J Econ Inequal (2012) 10:489–503
DOI 10.1007/s10888-011-9171-6

Inequality and growth: evidence from panel cointegration

Dierk Herzer · Sebastian Vollmer

Received: 26 February 2010 / Accepted: 1 February 2011 / Published online: 24 February 2011

Abstract This paper uses heterogeneous panel cointegration techniques to estimate the long-run effect of income inequality on per-capita income for 46 countries over the period 1970–1995. We find that inequality has a negative long-run effect on income, both for the sample as a whole and for important sub-groups within the sample (developed countries, developing countries, democracies, and non-democracies). The effect is economically important, with a magnitude about half as high as the magnitude of an increase in the investment share.

Keywords Inequality · Growth · Panel cointegration

JEL Classification O11 · O15 · C23

We are grateful to two anonymous referees for excellent suggestions that considerably improved this paper. Sebastian Vollmer acknowledges financial support from the German Academic Exchange Service and the German Research Foundation (grant VO 1592/3-1).

D. Herzer
Schumpeter School of Business and Economics, University of Wuppertal,
Gaußstr. 20, 42119 Wuppertal, Germany
e-mail: herzer@wiwi.uni-wuppertal.de

S. Vollmer (✉)
Center for Population and Development Studies, Harvard University,
9 Bow Street, Cambridge, MA 02138, USA
e-mail: svollmer@hsph.harvard.edu

S. Vollmer
Institute of Macroeconomics, University of Hannover, Hannover, Germany

S. Vollmer
Development Economics Research Group, University of Göttingen, Göttingen, Germany

1 Introduction

We know that distribution and inequality affect a society's ability to convert income into welfare. Assuming quasi-concave individual and social utility functions with respect to income, one can conclude that societies that experience a higher degree of equality are clearly better off than those with a lesser degree of equality, given that average incomes are the same. In fact, the well-known Atkinson [2] inequality measure can be interpreted as the percentage of potential welfare which is lost due to inequality, given a society's aversion to inequality.

But does inequality only affect the welfare that a society can generate from a given amount of income or does the distribution of the income pie also have implications for the size of the pie itself? One view would be that redistribution reduces incentives for well-off people (those who pay more than they receive) to generate additional income, thus causing economic growth to slow. A central idea behind Scandinavian-type welfare states is that redistribution influences levels of social inclusion of the less privileged (for example, through education) and enables society as a whole to benefit from their talents.

Alesina and Rodrik [1] study related questions in an endogenous growth model with distributive conflict among agents. Their main argument is that in societies in which large fractions of the population do not have access to the productive resources, there will be a large demand for redistribution. This redistributive conflict impedes economic growth. Empirically, they find that inequality in land and income ownership is negatively correlated with subsequent economic growth.

Galor and Moav [17] study the impact of inequality on the development process in the long run. In their model, inequality stimulates economic growth in the early stages of development, when physical capital accumulation is the primary source of growth, because it channels resources towards individuals with a higher propensity to save. In later stages of development, when human capital is the main engine of economic growth, this effect is reversed. Equality alleviates human capital accumulation and thus stimulates the growth process. Chambers and Krause [7] empirically test this model and find that the data overall support the hypotheses of Galor and Moav. De la Croix and Doepke [10] also focus on the importance of human capital. In their model, poor parents decide to have many children and invest little in education. Thus, an increase in inequality lowers average education and, subsequently, growth.

In this paper, we employ heterogeneous panel cointegration techniques to examine the long-run effect of income inequality on income per capita (and thus long-run growth). The empirical literature on the relationship between inequality and growth is so large that one might be tempted to apologize for adding another paper to it. However, if there is anything we can take away from the existing literature then, it is the fact that there is no consensus on the question of whether inequality affects growth positively, negatively, or at all. Heterogeneous panel cointegration estimators are robust (under cointegration) to a variety of estimation problems that often plague standard cross-country and panel regressions, including omitted variables, slope heterogeneity, and endogenous regressors [33]. To the best of our knowledge, this is the first paper that applies panel conintegration techniques to the relationship of inequality and growth. In what follows, we review a few important papers to illustrate how contradictory the findings in the literature are.

Persson and Tabellini [35] ask whether inequality is harmful for growth and conclude that it is. In their model, political decisions produce economic policies that tax investment and growth-promoting activities in order to redistribute income. They confirm their theoretical predictions with historical panel data and postwar cross-sectional data, but they only find a negative correlation between inequality and growth in democracies. Clarke [8] finds the same overall correlation, but in his paper it also holds for non-democracies. Deininger and Squire [11] find a negative correlation between initial asset (land) inequality and long-run growth. Further, they find that inequality reduces income growth for the poor, but not for the wealthy.

Perotti [34] also finds a negative association between inequality and growth. Although he finds some evidence that this association is stronger in democracies, he concludes that this finding is not very robust towards alternative specifications. Moreover, Perotti [34] tries to shed some light into the specific channels through which inequality affects growth. He finds that more equal societies have lower fertility rates and higher rates of investment in education. More unequal societies tend to be politically and socially unstable.

Barro [5] studies a panel of countries and finds little overall relationship between income inequality and growth. According to his paper, higher inequality tends to slow growth in poor countries and encourage it in rich countries. Forbes [13] also studies a panel data set and finds that in the short and medium term, an increase in a country's level of income inequality has a significant positive relationship to subsequent economic growth.

