

# CAMA

Centre for Applied Macroeconomic Analysis

---

## Inequality or poverty: which is bad for growth?

---

CAMA Working Paper 43/2016  
July 2016

**Robert Breunig**

Crawford School of Public Policy, ANU and  
Centre for Applied Macroeconomic Analysis, ANU

**Omer Majeed**

Crawford School of Public Policy, ANU

### Abstract

Recent research has highlighted a negative impact of inequality on economic growth. We re-evaluate this hypothesis focusing on both inequality and poverty and their interaction. We replicate previous results showing that inequality has a negative impact on growth. However, we show that when we account for both inequality and poverty, the negative effect of inequality on growth appears to be concentrated amongst countries with high poverty. This would argue for policies targeted towards alleviating poverty rather than policies about redistribution.

## **Keywords**

Inequality; Economic Growth; Poverty; Cross-Country Regressions

## **JEL Classification**

O47,D63,I39

## **Address for correspondence:**

(E) [cama.admin@anu.edu.au](mailto:cama.admin@anu.edu.au)

**ISSN 2206-0332**

[The Centre for Applied Macroeconomic Analysis](#) in the Crawford School of Public Policy has been established to build strong links between professional macroeconomists. It provides a forum for quality macroeconomic research and discussion of policy issues between academia, government and the private sector.

**The Crawford School of Public Policy** is the Australian National University's public policy school, serving and influencing Australia, Asia and the Pacific through advanced policy research, graduate and executive education, and policy impact.

# Inequality or poverty: which is bad for growth?

Robert Breunig \*and Omer Majeed  
Crawford School of Public Policy  
Australian National University

## Abstract

Recent research has highlighted a negative impact of inequality on economic growth. We re-evaluate this hypothesis focusing on both inequality and poverty and their interaction. We replicate previous results showing that inequality has a negative impact on growth. However, we show that when we account for both inequality and poverty, the negative effect of inequality on growth appears to be concentrated amongst countries with high poverty. This would argue for policies targeted towards alleviating poverty rather than policies about redistribution.

JEL CODES: O47,D63,I39

KEYWORDS: Inequality; Economic Growth; Poverty; Cross-Country Regressions

## Policy points/highlights

- Inequality in the absence of poverty does not appear to have a statistically significant effect on economic growth.
- As poverty increases, the effect of inequality on economic growth becomes negative and statistically significant.
- Poverty alleviation policies might therefore be more effective in producing economic growth than redistribution.

---

\*Robert Breunig ([robert.breunig@anu.edu.au](mailto:robert.breunig@anu.edu.au)) is Professor of Economics at the Crawford School of Public Policy, Australian National University. Omer Majeed is a doctoral candidate at the Crawford School of Public Policy. He can be contacted at [omer.majeed@anu.edu.au](mailto:omer.majeed@anu.edu.au). We thank Frederick Solt for his assistance with the data and for answering our questions about the data. We thank Paul Burke, Jakob Madsen and Raghendra Jha for helpful comments on an early draft of the paper.

# 1 Introduction

Recent research has re-focused attention on the impact of income inequality on economic growth. In this paper, we expand upon this by asking whether inequality and poverty, separately or jointly, impact economic growth. We focus on extreme, absolute poverty as measured by two or three dollars per day income.

Inequality has been hypothesized to negatively affect growth through several channels. Inequality may result in under-investment in education, health and physical capital leading to lower growth. We argue that such under-investment could equally, or perhaps even more likely, be the result of poverty rather than inequality, per se.

Poverty and inequality may also interact to have a negative impact on growth. The interaction between poverty and inequality may relate to mobility or the quality of institutions or other factors which could impact negatively on growth.

Economic growth regressions which control for average incomes and inequality, but not for poverty, may fail to capture disadvantage that harms growth. By adding the percentage of people below the poverty line, we are additionally controlling for the concentration of disadvantage in the population. The effect of poverty might be distinct from and in addition to effects from low average incomes and inequality.

Empirically, we ask two simple questions: is the negative relationship between income inequality and economic growth robust to the inclusion of poverty as an explanatory variable for economic growth? And, is the relationship between inequality and economic growth related to the level of poverty?

We find that including poverty does matter. Specifically, we find that the negative impact of inequality on economic growth is related to the level of poverty. When poverty is low (less than 25% or so), we find a statistically insignificant relationship between inequality and economic growth. For higher levels of poverty, we find that inequality negatively impacts economic growth. The negative effect of inequality on economic

growth grows as poverty rises.

The policy implications are clear: reduce inequality by attacking poverty rather than by redistributing incomes.

We provide background and briefly review some relevant literature in the next section. The standard growth regression approach that we use is reviewed in section 3. Detail of our data is provided in section 4. We then present regression results and focus on the marginal effect of inequality on economic growth at different levels of poverty in section 5. We conclude in the final section.

## 2 Background

There has been a renewed focus on the relationship between inequality and economic growth spurred by two recent papers Cingano (2014) and Ostry, Berg and Tsangarides (2014). Ostry et al. (2014) use newly compiled data by Solt (2009) to find that lower net inequality is correlated with faster and more durable growth. They also find that more unequal societies tend to redistribute more, but that redistribution does not have a major effect on economic growth. In their baseline regressions, they include initial income, inequality and redistribution. They add standard growth determinants such as investment, population growth and education to verify if their results hold with a wider set of control variables. The final specification of Ostry et al. (2014) is a full set of growth determinants including terms of trade shocks, political institutions, openness, debt liabilities as well as the covariates mentioned before.

Cingano (2014) also finds that increases in inequality have a negative impact on economic growth. The growth regressions in Cingano (2014) only control for initial income, education and investment. His paper further finds that inequality interacts with human capital to impede growth. While Ostry et al. (2014) focus on a sample of countries from around the world, Cingano (2014) focuses only on the OECD countries.

The relationship between inequality and economic growth has been well-studied over the past 25 years with papers reporting a range of results including claims that inequality harms growth, that inequality is irrelevant for growth and that inequality aids in growth. Theory is ambiguous as to the expected effects. Inequality can affect economic growth in a number of complex ways and through various channels (Cingano (2014), Halter, Oechslin and Zweimüller (2014), Lazear and Rosen (1979), Rosenzweig and Binswanger (1992) and Foellmi and Zweimüller (2006)). The empirical literature on economic growth and inequality partly reflects this; where some papers find that inequality has a negative impact on economic growth, others find a positive relationship between the two variables. Simple intuition also leads us to no obvious conclusion. It is clear that excessive inequality leading to social conflict and exclusion should harm growth. On the other hand, ‘perfect’ equality achieved by redistribution away from the successful to the less successful must certainly produce incentives that also harm growth.

Some previous papers support the claim that inequality reduces economic growth. Galor and Moav (2004) and Galor and Zeira (1993) emphasize that inequality will affect economic growth by depriving the poor of staying healthy and accumulating human capital. Perotti (1996) shows that more equal societies have lower fertility rates and higher investment in education. Both help to improve economic growth. Perotti (1996) also shows that inequality is linked to socio-political instability. Alesina and Perotti (1996) add to this literature by finding that increases in inequality in land and income ownership have a negative impact on economic growth.

Halter et al. (2014) find that higher inequality fosters performance and growth in the short run, nevertheless, inequality tends to have a negative effect on economic growth in the long run. Forbes (2000) finds that inequality can lead to increased economic growth in the short run. Increased inequality can also cause better incentives for innovation, entrepreneurship and higher profits, see Lazear and Rosen (1979), Rosenzweig

and Binswanger (1992) and Foellmi and Zweimüller (2006).

Establishing a relationship between inequality and economic growth is further obstructed by lack of data and, until recently, inadequate econometric techniques. Solt (2009) tries to overcome the first problem by creating an extensive dataset on inequality. We make use of this data set to aid in comparability of our results with others. The application of Generalized Methods of Moments (GMM) (Durlauf, Johnson and Temple (2005) and Roodman (2009)), specifically system GMM, improves the ability to handle endogeneity and reverse causality typically found in economic growth regressions.

