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Inequality and economic growth: the role of initial income

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Abstract We estimate a panel model where the relationship between inequality and GDP per capita growth depends on countries' initial incomes. Estimates of the model show that the relationship between inequality and GDP per capita growth is significantly decreasing in countries' initial incomes. Results from instrumental variables regressions show that in Low Income Countries transitional growth is boosted by greater income inequality. In High Income Countries inequality has a significant negative effect on transitional growth. For the median country in the world, that in the year 2015 had a PPP GDP per capita of around 10000USD, IV estimates predict that a 1 percentage point increase in the Gini coefficient decreases GDP per capita growth over a 5-year period by over 1 percentage point; the long-run effect on the level of GDP per capita is around -5%.

Keywords Economic growth · Income inequality · Human capital

JEL Codes O1

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1 Introduction

The relationship between economic growth and the distribution of income is an important topic in macroeconomics. The effect that income inequality has on economic growth has recently received also quite a bit of attention in policy circles. To speak to those debates, this paper provides estimates of the relationship between income inequality and GDP per capita for different levels of countries' initial incomes.

Economic theory suggests that inequality affects aggregate output and that the effects differ between rich and poor countries. Galor and Zeira (1993) proposed a model with credit market imperfections and indivisibilities in human capital investment to show that inequality affects aggregate output in the short run as well as in the long run. The Galor and Zeira model predicts that the effect of inequality differs across countries and time depending on initial wealth. Motivated by that theoretical work, we estimate a panel model that includes a measure of income inequality (the income Gini) and an interaction between income inequality and countries' initial GDP per capita.

Estimates of the panel model show that differences in initial incomes have a substantial effect on the relationship between income inequality and economic growth. At an initial income of 1000USD (below which countries are classified according to the World Bank as Low Income Countries) the predicted effect of a 1 percentage point increase in the Gini coefficient on the long-run level of GDP per capita is around 4%. At an initial income of 12000USD (above which countries are classified according to the World Bank as High Income Countries) a 1 percentage point increase in the Gini decreases the long-run level of GDP per capita by around 6%. The estimates from the model thus show that in Low Income Countries income inequality is positively correlated with transitional GDP per capita growth; in High Income Countries income inequality and growth are negatively correlated.

According to the instrumental variables estimates, the threshold above which inequality has a negative effect on growth is at an initial income of around 3000USD. The higher the initial income above the 3000USD threshold, the more negative is the effect of inequality on transitional growth and the long-run level of GDP per capita. For the median country in the world, that in the year 2015 had a PPP GDP per capita of around 10000USD, inequality has a significant negative effect on transitional growth: a 1 percentage point increase in the Gini decreases GDP per capita growth over a 5-year period by over 1 percentage point; the long-run effect on the level of GDP per capita is around −5%.

Evidence that our empirical findings are consistent with the Galor and Zeira (1993) model comes from estimates of the relationship between inequality and human capital. Panel model estimates show that the relationship between income inequality and human capital is significantly decreasing in countries' initial incomes. In poor countries income inequality and human capital are significantly positively correlated. In rich countries the relationship between income inequality and human capital is negative.

Identification of the causal effect of income inequality on aggregate output is complicated by the endogeneity of the former variable. Income inequality may be affected by countries' GDP per capita as well as other variables related to deep-rooted differences in countries' geography and history. We address this issue by estimating a panel model with country and time fixed effects. We instrument income inequality with the residual variation in income inequality that is not due to GDP per capita. In order to obtain the residual variation in income inequality that is not due to GDP per capita we build on the work of Brueckner et al. (2015). Brueckner et al. (2015) provide estimates of the causal effect that GDP per capita has on the income Gini for a large set of countries.

Using the residual variation in income inequality that is not due to GDP per capita as an instrument for inequality means that we use a zero covariance restriction to identify the effect of inequality on GDP per capita in a simultaneous equation model where inequality affects GDP per capita and vice versa.[1] The zero-covariance restriction generates an instrument for inequality. We document that this instrument has a highly significant first stage effect.

In the IV approach identification of a causal effect of inequality on GDP per capita requires that the instrument is uncorrelated with the second-stage error term. If there are time-varying variables that directly affect GDP per capita and income inequality, then an instrumental variables approach that uses the residual variation in inequality that is not due to GDP per capita yields inconsistent estimates. The sign of the bias arising from omitted variables is difficult to pin down. To allay concerns related to omitted variables bias, we document that our IV estimates are robust to controlling for a set of time-varying variables that have been used as controls in the empirical literature on growth and inequality. We also show that overidentification tests fail to reject the hypothesis that the instrument is uncorrelated with the second-stage error term.

It may be the case that our IV estimates only reflect a correlation between inequality and GDP per capita and not a causal effect of the former variable on the latter. That correlation is interesting, and a novel contribution to the literature, as it says something about how transitional growth is related to inequality that is not due to variation in countries' average incomes. Our instrumental variables approach has the objective to ensure that estimates are not biased due to reverse causality running from higher GDP per capita to less inequality as suggested by the model of Galor and Zeira (1993). The IV approach is not suited to provide an estimate of a causal effect of inequality on GDP per capita in a richer model where the distribution of income is driven by social policies, changes in tax policy, changes in trade policy, or changes in immigration policy—all of which may directly affect economic growth and are hard to measure in a cross-country time-series context.

The rest of the paper is organized as follows. Section 2 reviews related literature and clarifies the contribution of the paper to the literature. Section 3 describes the data. Section 4 explains the estimation framework. Section 5 discusses empirical results. Section 6 concludes.

2 Contribution to literature

This paper makes two contributions to the empirical literature on inequality and growth: one is conceptual, the other is methodological.[2] The conceptual contribution is to examine how the effect of inequality on transitional growth differs depending on countries' initial incomes. For that purpose, an econometric model is specified and estimated that includes an interaction term between inequality and initial income. The estimates from the model allow a comparison of subnational estimates for specific countries, such as the United States, with estimates based on cross-country time-series data. Second, the econometric model allows a test of the theoretical model of Galor and Zeira (1993). The theoretical model of Galor and Zeira predicts that the effect of inequality on transitional growth differs depending on the average wealth in the economy.

Panizza (2002) uses state-level panel data for the United States during 1940-1980. His GMM estimates show a significant negative effect of the Gini on transitional GDP per capita

[1] See Hausman et al. (1987) for econometric theory for identifying simultaneous equation models with zero covariance restrictions.

[2] For a review of mechanism through which inequality may affect growth, see Galor (2011).

growth. Specifically, column (9) of Table 7 in Panizza shows that a 1 percentage point increase in the Gini decreases GDP per capita growth by around 4 percentage points. In order to compare that result to the estimates of this paper, one needs information on the average income of the United States during the sample period analysed by Panizza. According to the World Development Indicators (2017) the United States had in 1960 (the mid-point of Panizza's sample period) a GDP per capita of around 17000USD; equal to around 9.7 logs. According to the estimates shown in Table 4 of this paper—for an initial income equal to 9.7 logs—the effect of a 1 percentage point increase in the Gini on GDP per capita growth over a five-year period is around − 2 percentage points.

Forbes (2000) was the first paper in the literature to estimate an effect of inequality on transitional GDP per capita growth using a dynamic panel model that includes country fixed effects. Her sample spanned the period 1966–1995 and covered 45 countries. Forbes found that inequality has a significant positive effect on transitional GDP per capita growth. The estimates in her paper, see column (1) of Table 3, show that the level of GDP per capita is around 5% higher in the long run due to a 1 percentage point increase in the Gini coefficient.[3] Using our instrumental variables approach and a model specification that does not include an interaction term between the Gini and initial income (as in Forbes), we find that the estimated coefficient on the Gini is positive and significantly different from zero. Instrumental variables estimates of a model which restricts the effect of inequality on GDP per capita to be the same across countries' initial incomes show that the level of GDP per capita is around 6% higher in the long run due to a 1 percentage point increase in the Gini.