Banerjee and Duflo [4] argue that the growth rate is an inverted U-shaped function of net changes in inequality. They further show how this non-linearity can explain the different findings in previous studies. However, their paper has little to say on the fundamental question of whether inequality is bad for growth. Knowles [24] argues that most evidence on the growth and inequality relationship is derived from inequality data which are not fully comparable, and that a negative correlation between income inequality and growth is not robust towards consistently measured income inequality. Voitchovsky [39] points out that for the countries in the Luxembourg Income Study, inequality at the top end of the distribution is positively correlated with growth, while inequality at the bottom of the distribution is negatively correlated with subsequent growth. Lundberg and Squire [27] argue that growth and inequality are joint determinants of other variables.

Panizza [30] studies growth and inequality in a cross-state panel for the United States. He concludes that there is no robust relationship between the two variables. Frank [14], in contrast, finds (for a new panel data set of U.S. states) that the long-run relationship between inequality and growth (or per-capita income) in the United States is positive and driven by the upper end of the income distribution. Davis [9] constructs a model that can account for both the negative relationship between growth and income inequality across countries and the positive relationship observed within countries over time.

Although the empirical inequality-growth literature has provided valuable insights into whether and how inequality may affect growth, it suffers from the limitations inherent in standard cross-country and panel regressions. One of the main criticisms of cross-country regressions is the implicit assumption of a common economic structure across countries. Production technologies, institutions, and policies, however, differ substantially between countries, and failure to account for such country-specific factors can lead to misleading result because of the "omitted-variables problem". Indeed, panel methods allow controlling for country-specific omitted variables, but the homogeneous panel estimators used in the inequality literature produce inconsistent and potentially misleading estimates of the average values of the parameters in dynamic models when the slope coefficients differ across cross-section units—the problem of slope heterogeneity (see [37]).

Another methodological problem with the cross-country approach used in the majority of studies is that changes in inequality may be a consequence of economic growth, as the Kuznets hypothesis suggests. Admittedly, the recent literature attempts to control for this endogeneity problem through instrumental variable methods. However, it is well known that instrumental variables regressions may lead to spurious results when the instruments are weak or invalid, and it is also well known that it is difficult to find variables that qualify as valid instruments.

A further problem with both cross-country and panel studies is the use of the growth rate of income as the dependent variable, while the level of inequality is used as an explanatory variable. Growth rates appear to be roughly constant over time, while global inequality indicators show, in general, large and persistent movements over time. In particular, since the early 1980s, inequality has increased sharply in most countries (see [15]). The empirical implication is that there cannot be a long-run relationship between the growth rate of income and the level of inequality over time; such unbalanced regressions (with stationary and non-stationary variables) can, even in cross-country analyses, produce misleading results (see [12]).

Finally, the use of time-averaged data, as is common practice in the cross-country inequality-growth literature, to eliminate business cycle effects must be viewed with skepticism. Ericsson et al. [12], for example, show that averaging data over time can induce a spurious contemporaneous correlation between the time-averaged data, even if the original series are not contemporaneously correlated; both the sign and magnitude of the induced correlation can differ from those in the underlying data (a problem that is not solved by instrumental variable estimation, including GMM). Nair-Reichert and Weinhold [29] point out that annual data provide information that is lost when averaging, especially when the data are highly persistent. Wan et al. [40] emphasize that it is not obvious that averaging over fixed time intervals will effectively eliminate business cycle effects; the length of the interval over which averages are computed is arbitrary, and there is no guarantee that business cycles are cut in the right way, as their length varies over time and across countries. Attanasio et al. [3] argue that by averaging, one commits oneself to the use of cross-sectional variability to estimate the parameters of interest and thus discards the possibility of accounting for cross-country heterogeneity in the parameters.

This paper attempts to overcome these problems by employing heterogeneous panel cointegration techniques to examine the long-run effect of income inequality on income per capita (and thus long-run growth) for 46 countries over the period 1970–1995 with annual observations, rather than with the long time-averages typical of the literature. Heterogeneous panel cointegration estimators are robust (under cointegration) to a variety of estimation problems that often plague empirical work, including omitted variables, slope heterogeneity, and endogenous regressors [33]. Moreover, panel cointegration methods can be implemented with shorter data spans than their time-series counterparts.

Admittedly, given the fact that we use annual rather than time-averaged data and that we consider the level rather than the growth rate of per capita income, our estimates are not directly comparable to those reported in previous cross-country (panel) studies. Nevertheless, we believe that this contribution gives some additional insight into the inequality and growth relationship, thus helping to establish common ground on the fundamental question of whether and how inequality affects economic growth.

In the next section, we describe the empirical model and the data. The empirical analysis is presented in Section 3, while Section 4 concludes.

2 Model and data

Although it is common practice in panel cointegration studies to estimate a bivariate long-run relationship, it would be unreasonable to assume that long-run changes in per-capita income are driven primarily by changes in income inequality. However, it is reasonable to assume that the investment rate is a major determinant of per-capita income over time, and inequality is the element of income of particular concern. Moreover, since investment may act as a proxy for a number of unobserved time-varying factors that can affect both inequality and income, it should be included in the analysis to control for nonstationary omitted variables. Thus, we consider a model of the form

$$\log(Income_{it}) = a_i + \delta_i t + \beta_{1i} \log\left(Invest_{it}\right) + \beta_{2i} Inequality_{it} + \varepsilon_{it}, \tag{1}$$

where a_i are country-specific fixed effects and $\delta_i t$ are country-specific time trends, included to control for any country-specific omitted factors that are either relatively stable over time or evolve smoothly over time. The variable $\log(Income_{it})$ is the log of real income per capita over time periods $t = 1, 2, ..., T$ and countries $i = 1, 2, ..., N$, $\log(Invest_{it})$ is the log of the percentage investment share of real GDP per capita, and $Inequality_{it}$ is the estimated household income inequality (EHII) in Gini format (measured in percentage points).