The literature on economic convergence asks whether low average incomes are associated with higher growth rates. A separate question, less well studied, is the impact of the concentration of poverty on economic growth. Theoretically, some authors have tried to establish a link between poverty and economic development, by hypothesizing that low income can confine people to a poverty trap as in Sachs (2005). When people are poor, they need their income for subsistence. Due to this, they are unable to invest in human capital, physical capital and their own health. As a result, investments in the economy are reduced and makes the workforce less productive. Further, often poor people do not have access to a pension scheme, so they use children as a means of insurance, see Perkins, Radelet, Lindauer and Block (2012). However, higher population growth can be bad for growth as, for a given income level, higher population growth will mean less capital per person resulting in lower growth according to a simple Solow-Swan model. Of course, the relationship can run in both directions. Poverty can foster an increase in population, which can retard economic growth, see Ravallion (2016).

The literature has shown that poverty can have a negative impact on investment and GDP growth, particularly when financial markets are not well developed; (Perry, 2006, chapter 1). Azariadis and Stachurski (2005) survey models of poverty traps and find a common theme that poverty impedes acquisition of physical and human capital

and also curtails adoption of modern technology. López (2006) endorses the hypothesis that poverty retards growth through various channels including education, institutions, health and physical capital accumulation. Bowels, Durlauf and Hoff (2006) discuss the large role that institutions play perpetuating poverty traps. López and Servén (2009) empirically show that higher levels of initial poverty reduces economic growth.

Our contribution in this paper is empirical. The empirical and theoretical literature cited above provide the rationale for our consideration of the effect on economic growth of poverty and inequality and their interaction.

### 3 Model and Estimation

We estimate the impact of inequality and poverty on economic growth as

$$y_{it} - y_{i,t-1} = \phi y_{i,t-1} + \theta_1 g_{i,t} + \theta_2 p_{i,t} + \theta_3 g_{i,t} \times p_{i,t} + \beta \mathbf{X}_{i,t} + \rho_t + \mu_i + \varepsilon_{it} \quad (1)$$

where  $i$  indexes country and  $t$  indexes 5-year time periods.  $y$  denotes the natural log of real gross domestic product (GDP) per capita. In our empirical specification, we use the 5 year compound average growth rate of GDP as the dependent variable.  $g$  is the Gini coefficient and  $p$  is the poverty headcount ratio. In our results section, we first impose  $\theta_2 = \theta_3 = 0$  to reproduce the standard literature which looks at the effect of inequality on economic growth. We then estimate the full model to examine the effect of poverty and its interaction with inequality on economic growth.

$\mathbf{X}$  is a vector of growth determinants. In our empirical specification, we use a variety of different sets of variables for the growth determinants as summarized in Table 1.

There are well-established problems of estimating growth equation like (1). The control variables suffer from endogeneity and measurement errors, see Roodman (2009), Arellano and Bond (1991) and Cingano (2014). One of the main problems in estimating equation (1) is that applying within transformations or taking first differences creates



Table 1: Different combinations of determinants of growth ( $\mathbf{X}$ ) used in empirical specification

<b>Variables</b>	<b>Set 1</b>	<b>Set 2</b>	<b>Set 3</b>	<b>Set 4</b>
Investment to GDP ratio	x	x	x	x
Years of Schooling	x	x	x	x
Log Population Growth		x	x	x
Price of Investment			x	x
Trade Share of GDP			x	x
Relative redistribution				x

a correlation between the lagged income variable and country fixed effects. Such approaches thus yield biased and inconsistent estimates.

First difference and system GMM techniques overcome these problems. First difference GMM remedies these problems by taking first difference of equation (1) to remove country fixed effects and using appropriately lagged values of  $y$  and  $X$  as internal instruments. However, the first difference transformation suffers from the problem of weak instruments if the right-hand side variables are highly persistent, which is likely to be a case for inequality, poverty and education variables as also recognized by Halter et al. (2014). System GMM overcomes this problem by building a system of level and first difference equations and using appropriately lagged variables as instruments from both the levels and the first difference equations. Further, the first difference methodology has the problems of magnifying the problems of unbalanced panels, so instead we use orthogonal deviations, constructed as in Roodman (2009). System GMM is also better than difference GMM in exploiting cross-country variation—Halter et al. (2014). Both one-step and two-step methodologies may be used in estimating system GMM equations. However, the two-step methodology is more efficient, see Bond, Hoeffler and Temple (2001). All the estimates we report use the two-step GMM procedure. Our results do not change significantly if we use the one-step methodology.<sup>1</sup>

We use one lag of the internal instruments in all the estimates we report. Our

---

<sup>1</sup>Results available from authors.

substantive results do not change if we use two lags. However, this results in a larger number of instruments, which can be problematic.

GMM estimates can suffer from instrument proliferation problems, as discussed by Roodman (2009). The Hansen (1982) test can be used to check for the exogeneity of instruments and also for the problem of too many instruments, or instrument proliferation. The null hypothesis of the test is that instruments are exogenous. When the p-value is small, we reject the null hypothesis and conclude that the instruments are invalid as exogeneity does not hold. On the other hand, Roodman (2009) shows that as the number of instruments becomes too large, the p-value of the Hansen test converges to one. For each model we estimate, we report the number of instruments. A rule of thumb is that when the p-value of the Hansen test is above .8, there may be a problem of instrument proliferation. In the two-step estimator we use, the Windmeijer correction Windmeijer (2005) as well as the small-sample correction Roodman (2009) are used.

We turn next to a detailed description of our data.

## 4 Data

For our data, we focus on five-year periods from 1956 to 2011.<sup>2</sup> We draw the data together from a variety of sources. Our full sample of countries for which we have GDP and other basic economic data consists of 152 countries. For some countries we have observations on all 12 time periods and for some countries we have as few as two observations. (We drop countries for which we have valid data for only one five-year period.)

Our income variable is taken from the Penn World Tables 8.1 (PWT) and is based on real gross domestic product (GDP) at 2005 constant national prices. To get the dependent variable, we divide GDP by population to create Gross Domestic Product

---

<sup>2</sup>Gini data only starts from 1960 onwards, but by using GDP values of 1956 we can increase our sample size as we use lagged GDP in the growth regressions.

per capita (GDPPC) and take a compound average growth rate over 5 years. This variable is different from Ostry et al. (2014) in two ways. First, we use compound average growth rates, more typically used in studies of economic growth. Secondly, we use real GDP in national constant prices as opposed to GDP using purchasing power parity (PPP) conversion to US dollars. PWT recommends using real GDP in national constant prices as it is not distorted by measurement errors in the PPP calculations.

We use an inequality dataset from Solt (2009) using version 5 of the standardized world income inequality database (SWIIDv5).<sup>3</sup> This data covers, to the best of our knowledge, the largest number of countries and spans the largest period for available inequality data. To capture inequality, we use the Gini coefficient based on net inequality, which is calculated by taking into account taxes and transfers.

‘Relative redistribution’ is also taken from Solt (2009). Relative redistribution is the difference between the market-income and net-income Gini indices divided by the market income Gini and multiplied by 100. Relative redistribution is positive if redistribution lowers inequality. It is negative if inequality goes up after government redistribution. Most countries have positive relative redistribution but a few have negative values.

To capture human capital, we use total years of schooling for ages 15-64 of the population, Barro and Lee (2013). Investment (gross fixed capital formation) as a percentage of GDP, trade shares and fertility rates were taken from the World Development Indicators (WDI). The price level of investment data were taken from Heston, Summers and Aten (2011). As there were some gaps in these datasets, and in line with the literature on economic growth, 5-year averages were taken for these variables.

