Institut der deutschen Wirtschaft Köln

IW-Report · 7/2016

The Inequality-Growth Relationship
An Empirical Reassessment

Working Paper Version

Autoren:

Galina Kolev
Telefon: 0221 4981-774
E-Mail: kolev@iwkoeln.de

Judith Niehues
Telefon: 0221 4981-768
E-Mail: niehues@iwkoeln.de

17. März 2016

© Institut der deutschen Wirtschaft Köln
Postfach 101942 · 50459 Köln
Konrad-Adenauer-Ufer 21 · 50668 Köln
www.iwkoeln.de
Nachdruck erlaubt

iw.KÖLN.WISSEN SCHAFFT KOMPETENZ.

Agenda

Abstract

Recently, some influential empirical studies found evidence in favour of a negative relationship between income inequality and economic growth, implying the conclusion that inequality reducing policies will foster economic growth. The studies have in common that they all rely on the System GMM dynamic panel estimator. We argue that this estimator is most likely to suffer from a severe weak instrument problem in the inequality-growth setting because lagged differences of inequality have practically no explanatory power for current inequality levels. Thus, it is biased in the direction of OLS and fails to control for country heterogeneity. Using traditional Fixed Effects models or Difference GMM estimators yields positive coefficients on the inequality variable. Furthermore, we find evidence for a nonlinear relationship between inequality and growth when considering a sample of developed and developing economies. Thus, the effect of net income inequality on growth seems to be negative only for less-developed countries and for countries with high levels of inequality, and non-significant or rather positive otherwise.

Keywords: Inequality, Economic Growth, Redistribution, System GMM

JEL-Codes: O15, O47, H23

I Introduction

The relationship between income inequality and economic growth has generated much debate among social scientists and policy makers. From a theoretical perspective, inequality can affect economic growth in various ways, both beneficial and harmful. In line with this, empirical studies which tested the inequality-growth relationship found quite differing results. One likewise robust and plausible finding reveals that negative effects from inequality on growth are more likely to be found in developing countries since constraints to human capital accumulation are more severe in those countries. Furthermore, Barro (2000) points out that growth-promoting aspects of inequality may be more relevant in richer economies.

Beyond the role of the level of economic development, Neves et al. (2016) show that the direction of effects also follows a certain time pattern: In the 1990s, when the literature on the relationship between inequality and economic growth began to emerge, most of the published studies found negative effects. At the beginning of this century, this tendency was reversed and empirical studies increasingly documented positive results. Recently, some prominent studies from the OECD (Cingano, 2014) and the IMF (Ostry et al., 2014) gained public and media attention by saying that inequality affects growth negatively whereas redistributive intervention does not necessarily reveal any harmful effects on economic growth. Neves et al. (2016) attribute this time pattern of reported effects to an *"economics research cycle"*, which mirrors the direction of predicted effects of the contemporaneous theoretical literature.

The more recent studies on the relationship between income inequality and growth all have in common that they apply the System GMM estimator developed by Blundell and Bond (1998). This estimator is an extension of the original (First) Difference GMM estimator (Arellano/Bond, 1991), which instruments first differences with lagged levels of the respective variables to overcome the dynamic panel bias. However, in the case of highly persistent variables, lagged levels may be weak instruments and Difference GMM will perform poorly in these settings. The System GMM estimator additionally instruments levels with past changes of the variables – thus, the instruments may be more relevant. Identification thus crucially relies on the lagged first differences having some explanatory power for current levels.

Using a dynamic panel approach we empirically reassess the relationship between income inequality and economic growth in both, OECD countries and a set of developed and developing countries. Specifically, we focus on the appropriateness of the estimation methods with regard to instrument validity and the influence of country-specific effects such as the level of economic development. We show that in the case of income inequality, lagged differences have barely any explanatory power for the levels equation of inequality, implying that the estimated coefficients are severely biased. We further reveal that the surprisingly negative effect of income inequality in a setting of mostly developed OECD countries is probably driven by the specific situation of the post-communist countries which are characterized by comparatively low average inequality levels given their state of economic development. This further suggests that System GMM fails to fully control for country-specific effects. Finally we provide evidence for a nonlinear impact of inequality when considering a sample of developed and developing countries. The effect of net income inequality on growth seems to be negative only for less-developed countries as well as for countries with high levels of inequality. The negative effect diminishes and becomes even positive for high income levels as well as for low levels of initial inequality.

The setup of the paper is organized as follows: In Section 2 we provide a brief review of the literature and discuss how inequality can influence growth. Section 3 describes the data and section 4 the estimation approach. Section 5 presents the results and Section 6 concludes by summarizing the main findings.

II Literature Review and Theoretical Mechanisms

The discussion in the theoretical and empirical literature thus far has suggested different channels for the relationship between inequality and economic growth. The main channel assuming negative effects of inequality on growth refers to the interconnection between inequality and education level on the one hand and the effect of education on economic growth on the other hand. Generally, inequality may harm growth if it obstructs the access to education or if it leads to lower average health status of the population (Perotti, 1996, Galor and Moav, 2004). Galor and Zeira (1993, 1998) refer to this argument as the “human capital accumulation” theory. Furthermore, inequality may impair political and economic stability and thus reduce the attractiveness of the economy for investment (Alesina and Perotti, 1996). In addition, Rodrik (1999) points out that inequality impedes the social consensus needed to have the flexibility to adjust to shocks and sustain growth. Last but not least, inequality may harm economic growth if it motivates the political actors to implement further redistribution measures, since generally redistribution hurts growth (Okun, 1975). According to the endogenous fiscal policy theory, greater inequality may become unacceptable to voters so their preferences move towards higher taxation and redistribution and away from pro-business policies (Bertola, 1993, Alexina and Rodrick, 1994, Perotti, 1996).

However, inequality may also have a positive impact on economic growth as it provides incentives for innovation and entrepreneurship (Lazear and Rosen, 1981). If the rates of return on investment – e.g., in education – are high, then inequality may motivate more people to seek education. Moreover, savings rates tend to be higher in upper income classes, meaning that in more unequal societies saving and investment and thus economic growth should be higher, *ceteris paribus* (Kaldor, 1957). In less developed countries there is an additional argument for the positive effect of inequality on economic growth. Higher inequality could boost economic growth since it allows at least a few individuals to accumulate the minimum income needed to achieve good education or to start a business (Barro, 2000).

The first set of significant empirical research analyzing the growth-inequality nexus dates back to the 1990s, where a bulk of studies estimated the effect of inequality, usually measured as the Gini coefficient, in a reduced-form growth equation using cross-section data from a relatively large number of countries (Alesina and Rodrik, 1994, Clarke, 1995, Perotti, 1996, Persson and Tabellini, 1994). The studies account for possible reverse causation by using growth rate of per capita GDP over a period of 20-30 years as dependent variable and the value for the inequality variable at the beginning of the period under consideration. The estimated coefficient of inequality is mostly negative. Persson and Tabellini (1994) and Perotti (1996) also investigate regional effects on the growth-inequality relationship and find that the coefficient becomes insignificant after including regional dummies into the regression.