Forbes also reported estimates for different income groups (e.g. below and above \$1000, \$3000, \$6000, respectively). Only in the group of countries below the specified threshold (i.e. the low-income group) is there a significant positive effect of inequality on transitional growth; in the group of countries above the specified threshold the effect is insignificant. Forbes's finding that inequality has a positive effect on transitional growth in poor countries is qualitatively the same as in our paper. What Forbes's analysis does not show is the effect of inequality on growth at relatively high levels of income. The advantage of our model that includes an interaction between inequality and initial income is that this model examines the effect of inequality on transitional growth for various levels of initial income. This matters as we find that for high levels of initial income, such as for example those of OECD countries, inequality has a statistically significant and quantitatively large negative effect on transitional growth.

The paper's methodological contribution is to propose an instrument for inequality that is strong in the econometric sense, i.e. it has a highly significant first-stage effect. The first stages in the IV regressions yield Kleibergen Paap F-statistics that are well in excess of 10; Staiger and Stock (1997) proposed a first-stage F-statistic of 10 as a rule-of-thumb below which instruments are declared weak. A number of recent papers (Castelló-Climent (2010), Halter et al. (2014), Ostry et al. (2014), and Dabla-Norris et al. (2015) have estimated effects of inequality on GDP per capita using lags as instruments. Kraay (2016) examines instrument strength and finds that the IV estimates reported in those papers suffer from weak instrument bias; i.e. the first-stage F-statistics are substantially below 10.

[3] The long-run effect is calculated as 0.0036/0.076 = 0.047 (see column (1) of Table 3 in Forbes). The relevant equation is $\ln y_t = \gamma \ln y_{t-1} + \beta \text{Inequality}_{t-1}$; see Eq. (2) in Forbes where control variables have been left out to simplify. The equation can be rewritten as $\Delta \ln y_t = \kappa \ln y_{t-1} + \beta \text{Inequality}_{t-1}$, where $\kappa = (\gamma - 1)$. Because $|\gamma| < 1$, a permanent increase in inequality has a permanent effect on the level of GDP per capita. This follows from solving the first-order difference equation and differentiating with respect to inequality, i.e. $\partial \ln(y)/\partial \text{Inequality} = \beta/(1-\gamma) = \beta/-\kappa$.

IV estimates based on weak instruments are biased towards least squares estimates (Bound et al. 1995). We show that the least squares estimate of the relationship between transitional GDP per capita growth and inequality yields a negative coefficient on inequality. Thus, least squares estimation suggests that the effect of income inequality on transitional GDP per capita is negative. This is the same result as obtained by recent papers that use lags as instruments. On the other hand, our identification approach that uses the residual variation in inequality not affected by GDP per capita as an instrument for inequality yields a positive coefficient on inequality.

3 Data

Income inequality Our main indicator of income inequality is the Gini. This variable is based on the area between the Lorenz curve and a hypothetical line of absolute equality. In the empirical analysis we use two different Ginis from the Standardized World Income Inequality Database (Solt 2016): (1) the market Gini that measures inequality in pre-tax, pre-transfer income; (2) the net Gini that measures inequality in post-tax, post-transfer income. These data are available from 1960 onward. As a robustness check, we will present estimates that are based on Gini data from the World Development Indicators (2017), available from 1980 onwards, and Gini data of Brueckner et al. (2015), available from 1960 onwards.[4]

Other data Data on real GDP per capita, investment, government consumption, and the relative price of investment are from the Penn World Table (Heston et al. 2012). Data on the share of population ages 15 years and above with tertiary education, the share of population ages 15 years and above with secondary education, and the average years of schooling are from Barro and Lee (2013). Descriptive statistics for the above variables are provided in Appendix Table 11.

4 Estimation framework

4.1 Identification of simultaneous equation model with a zero-covariance restriction

In this section we discuss identification of a simultaneous equation model using a zero-covariance restriction. The discussion corresponds to the case discussed in Hausman et al. (1987) on page 854. Consider an econometric model with two equations that shows a two-way causal relationship between GDP per capita and inequality:

[4] Brueckner et al.'s (2015) primary data source is the UN-WIDER World Income Inequality Database. The authors filtered the data to drop low-quality observations. The data were supplemented with data from the World Bank's POVCALNET database for developing countries. To ensure comparability between the two data sources, Brueckner et al. made adjustments to the data sets for individual countries so that the income shares consistently correspond to those of a consumption (or income) survey. The authors then identified and dropped duplicates; eliminated duplicate survey-years with inferior quality data from the WIID; eliminated survey-years for which no extra information (consumption/income; etc.) is available as well as survey-years for which the income shares add up to less than 99 or more than 101 percent. The authors then aggregated the inequality data to the 5-year level by taking a simple average of the observed annual observations over five years. In the regression analysis countries are only included for which inequality data are available for at least two or more consecutive 5-year intervals.

$$Y = bX + rR + e \tag{1}$$

$$X = aY + u \tag{2}$$

where the error terms *e* und *u* are uncorrelated; *R* is an exogenous variable that is uncorrelated with *u* and *e*. It follows from substituting (2) into (1) that

$$\rightarrow\ Y\ = (1 - ab)^{-1}\,(bu + rR + e)$$

$$\rightarrow\ X\ =\ (1 - ab)^{-1}\,(arR + ae + u)$$

R can be used as an instrument for *Y* in Eq. (2). The instrumental variables estimator for *a* in Eq. (2) is:

$$a^{IV} = \mathrm{cov}\,(R, X)\,/\mathrm{cov}\,(R, Y) = \mathrm{cov}\,(R,\ aY + u)\,/\mathrm{cov}\,(R, X) = a + \mathrm{cov}\,(R, u)\,/\mathrm{cov}\,(R, X) = a$$

where the last line follows from cov(u,R) = 0.

With a consistent estimate of *a* in hand, one can then generate a variable $Z = X - a^{IV}Y = u$. And use *Z* as an instrument to estimate *b* in Eq. (1). The IV estimate of *b* in Eq. (1) is:

$$b^{IV}\ =\ \mathrm{cov}\,(\mathrm{Z, Y})\,/\mathrm{cov}\,(\mathrm{Z,X}) = \mathrm{cov}\,(\mathrm{Z}, bX + rR + e)\,/\mathrm{cov}\,(\mathrm{Z, X})\ =\ b$$

where the last line follows from cov(e,u) = 0 and cov(u,R) = 0.

In the online appendix we present Monte Carlo results. The Monte Carlos are done for two models: without an interaction between *X* and a variable *I*, as shown in Eq. (1); and with such an interaction term. The Monte Carlos show that the IV estimator as described above is unbiased.

We note that what does not yield a consistent estimate of *b* is estimating Eq. (2) by least squares, obtaining the residual u^{LS}, and then using u^{LS} as an instrument for X in Eq. (1).[5] Least squares estimation of Eq. (1) also does not yield a consistent estimate of *b*.

