# Inequality, poverty and economic growth

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**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.
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## 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.

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# 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. Researchers have argued that inequality may result in under-investment in education, health and physical capital leading to lower growth. Such under-investment seems to us to be a result of a lack of resources, rather than inequality, per se. This argues for looking at poverty as an additional channel which may hinder economic growth

Poverty and inequality may also interact to have a negative impact on growth. As Stiglitz (2013) and others have argued, inequality can undermine the institutions that spread well-being to all members of society.

Economic growth regressions which control for average incomes and inequality, but not for poverty, may fail to capture disadvantage that harms growth. By adding information about poverty, we also control 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. Ravallion (2001) examines the micro data and shows that the inequality, growth and poverty relationship is quite complicated. Although we use macro data, we are in part taking up his call for for deeper empirical work on growth and distributional change.

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 incidence 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. This is suggestive that poverty-reduction policies might be more useful for promoting growth than simply 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) analyze 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; see 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 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, resulting in a less productive workforce. 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 in perpetuating poverty traps. López and Servén (2009) empirically show that higher levels of initial poverty reduce 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, inequality and their interaction.

# 3 Model and Estimation

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

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

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),

Table 1: Different combinations of determinants of growth (**X**) used in empirical specification

| **Variables** | **Set 1** | **Set 2** | **Set 3** | **Set 4** |
|---|---|---|---|---|
| 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 |

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 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 the case for inequality, poverty and education as 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.[1]

We use one lag of the internal instruments in all the estimates we report. Our 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 exogoneity 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 (2005) correction as well as the Roodman (2009) small-sample correction.

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.[2] 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

[1]Throughout, results that are mentioned but not presented in detail are available from authors.

[2]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.

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 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).[3] 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.[4]

'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

[3]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.

[4]The SWIID data is not without its problems, one being comparabilitiy across countries; see Alvaredo and Gasparini (2015)) It does however provide the largest, most comparable available data set for inequality research and is widely used in our reference literature. For comparability with other studies, we use this data set as provided without trying to address these problems in this paper. We do address the uncertainty in the data, as described in section 5.1 below.

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 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.

An alternative would be to use individual country poverty lines. These vary across countries dramatically and often for political reasons that do not solely reflect differences in income levels. Many country-specific poverty lines are based on relative measures so are actually measuing inequality as much as they measure poverty. We also think that individual country poverty lines are inappropriate for cross-country comparisons. Perry (2006) also uses these World Bank poverty lines.

Our data and key definitions are summarized in Table 2.

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.[5] 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

[5]OECD countries with Gross National Income above USD20,000.

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[a] 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[b]; 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 |

[a]Inequality (Gini) calculated before taxes and transfers is called market inequality.
[b]Calculated over country sample of column 3 of Table B.1, which avoids countries like Zimbabwe that experienced hyperinflation.

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 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, inequality is again statistically significant.

The results of Ostry et al. (2014) and Cingano (2014) appear to be quite dependent upon the set of control variables that are used. The addition of relative redistribution causes a large drop in sample size; we incude it for comparison with Ostry et al. (2014).

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 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.

Table 3: The effect of inequality on growth

| **Variables** | **No controls** | **Set 1** | **Set 2** | **Set 3** | **Set 4** |
|---|---|---|---|---|---|
| $ln(GDPPC)_{t-1}$ | $-0.0204$ (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

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.[6]

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

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

[6]Results available from the authors.

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.

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# 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

| | | | | | |
|---|---|---|---|---|---|
| $ln(GDPPC)_{t-1}$ | $-0.0204$ (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

| | | | | | |
|---|---|---|---|---|---|
| $ln(GDPPC)_{t-1}$ | $-1.99^{***}$ (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 × 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** |
|---|---|---|---|---|---|
| $ln(GDPPC)_{t-1}$ | $-1.11$ (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 × 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

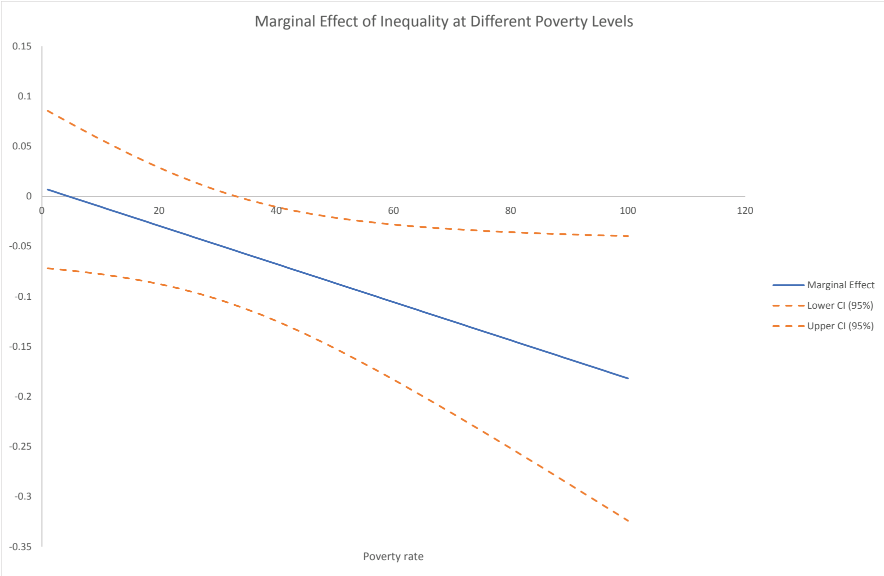


Figure 1: Marginal effect of inequality on economic growth at different levels of poverty Based upon parameter estimates of column 3 of Table 4.