The main challenge of the early studies on the relationship between inequality and economic growth consisted in the data scarcity and the quality of the available data on inequality. Deininger and Squire (1996) assembled a high-quality dataset on income distribution which was used in subsequent studies. As a result, a branch of empirical literature emerged where the reduced form equation was estimated using panel data (Li and Zou, 1998, Forbes, 2000, Barro, 2000, Deininger and Olinto, 2000). The studies analyzed the effect of inequality on economic growth in the following five-year period. Several studies delivered evidence of a positive coefficient of inequality in the growth regression (Li and Zou, 1998, Forbes, 2000). The analysis by Barro (2000) further showed that the coefficient of the relationship may vary depending on the level of development of the countries used in the dataset. Barro (2000) points out that the relationship between growth and inequality is negative in poor countries, positive in developed countries, and insignificant when both groups are pooled together in the empirical analysis. His study stresses the importance of accounting for the level of development of the economies used for the empirical analysis and explains why several studies could not deliver significant coefficients apparently due to this omitted variable bias, respectively misspecification. Pooling countries with very heterogeneous levels of development together and not accounting for a possible interaction between the level of development and inequality means estimating an average effect over all countries which would not be significantly different from zero if the effect is negative in less developed economies and positive in developed countries. This is a major drawback of most of the empirical analyses thus far.

Especially when using the human capital accumulation theory to motivate the possible negative effect of inequality on economic growth, it is very likely to find nonlinearities in the estimated relationship. The access to a certain minimum of education is limited for the population in less developed economies and depends on economic conditions, e.g., in terms of inequality. In developed countries, on the contrary, primary and even secondary education is mostly affordable even for the lower income classes. Therefore, the effect of inequality on economic growth may be negative in less developed countries, decreasing in absolute terms with the level of development and even becoming positive in high-income countries. The operationalization of this nonlinear relationship in the empirical analysis can be achieved, e.g., by including an interaction term between the initial level of GDP per capita and the inequality variable in the growth regressions (see below).

Furthermore, it is also possible to have a nonlinear relationship between inequality and economic growth depending on the level of inequality. For low levels of inequality there should not be any negative effect of increasing inequality on growth since it is unlikely that increasing inequality would lead to social unrest or shifting preferences towards more redistribution. If inequality is high, on the contrary, the coefficient may become negative. This type of nonlinearity can be captured by including a quadratic term of the inequality variable into the regression equation (see below). Apart from Barro (2000), the (non-)linearity of the relationship between inequality and economic growth was questioned in the analyses by Chen (2003) and Banerjee and Duflo (2003). The authors account for the level of inequality and for the changes in inequality as possible factors that could affect the estimated coefficient. Chen (2003) finds a statistically significant quadratic term in the regression analysis pointing toward an inverted U-shaped relationship between inequality and economic growth. Banerjee and Duflo (2003) point out that changes in the inequality variable are associated with lower growth in the short run, independent of the direction of these changes. Halter et al. (2014) investigate the effect of inequality on economic growth for different time horizons. Their results show that the effect of inequality on economic growth is positive in the short-run, defined as the following five years. In the medium to long-run on the contrary, defined as the five-year period beginning five years later, the effect becomes negative.

There is also a range of empirical papers using alternative measures of inequality. Voitchovsky (2005) shows for instance that the effect of top end inequality on economic growth is positive whereas bottom end inequality seems to be growth-harming. The same type of inequality effects on economic growth were also analyzed in an influential paper by the Organization for Economic Cooperation and Development (OECD) which reinforced the discussion on the inequality-growth nexus in 2014 (Cingano, 2014). Using the System GMM estimation technique the author investigates the relationship between economic growth and inequality for data covering most of the OECD countries over the past 30 years. The estimated coefficient of different inequality measures in the growth equation are negative and statistically significant. Cingano (2014) further evaluates the human capital accumulation theory and delivers evidence for human capital being a channel through which inequality may affect economic growth. Especially the gap between low income households and the rest of the population seems to be an important factor for economic growth, as increased income disparities depress skills development among individuals with poorer parental education background. On the other side, no evidence is found for an effect of the gap between high income households and the rest of the population on economic growth and educational outcomes.

A further politically influential study on the growth-inequality nexus came in 2014 from the research series of the International Monetary Funds (IMF). The authors analyze both growth over five-year horizons and the duration of growth spells in panel growth regressions and show that lower net inequality is correlated with faster and more durable growth (Ostry et al., 2014). They estimate a System GMM panel regression with more than 800 observations in the baseline. In a further regression, they control also for the impact of institutions as well as that of basic growth determinants such as education and investment to check for the robustness of the estimated coefficient. The estimated coefficient of net inequality ranges between -0.1435 and -0.0739. However, the analysis indicates that more unequal societies tend to redistribute more and that redistribution seems to harm economic growth.

Dominicis et al. (2008) and Neves et al. (2016) conduct a meta-analytic reassessment of the effects of inequality on growth. Dominicis et al. (2008) point out that the magnitude of the estimated effect of inequality on growth in the literature depends crucially on the estimation method, data quality and sample coverage. Overall, the results of the meta-analysis show that the effect tends to be negative and more pronounced in less developed countries. However, the effect becomes considerably weaker when regional dummies and additional measures of inequality are added. Regarding the methodology, Dominicis et al. (2008) stress that studies using fixed effects estimators seem to report stronger effect of inequality on economic growth.

Neves et al. (2016) extend the meta-analytic reassessment to more recent studies and show that the empirical literature on the inequality-growth nexus is biased towards statistically significant results. As the authors stress, this makes the empirical effect of inequality on economic growth seem larger in absolute terms than it actually is. Their analysis includes only papers published in peer-reviewed journals and corroborates Dominicis et al.'s (2008) findings that the effect of inequality on economic growth is more pronounced in developing countries and weaker when regional dummies are included. Furthermore, Neves et al. (2016) point out that the effect is negative and stronger in cross-section studies than in panel studies. In the estimations included in their meta-analysis the effect size estimates vary between a minimum of -0.135 (Knowles, 2005) and a maximum of 0.156 (Banergee and Duflo, 2003), with 36 negative and 13 positive coefficients. Neves et al. (2016) compute the average of the effect size using two commonly used estimators in meta-analyses. According to their calculation, the average effect of inequality on economic growth lies between -0.0145 and -0.0111. The authors conclude that the average impact of inequality on growth is "negative and statistically significant, but not economically meaningful" (Neves et al., 2016, p. 390). The average of the estimates implies that a substantial increase of 10 percentage points in the Gini coefficient reduces average annual growth rate by only 0.111 to 0.145 percentage points. However, a closer look at the data reveals that there are only few countries where inequality increased by 10 percentage points or more in the period 1990-2010 (Table 1). Using the estimates by Neves et al. (2016), Table 1 shows the effect of inequality changes on average annual economic growth in a range of countries for 1990-2010. The last column indicates that the effect of rising inequality on economic growth is negligible in most of the reported countries. In Germany for instance, increasing inequality from 25.6 to 28.6 was associated with a decline in economic growth by 0.04 percentage points per annum.