4.2 Dynamic panel model

Using an instrumental variables approach that imposes a zero-covariance restriction, the dynamic panel model we estimate is:

$$\ln(\mathrm{y})_{\mathrm{it}} - \ln(\mathrm{y})_{\mathrm{it}-1} = \mathrm{a_i} + \mathrm{b_t} + \beta_1 \mathrm{Inequality_{it}} + \beta_2 \mathrm{Inequality_{it}} * \ln\left(\mathrm{y_{it-1}}\right) + \varphi \ln(\mathrm{y})_{\mathrm{it}-1} + \mathrm{e_{it}} \tag{3}$$

where $\ln(\mathrm{y})_{\mathrm{it}}$ stands for the natural logarithmn of real GDP per capita in country i and period t; $\mathrm{Inequality_{it}}$ is the Gini in country *i* and period *t* minus the sample average Gini; $\mathrm{a_i}$ are country fixed effects; $\mathrm{b_t}$ are time fixed effects; $\mathrm{e_{it}}$ is an error term. We note that this equation can be re-written as:

$$\ln(\mathrm{y})_{\mathrm{it}} = \mathrm{a_i} + \mathrm{b_t} + \beta_1 \mathrm{Inequality_{it}} + \beta_2 \mathrm{Inequality_{it}} * \ln\left(\mathrm{y_{it-1}}\right) + (1+\varphi) \ln(\mathrm{y})_{\mathrm{it}-1} + \mathrm{e_{it}} \tag{3'}$$

[5] One can show this by noting that least squares estimation of *a* yields $\mathrm{a^{LS}} = \mathrm{cov(X,Y)/Var(Y)} = \mathrm{a} + \mathrm{cov(u,Y)/Var(Y)} = \mathrm{a} + (1-\mathrm{ab})^{-1}\mathrm{bVar(u)/Var(Y)} = \mathrm{a} + \mathrm{bias_1} \neq \mathrm{a}$ where $\mathrm{bias_1} = (1-\mathrm{ab})^{-1}\mathrm{bVar(u)/Var(Y)}$. It follows that $\mathrm{u^{LS}} = \mathrm{X} - \mathrm{a^{LS}Y} = \mathrm{X} - (\mathrm{a} + (1-\mathrm{ab})^{-1}\mathrm{bVar(u)/Var(Y)})\mathrm{Y} = \mathrm{u} - ((1-\mathrm{ab})^{-1}\mathrm{bVar(u)/Var(Y)})\mathrm{Y} = \mathrm{u} - \mathrm{bias_1}*\mathrm{Y}$. IV estimation that uses $\mathrm{u^{LS}}$ as an instrument for X in Eq. (1) yields $\mathrm{b^{IV1}} = \mathrm{cov(u^{LS},Y)/cov(u^{LS},X)} = 0$. This follows from noting that $\mathrm{cov(u^{LS},Y)} = \mathrm{cov(u - bias_1*Y,Y)} = \mathrm{cov(u,Y)} - \mathrm{bias_1*Var(Y)} = \mathrm{cov(u,\ Y)} - [(1-\mathrm{ab})^{-1}\mathrm{bVar(u)/Var(Y)}]*\mathrm{Var(Y)} = \mathrm{cov(u,Y)} - (1-\mathrm{ab})^{-1}\ \mathrm{bVar(u)} = \mathrm{cov(u,\ (1-ab)^{-1}(bu+e))} - (1-\mathrm{ab})^{-1}\mathrm{bVar(u)} = (1-\mathrm{ab})^{-1}\mathrm{bVar(u)} - (1-\mathrm{ab})^{-1}\mathrm{bVar(u)} = 0$.

We estimate Eq. (3') with 5-year non-overlapping panel data. The parameter φ is related to the convergence rate over a 5-year period.

The contemporaneous effect of the Gini on the natural logarithmn of GDP per capita is $\beta_1 + \beta_2 * \ln(y_{it-1})$. If φ is significantly negative, so that $1 + \varphi$ is below unity in absolute value (i.e. there is conditional convergence at the sample average Gini), then, at sample average Gini, the long-run effect of the Gini on the level of GDP per capita is $(\beta_1 + \beta_2 * \ln(y_{it-1}))/-\varphi$.

An important issue in the estimation of Eq. (3') is the endogeneity of inequality to GDP per capita. Brueckner et al. (2015) use an instrumental variables approach to identify the effect of GDP per capita on inequality. Their instrumental variables for GDP per capita are trade-weighted world income and the interaction between the international oil price and countries' net-export shares of oil in GDP. Specification tests reported by the authors do not reject the validity of these instruments. According to Brueckner et al. (2015) within-country variations in GDP per capita have a significant negative effect on income inequality. That is, in the equation below, α is negative:

$$\text{Inequality}_{it} = h_i + f_t + \alpha \ln (y)_{it} + u_{it} \tag{4}$$

The negative coefficient on GDP per capita is consistent with the model of Galor and Zeira (1993).

If α is negative in Eq. (4) then the least squares estimate of β in Eq. (3') is downward biased. That is, least squares estimation is biased towards finding a negative effect of income inequality on GDP per capita. We note that instrumental variables estimates based on weak instruments suffer from a similar bias (Bound et al. 1995).

In order to correct for reverse causality bias of β in the estimation of Eq. (3') we use the residual variation in inequality that is not due to GDP per capita: $Z_{it} = \text{Inequality}_{it} - \alpha \ln(y)_{it}$.[6] Using Z as an instrument for inequality ensures that the estimated β is not subject to reverse causality bias. Of course, this is under the assumption of a zero covariance between the error terms, as shown in Sect. 4.1.

In our baseline model we instrument both Inequality_{it} and $\text{Inequality}_{it} * \ln y_{it-1}$. The instruments are Z_{it} and $Z_{it} * \ln y_{it-1}$. There are two first stages, two endogenous variables, and two instruments. Table S1 in the online appendix shows that $\text{Inequality}_{it} * \ln y_{it-1}$ is not significantly affected by $\ln y_{it}$. We will therefore present also estimates of a model where there is only one endogenous variable (Inequality_{it}) and one instrument (Z_{it}); in that model $\text{Inequality}_{it} * \ln y_{it-1}$ is not instrumented.

5 Results

5.1 Model without interaction between inequality and initial income

In this section we discuss instrumental variables estimates of econometric models that do not include an interaction between inequality and initial income. We report these results to compare them with the existing literature, discussed in Sect. 2, that has estimated models in which the effect of inequality on GDP per capita is restricted to be the same across countries' initial incomes.

6 An analogous instrumental variables strategy has been used in the macro literature on fiscal policy, see e.g. Blanchard and Perotti (2002) or Fatas and Mihov (2003). Brueckner (2013) applies this instrumental variables strategy to estimating the effect of foreign aid on economic growth.

Table 1 presents estimates of an econometric model where lagged GDP per capita, the Gini, and country and time fixed effects are on the right-hand side of the equation; the interaction between the Gini and initial income, $\text{Inequality}_{it}*\ln y_{it-1}$, is not part of the model. As can be seen from Table 1, the estimated coefficient on the Gini is positive. One can reject the hypothesis that the estimated coefficient on inequality is equal to zero at the 1% significance level. Quantitatively the estimated coefficient on inequality is around unity. This is the case for the market Gini and for the net Gini; for the largest sample that includes transition economies and East Asian countries; and for sub-samples that exclude these countries.

The interpretation of the estimates in Table 1 is that inequality has a significant positive effect on transitional growth. Over a 5 year period, a 1 percentage point increase in the Gini raises GDP per capita growth by around 1 percentage point. Since the AR(1) coefficient on GDP per capita is significantly below unity, a permanent increase in the Gini has a significant effect on transitional growth; and a long-run effect on the level of GDP per capita.[7] The long-run effect of an increase in the Gini on GDP per capita is positive. A 1 percentage point increase in the Gini increases GDP per capita by around 6% in the long run. The long-run effect is significantly different from zero at the 1% significance level.

The bottom panel of Table 1 shows first stage estimates. As can be seen residual inequality has a positive effect on inequality.[8] The effect is significantly different from zero at the 1% level. The Kleibergen Paap F-statistics are well above the critical values tabulated in Stock and Yogo (2005) for instruments to be declared weak.[9] According to those tabulations one can reject at the 5% significance level the hypothesis that the IV size distortion is larger than 10%.

