth, our data has little to say. It is clear that the most compelling evidence on this point has to come from micro data. While some interesting evidence is beginning to trickle in,[34] we are only at the beginning of an enormous enterprise.

Notes

1. The authors note that this is not necessarily inconsistent with the cross-sectional relationship.
2. This is the data set used by Forbes (2000). We describe the data construction in more detail in the text. Table A1 in the appendix shows the list of countries in the sample and some descriptive statistics.
3. In this sample of countries, and using either Perotti or Barro control variables, the coefficient of inequality in 1960 on growth between 1960 and 1995 is -0.46, with a standard error of 0.028.
4. We were not able to exactly replicate Forbes (2000) result for the Arellano and Bond estimator (she obtains with the Perotti specification a coefficient of 0.13). The coefficients of the other regressors are similar.
5. For versions of this argument see Alesina and Rodrik (1994), Persson and Tabellini (1991) and, Benhabib and Rustichini (1998). For a contrarian point of view, arguing that neither of the two premises of this argument are true in the data, see Benabou (2000).
6. As in, for example, Acemoglu and Robinson (2000).
7. It must be kept in mind that the transfer could involve abolishing a distortionary tax. For this reason, the rest of the examples suggested above fit our purpose better—in those examples, the fact that there is an efficiency loss is independent of the direction of the transfer.
8. This interpretation clearly only makes sense if g is not too small.
9. Note that we are not worried about the direct effect of growth on distribution (the Kuznets curve effect) because that is presumably subsequent or contemporaneous to the growth episode. What worries us is the fact that there may also be an effect on the distribution prior to the growth episode.
10. See Alesina and Rodrik (1994), Persson and Tabellini (1991) and Alesina and Perotti (1996). The argument in Alesina and Perotti (1996) is most closely related to ours: Income inequality leads to political instability and hence to lower growth; indeed, instability may be a symptom of what we call grabbing.
11. See Alesina and Rodrik (1994), Persson and Tabellini (1991) and Benhabib and Rustichini (1998) for models of this class.
12. It should be stated at the outset that the effects of inequality on growth through these channels is unlikely to be realized over the time-scale of 5 or even 10 years. Therefore it is unlikely to provide a convincing justification for estimating a relation between short-run changes in inequality and changes in the growth rate. On the other hand, it tell us a lot about the more long-run effects of inequality on growth.
13. For such a model of the capital market, see Aghion, Banerjee and Piketty (1999).
14. This model is a close relative of the model in Banerjee and Newman (1994).
15. It may be objected that this conclusion rests on the clearly unreasonable prediction of convergence at the individual level, but this is not the case. There could be idiosyncratic shocks to the wealth of individuals

which would prevent long-run convergence at the individual level, but without affecting the fact of long-run convergence for the economy as a whole.