The small effects of inequality changes on growth reported in Table 1 indicate that the recent political debate lacks in empirical foundation. The debate was reinforced by results presented in the OECD study by Cingano (2014) showing that increasing inequality costs about 6 percent cumulative growth of GDP per capita in countries like Germany and the US over the period 1990 to 2010. The author calls for a shift in policy making towards more redistribution as a way not only to reduce inequality but also to increase economic growth. However, in the light of the summarized results of the recent empirical analyses on the growth-inequality nexus (cf. Neves et al., 2016), the reported effects seem widely overstated. In addition, this effect is an average effect and does not account for the level of development of the particular country or for the initial level of inequality.

Table 1:
Estimated effect of inequality changes 1990-2010 on economic growth

Country	Gini 1990	Gini 2010	Increase in inequality	Effect on average annual growth rate
Australia	31.3	33.3	2.0	0.03
Austria	25.4	28.4	3.0	0.04
Brazil	52.5	45.9	-6.6	-0.08
Canada	27.7	31.7	4.0	0.05
Switzerland	27.5	30.0	2.5	0.03
China	33.5	53.6	20.1	0.26
Germany	25.6	28.6	3.0	0.04
Spain	30.2	33.4	3.2	0.04
Finland	20.9	26.0	5.1	0.07
France	28.2	30.2	2.0	0.03
UK	33.1	35.7	2.6	0.03
India	45.2	51.4	6.2	0.08
Italy	30.8	32.7	1.9	0.02
Japan	27.3	30.9	3.6	0.05
Mexico	45.9	43.5	-2.4	-0.03
Norway	23.3	24.3	1.0	0.01
Russia	23.3	40.2	16.9	0.22
Sweden	18.0	23.8	5.8	0.07
USA	33.3	37.3	4.0	0.05

Percentage points; Gini refers to inequality in net income; The effect on growth is calculated using the average of the two estimates from Neves et al. (2016) amounting to 0.0128. For Germany we replace SWIID-data by Ginis from the OECD Income Distribution Database because they suggest a higher increase in income inequality over the observation period.

Source: SWIID, OECD-IDD, PWT 8.1

The importance of the level of development is highlighted by some recent estimations of the inequality-growth relationship by the German Council of Economic Experts (2015) in their Annual Economic Report 2015/16. They found that in high income countries (GDP per capita of at least 15,000 US $, in prices of 2005), in 69 percent out of 150 different System GMM specifications, the coefficient of inequality on growth turns out to be positive (larger than 0.05). When additionally controlling for human capital and investments, this increases to 87 percent out of 150 estimations. Rather the opposite is true for the estimates based on a more heterogeneous country sample. However, they conclude that the “wide range of statistically largely insignificant results highlights the unsuitability of this method for assessing the matter in question” (p. 238). Therefore, it remains questionable if the estimation technique used in recent empirical work should be applied in the context of the relationship between inequality and economic growth. This topic is further investigated in the present paper.

III Data

In the empirical part we estimate the effect of inequality on economic growth in a panel regression framework. In the first step, we try to check the robustness and find explanations for the negative effect of increasing inequality on growth found for OECD countries (see, e.g., Cingano, 2014). Therefore, the first data set used in our empirical analysis covers the OECD countries. It roughly replicates the setting of the OECD Working Paper by using a time period from 1970-2010 and growth of GDP per capita over periods of (non-overlapping) five years as dependent variable. Data on GDP per capita is from the OECD Annual National Accounts and measured in international dollar at constant prices (reference year 2010). Data on Gini coefficients of net income inequality stem from SWIID (Solt, 2014) because it offers Gini coefficients on a broad set of countries over a relatively long time horizon. Obviously, there might be a number of issues about the quality and comparability of inequality measures across countries and time. However, Neves et al. (2016) point out in their meta-analysis that “using or not high-quality data does not make a big difference in the estimation of the inequality-growth effect” (p. 396). In addition, SWIID-data are readily available, thus making the analysis easily replicable.

Since SWIID does not provide inequality data for Korea, this leaves us with a total of 33 OECD countries in our regressions. The further control variables such as human capital and capital formation as percent of GDP are taken from the Penn World Tables (PWT 8.1, Feenstra et al., 2015). The only reason why we did not run the baseline regressions with GDP per capita from PWT (which would allow for more observations) is that we were not able to find any significant negative effects for the inequality coefficient. The same reasoning holds for using Gini coefficients from SWIID instead of inequality data from the OECD Income Inequality Database. However, as mentioned above we replace SWIID-Gini coefficients in the case of Germany because the Gini coefficients provided from the OECD reflect a higher increase in inequality and a slightly different time trend. This replacement is hardly associated with any changes in the regression results. Data on top income tax rates and the measures of the progression of the income tax system stem from the World Tax Indicators provided by the Andrew of the Young School of Policy Studies (2010) and cover a time period from 1980-2005. Descriptive statistics of all variables are illustrated in table 2. The Gini coefficient of net income inequality ranges from 0.18 in

Sweden (1990) to 0.557 in Mexico (1975), thus representing a wide range of inequality levels in OECD countries. GDP per capita shows its lowest level of 10,145 US $ in Mexico; its highest value of 84,440 US $ can be found in Luxembourg.

Table 2: Summary statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
a) OECD sample					
Gini coefficient net income	205	0.300	0.066	0.180	0.557
GDP per capita (US $, 2010 prices)	205	29,583	11,874	10,145	84,440
Economic growth (five-year period)	205	0.106	0.080	-0.053	0.425
Total taxes / GDP	201	0.335	0.075	0.149	0.495
Toprate (income tax)	134	0.432	0.138	0.115	0.720
Average income tax progression	132	0.074	0.026	0.007	0.131
Marginal income tax progression	132	0.080	0.028	0.007	0.140
Human capital index	205	2.871	0.385	1.735	3.619
Gross capital formation / GDP	205	0.254	0.053	0.126	0.499
b) Extended sample					
Gini coefficient net income	682	0.370	0.101	0.176	0.682
GDP per capita (US $, 2005 prices)	682	10,764	10,216	528	70,252
Economic growth (five-year period)	682	0.130	0.189	-1.144	1.045
Human capital index	682	2.334	0.584	1.052	3.575
Gross capital formation / GDP	682	0.215	0.088	0.017	0.591

Source: a) OECD sample: Gini: OECD, SWIID; GDP, total taxes: OECD; Human capital index, Gross capital formation: Penn World Table 8.1 (Feenstra et al., 2015); Tax indicators: Andrew Young School World Tax Indicators; b) Extended sample: Gini: SWIID; GDP, Human capital index, Gross capital formation: PWT 8.1

In the second step we test for possible nonlinear effects of inequality on economic growth. For this exercise we extend the panel data set to cover a total of 113 countries over the time span 1950-2010. Again, growth of GDP per capita over a period of (non-overlapping) five years is the dependent variable in the regression equation. Data on GDP, human capital and share of investment in GDP stems from the Penn World Tables (PWT 8.1, Feenstra et al., 2015). Countries with less than three observations are excluded from the analysis. Net income inequality is measured by the Gini coefficient reported in the SWIID (Solt, 2014). The data set applied here includes developing and developed countries, as well as emerging economies. Per capita GDP ranges between 528 and 70,525 US $, measured at constant prices (reference year 2005). This broad data set allows us to investigate in how far the relationship between inequality and economic growth depends on the stage of development of the particular economy. Both countries with low and high inequality levels are included: net income inequality ranges between 0.176 and 0.682, providing sufficient data and variability to test for a nonlinear effect of inequality on economic growth.