Table 2 reports estimates of a model that is estimated in first differences.[10] The estimated coefficient on the change in the Gini is positive. The null that this estimated coefficient is equal to zero can be rejected at the 1% significance level. This is the case for the market Gini and the net Gini. The estimated coefficient on the change in the market Gini is around 1.6; for the net Gini it is around 1.5. Instrumental variables estimates of a model specified in first differences thus yield a contemporaneous effect of inequality on GDP per capita that is similar in size as a model specified in levels.

Table 3 shows estimates of a model that does not include the lagged dependent variable on the right-hand side of the estimating equation. Instrumental variables estimation of the static panel model yields coefficients on the Gini that are positive and significantly different from zero at the 1% significance level. The estimated coefficients on the Gini are around 4. The estimated coefficients on the Gini are of the same sign as in Table 1; and larger in size. The larger size is expected because of positive serial correlation in GDP per capita.

Table S2 in the online appendix shows estimates of a model that includes lags of inequality on the right-hand side of the equation. In the instrumental variables regression of column (1) inequality in period t, $t-1$ and $t-2$ is instrumented with residual inequality in period t, $t-1$, and $t-2$. The IV coefficients on inequality in period t and $t-2$ are positive and significantly different from zero at the 5% level; the IV coefficient on period $t-1$ inequality

[7] We performed the panel unit root test by Maddala and Wu (1999) and were able to reject the null hypothesis of a unit root in the level of log GDP per capita at the 1 percent significance level; both for a model with trend and for a model with drift.

[8] Figure S1 in the online appendix plots the bivariate relationship between inequality and residual inequality for the different Ginis used in the estimates shown in Table 1.

[9] As noted in Bazzi and Clemens (2013) the Stock and Yogo tabulations were developed in a pure cross-sectional context and some caution is warranted when applying them to the panel context.

[10] First-differencing eliminates information contained in the level of the series; first differencing also implies that the country fixed effects drop out.

Table 1 Model without interaction between inequality and initial income

Dependent variable is:	$\ln(y_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality variable is:	Market Gini	Net Gini	Market Gini	Net Gini	Market Gini	Net Gini
Sample	All Countries		Excluding Transition Countries		Excluding East Asian Countries	
Inequality_{it}	1.23***	1.18***	1.24***	1.15***	1.14***	1.06***
	(0.14)	(0.20)	(0.17)	(0.21)	(0.15)	(0.17)
$\ln(y_{it-1})$	0.79***	0.82***	0.79***	0.83***	0.76***	0.79***
	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)	(0.03)
First stage for $\textit{inequality}_{it}$						
Residual Inequality_{it}	0.85***	0.90***	0.85***	0.90***	0.86***	0.91***
	(0.02)	(0.02)	(0.02)	(0.01)	(0.02)	(0.02)
Kleibergen Paap F-statistic	2556	3658	2400	3642	2637	3707
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	768	768	725	725	738	738

The method of estimation is two-stage least squares. Bootstrapped standard errors are shown in parentheses. *Residual Inequalityit* = *Inequalityit* $-\alpha$*ln(yit)*, where α measures the effect that ln(yit) has on *Inequality*
*Significantly different from zero at the 10% significance level
**5% significance level
***1% significance level

Table 2 Model without interaction between inequality and initial income (first difference specification)

Dependent variable is:	$\Delta\ln(y_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality variable is:	Market Gini	Net Gini	Market Gini	Net Gini	Market Gini	Net Gini
Sample:	All Countries		Excluding Transition Countries		Excluding East Asian Countries	
ΔInequality$_{it}$	1.61***	1.47***	1.62***	1.45***	1.42***	1.25***
	(0.22)	(0.23)	(0.23)	(0.23)	(0.22)	(0.23)
$\Delta\ln(y_{it-1})$	0.23***	0.26***	0.23***	0.26***	0.16***	0.19***
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
First stage for $\Delta Inequality_{it}$						
ΔResidual Inequality$_{it}$	0.81***	0.88***	0.81***	0.88***	0.83***	0.90***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Kleibergen Paap F-statistic	1424	2823	1340	2748	1338	2855
Country FE	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	622	622	591	591	562	562

The method of estimation is two-stage least squares. Standard errors are shown in parentheses. $\Delta Residual\ Inequality_{it} = \Delta Inequality_{it} - \alpha \Delta ln(y_{it})$, where α measures the effect that $\ln(y_{it})$ has on *Inequality*

*Significantly different from zero at the 10% significance level

**5% significance level

***1% significance level

Table 3 Model without interaction between inequality and initial income (static panel)

Dependent variable is:	$\ln(y_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality Variable is:	Market Gini	Net Gini	Market Gini	Net Gini	Market Gini	Net Gini
Sample:	All Countries		Excluding Transition Countries		Excluding East Asian Countries	
Inequality_{it}	4.14***	4.25***	4.39***	4.43***	3.55***	3.55***
	(0.38)	(0.49)	(0.36)	(0.52)	(0.32)	(0.38)
First stage for $inequality_{it}$						
Residual Inequality_{it}	0.62***	0.72***	0.61***	0.71***	0.65***	0.75***
	(0.02)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
Kleibergen Paap F-statistic	914	1031	833	942	1112	1372
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	789	789	735	735	759	759

The method of estimation is two-stage least squares. Bootstrapped standard errors are shown in parentheses. $Residual\ Inequality_{it} = Inequality_{it} - \alpha ln(y_{it})$, where α measures the effect that $\ln(y_{it})$ has on *Inequality*

*Significantly different from zero at the 10% significance level

**5% significance level

***1% significance level

is positive but not significantly different from zero at the conventional significance levels. The sum of coefficients on period t to t − 2 inequality is around 2.7 and has a standard error of 0.8. The cumulative effect over 15 years (period t to t − 2) is thus positive; and one can reject that the cumulative effect is equal to zero at the 1% significance level. The Kleibergen Paap F-statistic is around 936. According to the tabulations of Stock and Yogo (2005) one can reject the hypothesis that the IV size distortion is larger than 10% at the 5% significance level.

For comparison, column (2) of Table S2 reports least squares estimates. The least squares estimates show negative coefficients on period t and t − 1 inequality; the coefficient on period t − 2 inequality is positive. Only for the period t − 1 effect can one reject the hypothesis that this coefficient is equal to zero at the 5% significance level. The coefficients on period t and t − 2 inequality are not significantly different from zero at the conventional significance levels. An F-test on the hypothesis that the coefficients on inequality in period t, t − 1, and t − 2 are jointly equal to zero yields a p value equal to 0.02. The sum of coefficients on period t, t − 1, and t − 2 inequality is equal to − 0.75 and has a standard error of around 0.49. The negative least squares coefficients on inequality can be explained by negative reverse causality bias: as GDP per capita in the economy increases inequality decreases (as predicted by the model of Galor and Zeira 1993; and shown empirically in Brueckner et al. 2015).

5.2 Model with interaction between inequality and initial income

Table 4 presents instrumental variables estimates of the econometric model specified in Eq. (3) that includes an interaction between inequality and initial income. The estimated coefficient on inequality_{it} is positive and significantly different from zero at the conventional significance levels. The estimated coefficient on inequality_{it} $^*\ln(y_{it-1})$ is negative and significantly different from zero at the conventional significance levels. The negative coefficient on inequality_{it} $^*\ln(y_{it-1})$ means that the relationship between GDP per capita and inequality is decreasing in countries' initial income. An F-test on the hypothesis that the coefficients on inequality_{it} and inequality_{it} $^*\ln(y_{it-1})$ are jointly equal to zero yields a p-value below 0.01.