Unlike most previous studies, we do not include human capital measures (such as male and female education) in our model. If we included human capital, the estimate of the long-run effect of inequality on per-capita income would preclude any effect operating through its impact on this variable. Specifically, if equality facilitates human capital accumulation and thus stimulates growth, as recent theoretical work by Galor and Moav [14] suggests, then, by including human capital measures in the regression, we would be omitting the growth effect of inequality that operates via human capital.

In addition, a regression consisting of cointegrated variables has a stationary error term, ε_{it}, implying that no relevant integrated variables are omitted; any omitted nonstationary variable that is part of the cointegrating relationship would enter the error term, thereby producing nonstationary residuals and thus leading to a failure to detect cointegration. If, on the other hand, there is cointegration between a set of variables, this same stationary relationship also exists in extended variable space (see [22]). Thus, an important implication of finding cointegration is that no relevant integrated variables in the cointegrating vector are omitted. Cointegration estimators are therefore robust (under cointegration) to the omission of variables that do not form part of the cointegrating relationship. This not only justifies a reduced form model (if cointegrated) but also identifies core variables that should be included, in our case for estimating the long-run effect of income inequality on per-capita income.

Income and investment data come from the Penn World Tables 6.3 (available at http://pwt.econ.upenn.edu/), while the EHII data are taken from the University of Texas Inequality Project (available at http://utip.gov.utexas.edu/data.html). The major advantage of the EHII data set is that the data are fully comparable across space and time. The EHII data set combines information from the United Nations Industrial Development Organization (UNIDO) data set with information from the Deininger and Squire data set, as well as other relevant information, such as the ratio of manufacturing employment to total population, the degree to which a country's population has become urbanized, and population growth (see [16] for a detailed discussion of the data set and its construction).

The data cover the period 1970–1995, the longest period available for a sufficiently large number of countries. Since we include 46 countries (so that we consider a panel with 46 cross-sectional units and 26 time-series observations per unit) the number of observations is 1,196. Table 1 lists the countries in our sample along with the average values for $\log(Income_{it})$, $\log(Invest_{it})$, and $Inequality_{it}$ over the period from 1970 to 1995. As can be seen, Kuwait is the country with the highest inequality rank, followed by Kenya, the Philippines, and Bolivia, while Sweden ranks at the bottom of the inequality scale. Average per-capita income is highest in Luxembourg, followed by Kuwait, the United States, and Norway, while the countries with the lowest level of development are in (descending order) Indonesia, Syria, Kenya, and India. Altogether, it appears that countries with higher inequality rates tend to have lower per capita incomes.

3 Results

This section examines the long-run effect of income inequality on per-capita income. Specifically, we use heterogeneous panel cointegration techniques that are robust to omitted variables, slope heterogeneity, and endogenous regressors. We begin this section by first examining the basic time-series properties of the data. Then, we test for the existence of a long-run or cointegrating relationship between $\log(Income_{it})$, $\log(Invest_{it})$, and $Inequality_{it}$. Thereafter, we estimate this relationship and examine the robustness of the results.

3.1 Time series properties

To examine the unit root properties of $\log(Income_{it})$, $\log(Invest_{it})$, and $Inequality_{it}$, we first use the panel unit root test of Levin et al. [26] (LLC). This test is based on the following ADF-type regression:

$$\Delta x_{it} = z_{it}\gamma_i + \rho x_{it-1} + \sum_{j=1}^{k_i} \varphi_{ij}\Delta x_{it-j} + \varepsilon_{it}, \quad i = 1, 2, \ldots, N, \quad t = 1, 2, \ldots, T, \quad (2)$$