IV Methods

As has been indicated, this study is based on an unbalanced, pooled cross-sectional time series (CSTS) of at most 682 cases in 113 developed and developing countries. To empirically estimate the theoretical mechanisms outlined in Section 2, we will use a reduced form equation such as

$$\ln y_{it} - \ln y_{it-1} = \alpha \ln y_{it-1} + \beta Ineq_{it-1} + \gamma X_{it-1} + \mu_i + \mu_t + \varepsilon_{it} \quad (1)$$

with $\ln y_{it}$ being the log of GDP per capita of country i at time point t, $Ineq_{it-1}$ represents the variable of interest, net income inequality measured by the Gini coefficient and X is a vector of control variables usually used in growth regressions (human capital, investment ratio, regional dummies). Finally, μ_i presents country-specific effects, μ_t period-specific effects, and ε_{it} the idiosyncratic error term. The lagged value of GDP per capita is included as a measure for initial stage of development to account for the convergence hypothesis. However, since it is used in the calculation of the growth rate on the left hand side of equation (1), this variable suffers from problems similar to those of a lagged dependent variable. If country fixed-effects are relevant, OLS will lead to biased and inconsistent estimates in this dynamic panel setting (dynamic panel bias). In fact, OLS will tend to produce an upward bias in the coefficient of the lagged dependent variable; for a fixed effects model, the opposite is true. Thus, a valid specification ("theoretically superior model") should produce coefficient estimates for the lagged dependent variable that lie within or near this range of estimates (Bond, 2002; Roodman, 2009b).

In order to overcome the dynamic panel bias, specific GMM estimation techniques have been developed. The Difference GMM estimator developed by Arellano and Bond (1991) first eliminates the country-specific effect by differencing the model and instrumenting the lagged dependent variable with lagged levels of this variable. As shown by Monte Carlo Simulations, Difference GMM generally exhibits the least bias in a dynamic panel setting. However, in the presence of persistent processes Difference GMM performs poorly, since lagged levels may convey little information on future changes, thus implying the problem of weak instruments and biased estimates. As Blundell and Bond (1998) revealed, in this setting past changes may be more predictive of current levels than past levels of current changes. Consequently, the instruments become more relevant. System GMM uses both the equation in differences and the equation in levels. Thus, System GMM also allows for including time-invariant variables in the level equation.

The Difference and System GMM regression approaches are particularly useful because they can deal with endogenous regressors and reverse causality. Since there are also theoretical mechanisms which link economic growth to inequality, this particular setting is likely to suffer from the problem of reverse causality. Generally, Difference and System GMM are intended to build internal instruments for the predetermined dependent and additional endogenous regressor variables.

Table 3: Simple test of weak instruments
Reduced form equations, OECD countries

VARIABLES		First differences		Levels	
GDP per capita	R^2	0.133	0.085	0.033	0.075
	F-test	31.06	3.14	6.88	2.77
	Prob > F	0.000***	0.029**	0.009***	0.046**
Income inequality	R^2	0.082	0.067	0.001	0.014
	F-test	18.09	2.42	0.24	0.47
	Prob > F	**0.000*** **	**0.070***	**0.626**	**0.700**
Human capital	R^2	0.163	0.287	0.058	0.100
	F-test	39.50	13.69	12.41	3.79
	Prob > F	0.000***	0.000***	0.001***	0.013**
Capital formation	R^2	0.244	0.066	0.131	0.090
	F-test	65.39	2.42	30.72	3.35
	Prob > F	0.000***	0.071*	0.000***	0.022**
Observations		205	106	205	106

First differences: Reduced form regression of Δx_{t-1} on x_{t-2} (column 1), and of Δx_{t-1} on x_{t-3}, x_{t-4}, x_{t-5} (column 2); Levels: Reduced form regression of x_{t-1} on Δx_{t-1} (column 3), and of x_{t-1} on Δx_{t-2}, Δx_{t-3}, Δx_{t-4} (column 4). See Blundell/Bond (2000), Table V, p. 336
*** p<0.01, ** p<0.05, *p<0.1
Source: own calculations based on data from OECD, SWIID, PWT 8.1

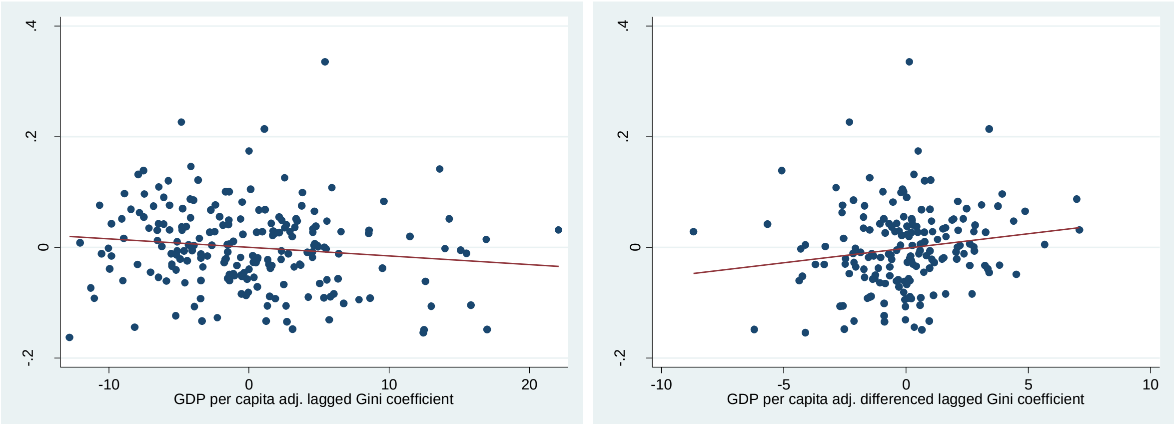
Yet, both estimators involve rather strict assumptions which are rarely questioned. Therefore, in this paper we first check if a) lagged levels have some explanatory power for first differences or if b) lagged differences are more predictive of current levels. Blundell and Bond (2000) and Roodman (2009a) propose a simple test of weakness by regressing the change of a variable on its lagged level(s) and vice versa. The results of this simple test in the setting of OECD countries are illustrated in Table 3. We see that except in the case of capital formation, past levels are more predictive of current changes than past changes on current levels. Specifically in the case of the inequality variable, past changes have practically no explanatory power for current levels. This also holds for the extended sample of 113 countries. Thus, the System GMM estimator is likely to suffer from a severe weak instrument problem and will produce large finite sample biases on the coefficients of lagged income inequality. This casts some doubts that System GMM really succeeds in isolating the exogenous component of income inequality on economic growth. Rather the coefficients will be biased by omitted variables – such as unobserved country-specific effects. Therefore, in the following empirical analysis, we basically follow Bond (2002) who suggests a careful “comparison of the consistent GMM estimators to simpler estimators like OLS levels and Within Groups, which are likely to be biased in opposite directions in the context of coefficients on lagged dependent variables in short T panels” (p.26f).

