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Does the Profile of Income Inequality Matter for Economic Growth?

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Distinguishing between the top and bottom end effects of the income distribution

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Abstract:
This paper investigates the importance of the shape of the income distribution as a determinant of economic growth in a panel of countries. Using comparable data on disposable income from the Luxembourg Income Study, results show that aggregate inequality measures, such as Gini coefficients, can mask key features of the relationship between inequality and growth. In particular, inequality at the top end and bottom end of the distribution appear to have opposite effects on growth. This finding supports the argument that the profile of the income distribution, and not only its spread, helps define the impact of inequality on growth.

Keywords: growth, inequality, income distribution, Gini coefficient
JEL Classification: O4, D3

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1. Introduction

Over the last decade, the increasing availability of income distribution data has led to a growing empirical literature on the influence of income inequality on a country's economic performance. Traditionally, the empirical analysis of this relationship has entailed estimating a coefficient on a measure of inequality in a growth regression, with other explanatory variables. In earlier studies, this relationship has been explored within a cross-country regression analysis (Persson and Tabellini 1994, Alesina and Rodrik 1994, to name a few[1]), but as data coverage has improved over time, research has recently shifted to more sophisticated panel data approaches (Forbes 2000, Barro 2000). Yet the way in which the influence of income inequality has been accounted for has remained almost identical: in these studies, the impact of inequality is typically captured by an inequality index, like quintile shares or a Gini coefficient.

A key point here is that if the influence of income inequality on economic growth is not only a function of the spread of the distribution but also of its shape, inference based on estimated inequality coefficients could be misleading. It is a well-known fact that these inequality indices could summarize different distributional configurations in the same way and thus mask the underlying patterns. More precisely, and focusing on the Gini coefficient in this argument, inequality could be concentrated at the top of the distribution in one case or at the bottom in another. The value of the Gini coefficient however could be the same in both cases.

This situation does actually regularly arise in reality. For example in France and Canada in 1995, based on income data from the Luxembourg Income study (LIS), there were similar levels of inequality measured by the Gini coefficient, which took the values of 0.288 and 0.285 respectively. But, a closer look at these distributions reveals that inequality at the top end of the distribution, measured by the 90/50 percentile ratio[2], was higher in France, with a ratio of 1.910, than in Canada, where the ratio was 1.850. The reverse was true for the bottom end inequality

[1] See Bénabou (1996) for a review of papers on this subject.
[2] The 90/50 percentile ratio is the ratio of the equivalised income of the individual placed at the 90th percentile in the distribution to the equivalised median income; see section 3.

measured by 50/10 percentile ratios of 1.856 in France and 2.097 in Canada, see table 3.2. Using the same dataset, there are numerous other instances in which an increase or decrease in inequality, measured by the Gini coefficient, is due on one occasion to a shift at the top end and on another to a movement at the bottom end of the distribution. For example, the rise in inequality in Sweden from 1980 to 1985 was the result of an increase in bottom end inequality while top end inequality remained unchanged. However, the later increase in inequality in 1990 was due to a rise in top end inequality while bottom end inequality decreased slightly, see graph 3.1. Also, many phases of apparent stability in inequality in a country can hide offsetting movements at both ends of the distribution.

Therefore, if for the same level of inequality, variations in the profile of the income distribution affect aggregate economic growth, the analysis of the impact of inequality on growth should not solely rely on indices like the Gini coefficient. Inference based on these coefficients is likely to suffer from two potential problems: first, the index does not always distinguish between varying configurations of the distribution. Second, if both the spread and the shape matter, a single measure could not differentiate between these two influences. The estimated inequality coefficients could turn out to be insignificant simply as a result of reflecting conflicting outcomes of income inequality on economic growth.

One way of taking into account the spread and the shape of the distribution would be to control separately for inequality measured at both the top and bottom ends of the distribution. This approach would allow for different effects as well as for independent shifts of inequality at both ends. As a consequence, not only changes in the spread but also variations in the profile of the distribution when the spread remains stable could be captured. Using data from the Luxembourg Income Study and a panel-data approach, the results of the empirical analysis show that top and bottom end inequality do have a significant and distinct effect on economic growth, supporting the argument that the shape of the income distribution is also an important determinant of the impact of inequality on growth.