Table 1 Countries and summary statistics

Country summary statistics							
Countries	Average of $\log(Income_{it})$	Average of $\log(Invest_{it})$	Average of $Inequality_{it}$	Countries	Average of $\log(Income_{it})$	Average of $\log(Invest_{it})$	Average of $Inequality_{it}$
Australia	9.892	3.329	33.463	Japan	9.928	3.650	36.625
Austria	9.976	3.398	34.632	Kenya	7.528	2.337	47.324
Barbados	9.840	3.491	43.634	Korea	8.857	3.630	38.930
Belgium	9.919	3.313	36.296	Kuwait	10.275	2.180	51.872
Bolivia	8.073	2.416	45.244	Luxembourg	10.409	3.332	32.923
Bulgaria	8.495	3.283	29.312	Malaysia	8.669	3.166	40.718
Canada	9.975	3.186	35.992	Malta	9.062	3.597	34.123
Chile	8.894	2.867	43.951	Mauritius	8.976	2.673	42.462
Colombia	8.547	2.701	42.666	Mexico	9.009	3.154	40.555
Cyprus	9.189	3.726	40.659	Netherlands	9.976	3.256	32.510
Denmark	9.896	3.211	30.936	New Zeal.	9.686	3.157	34.990
Ecuador	8.536	3.302	42.767	Norway	10.052	3.539	32.182
Egypt	8.013	2.576	40.109	Philippines	8.086	2.863	45.459
Finland	9.816	3.533	31.257	Poland	8.897	3.098	29.105
Greece	9.629	3.374	39.949	Singapore	9.578	3.921	39.087
Hungary	9.216	3.025	29.516	Spain	9.628	3.401	37.839
Iceland	10.002	3.538	36.212	Sweden	9.954	3.152	27.544
India	7.370	2.688	42.939	Syria	7.561	2.307	43.054
Indonesia	7.695	3.004	44.276	Turkey	8.412	2.974	42.909
Iran	8.703	3.197	38.717	UK	9.782	2.986	29.690
Ireland	9.551	3.459	37.472	USA	10.169	3.1108	37.187
Israel	9.629	3.443	40.356	Venezuela	9.133	3.0143	42.368
Italy	9.822	3.374	35.145	Zimbabwe	8.005	2.9604	43.656
Sample summary statistics							
Variables			Mean	Standard deviation	Minimum		Maximum
$\log(Income_{it})$			9.181	0.852	6.826		10.902
$\log(Invest_{it})$			3.150	0.449	0.837		4.139
$Inequality_{it}$			38.231	6.128	23.839		58.394

where k_i is the lag length, z_{it} is a vector of deterministic terms, such as fixed effects or fixed effects plus individual trends, and γ_i is the corresponding vector of coefficients. As can be seen from Eq. 2, the LLC unit root test pools the autoregressive coefficients across the cross-section units during the unit root test and thus restricts the first-order autoregressive parameters to be the same for all countries, $\rho_i = \rho$. Accordingly, the null hypothesis is that all time series have a unit root, H_0:$\rho = 0$, while the alternative hypothesis is that no series contains a unit root, H_1: $\rho = \rho_i < 0$, that is, all are (trend) stationary. To conduct the LLC-test statistic, the following steps are performed. The first is to obtain the residuals, $\hat{e}_{it}$, from individual regressions of Δx_{it} on its lagged values (and on z_{it}), $\Delta x_{it} = \sum_{j=1}^{k_i} \theta_{1ij}\Delta x_{it-j} + z_{it}\gamma_i + e_{it}$. Second, x_{it-1} is regressed on the lagged values of Δx_{it} (and on z_{it}) to obtain $\hat{v}_{it-1}$, that is, the residuals of this regression, $x_{it} = \sum_{j=1}^{k_i} \theta_{2ij}\Delta x_{it-j} + z_{it}\gamma_i + v_{it}$. In the third step, $\hat{e}_{it}$ is regressed on $\hat{v}_{it-1}$, $\hat{e}_{it} = \delta\hat{v}_{it-1} + \xi_{it}$. The standard error, $\hat{\sigma}_{ei}^2$, of this regression is then used to normalize the residuals $\hat{e}_{it}$ and $\hat{v}_{it-1}$ (to control for heterogeneity in the variances of the series), $\tilde{e}_{it} = \hat{e}_{it} / \hat{\sigma}_{ei}^2$, $\tilde{v}_{it-1} = \hat{v}_{it-1} / \hat{\sigma}_{ei}^2$. Finally, ρ is estimated from a regression of $\tilde{e}_{it}$ on $\tilde{v}_{it-1}$, $\tilde{e}_{it} = \rho\tilde{v}_{it-1} + \xi_{it}$. The conventional t-statistic for the autoregressive coefficient ρ has a standard normal limiting distribution if the underlying model does not include fixed effects and individual time trends (z_{it}). Otherwise, this statistic has to be corrected using the first and second moments tabulated by Levin et al. [26] and the ratio of the long-run variance to the short-run variance, which accounts for the nuisance parameters present in the specification. The limiting distribution of this corrected statistic is normal as $N \to \infty$ and $T \to \infty$.

However, the LLC test procedure assumes cross-sectional independence and thus may lead to spurious inferences if the errors, ε_{it}, are not independent across i. Therefore, we also use the cross-sectionally augmented IPS or CIPS panel unit root test proposed by Pesaran [36]. This test allows for cross-sectional dependence by augmenting the standard ADF regression with the cross-section averages of lagged levels and first-differences of the individual series. It involves the estimation of separate cross-sectionally augmented ADF (CADF) regressions for each country, thereby allowing for different autoregressive parameters for each panel member. Formally, the CADF regression model is given by

$$\Delta x_{it} = z_{it}\gamma_i + \rho_i x_{it-1} + \sum_{j=1}^{k_i} \varphi_{ij}\Delta x_{it-j} + \alpha_i\bar{x}_{t-1} + \sum_{j=0}^{k_i} \eta_{ij}\Delta\bar{x}_{t-j} + v_{it}, \tag{3}$$

where $\bar{x}_t$ is the cross-section mean of x_{it}, $\bar{x}_t$=$N^{-1}\sum_{i=1}^{N} x_{it}$. The null hypothesis is that each series contains a unit root, H_0:$\rho_i = 0$ for all i, while the alternative hypothesis is that at least one of the individual series in the panel is (trend) stationary, H_1:$\rho_i < 0$ for at least one i. To test the null hypothesis against the alternative hypothesis, the CIPS statistic is calculated as the average of the individual CADF statistics:

$$CIPS = N^{-1}\sum_{i=1}^{N_i} t_i, \tag{4}$$

where t_i is the OLS t-ratio of ρ_i in the above CADF regression. Critical values are tabulated by Pesaran [36].