V Results

a) OECD sample

In a first step, we analyze the relationship between income inequality and economic growth in a setting of OECD countries. More specifically, we set out to investigate the drivers of the significant negative effect of income inequality on subsequent growth periods found in Cingano (2014). First, we start with some illustrative descriptive results on the relationship between income inequality and economic growth for the observed OECD countries. It is interesting to mention that a bivariate relationship does not reveal any trend (rather a completely flat line) between the two variables. Therefore, we first regressed economic growth and lagged income inequality on GDP per capita levels to account for the impact of differences in the level of economic development. The residuals of these bivariate regressions are plotted in Figure 1 and represent the GDP per capita adjusted relationship between income inequality and economic growth on the left hand side – on the right hand side, adjusted growth levels are plotted against first differences of lagged Gini coefficients. We observe a slight negative relationship between the two variables in adjusted levels, and a positive relationship when we only look at changes in the Gini coefficients.

Figure 1: Inequality and economic growth in OECD countries
GPD per capita adjusted

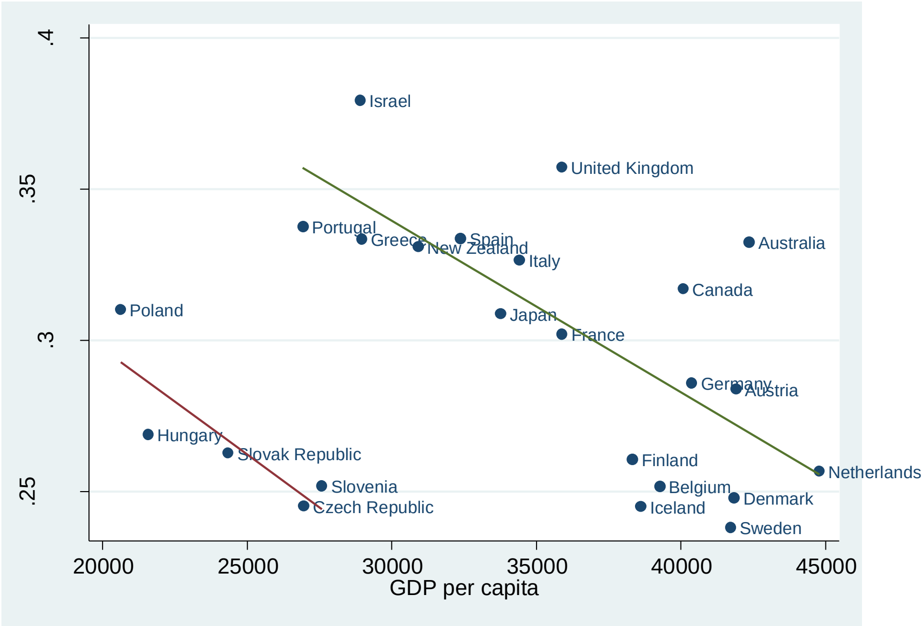


The graph on the left illustrates the relationship between economic growth and the lagged Gini coefficient of net income inequality. The graph on the right, in contrast, plots growth against the lagged Gini coefficient in first differences. All variables are adjusted to differences in GDP per capita levels.
Source: own calculations based on data from OECD, SWIID

Given that the negative relationship between inequality and growth only becomes evident when controlling for GDP per capita levels, we further investigated the relationship between income inequality and GDP per capita. Generally, we found a robust negative correlation between these two variables: Countries with a higher GDP per capita are in tendency associated with lower inequality levels. The post-communist countries from Eastern Europe emerge as a clear exception: Given their level of economic development, they are characterized by comparatively low income inequality levels (Figure 2). We will further investigate this observation in our regression analysis.

Table 4 illustrates our regression results in the setting of OECD countries. First we simply regress the lagged level of initial income and the lagged Gini coefficient of net income inequality on five-year economic growth periods. This corresponds to the baseline regression in Cingano (2014) which he also uses to compute the counterfactual growth effects. We first run a simple OLS regression and then a traditional Fixed Effects model, since *“theoretically superior estimators”* for the level of lagged GDP per capita should lie between the estimated coefficients of these two models (Roodman, 2009b). In column (3), we estimate the same equation with System GMM and the full set of instruments. In column ((4)-(6)) we substantially reduce the instrument count by only using two lags for the inequality variable and one lag and collapsed instruments for all further variables (Cingano, 2014). In column (7), we estimate a model with Difference GMM. All estimations include time dummies.

Figure 2: GDP per capita and income inequality in selected OECD countries
In 2010



For illustrative reasons those OECD countries with very high inequality levels or very high GDP per capita are not represented in this graph.
Source: OECD, SWIID

In line with Figure 2, we find a slightly significant negative effect of the inequality variable when estimating a simple OLS model (*p*-value = .097). Including country fixed effects turns the sign and yields a weakly positive significant effect (*p*-value = .102). This suggests that for a given level of GDP per capita, lower inequality levels are associated with higher growth rates. However, controlling for unobserved country heterogeneity (and thus the *level* of inequality), rather *increases* in inequality foster economic growth. When using System GMM with all internal instruments (column (3)), we find a coefficient on initial income which indeed lies tightly between the OLS and FE estimates. However, the Gini coefficient is statistically not significant and the Hansen-statistic of 1.00 hints at the problem of instrument proliferation (Roodman, 2009a). In columns (4) and (5) we find a significant negative effect – even though the coefficient on initial income in the first row does not lie in or very close to the range between the OLS and FE model, indicating some degree of model misspecification. When including a dummy for post-communist countries, its coefficient shows up positive and significant (column (6)). Simultaneously, the negative inequality effect and the income convergence effect vanish. This first suggests that the System GMM specification might not succeed in fully controlling for country-specific effects. Second, this provides evidence that the observed negative effect of income inequality on growth might be driven by the specific characteristics of post-communist countries – which have low inequality levels and comparatively high economic growth due to income convergence processes. The Difference GMM specification in column (7) again yields a positive inequality coefficient (*p*-value = .108). Yet, the implausible coefficient on investment also casts some doubts on this specification.