The paper is organised as follows: section 2 discusses why we could expect the shape of the income distribution to matter in addition to its spread. Data on income distribution and an explanation on how the inequality measures are computed are described in section 3. As well, this section incorporates some statistical description of the evolution of income inequality in the sample and, more specifically, on developments in top and bottom inequality. Section 4 presents the model used for the estimations, the econometric method and the regression results. Section 5 discusses the findings of the analysis and concludes.

2. Why would we expect the profile of the distribution to matter for growth?

In the theoretical and empirical literature, the two variables income distribution and economic growth often appear to be endogenously determined. The initial income distribution affects the rate of growth of the economy and the rate of growth shapes the evolution of the distribution. The present analysis, however, will focus on one direction of the relationship - the impact of income inequality on growth.

Initial empirical analysis of this relationship tended to support the argument that income inequality has an adverse influence on economic growth (see Bénabou 1996 for a review of these studies), although the effect appeared to be quite sensitive notably to the introduction of regional dummies and sample selection (Bourguignon 1996, Perotti 1996). More recently, with the introduction of the Deininger and Squire (1996) panel dataset, it became possible to control for unobserved time-invariant heterogeneity between countries and to reduce the measurement error in inequality statistics. Based on this data, Forbes (2000) finds that income inequality has a robust positive effect on subsequent economic growth in a sample of developed and developing countries, while in the analysis of Barro (2000) inequality appears to encourage growth only within rich countries, and to slow it down in poorer countries. But, the debate remains in the empirical literature as to whether the ultimate effect of income inequality on growth is positive, negative or non-existent.

In the theoretical literature, however, income distribution forms part of a more complex relationship with economic growth than a straightforward positive or negative association would suggest. In this literature, inequality is found to have simultaneously an inhibiting as well as a stimulating influence on economic performance. One could look at the beneficial or detrimental impacts of the income distribution on growth in terms of the consequences that inequality might have on economic behaviours of individuals located in different parts of the distribution, namely at the top versus the bottom end of the distribution[3]. In other words, the question is whether inequality at the top end of the distribution can influence the activities of richer people in a different way than that in which bottom end inequality affects poorer individuals' decisions.

At the top of the distribution individuals tend to be wealthy enough to undertake their investment plans, or have access to capital markets if they need to borrow in order to invest. These individuals might also represent the main source of savings in the economy especially if, as in some of the Keynesian literature, the saving rate is increasing with income or if the propensity to save is higher on income from capital than from wages. Larger investors might also be more able to spread the risk of their investment and get a higher return. If is the case, more inequality at the top end of the distribution could promote economic growth as it boosts funds available for investment. This valuable dynamic is further reinforced if rich people's investments create a positive externality in the economy that increases the productivity of subsequent investment[4] (Galor and Tsiddon 1996, Perotti 1993).

Nevertheless, this process initiated by the better off could come to a halt or the economy could end up in a sub-optimal equilibrium if not enough wealth trickles down the distribution, that is if some agents are left behind in the growth process (e.g. Galor and Zeira 1993, Banerjee and Newman 1993, Aghion and Bolton 1997). The trickle down process can take place in many different ways, for example via the wage rate (Galor and Tsiddon 1996, Banerjee and Newman

[3] For simplicity, we consider top versus bottom end only at this stage in the analysis.
[4] For example, if the wage rate increases with the average education level in the economy.

1993), through the interest rate (Aghion and Bolton 1997) or through redistribution (Perotti 1993). Moreover, if the poor are left behind, so that inequality increases at the bottom end of the distribution, not only will more people become credit constrained but also fewer of the productive investments will be undertaken, if productivity is decreasing with income[5] (Aghion and Howitt 1998, Bénabou 1996).

But even if poor people have access to a capital market, growth is likely to be hampered when individuals' effort put into their investment project is decreasing with the share of private relative borrowed wealth (Aghion and Bolton 1997). Additionally, when consumption patterns are inter-related (Nurkse 1953) people will consume up to their country's consumption standard and not according to their own income. As the distance between the lower and the middle class increases, savings and investments will decrease as individuals try to keep up with the consumption standard and give up on extra savings. Also, bottom inequality is often recognized as the source of counter-productive activities. For example, as a result of unequal private resources, Aghion and Howitt (1998) have considered the possibility of poor individuals free-riding on rich people's effort instead of cooperating, negatively affecting the growth rate.