Table 2 reports the test results for the variables in levels and in first differences. Both the LLC and the CIPS test statistics are unable to reject the null hypothesis

Table 2 Panel unit-root tests

Variables	Deterministic terms	Pesaran [36]	Levin et al. [26]
Levels			
$\log(Income_{it})$	Intercept, trend	−2.19	0.81
$\log(Invest_{it})$	Intercept, trend	−2.02	−0.05
$Inequality_{it}$	Intercept, trend	−2.46	1.28
First differences			
$\Delta\log(Income_{it})$	Intercept	−2.36[a]	−7.30[a]
$\Delta\log(Invest_{it})$	Intercept	−2.31[a]	−4.18[a]
$\Delta Inequality_{it}$	Intercept	−2.45[a]	−4.15[a]

Two lags were selected to adjust for autocorrelation. The test statistics of Levin et al. [26] are distributed as N(0,1) under the unit-root null hypothesis. The relevant 1% (5%) critical value for the cross-sectionally augmented Dickey-Fuller (CADF) statistic suggested by Pesaran [36] is −2.73 (−2.61), with an intercept and a trend, and −2.23 (−2.11), with an intercept
[a]Indicate significance at the 1% level

that $\log(Income_{it})$, $\log(Invest_{it})$, and $Inequality_{it}$ have a unit root in levels. Since the unit root hypothesis can be rejected for the first differences, it can be concluded that the variables are integrated of order 1, I(1).[1] Thus, the next step in our analysis is an investigation of the cointegration properties of the variables.

3.2 Cointegration

We test for cointegration using the Larsson et al. [25] approach, which is based on Johansen's [21] maximum likelihood procedure. Like the Johansen time series cointegration test, the Larsson et al. panel cointegration test treats all variables as potentially endogenous, thus avoiding the normalization problems inherent in residual-based cointegration tests. Moreover, in contrast to residual-based cointegration tests, the Larsson et al. procedure allows the determination of the number of cointegrating vectors.

The Larsson et al. approach involves estimating the Johansen vector error-correction model for each country separately:

$$\Delta y_{it} = \Pi_i y_{it-1} + \sum_{i=1}^{k_i-1} \Gamma_{ik} \Delta y_{it-k} + z_{it}\gamma_i + \varepsilon_{it}, \tag{5}$$

[1]Strictly speaking, of course, the stochastic process for Gini coefficients and investment shares cannot be a pure unit root process. Both Gini inequality measures and investment rates are bounded (between zero and 100), but we know that a unit root process will cross any finite bound with probability one. Nevertheless, as argued by Jones [23], it may be the case that in the relevant range, such variables are well characterized by a unit root process. Specifically, if the determining factors of Gini coefficients and investment shares, such as tastes, time preferences, and government policies, change over time, we observe Gini coefficient series and investment rate series with permanent movements that can be well approximated by a unit root process. Pedroni [33], for example, using panel unit-root tests, finds for a sample of 31 countries that the unit root hypothesis cannot be rejected for the (log) investment rate, and the individual country unit root tests used by Guest and Swifty [19] suggest that the Gini coefficients for all countries in their study (UK, USA, Australia, Japan, and Sweden) are I(1). Thus, our results are consistent with previous findings that inequality measures and investment shares can generally be approximated by an I(1) process.

where y_{it} is a $p \times 1$ vector of endogenous variables (y_{it} = [log($Income_{it}$), log($Invest_{it}$), $Inequality_{it}$]′; p is the number of variables) and Π_i is the long-run matrix of order$p \times p$. If Π_i is of reduced rank, $r_i < p$, it is possible to let $\Pi_i = \alpha_i \beta_i$, where β_i is a $p \times r_i$ matrix, the r_i columns of which represent the cointegrating vectors, and α_i is a $p \times r_i$ matrix whose p rows represent the error correction coefficients. The null hypothesis is that all of the N countries in the panel have a common cointegrating rank, i.e. at most r (possibly heterogeneous) cointegrating relationships among the p variables: $H_0 : rank(\Pi_i) = r_i \leq r$ for all $i = 1,...,N$, whereas the alternative hypothesis is that all the cross-sections have a higher rank: $H_1 : rank(\Pi_i) = p$ for all $i = 1, ..., N$. To test H_0 against H_1, a panel cointegration rank trace-test statistic is computed by calculating the average of the individual trace statistics, $LR_{iT}\{H(r)|H(p)\}$:[2]

$$\overline{LR}_{NT}\{H(r)\,|H(p)\} = \frac{1}{N}\sum_{i=1}^{N} LR_{iT}\,\{H\,(r)\,|H\,(p)\},\tag{6}$$

and then standardizing it as follows:

$$\Psi_{\overline{LR}}\,\{H\,(r)\,|H\,(p)\} = \frac{\sqrt{N}\left(\overline{LR}_{NT}\,\{H\,(r)\,|H\,(p)\} - E\,(Z_k)\right)}{\sqrt{Var\,(Z_k)}} \Rightarrow N\,(0,\ 1)\,,\tag{7}$$

where $E(Z_k)$ and $Var(Z_k)$ are, respectively, the mean and variance of the asymptotic trace statistic. $E(Z_k)$ and $Var(Z_k)$ are computed by Larsson et al. [25] for the model without deterministic terms. For the model we use (the model with a constant and a trend in the cointegrating relationship), the asymptotic values of $E(Z_k)$ and $Var(Z_k)$ are reported by Breitung [6].