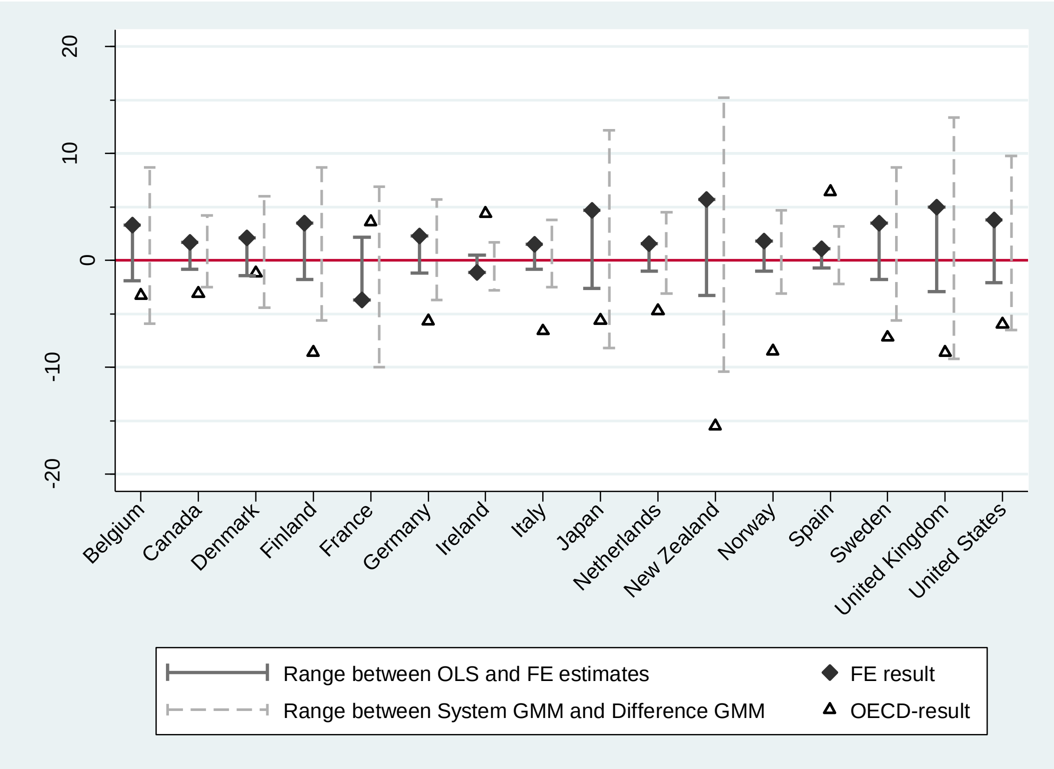
Table 4: Inequality and growth in OECD countries
Dependent Variable: growth of GDP per capita (five-year period)

VARIABLES	(1) OLS	(2) FE	(3) System GMM	(4) System GMM	(5) System GMM	(6) System GMM	(7) Difference GMM
Ln GDP per capita	-0.073***	-0.258***	-0.071***	-0.057	-0.053	0.158	-0.156
	(0.017)	(0.089)	(0.024)	(0.045)	(0.045)	(0.101)	(0.259)
Net inequality	**-0.155***	**0.347^**	**-0.194**	**-0.482****	**-0.484***	**0.099**	**0.805^**
	(0.093)	**(0.206)**	**(0.247)**	**(0.222)**	**(0.279)**	**(0.490)**	**(0.501)**
Human capital					-0.010	-0.040	0.047
					(0.041)	(0.041)	(0.063)
Investment					0.118	-0.169	-0.605**
					(0.203)	(0.264)	(0.268)
Post-communist						0.243**	
						(0.115)	
Period Effects	✓	✓	✓	✓	✓	✓	✓
Observations	205	205	205	205	205	205	172
Number of countries	33	33	33	33	33	33	33
Number of instruments			78	30	34	34	35
A-B test 2nd-order corr			0.751	0.606	0.538	0.873	0.535
Hansen test			1.000	0.376	0.350	0.409	0.292

All estimations with robust/clustered standard errors.
*** p<0.01, ** p<0.05, *p<0.1, ^p<0.11
Source: own calculations based on data from OECD, SWIID, PWT 8.1

In Figure 3, we compute the estimated changes in economic growth rates over the period 1990-2010 due to changes in income inequality between 1985 and 2005 (compare Cingano 2014, A.3.2.1) – for columns (1), (2), (4) and (7). For reasons of comparison, we also plot the results of the OECD Working Paper. We see that both GMM estimation methods reveal far higher impacts on economic growth compared to OLS and FE models (in opposite directions), which thus might be assumed to provide a good range for plausible estimates of the effect from income inequality on economic growth. In Germany, for example, the OLS results suggest that economic growth would have been 1.2 percentage points higher, if there was no increase in income inequality. On the other hand, according to the FE model, economic growth would have been 2.3 percentage points *lower*, if there was no increase in income inequality. Assuming that country-specific effects play some larger role than the dynamic panel bias, this strongly casts doubts on the causal conclusion that the increase in inequality was harmful for economic growth in Germany. In France, for example, the direction of estimated effects is rather the opposite, since the Gini coefficients reveal a decrease in net income inequality over the period 1985-2005.

Figure 3: Effects of inequality on growth – impact of estimation method
Estimated change in percentage points



The chart shows the estimated consequences of changes in inequality (1985-2005) on cumulative GDP per capita growth over the period 1990-2010. We apply the same method of computation as in figure 3, Cingano (2014).
Source: own calculations based on data from OECD, SWIID, PWT 8.1

In Table 5, we reassess the relationship between economic growth and governmental redistribution. Previous studies (Cingano, 2014; Ostry et al., 2014) only included an indicator of *effective* redistribution, as measured by the difference between the Gini coefficient of market income inequality (before taxes and transfers) and the Gini coefficient of net income inequality (after taxes and transfers). Here, we also investigate the impact of characteristics of the tax system such as total taxes as percent of GDP, the top income tax rate and measures of the degree of progressivity of the income tax system. The idea is that the government will not be able to directly increase *effective* redistribution, which is inherently dependent on the degree of inequality in market incomes. Due to the volatility of the results based on the System GMM estimator, we only present OLS and FE estimations to provide a plausible range of coefficient estimates. As it turns out, the characteristics of the tax system only reveal negative effects, when significant. This casts some doubt on the conclusion that increasing governmental redistribution will have no detrimental effects on economic growth.

Table 5: Tax structure and economic growth in OECD countries
Dependent Variable: growth of GDP per capita (five-year period)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	OLS	FE	OLS	FE	OLS	FE	OLS	FE
Ln GDP per capita	-.082***	-.296***	-.079***	-.458***	-.080***	-.453***	-.063***	-.452***
	(0.018)	(0.083)	(0.022)	(0.078)	(0.023)	(0.080)	(0.021)	(0.084)
Net inequality	-0.182	0.064	-0.179	0.114	-0.173	0.137	-0.189	0.140
	(0.125)	(0.193)	(0.130)	(0.356)	(0.144)	(0.369)	(0.127)	(0.383)
Total taxes/GDP	**0.044**	**-0.291***						
	(0.084)	**(0.171)**						
Toprate			**0.027**	**-0.232***				
			(0.044)	**(0.128)**				
Average tax rate progression					**0.037**	**-0.632**		
					(0.392)	**(0.457)**		
Marginal tax rate progression							**-0.714****	**-0.405**
							(0.295)	**(0.489)**
Period Effects	✓	✓	✓	✓	✓	✓	✓	✓
R-squared	0.365	0.507	0.382	0.64	0.377	0.635	0.418	0.632
Observations	201	201	134	134	132	132	132	132
Number of countries	33	33	30	30	30	30	30	30

All estimations with robust/clustered standard errors.
*** p<0.01, ** p<0.05, *p<0.1
Source: own calculations based on data from OECD, SWIID, WTI

b) Extended sample

In the next step we investigate the growth-inequality nexus using an extended dataset of 113 countries over the time period 1960-2010. In the first specification, growth of GDP per capita is regressed on net inequality as well as standard control variables (log of GDP per capita, human capital index and share of investment in GDP). The other two specifications should account for possible nonlinearities (see below). Values at the beginning of the five year growth period are used for all explanatory variables as a first step to account for possible reverse causation. The estimation is proceeded using pooled OLS regression, fixed-effects regression as well as the System GMM estimator described above. Time-fixed effects are included independent of the estimation method and the specification.