Consequently, we could expect that a shift in inequality in which the rich agents get richer relative to the middle and lower classes to have a different impact on economic growth than a change implying the poor losing ground relative to the median and top incomes. This hypothesis is investigated using a standard growth model where the novelty is a larger set of explanatory variables to account for the effect of income distribution.

[5] If investment in primary education is more productive than investment in tertiary education, e.g.

3. Income distribution data

3.1 Description of the dataset

The income distribution variables in this analysis come from the Luxembourg Income Study (LIS). This dataset offers several advantages for the purposes of this analysis as compared to other datasets. First, the LIS dataset provides income information from household surveys[6] with a high degree of cross-national and over-time comparability[7].

Second, the household income variable reflects a large coverage of different income sources: to each household's wage and salary income is added gross self-employment income, which gives total earnings. Then is also included cash property income[8], private and public sector pensions as well as public transfers, i.e. social retirement pensions, family allowances, unemployment compensation, sick pay, etc. and other cash income. Finally, deducting personal income tax and mandatory social security contribution yields disposable income (see also Atkinson et al., 1995 or the LIS website). Although the reporting of income sources is getting more comprehensive over time, several notions of income are still excluded from the disposable income on which these inequality measures are based. For example, non-cash benefits from housing, medical care or education, the imputed value of owner-occupied housing, in-kinds earnings, the net gains/losses from selling/buying assets and indirect and property taxes are not included.

Finally, this dataset allows direct access to raw individual income data from the household surveys. Access to raw data gives the advantage of increased precision in the calculation of inequality measures since based on a large number of data points. In addition it provides a greater flexibility in the choice of inequality measures as well as uniformity and full comparability in the computation of inequality indices, across countries and over time.

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[6] Most surveys were conducted through interviews but some household income data was collected from administrative records or from a combination of both sources.
[7] These surveys conducted in different countries for different purposes are made comparable through a "lissification" process. In other words, the original datasets are reorganised to correspond to the LIS variable structures, which include both "harmonised" (country-specific) and "standardised" variables (variables with common categories for all countries). See the LIS website for more information.
[8] Cash property income includes cash interest, rent, dividends, annuities, etc. but excludes capital gains, lottery winnings, inheritances, insurance settlements, and all other forms of lump sum payments.

3.2 Computation of inequality measures

This paper follows the standardisation proposed by LIS on their website (see also Gottschalk and Smeeding, 1997) for the computation of inequality measures. Inequality indices are based on the individual equivalised income defined as the household annual net disposable income divided by an equivalence scale. The equivalence scale used is the square root of the number of persons in the household. All households surveyed and their members are included. These inequality measures also include a correction for the sample bias using person weights. The bottom of the distribution is recoded at 1 percent of equivalised mean income and the top at 10 times the median of non-equivalised income. Missing values and zero incomes have been excluded from the measures of income inequality reported.

The point dividing between the top and bottom of the income distribution is arbitrarily set at the median. Thus, ratios of income percentile on either side of the median are used to measure top and bottom end inequality. More precisely, bottom end inequality is measured by income percentile ratios such as the 50/10 ratio, i.e. the ratio of the equivalised individual median income to the 10^{th} percentile equivalised individual income. The 10^{th} percentile is the equivalised individual income below which lie the poorest 10 percent of people in the distribution. Other bottom end inequality indices considered in the analysis are the 50/20 and 40/10 ratios, while the 90/50, 90/75 and 95/80 ratios refer to top end inequality.

These measures give an indication of the distance between the top and median income, and between the median and lower incomes. They are easy to compute but are obviously not perfect. The 90/50 ratio, for example, cannot capture income variations between the 60^{th} and 70^{th} percentiles. As a result, the top or bottom inequality ranking of countries might change depending on which ratio is considered. Also, these indices are sensitive to mis-measurement at the percentile considered, though they do avoid the more common problem of mis-measurement at both extremes of the distribution. As a cross check, top and bottom quintile share ratios are used instead. The quintiles share ratios considered are Q5/Q3 for top inequality and Q3/Q1 for bottom inequality. The conclusions of the analysis are robust to these changes.