However, the Johansen trace statistics are biased toward rejecting the null hypothesis in small samples. To avoid the Larsson et al. test, as a consequence of this bias, also overestimating the cointegrating rank, we compute the standardized panel trace statistics based on small-sample corrected country-specific trace statistics. Specifically, we use the small-sample correction factor suggested by Reinsel and Ahn [38] to adjust the individual trace statistics as follows:

$$LR_{iT}\,\{H\,(r)\,|H\,(p)\} \times \left[\frac{T - k_i \times p}{T}\right],\tag{8}$$

where k_i is the lag length of the models used in the test.

We apply the Larsson et al. [25] approach to both the raw data and to data that have been demeaned over the cross-sectional dimension to account for possible cross-sectional dependence due to common shocks or spillovers among countries at the same time. The results are presented in Table 3. For completeness, we also report the standard panel and group ADF and PP test statistics suggested by Pedroni

[2]The trace statistic tests the null hypothesis that the number of distinct cointegration vectors is less than or equal to r against the general alternative of p cointegrating vectors and is expressed as

$$TR = T\sum_{j=r+1}^{p} \ln\left(1 - \lambda_j\right)$$

where $\lambda_{r+1}, \ldots, \lambda_p$ are the $p - r$ smallest squared canonical correlations between y_{t-k} and Δy_t series corrected for the effect of the lagged difference of the y_t process (for details, see Johansen [21]).

Table 3 Panel cointegration tests

	Cointegration rank					
	$r = 0$		$r = 1$		$r = 2$	
Larsson et al. [25]	Raw data	Demeaned data	Raw data	Demeaned data	Raw data	Demeaned data
Panel trace statistics	5.88[a]	5.05[a]	−0.66	−0.65	−2.97	−2.98
	Panel cointegration statistics			Group mean panel cointegration statistics		
Pedroni [31]	Raw data	Demeaned data		Raw data	Demeaned data	
PP *t*-statistics	−2.44[b]	−3.16[a]		−2.45[b]	−3.27[a]	
ADF *t*-statistics	−2.63[b]	−3.41[a]		−4.24[a]	−4.75[a]	

All test statistics are asymptotically normally distributed. Each test is one-sided. The number of lags was determined by the Schwarz criterion with a maximum number of three lags

[a] Indicate a rejection of the null hypothesis of no cointegration at the 1% level

[b] Indicate a rejection of the null hypothesis of no cointegration at the 5% level

[31]. As can be seen, all tests suggest that $\log(Income_{it})$, $\log(Invest_{it})$, and $Inequality_{it}$ are cointegrated. The panel trace statistics clearly support the presence of one cointegrating vector. Also, the ADF and the PP statistics reject the null hypothesis of no cointegration at least at the 5% level, implying that there exists a long-run relationship between per-capita income, investment, and inequality.

3.3 Long-run relationship

We estimate the long-run growth effect of inequality using the between-dimension group-mean panel DOLS estimator suggested by Pedroni [32]. Between estimators allow for greater flexibility in the presence of heterogeneous cointegrating vectors, whereas under the within-dimension approach the cointegrating vectors are constrained to be the same for each country.

The DOLS regression in our case is given by

$$\begin{aligned}\log\left(Income_{it}\right) &= a_i + \delta_i t + \beta_{1i}\log\left(Invest_{it}\right) + \beta_{2i} Inequality_{it} \\ &+ \sum_{j=-k_i}^{k_i} \Phi_{1ij}\Delta\log\left(Invest_{it-j}\right) + \sum_{j=-k_i}^{k_i} \Phi_{2ij}\Delta Inequality_{it-j} + \varepsilon_{it}\,,\end{aligned} \tag{9}$$

where Φ_{1ij} and Φ_{2ij} are coefficients of lead and lag differences which account for possible serial correlation and endogeneity of the regressors. Thus, an important feature of the DOLS procedure is that it generates unbiased estimates for variables that cointegrate even with endogenous regressors. Consequently, in contrast to cross-section and conventional panel approaches, the approach does not require exogeneity assumptions nor does it require the use of instruments. In addition, the group-mean panel DOLS estimator is superconsistent under cointegration, and is robust to the omission of variables that do not form part of the cointegrating relationship.

The between estimator for β is calculated as

$$\hat{\beta}_m = N^{-1}\sum_{i=1}^{N}\hat{\beta}_{mi}, \tag{10}$$

where

$$t_{\hat{\beta}_m} = N^{-1/2} \sum_{i=1}^{N} t_{\hat{\beta}_{mi}} \tag{11}$$

is the corresponding t-statistic of $\hat{\beta}_m$ $(m = 1, 2)$ and $\hat{\beta}_{mi}$ is the conventional time-series DOLS estimator applied to the ith country of the panel.

The DOLS estimates for the coefficients on the investment rate and inequality are reported in Table 4. To account for the possible cross-sectional dependence through common time effects, we again present results for the raw data as well as for the data that have been demeaned with respect to the cross-sectional dimension for each period. As can be seen, the unadjusted and demeaned data produce almost identical values, suggesting that the estimation results are not affected by the presence of possible cross-sectional dependencies. The results show that the coefficient on $\log(Invest_{it})$ is highly significant and positive, as expected. The estimated coefficient of the inequality variable, in contrast, is highly significant and negative.