According to the World Development Indicators, the median country in the world had a year 2015 PPP GDP per capita of around 10000USD (9.2 logs). According to the estimates shown in Table 4, at an initial income of 10000USD, the predicted effect of an increase in income inequality on transitional growth is negative. Specifically, the estimates in column (1) of Table 4 show that at an initial income of 10000USD a 1 percentage point increase in the market Gini decreases GDP per capita growth over a 5-year period by around 1.6 percentage point; the long-run (cumulative) effect on the level of GDP per capita is around − 5%. For the net Gini, see column (2) of Table 4, the long-run effect is around − 4%.

For Low Income Countries, the estimates in Table 4 imply that an increase in income inequality has a significant positive effect on transitional growth. Consider, for example, a country with an initial income of 1000USD. At an initial income of 1000USD (6.9 logs) a 1 percentage point increase in the Gini increases GDP per capita growth over a 5-year period by around 1 percentage points; the long-run effect on the level of GDP per capita is around 4%.

For High Income Countries, the estimates in Table 4 imply that an increase in income inequality has a significant negative effect on transitional growth. Consider, for example, a country with an initial income of 50000USD. At an initial income of 50000USD (10.8 logs) a 1 percentage point increase in the market Gini decreases GDP per capita growth over a 5-year period by around 4 percentage points; the long-run effect on the level of GDP per capita is around − 12%.

Table 4 Model with interaction between inequality and initial income

Dependent variable is:	$\ln(y_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality Variable is:	Market Gini	Net Gini	Market Gini	Net Gini	Market Gini	Net Gini
Sample	All Countries		Excluding Transition Countries		Excluding East Asian Countries	
Inequality_{it}	9.26***	6.35***	10.11***	5.93***	5.54**	7.93***
	(2.11)	(2.30)	(3.53)	(2.00)	(2.74)	(1.83)
Inequality_{it} $*\ln(y_{it-1})$	−1.19***	−0.78**	−1.32**	−0.72**	−0.65*	−1.04***
	(0.31)	(0.35)	(0.51)	(0.29)	(0.39)	(0.28)
$\ln(y_{it-1})$	0.70***	0.78***	0.71***	0.79***	0.73***	0.75***
	(0.06)	(0.04)	(0.06)	(0.04)	(0.04)	(0.04)
Kleibergen Paap F-Statistic	14	15	13	15	10	15
First stage: $Inequality_{it}$						
Residual Inequality_{it}	0.76***	0.93***	0.75***	0.93***	0.81***	0.95***
	(0.03)	(0.02)	(0.03)	(0.02)	(0.04)	(0.02)
Residual Inequality_{it} $*\ln(y_{it-1})$	0.01***	−0.00**	0.01***	−0.00**	0.01*	−0.01***
	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.01)
First stage: $Inequality_{it}$ $*ln(y_{it-1})$						
Residual Inequality_{it}	4.52***	6.52***	4.50***	6.53***	4.85***	6.70***
	(0.24)	(0.19)	(0.25)	(0.21)	(0.27)	(0.17)
Residual Inequality_{it} $*\ln(y_{it-1})$	0.15***	−0.08***	0.15***	−0.08***	0.12***	−0.09***
	(0.02)	(0.01)	(0.02)	(0.01)	(0.03)	(0.01)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	768	768	725	725	738	738

The method of estimation is two-stage least squares. Bootstrapped standard errors are shown in parentheses. *Residual* $Inequality_{it} = Inequality_{it} - \alpha ln(y_{it})$, where α measures the effect that $\ln(y_{it})$ has on *Inequality*

*Significantly different from zero at the 10% significance level

**5% significance level

***1% significance level

It is noteworthy that, qualitatively, the instrumental variables estimates (reported in Table 4) and least squares estimates (reported in Table 5) show the same result. The estimated coefficients on $\text{inequality}_{\text{it}}$ are positive and significantly different from zero at the 1% significance level; the coefficients on $\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ are negative and significantly different from zero at the 1% significance level. Quantitatively, the IV coefficient on inequality is larger than the LS coefficient. An explanation for why the IV coefficient on inequality is larger than the LS coefficient is negative reverse causality bias: inequality decreases as GDP per capita increases.

The IV estimates shown in Table 4 are based on a strong instrument set. The Kleibergen Paap F-statistics are in excess of 10. According to the tabulations provided in Stock and Yogo (2005), one can reject that the IV size distortion is larger than 10% at the 5% significance level. Table S3 shows estimates where only $\text{inequality}_{\text{it}}$ is instrumented. This yields coefficients on $\text{inequality}_{\text{it}}$ and $\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ that are of the same sign as in Table 4 where both $\text{inequality}_{\text{it}}$ and $\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ are instrumented. In Table S3 the size of the coefficients on $\text{inequality}_{\text{it}}$ and $\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ is somewhat larger than in Table 4. The standard errors are smaller in Table S3 than in Table 4; and this is expected since there is only one endogenous variable in Table S3 while there are two endogenous variables in Table 4. In Table S3 the Kleibergen Paap F-statistic is more than 10 times the size of the Kleibergen Paap F-statistic in Table 4.

Table 6 presents difference-GMM estimates. Difference-GMM estimation yields coefficients on $\Delta\text{inequality}_{\text{it}}$ and $\Delta\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ that are of the same sign as the baseline estimates shown in Table 4. The coefficient on $\Delta\text{inequality}_{\text{it}}$ is positive and significantly different from zero at the 1% significance level. The coefficient on $\Delta\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ is negative and significantly different from zero at the 1% signifcance level. Autocorrelation tests show that there is significant first-order serial correlation (p value below 0.01); but no significant second-order serial correlation (p value above 0.1). The Hansen J tests yield p values above 0.1. Hence, one cannot reject the hypothesis that the instruments are valid at the conventional significance levels.

In Table 7 we report two-stage least squares estimates that use the time-varying instrument for inequality developed by Scholl and Klasen (2016). Scholl and Klasen's instrument is the interaction between the ratio of wheat to sugar production (following Easterly's 2007, cross-sectional study) and the lagged oil price. One can see that the coefficient on inequality is significantly positive while the coefficient on the interaction between inequality and initial income is significantly negative. Moreover, one can see that IV estimation based on the Klasen and Scholl instrument yields coefficients on inequality (and the interaction between inequality and initial income) that are of similar size as the coefficients generated by instrumental variables estimation that uses the residual variation in inequality that is not due to GDP per capita.

In columns (2), (4), and (6) of Table 7 we report IV estimates that use both instruments (and their interactions with initial income), i.e. the Klasen and Scholl instrument and the residual variation in the Gini that is not due to GDP per capita. With four instruments and two endogenous variables the model is overidentified and we can compute the Hansen J test. The p value from the Hansen test is above 0.1. Hence, the Hansen test does not reject instrument validity.