The poverty headcount ratio (2 dollars a day at purchasing price parity) is also taken

---

<sup>3</sup>We obtained the data at the standardized world income inequality database website (<http://myweb.uiowa.edu/fsolt/swiid/FAQ/FAQ.html>) That dataset provides 100 multiple imputations for the value of the Gini for each country at each point in time. We use the STATA code provided on the website to create point estimates for each country at each point in time. We construct the 5-year averages for the Gini and ‘relative redistribution’ (see below) from these point estimates. We also create standard errors for each Gini observation to measure the precision with which the Gini is estimated. We use this standard error to eliminate imprecisely measured values of the Gini coefficient in our robustness checks.

from the WDI. As there are missing values for the poverty variable and given that the poverty rates show a high degree of persistence, 2005 values were carried forward to 2011 for the missing observations. WDI has discontinued poverty data for high-income economies. As a result, data for high-income economies is taken from the CEIC database (<http://www.ceicdata.com/en>) where the data is available.

Our data and key definitions are summarized in Table 2.

Table 2: Variable definitions and sources

Variables	Definition and Source	Obs.	Mean	St. Dev.
ln(Income [GDP])	Real Gross Domestic Product per capita (GDPPC) at 2005 national prices; Penn World Tables 8.1	1,452	8.41	1.18
Growth rate	5 year compound average growth rate based on real GDPPC	1,367	2.11	3.41
Relative redistribution	Market inequality <sup>a</sup> less net inequality (Gini), divided by market inequality multiplied by 100	424	21.54	15.82
Investment	Gross fixed capital formation as a percentage of GDP; World Development Indicators	1,233	21.78	7.11
ln(Years of Schooling)	Average for ages 15-64 of the population, Barro and Lee (2013)	1,506	1.31	0.99
ln(Population Growth)	Five-year average growth; World Development Indicators	1,579	0.34	1.33
Price of Investment	Price level of investment <sup>b</sup> ; Heston et al. (2011)	1,519	85.38	169.71
Trade Share of GDP	Trade as a percentage of GDP	1,343	72.96	49.01
Gini coefficient	Gini based on income after taxes and transfers; Solt (2009) SWIIDv5	1,041	37.25	9.9
Poverty	Headcount ratio based on \$2 (\$3.10) a day on purchasing power parity; World Development Indicators	556	29.32	31.74

<sup>a</sup>Inequality (Gini) calculated before taxes and transfers is called market inequality.

<sup>b</sup>Calculated over country sample of column 3 of Table B.1, which avoids countries like Zimbabwe that experienced hyperinflation.

In section 5.1, we undertake several robustness checks with respect to our definition

of poverty. We replace poverty with zero for high-income OECD economies.<sup>4</sup> These rich countries have very few individuals living on less than \$2 a day so zero is a reasonable estimate. Recently, the World Bank changed its definition of poverty to \$3.10 a day at purchasing price parity. As this variable is missing for the high-income economies and there are no historical records to fill this gap, we prefer the poverty headcount ratio at \$2 dollars a day to maximize the sample sizes in our regressions. We use this alternate version of poverty to check the robustness of our results in section 5.1. The correlation between the poverty headcount ratio measured using \$3.10 a day and that using \$2 a day is above 97 percent.

#### **4.1 Estimation sample**

The panel is unbalanced. There are 16 countries for which we have inequality and gross domestic product data on all 12 years from 1956 - 2011. In the simplest growth regression, these countries each contribute 11 observations to the estimation (dropping one year for lagged gross domestic product variable). 12 countries only contribute one observation as these countries only have two consecutive observations where gross domestic product and inequality data are available. In the simplest regression where we only include inequality and gross domestic product, we have 950 observations from these 152 countries. On average, each country contributes just over 6 observations.

Appendix B provides more information on which countries are included in our sample and how that changes with different sets of control variables. As we add more control variables to the regression, sample sizes decrease because of missing values in some of the explanatory variables. We estimate all models on the largest possible set of observations. We also provide estimates on a smaller set of countries/observations for which we have complete data on all required variables. We do this to help disentangle the different effects of changing the explanatory variable set from those caused by changing the

---

<sup>4</sup>OECD countries with Gross National Income above USD20,000.

sample composition. These estimates are discussed in section 5.1.

As data on poverty is limited, our sample size drops to 128 countries once the poverty variables are included in the regressions. As we add the various independent variables to the regression, the number of countries drops to 109 (set 1), 99 (set 2), 98 (set 3) and 50 (set 4). Table B.1 shows the countries that are included in each of the regressions that include both poverty and inequality.

We next turn to a discussion of our results.

## 5 Results

In Table 3 we present the generalized method of moments estimates from cross-country regressions on our full sample of data using the approach of Arellano and Bond (1991). In the second column, we include only lagged gross domestic product per capita (GDPPC) and the Gini coefficient. In columns three through six, we progressively add those control variables which are typically used in the literature. (See the definition of Set 1 through Set 4 in Table 1.)

We find a negative effect of inequality on growth, but it seems fairly fragile. As we add additional control variables, its absolute size and statistical significance decreases. Based upon the regression with no controls, we can see that a one percentage point increase in the Gini coefficient results in a .183 percentage point decrease in the five-year average compound growth rate. When we add the investment to GDP ratio and years of schooling, this falls to -0.144. When we further add log population growth, this drops to -0.05. When we add price of investment and trade share of GDP, the coefficient falls to -0.03 and becomes insignificant. In the last column, when we add relative redistribution, there is a dramatic drop in sample size and inequality is again statistically significant.

We find a positive and significant effect of investment on growth. Years of schooling

is not statistically significant in these regressions. Log population growth is negative, as expected, but the t-value is only around 1.25.

In the model with no controls, the p-value of the Hansen test is very small indicating that we reject the null hypothesis of the exogeneity of the instruments. In the last two columns, the p-value for the Hansen test for exogeneity of the instruments approaches or equals one which is generally a sign of instrument proliferation, as discussed above. Only the models which control for investment to GDP ratio, years of schooling and population growth (with or without population growth) generate suitable values for the Hansen test. These two columns (set 1 and set 2) are thus our preferred models for this specification.

We also present the tests of Arellano and Bond (1991) for serial correlation in the first-differenced errors. There is no significant evidence of serial correlation at order two and three in the first-differenced errors for our preferred specifications.

Note that the number of instruments actually decreases when we add relative redistribution. The reason for this is that the number of years that we use in the data reduces as relative redistribution data is not available in the 1960s and early 1970s. As the number of years we use decreases, so does the instrument set.

In Appendix Table A.1 we present estimates of the simple model with no controls but using the same sample composition from the five columns of Table 3. Recall that sample size changes due to missing values in the explanatory variables. The estimate of the effect of inequality on economic growth are fairly consistent across all of the sample compositions except for the last column that includes relative redistribution.

The decreasing effect of inequality as we add additional control variables is caused by the additional explanatory variables picking up some of the explanatory power of inequality, not the changing sample composition. If anything, when we look at Appendix Table A.1, the effect of inequality seems stronger with the smaller sample sizes. We also

conclude that the restricted sample which we are forced to use when we include relative redistribution is very different than the other samples. In this case, the sample restriction seems to be contributing substantially to changed parameter estimates.

In Table 4 we present similar results except that we now add a control for poverty (measured as the percentage of people below the poverty line) and we interact poverty and inequality. Some care needs to be exercised in interpreting the coefficients in Table 4 as the coefficient on lagged GDP can no longer be viewed as a pure ‘convergence’ parameter since the correlation between poverty and GDP is quite high—around 84%. Correlation between poverty and inequality is 43% so the inclusion of poverty does provide additional information.

We have fewer observations because poverty data is missing for some countries. Looking at Table 4, we again prefer the models that control for investment to GDP ratio and years of schooling (with or without population growth, investment price and trade share of GDP) based upon the Hansen test. Looking at the columns labeled ‘Set 1’, ‘Set 2’ and ‘Set 3’, for example, we see strong evidence of convergence; lagged GDP is negative and poverty is positive. Inequality is statistically insignificant on its own, but the interaction between poverty and inequality is negative and statistically significant. Population growth is negative, but not quite statistically significant in these regressions. Investment and years of schooling both contribute positively to economic growth and are statistically significant.