16. It has also been argued that the production function for human capital derived from health is S-shaped (see Dasgupta and Ray (1986) and the response by Srinivasan, 1994). There is some debate about the actual shape of the production function for human capital derived from education, with the current weight of opinion leaning towards the view that it is fairly linear, at least in developed economies (Angrist and Krueger, 1999).
17. There are other ways to generate this shape: For example, the assumption that bequests are a luxury good, and therefore subject to strong income effects will also give us this shape.
18. The exact experiment is moving half the population to $w^* - \Delta w_1$ and the rest to $w^* + \Delta w_1$.
19. The possibility of divergence in this type of economy was first formalized in Galor and Zeira (1993).
20. In principle, this is also true in our basic model, but there the effect is likely to be monotonic and there is no obvious source of non-linearity (though there is also no reason to believe it is linear).
21. See Piketty (1997). For a more general discussion of the issue of convergence in this class of models, see Banerjee and Newman (1993).
22. There is, however, a counteracting effect: Poorer economies with high levels of inequality may actually have low interest rates because a few people may own more wealth than they can invest in their own firms, and the rest may be too poor to borrow. For a model where this effect plays an important role, see Aghion and Bolton (1997).
23. Allowing λ to vary also implies that the causal effects of inequality will vary with financial development (which is how Barro (2000) explains his results). The OLS coefficient is therefore a weighted average of different parameters, where the weights are the country-specific contributions to the overall variance in inequality (Krueger and Lindahl, 2001). It is not at all clear that we are particularly interested in this set of weights.
24. See Acemoglu and Zilibotti (1997) and Greenwood and Jovanovic (1999) for theories of growth with endogenous financial development.
25. For example, in Bulgaria, the gini coefficient went down by 3.7 percentage points between 1975 and 1980, and up by 7.2 between 1980 and 1985. In Brazil, it went up by 4.3 percentage point between 1970 and 1975, down by 4.2 percentage point between 1975 and 1980, and up again by 4 percentage point between 1980 and 1985. Columbia, Hong-Kong, Sri Lanka, Sweden, and Venezuela are the other countries with consecutive increases and decreases in the gini coefficient of more than 3 percentage points.
26. In addition, Barro includes the average growth of terms of trade over the period, indices of democracy and the rule of law, the square of the logarithm of GDP, the square of the democracy index, and the average inflation in the period. He implements a three stage least squares method, where he uses lagged values of the regressor as an instrument for current values. As inequality is an instrument for itself in his specification, we will focus on the reduced form and use the instruments as control variables. In particular, we follow Barro and control for y_{it-a}, not y_{it}, in the regression (although this does not affect our results to control for y_{it} instead).
27. The high quality data set includes only those observations which satisfy the following criteria: The survey comes from a national coverage, the information is based on direct surveys of incomes, the surveys sample the complete population (not only those earning an income), the data does not come from tax records, and, finally, the data gives a clear reference to the primary source. The list of countries in the sample, as well as the summary statistics for the log(GDP) and the gini coefficients, are shown in Table A1.
28. This is the sample used in Forbes (2000) and Li and Zou (1998). The Deininger and Squire data set provides the year in which the observation was taken. To construct a measure of inequality every 5 years, we follow Forbes (2000) and we chose the closest measure in the 5 years preceding the relevant date if the measure was not available for this particular year. We also follow previous studies in adding 6.6 to the gini when it was constructed from expenditure instead of income. However, still following the other studies, we did not attempt to correct the gini coefficient for whether it was gross or net of taxes, and whether the unit of measurement was the household or the individual.
29. In an attempt to expand the sample size, Barro proposed adding some observations that were rejected by Deininger and Squire on the grounds that they were not identified by a clear primary source. The coverage increases substantially, at the expense of an additional reduction in the accuracy of measurement.
30. All of these equations are estimated using a random effect specification, to allow for correlation of growth rates between countries over time.
31. We present the results with only a linear term in the gini coefficient because we did not find any strong non-

linearity when we looked at the $h(\cdot)$ function separately, but the exact same results are obtained if we introduce higher-ordered polynomials as well.

32. This is implemented by first regressing all the control variables (y_{it}, g_{it} and X_{it}) and the dependent variable $\Delta y_{it+a} = y_{it+a} - y_{it}$ non-parametrically on $\Delta g_{it} = g_{it} - g_{it-a}$ and forming the residuals of this non-parametric regression. Estimates of the parameters α and β are then obtained from the OLS regression of the residual of the dependent variables on the residuals of the control variables. Finally, the function $ah(\cdot)$ is estimated by estimating non-paramctrically the function: $\hat{E}(\Delta y_{+a}|\Delta g)$, $\hat{E}(\Delta y|\Delta g)$, $\hat{E}(X|\Delta g)\hat{\beta}$ and forming the difference $\hat{E}(\Delta y + a|\Delta g) - (a\hat{\alpha} + 1)\hat{E}(\Delta y|\Delta g) - a\hat{E}(X|\Delta g)\hat{\beta}$.
33. For example, we did not deal with the inconsistency introduced by the lagged endogenous regressor.
34. For example, Banerjee et al (2001) show, using a panel of data from sugar cooperatives in India, that the most unequal cooperatives (in terms of land ownership among cooperative members) are the least productive, with a difference of more than 50 percent (measured by capacity, which is a proxy for output) between the most and least egalitarian cooperatives.

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