Table 5 Model with interaction between inequality and initial income (least squares estimation)

Dependent variable is:	$\ln(y_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality Variable is:	Market Gini	Net Gini	Market Gini	Net Gini	Market Gini	Net Gini
Sample	All Countries		Excluding Transition Countries		Excluding East Asian Countries	
Inequality_{it}	1.61***	1.11***	1.74***	1.16***	1.38***	1.02***
	(0.51)	(0.46)	(0.51)	(0.47)	(0.51)	(0.45)
Inequality_{it}	−0.21***	−0.16***	−0.23***	−0.17***	−0.18***	−0.16**
$*\ln(y_{it-1})$	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)
$\ln(y_{it-1})$	0.80***	0.82***	0.81***	0.83***	0.78***	0.79***
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	768	768	725	725	738	738

The method of estimation is least squares. Standard errors (shown in parentheses) are Huber robust and clustered at the country level
*Significantly different from zero at the 10% significance level
**5% significance level
***1% significance level

Table 6 Model with interaction between inequality and initial income (difference-GMM estimation)

Dependent variable is:	$\Delta \ln(y_{it})$					
	(1)	(2)	(3)	(4)	(5)	(6)
Inequality variable is:	Market Gini	Net Gini	Market Gini	Net Gini	Market Gini	Net Gini
Sample	All Countries		Excluding transition Countries		Excluding East Asian Countries	
$\Delta \text{Inequality}_{it}$	20.00***	23.68***	19.30***	24.43***	19.28***	23.41***
	(4.11)	(3.56)	(4.13)	(3.86)	(4.29)	(3.93)
$\Delta \text{Inequality}_{it}$	−2.71***	−3.35***	−2.63***	−3.47***	−2.61***	−3.32***
$*\Delta \ln(y_{it-1})$	(0.53)	(0.48)	(0.54)	(0.52)	(0.55)	(0.53)
$\Delta \ln(y_{it-1})$	0.26***	0.35***	0.27***	0.38***	0.26***	0.37***
	(0.08)	(0.09)	(0.08)	(0.11)	(0.07)	(0.10)
AR(1) test, *p* value	0.00	0.01	0.00	0.00	0.00	0.00
AR(2) test, *p* value	0.75	0.51	0.97	0.51	0.83	0.58
Hansen J-test, *p* value	0.15	0.20	0.14	0.30	0.11	0.29
Country FE	No	No	No	No	No	No
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	614	614	590	590	595	595

The method of estimation is difference GMM. Standard errors are shown in parentheses. The instrument for Δ*Inequality* is $\Delta \textit{Residual Inequality}_{it} = \Delta \textit{Inequality}_{it} - \alpha \Delta \ln(y_{it})$, where α measures the effect that $\ln(y_{it})$ has on *Inequality*

*Significantly different from zero at the 10% significance level

**5% significance level

***1% significance level

Table 7 Model with interaction between inequality and initial income (alternative instrument)

Dependent variable is:	$\ln(y_{it})$					
Sample:	All countries		Excluding transition countries		Excluding East Asian countries	
	(1)	(2)	(3)	(4)	(5)	(6)
$Inequality_{it}$	9.67***	9.13***	9.21***	9.29***	9.04**	6.98***
	(3.66)	(2.16)	(2.11)	(1.79)	(3.82)	(2.21)
$Inequality_{it}$ *$\ln(y_{it-1})$	−1.16*** (0.46)	−1.10*** (0.28)	−1.19*** (0.31)	−1.13*** (0.24)	−1.07** (0.48)	−0.82*** (0.29)
$\ln(y_{it-1})$	0.61***	0.61***	0.61***	0.61***	0.60***	0.61***
	(0.06)	(0.05)	(0.06)	(0.05)	(0.06)	(0.05)
Hansen J, *p* value		0.98		0.86		0.77
Kleibergen Paap F-Statistic	13	18	13	17	13	13
First Stage: $Inequality_{it}$						
$SWratio_i$*Oil $price_{t-2}$	0.44***	0.09*	0.32***	0.06	0.45***	0.08
	(0.14)	(0.05)	(0.14)	(0.05)	(0.14)	(0.05)
$SWratio_i$*Oil $price_{t-2}$ *$\ln(y_{it-1})$	−0.05*** (0.01)	0.01** (0.00)	−0.05*** (0.01)	0.01** (0.0)	−0.05*** (0.01)	0.01 (0.01)
Residual $Inequality_{it}$		0.73***		0.72***		0.79***
		(0.05)		(0.05)		(0.05)
Residual $Inequality_{it}$ *$\ln(y_{it-1})$		0.02*** (0.01)		0.02*** (0.01)		0.01** (0.00)

Table 7 continued

Dependent variable is:	$\ln(y_{it})$					
Sample:	All countries		Excluding transition countries		Excluding East Asian countries	
	(1)	(2)	(3)	(4)	(5)	(6)
*First Stage: $Inequality_{it}$ *$ln(y_{it-1})$*						
$SWratio_i$*Oil $price_{t-2}$	4.10***	1.27***	3.27***	1.04**	4.19***	1.23***
	(1.11)	(0.47)	(1.16)	(0.48)	(1.16)	(0.05)
$SWratio_i$*Oil $price_{t-2}$ *$\ln(y_{it-1})$	−0.37***	0.15***	−0.36***	0.16***	−0.40***	0.12***
	(0.10)	(0.05)	(0.10)	(0.05)	(0.10)	(0.05)
Residual $Inequality_{it}$		4.29***		4.23***		4.80***
		(0.38)		(0.38)		(0.41)
Residual $Inequality_{it}$ *$\ln(y_{it-1})$		0.25***		0.26***		0.19***
		(0.04)		(0.04)		(0.04)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	487	487	472	472	463	463

The method of estimation is two-stage least squares. The inequality variable is the market Gini from Solt (2016). *Residual* $Inequality_{it}=Inequality_{it} - \alpha ln(y_{it})$, where α measures the effect that $\ln(y_{it})$ has on *Inequality*. Bootstrapped standard errors are shown in parentheses

*Significantly different from zero at the 10% significance level

**5% significance level

***1% significance level

5.3 Robustness

5.3.1 Additional controls

Table S5 presents estimates of a model that includes additional time-varying variables as controls. The empirical literature on inequality and growth that estimates panel models with fixed effects includes only a few time-varying control variables. Forbes (2000), for example, includes as controls years of schooling and the relative price of investment. More recent papers follow that tradition. Halter et al. (2014) includes the same set of control variables as Forbes in the baseline. In a robustness check, Halter et al. (2014) includes as additional control variables the investment rate and population growth. Following that literature, Table S5 shows estimates of a model that includes average years of schooling, the investment rate, population growth, and the relative price of investment. The model also includes trade-weighted world income and the oil price shocks variable to control for external shocks. As can be seen from Table S5, the estimated coefficients on $\text{inequality}_{\text{it}}$ and $\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ are significantly different from zero at the 1% significance level. Quantitatively, the estimated coefficients on $\text{inequality}_{\text{it}}$ and $\text{inequality}_{\text{it}}$ $*\ln(y_{\text{it}-1})$ are similar to the baseline estimates shown in Table 4.

5.3.2 Interaction inequality and income in 1970

Table S6 presents instrumental variables estimates of Eq. ($3'$) where inequality is interacted with GDP per capita in 1970.[11] For the time period analysed, most of the variation in national incomes comes from the cross-section of countries. One would therefore expect similar results if the estimated model includes an interaction term constructed as inequality times income in 1970 (instead of inequality times income in period $t-1$). Table S6 shows that this is indeed the case. The estimated coefficient on inequality is significantly positive while the coefficient on the interaction between inequality and income in 1970 is significantly negative. Panel B of Table S6 re-estimates the model in first-differences. One can see that this yields similar results to the estimates of the level specification shown in Panel A.

5.3.3 Static panel model

Table S7 presents estimates from a static panel model where the natural logarithm of GDP per capita is regressed on inequality and the interaction between inequality and income in 1970.[12] The estimates of the static panel model show that the coefficient on inequality is significantly positive while the coefficient on the interaction between inequality and income in 1970 is significantly negative. It is noteworthy that the magnitude of the estimated effect that the Gini has on GDP per capita is similar in the static panel model as the long-run effect that can be computed from the dynamic panel model. Consider, for example, a country with a 1970 income of around 5000USD. According to the static panel estimates shown in Table S7, a one percentage point increase in the Gini reduces GDP per capita by around 0.2–0.5 log points.

[11] For the subsequent analysis the sample is restricted to the 1970–2010 period; i.e. GDP per capita in 1970 is the average income at the beginning of the sample period.