In Figure 1 we plot the marginal effect of inequality on economic growth from the estimated coefficients of the column labeled ‘Set 2’ in Table 4. (This would be our preferred model.) The graph of marginal effects from the columns labeled ‘Set 1’ and ‘Set 3’ are quite similar.<sup>5</sup>

We can see that at low levels of poverty, inequality has an insignificant effect on

---

<sup>5</sup>Results available from the authors.



economic growth. When poverty is higher, the negative effect of inequality becomes statistically significant. The effect is statistically significant at the 10 per cent level at a poverty rate of 29% and significant at the 5 per cent level at poverty rates above 33%.

Table 3: The effect of inequality on growth

Variables	No controls	Set 1	Set 2	Set 3	Set 4
$\ln(GDP/PC)_{t-1}$	-0.0204 (0.446)	-0.348 (0.339)	-0.588* (0.318)	-0.654*** (0.249)	0.175 (0.555)
Gini coefficient	-0.183*** (0.0615)	-0.144** (0.0568)	-0.0501* (0.0281)	-0.0309 (0.0332)	-0.0842 (0.101)
Investment to GDP ratio		0.190*** (0.053)	0.197*** (0.0420)	0.168*** (0.0459)	0.251*** (0.0620)
Years of Schooling		-0.508 (0.673)	-0.0509 (0.521)	0.231 (0.401)	0.970 (1.59)
Log Population Growth			-0.341 (0.286)	-0.320 (0.225)	-0.295 (0.321)
Price of Investment				-0.00013 (0.00059)	-0.00767 (0.0232)
Trade share of GDP				0.0114*** (0.00290)	0.00093 (0.0046)
Relative redistribution					-0.123* (0.0707)
Sample size	950	823	760	755	347
Hansen test (p-value)	0.00	0.28	0.32	0.98	1.00
Number of instruments	36	72	89	125	105
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.00***	0.00***	0.00***	0.00***	0.03**
AR(2)	0.11	0.25	0.76	0.81	0.22
AR(3)	0.76	0.76	0.93	0.97	0.12

Dependent variable: 5-year average growth rate of GDP

GMM estimation with robust standard errors in parentheses

\*\*\*, \*\*, \* indicates significance at one, five and ten per cent respectively

All regressions include time dummies

Set 1: Investment to GDP ratio and log years of schooling

Set 2: Set 1 and log population growth

Set 3: Set 2 and price of investment and trade share of GDP

Set 4: Set 3 and relative redistribution

Table 4: The effect of inequality and poverty on growth

Variables	No controls	Set 1	Set 2	Set 3	Set 4
$\ln(GDPPC)_{t-1}$	-1.99*** (0.742)	-1.26*** (0.431)	-1.18** (0.568)	-1.14* (0.616)	-0.679 (0.662)
Gini coefficient	-0.136* (0.0760)	-0.0359 (0.0521)	0.00865 (0.0408)	0.00196 (0.0566)	0.0308 (0.129)
Poverty headcount	-0.0773 (0.132)	0.0238 (0.0519)	0.0605 (0.0497)	0.0764 (0.0614)	0.129 (0.0928)
Gini $\times$ Poverty	-0.00023 (0.0030)	-0.00123 (0.001116)	-0.00191** (0.00097)	-0.00231* (0.00130)	-0.00309 (0.00251)
Investment to GDP ratio		0.175*** (0.0496)	0.181*** (0.0476)	0.171*** (0.0421)	0.259*** (0.0592)
Years of Schooling		1.07* (0.606)	0.997* (0.604)	1.13** (0.555)	2.11 (1.67)
Log Population Growth			-0.323 (0.214)	-0.361 (0.266)	-0.614* (0.310)
Price of Investment				-0.0148 (0.0110)	-0.0104 (0.0152)
Trade share of GDP				0.00507 (0.00572)	-0.00315 (0.0103)
Relative redistribution					-0.0437 (0.0597)
Sample size	530	465	410	407	236
Hansen test (p-value)	0.02	0.20	0.44	0.41	1.00
Number of instruments	37	61	73	94	104
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.32	0.01**	0.00***	0.00***	0.00***
AR(2)	0.01***	0.02**	0.63	0.95	0.78
AR(3)	0.57	0.85	0.32	0.55	0.65

Dependent variable: 5-year average growth rate of GDP

GMM estimation with robust standard errors in parentheses

\*\*\*, \*\*, \* indicates significance at one, five and ten per cent respectively

All regressions include time dummies

Set 1: Investment to GDP ratio and log years of schooling

Set 2: Set 1 and log population growth

Set 3: Set 2 and price of investment and trade share of GDP

Set 4: Set 3 and relative redistribution

Countries such as South Africa, Bhutan and Guatemala have poverty rates around 29 per cent in 2011 and countries such as Tajikistan and Georgia have poverty rates around 33 per cent.

In Appendix Table A.2 we explore whether or not our results about inequality and poverty are driven by smaller sample sizes. This doesn't appear to be the case. If we estimate the simple model from Table 3 without controls we find that the effect of inequality on economic growth is statistically significant and roughly stable across all sample compositions that we consider. Results from Table 4 do not seem to be driven by the restricted sample of countries with available data on poverty.

Appendix Table A.3 examine the effect on the simple regression without controls of the varying sample sizes in Table 4 as we add more variables (and lose observations where data is missing). Looking at Table A.3, the coefficients for the simplest model from Table 4 are very stable across all sample compositions. The basic picture we get across the various sample sizes is consistent and the marginal effects are quite similar to those shown in Figure 1.

In the next sub-section, we expand the sample size we use by treating poverty as negligible in rich OECD countries to see whether this alters the results. We also re-estimate our model removing values for the Gini coefficient that have a high degree of uncertainty associated with them. The results don't change much.

## 5.1 Robustness checks

There are 136 country/year observations for wealthy OECD countries where poverty data is missing. In all of these countries, for years when we can observe the poverty rate, it is below 2 per cent. As a robustness check, we replace these missing poverty values with a value of zero which will be approximately correct given the observed values of poverty in the data.

Table C.1 presents the results from re-estimating Table 4 using this 'imputed' poverty

data. The results are broadly similar although statistical significance of the individual coefficients falls. Figure 2 provides the marginal effects from Table C.1. We find that the pattern of marginal effects is extremely similar. Inequality begins to have a statistically significant and negative impact on economic growth at slightly lower poverty rates—the marginal effects are statistically significant at the 10 per cent level at poverty rates of about 24 per cent and significant at the 5 per cent level for poverty rates about 28 per cent.

Some countries have inequality data which is poorly measured. We remove from the data any countries whose standard error of the Gini coefficient estimate is more than two standard deviations larger than the mean standard error of the Gini coefficient as measured across all of the country observations.

We re-estimate Table 4 without these suspect observations (and without the missing poverty values that had been replaced with zero in the previous robustness check) and report the results in Table C.2 and Figure 3. Inequality begins to have a statistically significant, negative effect on economic growth at a poverty rate of 36 per cent at the 10 per cent significance level.

The World Bank recently changed its definition of poverty, raising the daily income cut-off to \$3.10. We re-estimate our models using this definition of poverty. Our sample size changes slightly because there are fewer countries for which this new definition of poverty is available and the set of countries for which it is available is slightly different. The results of this investigation are presented in Figure 4.

The overall impression is similar, though we now find that inequality has a positive and statistically significant effect on economic growth for poverty rates below about 10 per cent. Russia and Turkey have poverty rates about 10 per cent using the \$3.10 per day measure. Inequality has a negative effect on economic growth at high poverty rates, above 60 per cent. This would be similar to the poverty rate in Honduras.

Note that in the sample which generates Figure 4, 98% of the countries have gross national income less than USD20,000 per day. It would appear that middle income countries with low poverty may benefit slightly from inequality using this definition. Given the smaller sample sizes, our preference is to exercise caution in pushing the interpretation of these results too far.