Table 6: Inequality and growth in an extended sample of countries: Accounting for nonlinearities
Dependent Variable: growth of GDP per capita (five-year period)

VARIABLES	(1) OLS	(2) FE	(3) System GMM	(4) OLS	(5) FE	(6) System GMM	(7) OLS	(8) FE	(9) System GMM
Ln GDP per capita	-.042***	-.351***	-.033	-.131***	-.460***	-.333***	-.038***	-.342***	-.009
	(0.013)	(0.051)	(0.038)	(0.035)	(0.073)	(0.110)	(0.013)	(0.052)	(0.036)
Net inequality	**-0.008**	**0.742*****	**1.139*****	**-2.152*****	**-1.744**	**-7.034*****	**1.631*****	**2.174****	**8.512*****
	(0.088)	**(0.234)**	**(0.373)**	**(0.765)**	**(1.470)**	**(2.575)**	**(0.516)**	**(0.972)**	**(1.986)**
Ln GDP per capita *inequality				**0.245*****	**0.302***	**0.940*****			
				(0.083)	**(0.173)**	**(0.311)**			
Inequality^2							**-2.037*****	**-1.790**	**-9.722*****
							(0.614)	**(1.161)**	**(2.314)**
Human capital	0.044*	0.208***	0.144	0.043*	0.205***	0.055	0.051**	0.210***	0.125
	(0.024)	(0.078)	(0.101)	(0.0240)	(0.076)	(0.107)	(0.024)	(0.077)	(0.089)
Investment	0.361***	0.014	0.815***	0.365***	0.002	0.528*	0.357***	0.020	0.568**
	(.127)	(.161)	(0.239)	(0.126)	(0.159)	(0.303)	(0.124)	(0.157)	(0.247)
Period Effects	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	682	682	682	682	682	682	682	682	682
Number of countries	113	113	113	113	113	113	113	113	113
Number of instruments			100			110			110
A-B test 2nd-order corr			0.726			0.673			0.981
Hansen test			0.304			0.223			0.248

All estimations with robust/clustered standard errors.
*** p<0.01, ** p<0.05, *p<0.1
Source: own calculations based on data from PWT 8.1, SWIID

The results of the empirical analysis in a broader sample of countries are presented in Table 6. The coefficients of all control variables are correctly signed and significant in most of the regressions. In the first specification (columns (1)-(3)) the coefficient of net inequality is insignificant in the pooled OLS regression and positive and significant in the fixed-effects regression as well as in the regression using the System GMM estimator. As in the case of OECD countries, the value of the coefficient in the System GMM regression is higher than that in the fixed-effects regression which should most plausibly represent an upper bound for the expected value of the coefficient. Therefore, the results should be interpreted with caution. Still, the empirical analysis indicates that the relationship between growth and net inequality is rather positive, if significant.

In columns (4)-(6) of Table 6 an interaction term between the GDP per capita variable and net inequality is included. The underlying hypothesis is that the sign and the magnitude of the relationship between economic growth and inequality depends on the level of development of the particular economies. Specifically, some of the theories pointing towards negative effects of inequality on growth are likely to be valid only for less developed countries. It is, for instance, more likely that higher inequality lowers human capital in developing countries than it would be the case in advanced economies. According to Cingano (2014) this is the main channel connecting inequality and growth. However, if this argument is valid only for developing countries, then the coefficient of net inequality will be negative and the coefficient of the interaction term will be positive. In fact, the results presented in table 3 are supportive for this hypothesis. Both the pooled OLS regression and the System GMM estimator deliver significantly negative coefficients for the inequality variable and significantly positive coefficients for the interaction term. Therefore, economic growth seems to be negatively correlated with net income inequality for countries with low initial level of GDP per capita. However, the effect becomes weaker with increasing GDP and even positive for the case of developed countries. Independent of the estimation method, the threshold value for GDP per capita lies below 9,000 US $, meaning that for countries with higher GDP per capita the empirical analysis indicates positive correlation between growth and inequality.

In the last specification in Table 6 we test for further nonlinearities of the relationship between growth and inequality by introducing a quadratic term of the inequality variable (columns (7)-(9)). The hypothesis is that rising inequality is positively related to economic growth as long as it remains below a certain level. Some of the theories explaining the negative relationship between income inequality and economic growth are only reasonable for higher initial inequality. For instance, it is very unlikely that increasing inequality would lead to social unrest and therefore to lower growth if inequality is very low. This argument becomes valid for higher inequality levels. If this is the case, the coefficient of the quadratic term in the regression equation would be negative, indicating an inverted U-shaped relationship between inequality and economic growth. The empirical analysis in this section supports this hypothesis. Both in the pooled OLS and the System GMM regression the coefficient of the quadratic term is negative and the threshold value for the Gini coefficient lies - depending on the estimation technique - between 35 and 54. Therefore, the empirical analysis indicates that for low levels of Gini the correlation between net income inequality and economic growth is positive. Turning back to the current inequality values reported in table 1, there are only a few countries where it is possible that rising inequality may impede economic growth – these are the BRIC countries, Mexico, UK, and US. In all other countries the coefficient of inequality in the growth equation is still in the positive area, if significant.

VI Conclusion

The present analysis illustrates some crucial points in the empirical investigation of the effect of income inequality on economic growth. First, we showed that the methodology used in previous studies is questionable since the System GMM estimator is likely to suffer from a severe weak instrument problem and will produce large biases on the coefficients of lagged income inequality. Second, our analysis demonstrates that the negative effect of inequality on economic growth estimated using a dataset of OECD countries in the empirical analysis by Cingano (2014) is not robust and may be ascribed rather to specific characteristics of post-communist countries. Furthermore, estimations on the impact of the (income) tax structure on economic growth reveal negative effects, when statistically significant. This casts some doubts on the conclusion that increasing governmental redistribution does not harm economic growth.