[12] GDP per capita in 1970 does not show up in Table S7 because the variable is perfectly collinear with the country fixed effects.

5.3.4 Model with lagged inequality

Inequality may have delayed effects. Table S8 in the online appendix reports estimates of a model that includes period t and $t-1$ inequality as well as the interaction of that variable with GDP per capita in 1970. As can be seen, the estimated coefficients on period t and $t-1$ inequality are positive and significantly different from zero at the conventional significance levels. The estimated coefficients on the interaction between inequality and GDP per capita in 1970 are significantly negative, both in period t and period $t-1$. This suggests that there exist delayed effects that qualitatively are the same as the contemporaneous effect. The cumulative effects (over periods t and $t-1$) are of similar magnitude as the long-run effect of the dynamic panel model. Consider, for example, a country with a 1970 income of around 5000USD: According to the estimates in Table S8, the cumulative effect on GDP per capita of a 1 percentage point increase in the Gini is around -0.2 to -0.5 log points.[13]

5.4 Relation between human capital and inequality

In the Galor and Zeira (1993) model the mechanism through which inequality affects GDP per capita is human capital.[14] The Galor and Zeira (1993) model predicts that the effect of inequality on human capital is a decreasing function of average income in the economy. In relatively poor countries, an increase in inequality leads to an increase of the average human capital of the population. In countries with relatively high average income the opposite is the case.

Table 8 shows estimates of the relationship between income inequality and the share of population with tertiary education. Panel A contains two-stage least squares estimates. In Panel B least squares estimates are reported. One can see that the estimated coefficients on inequality are significantly positive while the coefficients on the interaction between inequality and initial income are significantly negative. This is the case regardless of whether the measure of inequality is the market Gini or the net Gini; or whether transition countries are part of the sample or excluded from the sample. The interpretation of these estimates is that the relationship between the Gini and human capital is significantly decreasing in

[13] The cumulative effect is calculated as the sum of coefficients on period t and t-1 *inequality* and *inequality*ln(y_{1970})*. For a country with income of 5000USD in 1970, a value of 8.5 needs to be plugged in for *ln(y_{1970})*.

[14] In the Galor and Zeira model there are: (1) fixed costs to human capital accumulation; (2) financial market imperfections. The financial market imperfections arise because of moral hazard, i.e. borrowers can default [see Brueckner et al. (2010) for some empirical evidence that supports the importance of moral hazard in credit markets]. A positive risk of default means that the lending rate exceeds the deposit rate. Due to the interest rate spread, only children of sufficiently rich parents accumulate human capital. In economies where average income is high, a reduction in inequality (such that rich families are made poorer but can still pay the cost of education) makes some of the relatively poorer families (that before redistribution were unable to pay the cost of education) send their children to university. This implies that the share of population ages 15 and above with tertiary education increases when inequality decreases. In economies where average income is low, a decrease in inequality (such that poor families are made richer but still cannot pay the cost of education) prevents some of the relatively richer families (that before redistribution were able to pay the cost of education) to send their children to university. This implies that the share of population ages 15 and above with tertiary education decreases when inequality decreases. Hence, inequality and education are positively related in poor countries but negatively related in rich countries. The same holds for the relationship between inequality and GDP per capita since in the Galor and Zeira model human capital has a positive effect on aggregate output. Evidence that education has a significant positive effect on GDP per capita in both rich and poor countries is provided, for example, in Barro (2013). Galor (2011) find that in the United States during 1880–1940 land inequality had a significant negative effect on educational expenditures.

Table 8 Relationship between inequality and human capital

Dependent variable is:	Share of population tertiary education			
	(1)	(2)	(3)	(4)
Inequality variable is	Market Gini	Net Gini	Market Gini	Net Gini
Sample	Including Transition Countries		Excluding Transition Countries	
Panel A: 2SLS				
$\text{Inequality}_{\text{it}}$	0.57***	0.59***	0.49***	0.54***
	(0.16)	(0.13)	(0.15)	(0.12)
$\text{Inequality}_{\text{it}}$ *$\ln(y_{\text{it}-1})$	−0.06***	−0.08***	−0.05**	−0.08***
	(0.02)	(0.02)	(0.02)	(0.02)
$\ln(y_{\text{it}-1})$	0.02***	0.02***	0.02***	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	768	768	725	725
Panel B: LS				
$\text{Inequality}_{\text{it}}$	0.41***	0.46***	0.43**	0.48***
	(0.16)	(0.16)	(0.17)	(0.16)
$\text{Inequality}_{\text{it}}$ *$\ln(y_{\text{it}-1})$	−0.04*	−0.06***	−0.04*	−0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
$\ln(y_{\text{it}-1})$	0.02**	0.03***	0.02**	0.03***
	(0.01)	(0.01)	(0.01)	(0.01)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	768	768	725	725

The method of estimation in Panel A is two-stage least squares; Panel B least squares. Bootstrapped standard errors are shown in parentheses. The instrument for *Inequality* is *Residual Inequality*$_{it}$=*Inequality*$_{it}$ $-\alpha \ln(y_{it})$, where α measures the effect that $\ln(y_{\text{it}})$ has on *Inequality*
*Significantly different from zero at the 10% significance level
**5% significance level
***1% significance level

countries' initial incomes. Noteworthy is that this result emerges both in two-stage least squares estimation and in least squares estimates.

The two-stage least squares coefficient on inequality is larger than the coefficient on inequality that is generated by least squares estimation. This suggests that least squares estimation of the effect that inequality has on human capital suffers from endogeneity bias. The sign of the bias is negative. A negative bias of least squares estimation is consistent with the Galor and Zeira model: in that model, higher average income leads to an increase of the average human capital in the population; as more people accumulate human capital inequality decreases.[15] Endogeneity bias decreases the coefficient on inequality that is obtained by least squares estimation. Two-stage least squares estimation that uses the residual variation in inequality that is not due to GDP per capita as an instrument is not subject to this bias.

Table 9 repeats estimation for the sample that excludes high and low values of inequality. In columns (1) and (2) observations are excluded from the sample that fall within the top

[15] Brueckner et al. (2015) document that national income—through its effect on human capital—has a negative impact on inequality.

Table 9 relationship between inequality and human capital (excluding top or bottom 5th percentile of inequality)

Dependent variable is	Share of population tertiary education			
	(1)	(2)	(3)	(4)
Inequality variable is:	Market Gini	Net Gini	Market Gini	Net Gini
Sample	Excluding Top 5th Percentile		Excluding Bottom 5th Percentile	
Panel A: 2SLS				
Inequality_{it}	0.61***	0.64***	0.48***	0.56***
	(0.16)	(0.13)	(0.19)	(0.14)
Inequality_{it} $*\ln(y_{it-1})$	− 0.07***	−0.09***	−0.05*	−0.07***
	(0.02)	(0.02)	(0.02)	(0.02)
$\ln(y_{it-1})$	0.02***	0.03***	0.02***	0.02***
	(0.01)	(0.01)	(0.01)	(0.01)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	736	736	736	736
Panel B: LS				
Inequality_{it}	0.48***	0.53***	0.31	0.43**
	(0.18)	(0.16)	(0.19)	(0.18)
Inequality_{it} $*\ln(y_{it-1})$	−0.05**	−0.07***	−0.03	−0.06**
	(0.02)	(0.02)	(0.03)	(0.03)
$\ln(y_{it-1})$	0.02*	0.03***	0.02**	0.03**
	(0.01)	(0.01)	(0.01)	(0.01)
Country FE	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
Observations	736	736	736	736

The method of estimation in Panel A is two-stage least squares; Panel B least squares. Bootstrapped standard errors are shown in parentheses. The instrument for *Inequality* is *Residual* $Inequality_{it}=Inequality_{it}-\alpha ln(y_{it})$, where α measures the effect that $\ln(y_{it})$ has on *Inequality*
*Significantly different from zero at the 10% significance level
**5% significance level
***1% significance level

5th percentile of the Gini. Columns (1) and (2) excludes observations within the bottom 5th percentile of the Gini. Both two-stage least squares and least squares estimates show that the relationship between human capital and inequality is decreasing in countries' initial incomes. Two-stage least squares estimation yields larger coefficients on inequality than least squares estimation.