If we impute zero poverty values to wealthy OECD countries, we find that significance levels drop (as we did before) and the overall pattern is similar to the first 3 figures. These results are summarized in Figure 5.

Both Figure 4 and Figure 5 are based upon the model where we control for Investment to GDP ratio, Years of Schooling and Log Population Growth.

Our results do not seem to be driven by choice of sample size, by missing poverty data in rich countries, by poor quality inequality measurement or by choice of cut-off in defining poverty.

## 6 Conclusions

This paper offers new insights into the important relationship between inequality, poverty and economic growth. The central findings of this paper suggest that the proposition that inequality is harmful to economic growth on its own may be too strong. The results in this paper demonstrate that inequality interacts with high levels of poverty to negatively and significantly impact economic growth.

We find that when poverty is low (less than 25%), the relationship between inequality and economic growth is statistically insignificant. For higher levels of poverty, inequality negatively effects economic growth. This negative impact increases as poverty increases.

Our results, for the most part, do not suggest that inequality has a positive role to play in economic growth. There are a variety of reasons why countries might want to reduce inequality (and poverty) even if that has no impact on economic growth. These

reasons may include inequality's impact on social cohesion and long-term institutions.

The policy implication of this paper is that reducing inequality on its own may not improve economic growth prospects. Instead poor countries may find that reducing poverty would be more beneficial for economic growth rather than redistribution that does not reduce poverty.

## References

- Alesina, A. and Perotti, R. (1996). Income distribution, political instability and investment, *European Economic Review* **40**(6): 1203–1228.
- Arellano, M. and Bond, S. (1991). Some tests of specification for panel data: Monte carlo evidence and an application to employment equations, *Review of Economic Studies* **58**(2): 277–297.
- Azariadis, C. and Stachurski, J. (2005). Poverty traps, *Handbook of Economic Growth* **1**(1).
- Barro, R. and Lee, W. (2013). A new data set of educational attainment in the world, 1950–2010, *Journal of Development Economics* **104**: 184–198.
- Bond, S., Hoeffler, A. and Temple, J. (2001). GMM estimation of empirical growth models. CEPR Discussion Papers.
- Bowels, S., Durlauf, S. and Hoff, K. (2006). *Poverty Traps*, Russell Sage Foundation. Princeton University Press, Princeton, NJ.
- Cingano, F. (2014). Trends in income inequality and its impact on economic growth. OECD Social, Employment and Migration Working Papers, No. 163, OECD Publishing. <http://dx.doi.org/10.1787/5jxrjncwv6j-en>.
- Durlauf, S. N., Johnson, P. A. and Temple, J. (2005). Growth econometrics, *Handbook of economic growth* **1**: 555–677.
- Foellmi, R. and Zweimüller, J. (2006). Income distribution and demand-induced innovations, *The Review of Economic Studies* **73**: 941–960.
- Forbes, K. J. (2000). A reassessment of the relationship between inequality and growth, *American Economic Review* **90**(4): 869–887.
- Galor, O. and Moav, O. (2004). From physical to human capital accumulation: Inequality and the process of development, *The Review of Economic Studies* **71**: 1001–1026.
- Galor, O. and Zeira, J. (1993). Income distribution and macroeconomics, *The Review of Economic Studies* **60**: 35–52.
- Halter, D., Oechslin, M. and Zweimüller, J. (2014). Inequality and growth: the neglected time dimension, *Journal of Economic Growth* **19**((1)): 81–1044.
- Hansen, L. (1982). Large sample properties of generalized method of moments estimators, *Econometrica* **50**: 1029–1055.
- Heston, A., Summers, R. and Aten, B. (2011). *Penn World Table Version 7.0*, Center for International Comparisons of Production. Income and Prices at the University of Pennsylvania., Pennsylvania, USA.
- Lazear, E. P. and Rosen, S. (1979). Rank-order tournaments as optimum labor contracts, *Journal of Political Economy* **89**(5): 841–64.



- López, H. (2006). Does poverty matter for growth, in G. E. Perry, O. S. Arias, J. H. López, W. F. Maloney and L. Servén (eds), *Poverty reduction and growth: virtuous and vicious circles*, World Bank Publications, Washington, DC, chapter 6, pp. 103–128.
- López, H. and Servén, L. (2009). Too poor to grow. Policy Research working paper; no. WPS 5012. World Bank. <https://openknowledge.worldbank.org/handle/10986/4204>.
- Ostry, J., Berg, A. and Tsangarides, C. (2014). Redistribution, inequality, and growth. IMF Staff Discussion Note. February 2014. SDN/14/02. <https://www.imf.org/external/pubs/ft/sdn/2014/sdn1402.pdf>.
- Perkins, D. H., Radelet, S., Lindauer, D. L. and Block, S. A. (2012). *Economics of Development*, W.W. Norton, New York, NY.
- Perotti, R. (1996). Growth, income distribution, and democracy: what the data say, *Journal of Economic Growth* **1**(2): 149–187.
- Perry, G. (2006). *Poverty reduction and growth: virtuous and vicious circles*, World Bank Publications, Washington, DC.
- Ravallion, M. (2016). *The Economics of Poverty: History, Measurement, and Policy*, Oxford University Press, New York, NY.
- Roodman, D. (2009). How to do xtabond2: An introduction to difference and system GMM in Stata, *Stata Journal* **9**(1): 86–136(51).  
**URL:** <http://www.stata-journal.com/article.html?article=st0159>
- Rosenzweig, R. and Binswanger, P. (1992). *Wealth, weather risk, and the composition and profitability of agricultural investments*, World Bank Publications, Washington, DC.
- Sachs, J. (2005). *The End of Poverty: How We Can Make It Happen In Our Lifetime*, Penguin Group, London, UK.
- Solt, F. (2009). Standardizing the world income inequality database, *Social Science Quarterly* **90**: 231–242.
- Windmeijer, F. (2005). A finite sample correction for the variance of linear efficient two-step gmm estimators., *Journal of econometrics* **126**(1): 25–51.

## A Appendix: Effect of changing sample sizes

Table A.1: The effect of inequality on growth  
 Simple model with no controls  
 Effect of restricting sample size to sub-samples considered in Table 3

$\ln(GDPPC)_{t-1}$	-0.0204 (0.446)	-0.342 (0.476)	-0.748 (0.523)	-0.562 (0.493)	-0.551 (0.520)
Gini coefficient	-0.183*** (0.0615)	-0.275*** (0.0745)	-0.269*** (0.0941)	-0.246*** (0.0926)	-0.0639 (0.0595)
Sample size	950	823	760	755	347
Hansen test (p-value)	0.00	0.02	0.02	0.02	0.00
Number of instruments	36	36	36	36	24
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.00***	0.00***	0.00***	0.00***	0.00***
AR(2)	0.11	0.23	0.86	0.84	0.94
AR(3)	0.76	0.99	0.90	0.91	0.90

Dependent variable: 5-year average growth rate of GDP

GMM estimation with robust standard errors in parentheses

\*\*\*, \*\*, \* indicates significance at one, five and ten per cent respectively

Regressions include time dummies

Table A.2: The effect of inequality on growth  
Simple model with no controls  
Effect of restricting sample size to sub-samples considered in Table 4

$\ln(GDP)_{t-1}$	-0.0204 (0.446)	-0.612 (0.412)	-0.648 (0.483)	-0.570 (0.507)	-1.24** (0.564)
Gini coefficient	-0.183*** (0.0615)	-0.146** (0.0632)	-0.138* (0.0757)	-0.130* (0.0797)	-0.165** (0.0674)
Sample size	950	465	410	407	236
Hansen test (p-value)	0.00	0.00	0.00	0.00	0.02
Number of instruments	36	19	19	19	19
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.00***	0.17	0.12	0.10	0.00***
AR(2)	0.11	0.49	0.91	0.92	0.65
AR(3)	0.76	0.35	0.80	0.83	0.60