A common drawback of most empirical studies analysing the growth-inequality relationship lies in a possible misspecification of the model. They do not account for the hypothesis that the effect of inequality on economic growth could be nonlinear depending on the stage of development and / or the initial level of inequality. Our analysis delivers evidence in favour of this hypothesis. Economic growth seems to be negatively correlated with net income inequality for countries with low initial level of GDP per capita. However, the effect becomes weaker with increasing GDP and even positive for the case of developed countries. Moreover, the empirical analysis indicates that for low levels of Gini coefficients, the correlation between net income inequality and economic growth is positive and becomes negative for inequality levels far above those in most of the European countries.

The present empirical analysis of the growth-inequality nexus indicates therefore that the results of recent studies calling for more redistribution as a way not only to reduce inequality but also to increase economic growth should be taken with caution. In developed countries with inequality levels below average like for instance Germany, Sweden, or Norway subdued economic dynamics in recent years are not the result of increasing inequality and thus, purely increasing governmental redistribution is the wrong way to tackle the problem.

References

Alesina, Alberto / Perotti, Roberto, 1996, Income distribution, political instability and investment, in: European Economic Review, Vol. 40, pp. 1203−1228

Alesina, Alberto / Rodrik, Dani, 1994, Distributive politics and Economic growth, in: The Quarterly Journal of Economics, Vol. 109, No. 2, pp. 465−490

Andrew Young School of Policy Studies, 2010, Andrew Young School World Tax Indicators (Volume 1) [Data file, data description, and data appendix]. Retrieved from http://aysps.gsu.edu/isp/wti.html [retrieved: June 2015]

Arellano, Manuel / Bond, Stephen R., 1991, Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations, in: Review of Economic Studies 58: pp. 277-297

Arellano, Manuel / Bover, Olympia, 1995, Another look at the instrumental variable estimation of error-components models, in: Journal of Econometrics 68, pp. 29-51

Banerjee, Abhijit V. / Duflo, Esther, 2003, Inequality and growth: What can the data say?, in: Journal of Economic Growth, Vol. 8, No. 3, pp. 267−299

Barro, Robert J., 2000, Inequality and Growth in a Panel of Countries, in: Journal of Economic Growth, Vol. 5, No. 1, pp. 5−32

Bertola, Giuseppe, 1993, Factor Shares and savings in endogeNo.us growth, in: American Economic Review, Vol. 83, No. 5, pp. 1184−1198

Blundell, Richard / Bond, Stephen, 1998, Initial conditions and moment restrictions in dynamic panel data models, in: Journal of Econometrics 87, pp. 115-143.

Blundell, Richard / Bond, Stephen, 2000, GMM estimation with persistent panel data: an application to production functions, in: Econometric Reviews, Vol. 19, No. 3, pp. 321–340

Bond, Stephen, 2002, Dynamic panel data models: A guide to micro data methods and practice, Working Paper CWP09/02, Cemmap, Institute for Fiscal Studies

Chen, Been-Lon, 2003, An inverted-U relationship between inequality and long-run growth, in: Economic Letters, Vol. 79, No. 2, pp. 205−212

Cingano, Federico, 2014, Trends in income inequality and its impact on Economic growth, OECD SEM Working Paper 163

Clarke, Georg R. G., 1995, More evidence on income distribution and growth, in: Journal of Development Economics, Vol. 47, No. 2, pp. 403−427

Deiniger, Klaus / Olinto, Pedro, 2000, Asset distribution, inequality, and growth, World Bank Policy Research Paper 2375

Deininger, Klaus / Squire, Lyn, 1998, New ways of looking at old issues: Inequality and growth, in: Journal of Development Economics, 57 Vol., pp. 259−287

Dominics, Laura De / Florax, Raymond J. G. M. / Groot, Henri L. F., 2008, A meta-analysis on the relationship between inequality and Economic growth, in: Scottish Journal of Political Economy, Vol. 55, pp. 654−682

Feenstra, Robert C. / Inklaar, Robert / Timmer, Marcel P., 2015, The Next Generation of the Penn World Table, in: American Economic Review 105 (10): 3150-3182

Forbes, Kristin J., 2000, A reassessment of the relationship between inequality and growth, in: American Economic Review, Vol. 90, pp. 869−887

Galor, Oded / Moav, Omer, 2004, From Physical to Human Capital Accumulation: Inequality and the Process of Development, in: Review of Economic Studies, Vol. 71, No. 4, pp.1001−1026

Galor, Oded / Zeira, Joseph, 1993, Income distribution and macroeconomics, in: Review of Economic Studies, Vol. 60, pp. 35−52

German Council of Economic Experts, 2015, Focus on Future Viability, Annual Economic Report 2015/16

Halter, Daniel / Oechslin, Manuel / Zweimüller, Josef, 2014, Inequality and growth: The neglected time dimension, in: Journal of Economic Growth, Vol. 19, No. 1, pp. 81−84

Kaldor, Nicholas, 1957, A Model of Economic Growth, in: The Economic Journal, Vol. 67, No. 268, pp. 591−627

Knowles, Stephen, 2005, Inequality and Economic growth: The empirical relationship reconsidered in the light of comparable data, in: Journal of Development Studies, Vol. 41, No. 1, pp. 135−139

Lazear, Edward P. / Rosen, Sherwin, 1981, Rank-Order Tournaments as Optimum Labor Contracts, in: Journal of Political Economy, Vol. 89, No. 5, pp. 841−864

Li, Hongyi / Zou, Heng-fu, 1998, Income inequality is No.t harmful for growth: Theory and evidence, in: Review of Development Economics, Vol. 2, No. 3, pp. 318−384

Neves, Pedro Cunha / Afonso, Óscar / Silva, Sandra Tavares, 2016, A Meta-Analytic Reassessment of the Effects of Inequality on Growth, in: World Development, Vol. 78, No. C, pp. 386−400

Okun, Arthur M., 1975, Equality and Efficiency: the Big Trade-Off, Washington

Ostry, Jonathan D. / Berg, Andrew / Tsangarides, Charalambos, 2014, Redistribution, Inequality, and Growth, IMF Staff discussion Note, February

Perotti, Roberto, 1996, Growth, income distribution, and democracy: What the data say, in: Journal of Economic Growth, Vol. 1, pp. 149−187

Persson, Torsten / Tabellini, Guido, 1994, Is inequality harmful for growth?, in: American Economic Review, Vol. 84, No. 3, pp. 600−621

Rodrik, Dani, 1999, Where Did All the Growth Go? External Shocks, Social Conflict, and Growth Collapses, in: Journal of Economic Growth, Vol. 4, No. 4, pp. 385−412

Roodman, David. 2009a. A Note on the theme of too many instruments, in: Oxford Bulletin of Economics and Statistics 71, pp. 135-158

———. 2009b. How to do xtabond2: An introduction to difference and system GMM in Stata, in: Stata Journal 9, pp. 86-136

Solt, Frederick, 2014, The Standardized World Income Inequality Database, Working paper. SWIID Version 5.0, October 2014

Voitchovsky, Sarah, 2005, Does the profile of Economic inequality matter for Economic growth? Distinguishing between the effects of inequality in different parts of the income distribution, in: Journal of Economic Growth, Vol. 10, pp. 273−296