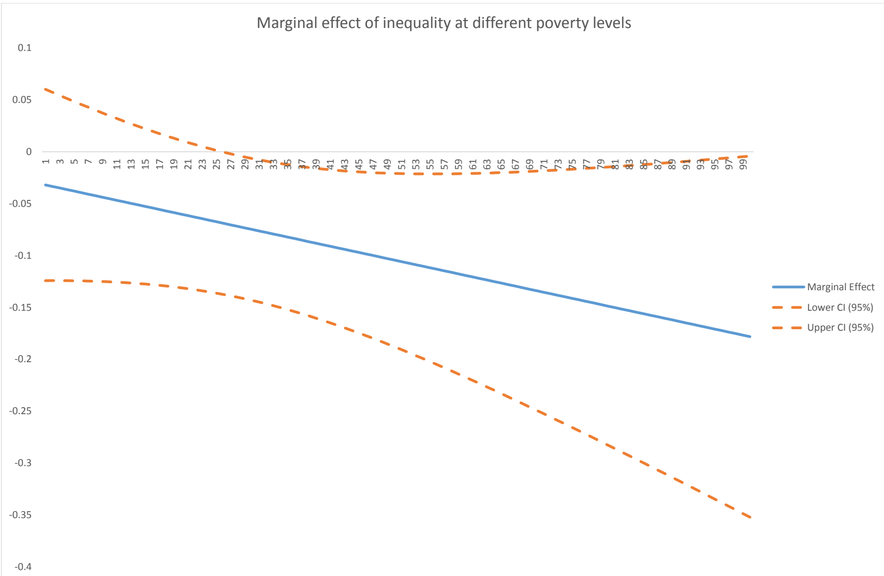


Figure 2: Marginal effect of inequality on economic growth at different levels of poverty Based upon parameter estimates of column 3 of Table C.1.


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.

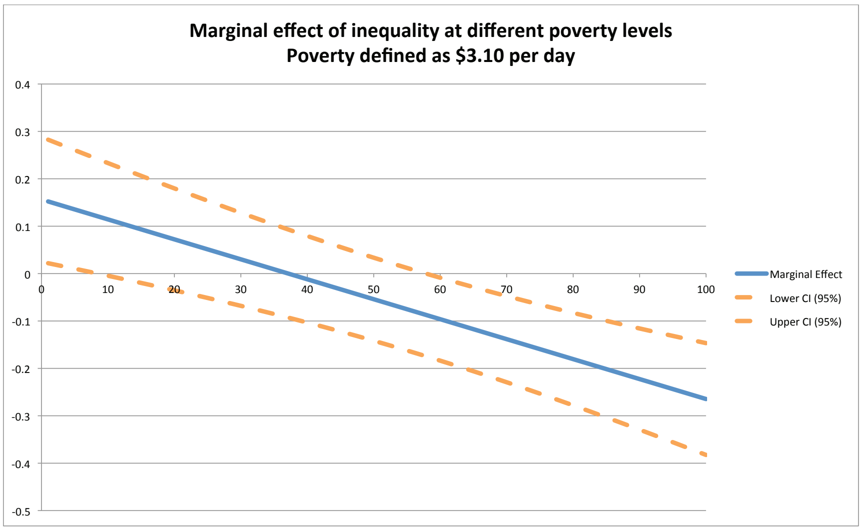


Figure 4: Marginal effect of inequality on economic growth at different levels of poverty
Based upon $3.10 per day definition of poverty
Controls for investment, years of schooling and population growth

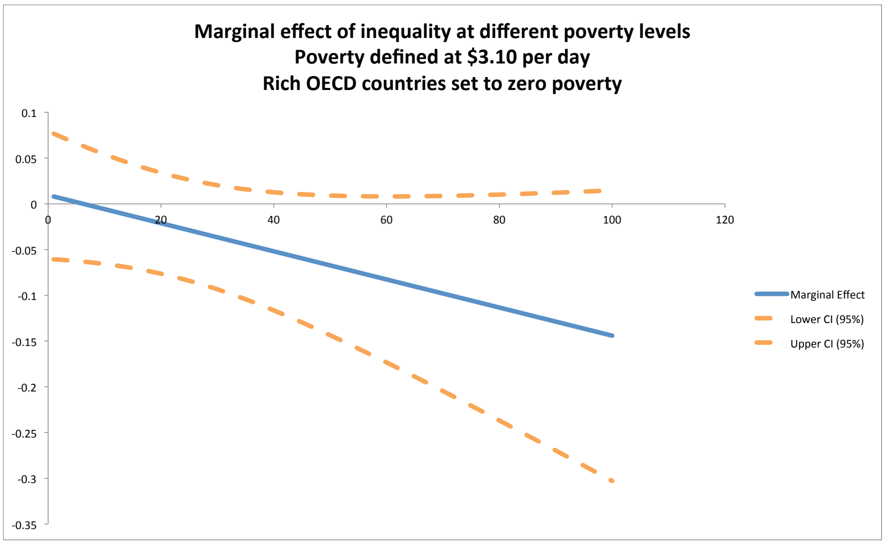


Figure 5: Marginal effect of inequality on economic growth at different levels of poverty
Based upon $3.10 per day definition of poverty (rich country poverty set to 0)
Controls for investment, years of schooling and population growth