Dependent variable: 5-year average growth rate of GDP

GMM estimation with robust standard errors in parentheses

\*\*\*, \*\*, \* indicates significance at one, five and ten per cent respectively

Regressions include time dummies

Table A.3: The effect of inequality and poverty on growth  
Simple model with no controls  
Effect of restricting sample size to sub-samples considered in Table 4

$\ln(GDP)_{t-1}$	-1.99*** (0.742)	-1.56* (0.835)	-1.78* (0.935)	-1.83* (0.928)	-1.24 (0.823)
Gini coefficient	-0.136* (0.0760)	-0.113 (0.0704)	-0.121* (0.0715)	-0.124* (0.0724)	-0.130** (0.059)
Poverty headcount	-0.0773 (0.132)	0.0484 (0.104)	0.0405 (0.102)	0.0464 (0.104)	0.0347 (0.0736)
Gini $\times$ Poverty	-0.00023 (0.0030)	-0.00261 (0.00233)	-0.00235 (0.00207)	-0.00261 (0.00212)	-0.00032 (0.0020)
Sample size	530	465	410	407	236
Hansen test (p-value)	0.02	0.01	0.02	0.03	0.13
Number of instruments	37	37	37	37	37
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.32	0.02**	0.00***	0.00***	0.00***
AR(2)	0.01***	0.03**	0.97	0.98	0.79
AR(3)	0.57	0.54	0.62	0.65	0.50

Dependent variable: 5-year average growth rate of GDP

GMM estimation with robust standard errors in parentheses

\*\*\*, \*\*, \* indicates significance at one, five and ten per cent respectively

Regressions include time dummies

## B Appendix: Sample composition

Table B.1: Country list of sample composition for regression models

Baseline	Baseline & poverty variable	Baseline & poverty variable & set 1	Baseline & poverty variable & set 2*	Baseline & poverty variable & set 4
Albania	Albania	Albania	Argentina	Argentina
Angola	Angola	Argentina	Australia	Australia
Argentina	Argentina	Armenia	Austria	Austria
Armenia	Armenia	Australia	Bangladesh	Belgium
Australia	Australia	Austria	Belgium	Brazil
Austria	Austria	Bangladesh	Belize	Canada
Azerbaijan	Azerbaijan	Belgium	Benin	Chile
The Bahamas	Bangladesh	Belize	Bolivia	China
Bangladesh	Belarus	Benin	Botswana	Colombia
Barbados	Belgium	Bolivia	Brazil	Costa Rica
Belarus	Belize	Botswana	Burundi	Czech Republic
Belgium	Benin	Brazil	Cambodia	Denmark
Belize	Bhutan	Bulgaria	Cameroon	Dominican Republic
Benin	Bolivia	Burundi	Canada	El Salvador
Bhutan	Bosnia and Herzegovina	Cambodia	Central African Republic	Finland
Bolivia	Botswana	Cameroon	Chile	France
Bosnia and Herzegovina	Brazil	Canada	China	Germany
Botswana	Bulgaria	Central African Republic	Colombia	Greece
Brazil	Burkina Faso	Chile	Republic of Congo	Guatemala
Bulgaria	Burundi	China	Costa Rica	Honduras
Burkina Faso	Cambodia	Colombia	Cote d'Ivoire	Iceland
Burundi	Cameroon	Republic of Congo	Croatia	India
Cambodia	Canada	Costa Rica	Czech Republic	Ireland

Table B.1: Country list of sample composition for regression models (continued)

Baseline	Baseline & poverty variable	Baseline & poverty variable & set 1	Baseline & poverty variable & set 2*	Baseline & poverty variable & set 4
Cameroon	Central African Republic	Cote d'Ivoire	Denmark	Israel
Canada	Chad	Croatia	Dominican Republic	Italy
Central African Republic	Chile	Czech Republic	Ecuador	Kazakhstan
Chad	China	Denmark	"Egypt, Arab Rep."	Kenya
Chile	Colombia	Dominican Republic	El Salvador	Kyrgyz Republic
China	Comoros	Ecuador	Fiji	Mexico
Colombia	Republic of Congo	Egypt	Finland	Netherlands
Comoros	Costa Rica	El Salvador	France	Norway
Republic of Congo	Cote d'Ivoire	Estonia	Gabon	Panama
Costa Rica	Croatia	Fiji	Gambia	Paraguay
Cote d'Ivoire	Czech Republic	Finland	Germany	Philippines
Croatia	Denmark	France	Ghana	Poland
Cyprus	Djibouti	Gabon	Greece	Romania
Czech Republic	Dominican Republic	Gambia	Guatemala	Slovak Republic
Denmark	Ecuador	Germany	Honduras	Slovenia
Djibouti	Egypt	Ghana	Iceland	South Africa
Dominica	El Salvador	Greece	India	Spain
Dominican Republic	Estonia	Guatemala	Indonesia	Sri Lanka
Ecuador	Ethiopia	Honduras	Iran	Sweden
Egypt	Fiji	Hungary	Ireland	Switzerland
El Salvador	Finland	Iceland	Israel	Tajikistan
Estonia	France	India	Italy	Thailand
Ethiopia	Gabon	Indonesia	Jamaica	United Kingdom
Fiji	Gambia	Iran	Jordan	United States
Finland	Georgia	Ireland	Kazakhstan	Uruguay
France	Germany	Israel	Kenya	Venezuela, RB
Gabon	Ghana	Italy	Kyrgyz Republic	Vietnam
Gambia	Greece	Jamaica	Lao PDR	
Georgia	Guatemala	Japan	Lesotho	
Germany	Guinea	Jordan	Liberia	
Ghana	Guinea-Bissau	Kazakhstan	Malawi	
Greece	Honduras	Kenya	Malaysia	
Grenada	Hungary	Kyrgyz Republic	Maldives	
Guatemala	Iceland	Lao PDR	Mali	

Table B.1: Country list of sample composition for regression models (continued)

Baseline	Baseline & poverty variable	Baseline & poverty variable & set 1	Baseline & poverty variable & set 2*	Baseline & poverty variable & set 4
Guinea	India	Latvia	Mauritania	
Guinea-Bissau	Indonesia	Lesotho	Mauritius	
Honduras	Iran	Liberia	Mexico	
Hong Kong	Ireland	Lithuania	Morocco	
Hungary	Israel	Malawi	Mozambique	
Iceland	Italy	Malaysia	Namibia	
India	Jamaica	Maldives	Nepal	
Indonesia	Japan	Mali	Netherlands	
Iran	Jordan	Mauritania	Niger	
Ireland	Kazakhstan	Mauritius	Norway	
Israel	Kenya	Mexico	Pakistan	
Italy	Kyrgyz Republic	Morocco	Panama	
Jamaica	Lao PDR	Mozambique	Paraguay	
Japan	Latvia	Namibia	Peru	
Jordan	Lesotho	Nepal	Philippines	
Kazakhstan	Liberia	Netherlands	Poland	
Kenya	Lithuania	Niger	Romania	
Republic of Korea	Macedonia, FYR	Norway	Rwanda	
Kyrgyz Republic	Madagascar	Pakistan	Senegal	
Lao PDR	Malawi	Panama	Sierra Leone	
Latvia	Malaysia	Paraguay	Slovak Republic	
Lebanon	Maldives	Peru	Slovenia	
Lesotho	Mali	Philippines	South Africa	
Liberia	Mauritania	Poland	Spain	
Lithuania	Mauritius	Romania	Sri Lanka	
Luxembourg	Mexico	Russian Federation	Sudan	
Macedonia, FYR	Moldova	Rwanda	Swaziland	
Madagascar	Montenegro	Senegal	Sweden	
Malawi	Morocco	Sierra Leone	Switzerland	
Malaysia	Mozambique	Slovak Republic	Syrian Arab Republic	
Maldives	Namibia	Slovenia	Tajikistan	
Mali	Nepal	South Africa	Tanzania	
Malta	Netherlands	Spain	Thailand	
Mauritania	Niger	Sri Lanka	Togo	
Mauritius	Nigeria	Sudan	Trinidad and Tobago	
Mexico	Norway	Swaziland	Tunisia	
Moldova	Pakistan	Sweden	Turkey	