Table 10 presents two-stage least squares estimates that use as instrument the interaction between the sugar-wheat ratio and the lagged oil price. One can see that two-stage least squares estimation with this alternative instrument yields significant positive coefficients on inequality and significant negative coefficients on the interaction between inequality and initial income. This is the case for the largest sample (column (1)) as well as for sub-samples that exclude the top and bottom 5th percentile of the Gini (column (2)) and transition economies (column (3)). Again it is noteworthy that coefficients on inequality generated by the two-stage least squares estimation are larger than those generated by least squares estimation.

Table 10 Relationship between inequality and human capital (alternative instrument)

Dependent variable is	Share of population tertiary education		
	(1)	(2)	(3)
		Excluding Top and Bottom 5th Percentile of Inequality	Excluding Top and Bottom 5th Percentile of Inequality and Transition Countries
Inequality_{it}	1.48**	2.65**	2.57**
	(0.74)	(1.29)	(1.29)
Inequality_{it} $*\ln(y_{it-1})$	−0.16*	−0.27*	−0.26*
	(0.09)	(0.15)	(0.16)
$\ln(y_{it-1})$	0.01	−0.00	−0.00
	(0.01)	(0.02)	(0.02)
First Stage: $Inequality_{it}$			
$\text{SWratio}_i*\text{Oil price}_{t-2}$	0.44***	0.32***	0.28**
	(0.14)	(0.14)	(0.12)
$\text{SWratio}_i*\text{Oil price}_{t-2}$ $*\ln(y_{it-1})$	−0.05***	−0.03**	−0.03**
	(0.01)	(0.01)	(0.01)
First Stage: $Inequality_{it}$ $*ln(y_{it-1})$			
$\text{SWratio}_i*\text{Oil price}_{t-2}$	4.10***	3.09***	2.77***
	(1.11)	(1.02)	(1.04)
$\text{SWratio}_i*\text{Oil price}_{t-2}$ $*\ln(y_{it-1})$	−0.37***	−0.19*	−0.18*
	(0.10)	(0.10)	(0.10)
Country FE	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
Observations	487	436	428

The method of estimation is two-stage least squares. The inequality variable is the market Gini from Solt (2016). Robust standard errors are shown in parentheses
*Significantly different from zero at the 10% significance level
**5% significance level
***1% significance level

The main message of these estimates is that the relationship between inequality and human capital depends on countries' initial incomes: In countries where initial incomes are low inequality has a significant positive relationship with human capital; in countries with high initial incomes the relationship between inequality and human capital is negative.[16]

5.5 Further results

In our working paper version (Brueckner and Lederman 2015) we presented a number of further results. The first extension is to interact initial (i.e. 1970) average years of schooling with income inequality. If schooling is a determinant of GDP per capita then one should find similar results to those in Sect. 5.3. The second extension is to include in the model an interaction between income inequality and the GDP share of government consumption (in

[16] In the online appendix we document robustness to including in the model additional control variables (Table S9); restricting the sample to the 1970–2010 period and using as initial income the GDP per capita of countries in 1970 (Table S10); using alternative measures of human capital such as average years of schooling of the population and the share of population with secondary education (Table S11); including in the model current and lagged inequality as well as interactions of those variables with initial income (Table S12).

addition to an interaction between schooling and income inequality). This extension allows to answer the question whether initial cross-country differences in schooling have an effect on the impact that income inequality has on GDP per capita independent of a relationship between schooling and the size of government.

Table 9 in Brueckner and Lederman (2015) shows estimates of an econometric model where initial (1970) average years of schooling in the population are interacted with income inequality. The estimated coefficient (standard error) on the interaction term between average years of schooling and the Gini coefficient is -0.49 (0.09), see column (1). This suggests that the effect of income inequality on transitional GDP per capita growth is significantly decreasing in countries' initial level of human capital.

To illustrate the implied difference in effects, it is useful to consider some specific values of the average years of schooling in the sample. At the 25th percentile, the average years of schooling is around 4.2 years. Plugging the value of 4.2 into the estimates shown in column (1) of Table 9 yields a predicted effect of 0.5 with a standard error of 0.2; that is, a one percentage point increase in the Gini coefficient increases GDP per capita by around 0.5 percent. Consider now the sample median of average years of schooling. The sample median is around 6.4 years. The predicted marginal effect (standard error) at the median value of schooling is -0.56 (0.22). It is also instructive to consider the effect at the 75th percentile. At the 75th percentile the value for average years of schooling is around 8.6 years. The predicted marginal effect (standard error) is in that case -1.64 (0.39).

Table 10 of Brueckner and Lederman (2015) shows that the interaction between initial years of schooling and inequality is robust to restricting the sample to: (1) Asia (column (1)); (2) Latin America and the Caribbean (column (2)); the pre-1990 period (column (3)); and the post-1990 period (column (4)). As can be seen from Table 10, the coefficient on the Gini is significantly positive while the coefficient on the interaction between the Gini and schooling is significantly negative.

Table 11 of Brueckner and Lederman (2015) reports estimates from an econometric model that includes an interaction between income inequality and schooling as well as an interaction between income inequality and government size (as measured by the GDP share of government consumption). The table shows that there is a negative interaction effect between income inequality and the size of government. Hence, income inequality is less beneficial for transitional GDP per capita growth in countries with a high share of government consumption in GDP. The table also shows that the interaction between income inequality and schooling remains negative and significant when controlling for an interaction between income inequality and government size.

6 Conclusion

This paper provided panel estimates of the relationship between income inequality and GDP per capita growth. Motivated by the theoretical work of Galor and Zeira (1993), the econometric model included an interaction between measures of income inequality and countries' initial GDP per capita. Estimates of the model showed that the relationship between inequality and GDP per capita growth is significantly decreasing in countries' initial GDP per capita. Instrumental variables estimates suggest that inequality has a negative effect on transitional growth and the long-run level of GDP per capita for the median country with a year 2015 PPP GDP per capita of around 10000USD. For Low Income Countries, the growth effects of income inequality are positive. The paper also documented that the relationship between inequality and human capital is significantly decreasing in countries' initial GDP per capita. Overall, the empirical results provide support for the hypothesis that income inequality is beneficial for transitional growth in poor countries but that it is detrimental for growth in economies with high average income.

Appendix

See Table 11.

Table 11 Descriptive statistics

Variable	Source	Mean	SD
Gini	Brueckner et al. (2015)	0.39	0.11
Gini	WDI (2017)	0.39	0.10
Net Gini	Solt (2016)	0.38	0.11
Market Gini	Solt (2016)	0.46	0.10
Ln GDP per capita	Heston et al. (2012)	6.82	1.09
ΔLn GDP per capita	Heston et al. (2012)	0.28	0.19
Investment/GDP	Heston et al. (2012)	0.23	0.09
Government Consumption/GDP	Heston et al. (2012)	0.09	0.05
Population Growth	Heston et al. (2012)	0.08	0.06
Relative Price of Investment	Heston et al. (2012)	0.76	1.36
Average Years of Schooling	Barro and Lee (2013)	6.45	2.67
Share of Pop. Secondary Education	Barro and Lee (2013)	0.32	0.17
Share of Pop. Tertiary Education	Barro and Lee (2013)	0.08	0.07

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