More precisely, the elasticity of per capita income with respect to the investment rate is estimated to be 0.340 (with the raw data), suggesting that an increase in the investment/GDP ratio by 1% increases GDP per capita by 0.340%, on average. This result is consistent with the empirical findings of Pedroni [33] who obtained estimates of 0.18 to 0.48 using similar estimation techniques, and it is also in line with the Solow model, which predicts that the coefficient on the log of the investment rate in the steady state should be roughly about 0.5 (see [28]). The inequality coefficient is −0.013 (using the raw data), implying that, in the long-run, a one percentage point increase in the EHII index, leads to a decrease in per-capita income by 0.013%.

To compare the two effects, we standardize the estimated coefficients by multiplying them by the ratio of the standard deviations of the independent and dependent variables (given in Table 1). The standardized coefficients imply that, in the long-run, a one-standard-deviation increase in the investment variable is associated with an increase in the per-capita income variable equal to 19.55% of a standard deviation in that variable, while a one-standard-deviation increase in $Inequality_{it}$ reduces per-capita income by 9.35% of a standard deviation in the per-capita income variable. From this, it can be concluded that the effect of a decrease in inequality on per-capita income is about half as large as the effect of an increase in the investment share. Thus, a reduction in income inequality has an economically large effect.

However, as discussed at the beginning of this paper, Barro [5] reports a positive correlation between income inequality and growth among rich countries, but a negative correlation for poor countries. Persson and Tabellini [35] find that the effect of inequality on growth is negative and significant for democracies, but insignificant for non-democracies. In light of these findings, we re-estimate the DOLS regression (with the raw data) for four subsamples: developed countries, developing countries,

Table 4 DOLS estimates

	$\log(Invest_{it})$	$Inequality_{it}$
Raw data	0.340[a] (24.87)	−0.013[a] (−7.40)
Demeaned data	0.345[a] (24.04)	−0.009[a] (−3.45)

t-statistics in parentheses. The DOLS regression was estimated with one lead and one lag
[a]Indicate significance at the 1% level

Table 5 DOLS estimates for subsamples

	Log($Invest_{it}$)	$Inequality_{it}$	Number of countries in the subsample
Developed countries	0.383^{a} (21.38)	-0.013^{a} (-3.51)	22
Developing countries	0.299^{a} (13.96)	-0.013^{a} (-6.88)	24
Democracies	0.361^{a} (23.29)	-0.015^{a} (-6.73)	30
Non-democracies	0.318^{a} (10.17)	-0.011^{a} (-3.44)	13

t-statistics are in parentheses. A country is classified as a non-democracy if the Polity democracy score is less than 6 for more than 75% of the time between 1970 and 1995. We do not have data on democracy for Barbados, Iceland, and Malta, forcing us to exclude these countries from the analysis
[a] Indicate significance at the 1% level

democracies, and non-democracies. The resulting coefficients are listed in Table 5. Regardless which sub-sample is used, the long-run relationship between inequality and per-capita income remains negative and significant, suggesting that there are no significant differences in the effects of inequality between rich and poor countries or between democratic and non-democratic countries.

4 Conclusions

This paper examined the long-run relationship between income inequality and economic growth using panel cointegration techniques designed to deal with problems plaguing previous studies of the inequality-growth nexus: omitted variables, country heterogeneity, endogeneity, neglected long-run level relationships between the level of income inequality and the level of per-capita income, and averaging data over time. Employing annual (rather than time-averaged) data for 46 developing countries over the period 1970–1995, we found that the long-run effect of inequality on growth is negative (on average) and that there are no significant differences in the effects of inequality between rich and poor countries or between democratic and non-democratic countries.

The effect of inequality on per-capita income is not only statistically significant, but also economically important. The effect of inequality on per-capita income is about half as large as the effect of an increase in the investment share on per-capita income. Thus, redistributive policies not only affect the distribution of the pie, but can also expand the pie itself.

Taking Galor and Moav [17] seriously, redistributive politics should focus on alleviating human capital accumulation for those at the bottom of the income distribution. In a world where human capital has become more important for economic growth than physical capital, inequality keeps people from human capital accumulation and therefore harms economic development. Golden and Katz [18] argue that the economic success of the United States in the twentieth century is to a large extend due to the fact that the United States expanded free public secondary education to almost the entire population long before European countries followed. Admittedly our analysis has little to say about the channels from inequality reduction to growth, but interpreting our results in the context of Galor and Moav [17] and Golden and Katz [18] seems most plausible. Given that we estimate a growth effect of inequality reduction that is about half as high as the effect of an increase in the investment share, the prospective payoffs of redistributive policies (through education) are huge.