Table B.1: Country list of sample composition for regression models (continued)

Baseline	Baseline & poverty variable	Baseline & poverty variable & set 1	Baseline & poverty variable & set 2*	Baseline & poverty variable & set 4
Mongolia	Panama	Switzerland	Uganda	
Montenegro	Paraguay	Syrian Arab Republic	United Kingdom	
Morocco	Peru	Tajikistan	United States	
Mozambique	Philippines	Tanzania	Uruguay	
Namibia	Poland	Thailand	"Venezuela, RB"	
Nepal	Romania	Togo	Vietnam	
Netherlands	Russian Federation	Trinidad and Tobago	"Yemen, Rep."	
New Zealand	Rwanda	Tunisia	Zambia	
Niger	Sao Tome and Principe	Turkey		
Nigeria	Senegal	Uganda		
Norway	Serbia	Ukraine		
Pakistan	Sierra Leone	United Kingdom		
Panama	Slovak Republic	United States		
Paraguay	Slovenia	Uruguay		
Peru	South Africa	"Venezuela, RB"		
Philippines	Spain	Vietnam		
Poland	Sri Lanka	"Yemen, Rep."		
Portugal	St. Lucia	Zambia		
Romania	Sudan			
Russian Federation	Suriname			
Rwanda	Swaziland			
Sao Tome and Principe	Sweden			
Senegal	Switzerland			
Serbia	Syrian Arab Republic			
Sierra Leone	Tajikistan			
Singapore	Tanzania			
Slovak Republic	Thailand			
Slovenia	Togo			
South Africa	Trinidad and Tobago			
Spain	Tunisia			
Sri Lanka	Turkey			
St. Lucia	Turkmenistan			
St. Vincent and the Grenadines	Uganda			
Sudan	Ukraine			

Table B.1: Country list of sample composition for regression models (continued)

Baseline	Baseline & poverty variable	Baseline & poverty variable & set 1	Baseline & poverty variable & set 2*	Baseline & poverty variable & set 4
Suriname	United Kingdom			
Swaziland	United States			
Sweden	Uruguay			
Switzerland	Venezuela			
Syrian Arab Republic	Vietnam			
Tajikistan	Republic of Yemen			
Tanzania	Zambia			
Thailand				
Togo				
Trinidad and Tobago				
Tunisia				
Turkey				
Turkmenistan				
Uganda				
Ukraine				
United Kingdom				
United States				
Uruguay				
Uzbekistan				
Venezuela				
Vietnam				
Republic of Yemen				
Zambia				
Zimbabwe				

\*Set two and three are the same except for Namibia which gets dropped in set 3



## C Appendix: Robustness checks

Table C.1: The effect of inequality and poverty on growth  
Rich countries set to zero poverty

Variables	No controls	Set 1	Set 2	Set 3	Set 4
$\ln(GDPPC)_{t-1}$	-2.17*** (0.530)	-1.57*** (0.478)	-1.86*** (0.674)	-1.76*** (0.586)	-0.681 (0.768)
Gini coefficient	-0.0768 (0.0568)	-0.0448 (0.0458)	-0.0305 (0.0478)	-0.0513 (0.0445)	-0.0595 (0.0928)
Poverty headcount	-0.0326 (0.112)	0.0153 (0.0522)	0.0208 (0.0587)	0.0319 (0.0528)	0.0916 (0.101)
Gini $\times$ Poverty	-0.00158 (0.00267)	-0.00133 (0.00118)	-0.00148 (0.00114)	-0.00176 (0.00116)	-0.00235 (0.00260)
Investment to GDP ratio		0.204 *** (0.0509)	0.219 *** (0.0516)	0.194 *** (0.0418)	0.254 *** (0.0600)
Years of Schooling		1.10 ** (0.455)	1.07 ** (0.537)	1.07 * (0.616)	0.960 (1.59)
Log Population Growth			-0.403 (0.265)	-0.308 (0.221)	-0.190 (0.363)
Price of Investment				-0.0132 (0.00964)	-0.0132 (0.0152)
Trade share of GDP				0.00379 (0.00488)	-0.00080 (0.00855)
Relative redistribution					-0.0589 (0.0438)
Sample size	666	590	532	529	313
Hansen test (p-value)	0.07	0.60	0.91	1.00	1.00
Instruments	56	92	109	145	125
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.04**	0.00***	0.00***	0.00***	0.00***
AR(2)	0.02**	0.02**	0.58	0.98	0.59
AR(3)	0.48	0.51	0.45	0.79	0.50

See footnotes in Table C.2

Table C.2: The effect of inequality and poverty on growth  
Removing Gini coefficients with high standard errors

Variables	No controls	Set 1	Set 2	Set 3	Set 4
$\ln(GDP)_{t-1}$	-1.11 (0.790)	-1.16* (0.456)	-1.14* (0.665)	-0.605 (0.542)	-0.518 (0.660)
Gini coefficient	-0.0440 (0.0965)	0.0159 (0.0615)	0.0213 (0.0501)	0.0642 (0.0577)	0.172 (0.177)
Poverty headcount	0.00348 (0.112)	0.106 (0.0722)	0.0712 (0.0576)	0.130 ** (0.0618)	0.243* (0.126)
Gini $\times$ Poverty	-0.00174 (0.00266)	-0.00326* (0.00175)	-0.00229* (0.00118)	-0.00335** (0.00132)	-0.00592* (0.00349)
Investment to GDP ratio		0.192 *** (0.0535)	0.205 *** (0.0468)	0.182 *** (0.0441)	0.274 *** (0.0693)
Years of Schooling		1.33 * (0.683)	0.716 (0.737)	0.831 (0.596)	2.11 (1.43)
Log Population Growth			-0.363 (0.286)	-0.410 (0.261)	-0.689** (0.297)
Price of Investment				-0.0154 (0.0122)	-0.0121 (0.0146)
Trade share of GDP				0.00003 (0.00582)	0.00745 (0.00902)
Relative redistribution					0.0172 (0.0971)
Sample size	472	423	371	370	229
Hansen test (p-value)	0.02	0.16	0.53	0.72	1.00
Number of instruments	37	61	72	92	102
Serial correlation tests (p-values) for AR(p) in first differences:					
AR(1)	0.21	0.05**	0.00***	0.00***	0.00***
AR(2)	0.01**	0.02**	0.35	0.90	0.69
AR(3)	0.28	0.58	0.15	0.27	0.50

Dependent variable: 5-year average growth rate of GDP

GMM estimation with robust standard errors in parentheses

\*\*\*, \*\*, \* indicates significance at one, five and ten per cent respectively

All regressions include time dummies

Set 1: Investment to GDP ratio and log years of schooling

Set 2: Set 1 and log population growth

Set 3: Set 2 and price of investment and trade share of GDP

Set 4: Set 3 and relative redistribution

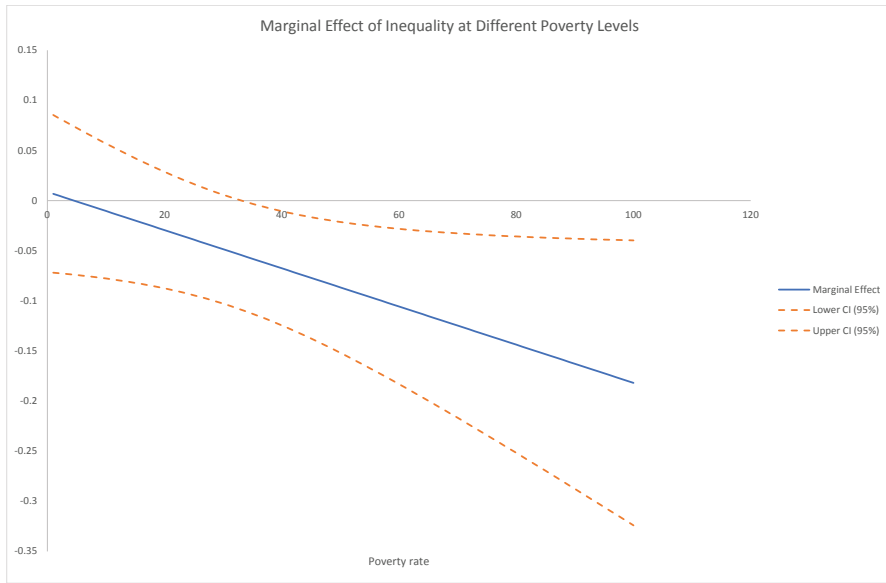


Figure 1: Marginal effect of inequality on economic growth at different levels of poverty Based upon parameter estimates of column 3 of Table 4.

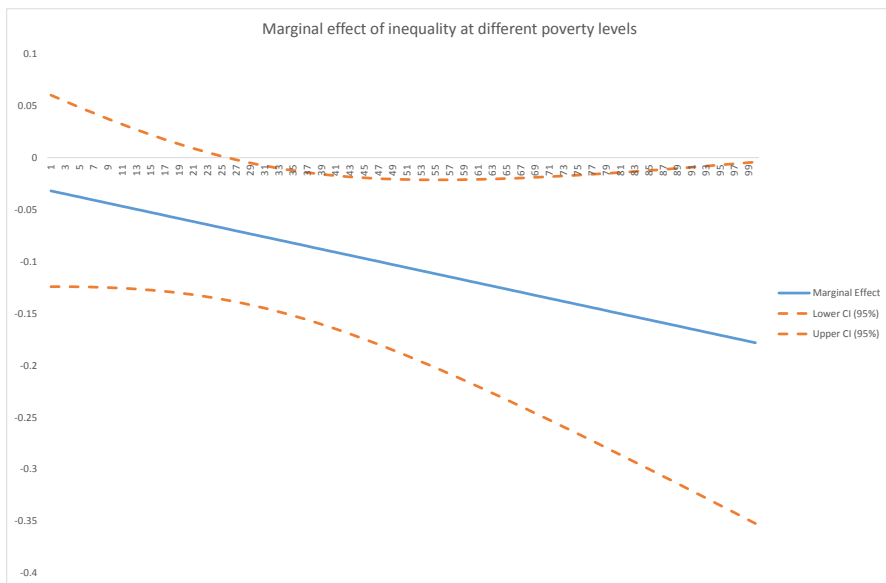


Figure 2: Marginal effect of inequality on economic growth at different levels of poverty Based upon parameter estimates of column 3 of Table C.1.

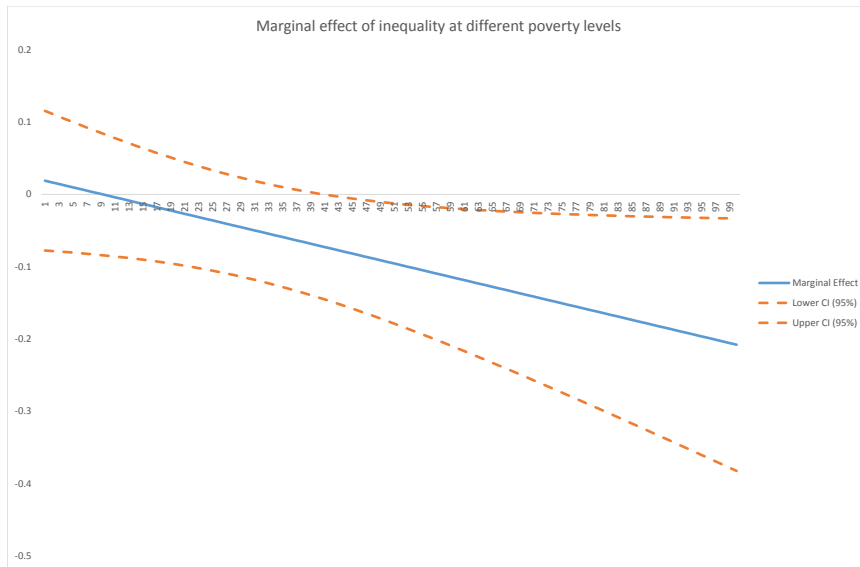


Figure 3: Marginal effect of inequality on economic growth at different levels of poverty Based upon parameter estimates of column 3 of Table C.2.

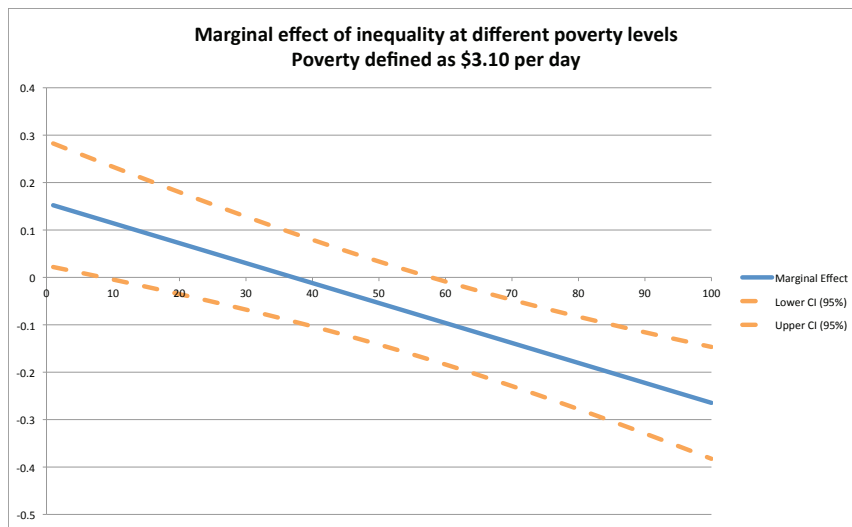


Figure 4: Marginal effect of inequality on economic growth at different levels of poverty Based upon \$3.10 per day definition of poverty Controls for investment, years of schooling and population growth

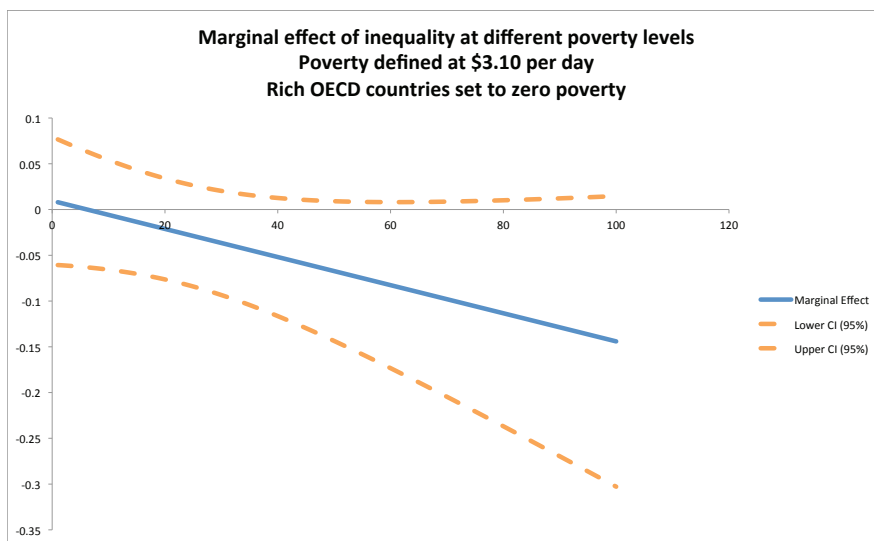


Figure 5: Marginal effect of inequality on economic growth at different levels of poverty  
 Based upon \$3.10 per day definition of poverty (rich country poverty set to 0)  
 Controls for investment, years of schooling and population growth