References

1. Alesina, A., Rodrik, D.: Distributive politics and economic growth. Q. J. Econ. **109**, 465–490 (1994)
2. Atkinson, A.B.: On the measurement of inequality. J. Econ. Theory **2**, 244–263 (1970)
3. Attanasio, O.P., Picci, L., Scorcu, A.E.: Saving, growth, and investment: a macroeconomic analysis using a panel of countries. Rev. Econ. Stat. **82**, 182–211 (2000)
4. Banerjee, A.V., Duflo, E.: Inequality and growth: what can the data Say? J. Econ. Growth **8**, 267–299 (2003)
5. Barro, R.J.: Inequality and growth in a panel of countries. J. Econ. Growth **5**, 5–32 (2000)
6. Breitung, J.: A parametric approach to the estimation of cointegrating vectors in panel data. Econom. Rev. **24**, 151–173 (2005)
7. Chambers, D., Krause, A.: Is the relationship between inequality and growth affected by physical and human capital accumulation? J. Econ. Inequal. doi:10.1007/s10888-009-9111-x. (2010)
8. Clarke, G.R.G.: More evidence on income distribution and growth. J. Dev. Econ. **47**, 403–427 (1995)
9. Davis, L.S.: Explaining the evidence on inequality and growth: informality and redistribution. B.E.J. Macroecon. (Contributions) 7, Issue 1, Article 7. (2007)
10. de la Croix, D., Doepke, M.: Inequality and growth: why differential fertility matters. Am. Econ. Rev. **93**, 1091–1113 (2003)
11. Deininger, K., Squire, L.: New ways of looking at old issues: inequality and growth. J. Dev. Econ. **57**, 259–287 (1998)
12. Ericsson, N.R., Irons, J.S., Tryon, R.W.: Output and inflation in the long-run. J. Appl. Econ. **16**, 241–253 (2001)
13. Forbes, K.J.: A reassessment of the relationship between inequality and growth. Am. Econ. Rev. **90**, 867–889 (2000)
14. Frank, M.W.: Inequality and growth in the United States: evidence from a new state-level panel of income inequality measures. Econ. Inq. **47**, 55–68 (2009)
15. Galbraith, J.K.: Global inequality and global macroeconomics. J. Policy Model. **29**, 587–607 (2007)
16. Galbraith, J.K.: Inequality, unemployment and growth: new measures for old controversies. J. Econ. Inequal. **7**, 189–206 (2009)
17. Galor, O., Moav, O.: From physical to human capital accumulation: inequality and the process of development. Rev. Econ. Stud. **71**, 1001–1026 (2004)
18. Golden, C., Katz, L.: The race between education and technology. Harvard University Press, Cambridge (2008)
19. Guest, R., Swift, R.: Fertility, income inequality, and labor productivity. Oxford Econ. Pap. **60**, 597–618 (2008)
20. Im, K.S., Pesaran, M.H., Shin, Y.: Testing for unit roots in heterogeneous panels. J. Econom. **115**, 53–74 (2003)
21. Johansen, S.: Statistical analysis of cointegrating vectors. J. Econ. Dyn. Control **12**, 231–254 (1988)
22. Johansen, S.: Modelling of cointegration in the vector autoregressive model. Econ. Model. **17**, 359–373 (2000)
23. Jones, C.: Time series tests of endogenous growth models. Q. J. Econ. **110**, 495–525 (1995)
24. Knowles, S.: Inequality and economic growth: the empirical relationship reconsidered in the light of comparable data. J. Dev. Stud. **41**, 135–159 (2005)
25. Larsson, R., Lyhagen, J., Löthegren, M.: Likelihood-based cointegration tests in heterogeneous panels. Econom. J. **4**, 109–142 (2001)

26. Levin, A., Lin, C.-F., Chu, C.-S.J.: Unit root test in panel data: asymptotic and finite-sample properties. J. Econom. **108**, 1–24 (2002)
27. Lundberg, M., Squire, L.: The simultaneous evolution of growth and inequality. Econ. J. **113**, 326–344 (2003)
28. Mankiw, N.G., Romer, D., Weil, D.N.: A contribution to the empirics of economic growth. Q. J. Econ. **107**, 407–437 (1992)
29. Nair-Reichert, U., Weinhold, D.: Causality tests for cross-country panels: a new look at FDI and economic growth in developing countries. Oxford Bull. Econ. Statist. **63**, 153–171 (2001)
30. Panizza, U.: Income inequality and economic growth: evidence from American data. J. Econ. Growth **7**, 25–41 (2002)
31. Pedroni, P.: Critical values for cointegration tests in heterogeneous panels with multiple regressors. Oxford Bull. Econ. Statist. **61**, 653–670 (1999)
32. Pedroni, P.: Purchasing power parity tests in cointegrated panels. Rev. Econ. Stat. **83**, 727–731 (2001)
33. Pedroni, P.: Social capital, barriers to production and capital shares: implications for the importance of parameter heterogeneity from a nonstationary panel approach. J. Appl. Econ. **22**, 429–451 (2007)
34. Perotti, R.: Growth, income distribution, and democracy: what the data say. J. Econ. Growth **1**, 149–187 (1996)
35. Persson, T., Tabellini, G.: Is inequality harmful for growth? Am. Econ. Rev. **84**, 600–621 (1994)
36. Pesaran, M.H.: A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econometrics **22**, 265–312 (2007)
37. Pesaran, M.H., Smith, R.: Estimating long-run relationships from dynamic heterogeneous panels. J. Econometrics **68**, 79–113 (1995)
38. Reinsel, G.C., Ahn, S.K.: Vector autoregressive models with unit roots and reduced rank structure: estimation, likelihood ratio test and forecasting. J. Time Anal. **13**, 353–357 (1992)
39. Voitchovsky, S.: Does the profile of income inequality matter for economic growth? J. Econ. Growth **10**, 273–296 (2005)
40. Wan, W., Lu, M., Chen, Z.: The inequality–growth nexus in the short and long run: empirical evidence from China. J. Comp. Econ. **34**, 654–667 (2006)