3.3 Selection of household surveys

This study considers a 5-year growth model in a selection of countries where the availability of income distribution data is the sample size limiting factor. Consequently, the sample comprises observations for an unbalanced panel of 25 countries for which inequality data are available at the beginning of a 5-year growth period. In general, if data were not available for the exact year needed, the survey from the nearest year was used instead. The surveys used in the analysis and their years of reference are described in Appendix A.

For France, Germany, Switzerland, Ireland and the Netherlands, different types of household surveys were employed over the period covered. This change of survey may cause some discontinuity in the data. For example, for France in 1985 two household surveys are available, both dated 1984. One comes from the French Survey of Income from Income Tax and the other from the Family Budget Survey. Although both surveys report roughly the same level of overall inequality measured by Gini coefficients of 0.292 and 0.298 respectively, the levels of top and bottom inequality appear to be quite different in each case. In the French Survey of Income from Income Tax of 1984, the 90/50 and 50/10 ratios are 1.93 and 1.796 respectively whereas the figures are 1.83 and 2.142 using the Family Budget Survey[9]. When multiple choices were available, the datasets were chosen as a compromise between getting the closest year possible and minimizing survey discontinuity.

Furthermore, inequality measures for Switzerland in 1985, Spain in 1985, Ireland in 1990 and Austria in 1990 were obtained by linear interpolation based on immediately adjacent observations. It should also be noted that data for Germany refers to West Germany only until 1990 and to reunited Germany thereafter. Finally, data for Austria in 1995 does not include self-employment income. The results are robust to the exclusion of these countries, see appendix D.

[9] These differences can partly be explained by the usual lower response rate of richer households in budget surveys and by the imputation of benefits in tax records.

3.4 Some summary statistics

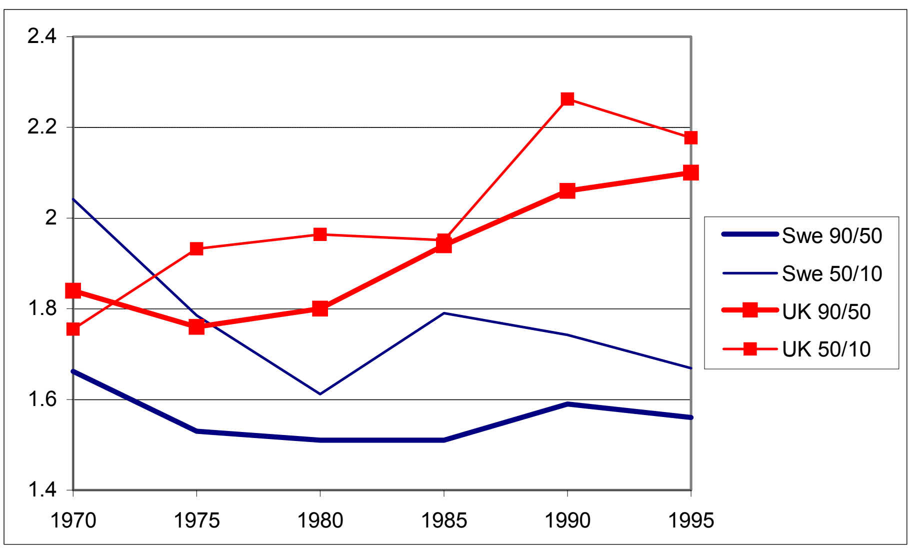
Behind all dramatic as well as more modest movements in the Gini coefficients over time appears a wide range of shifts at both ends of the income distributions. The Gini coefficients of the surveys included in the analysis are summarized in table 3.1.

Table 3.1: Gini coefficients

Countries	Years					
	1970	1975	1980	1985	1990	1995
Australia			0.281	0.292	0.304	0.311
Austria				0.227	0.252	0.277
Belgium				0.227	0.232	0.260
Canada	0.316	0.289	0.284	0.283	0.281	0.285
Czech Republic					0.207	0.259
Denmark				0.254	0.236	0.263
Finland				0.209	0.210	0.226
France			0.293	0.298	0.287	0.288
Germany	0.271	0.264	0.244	0.249	0.247	0.261
Hungary					0.283	0.323
Ireland				0.328	0.332	0.336
Israel			0.303	0.308	0.305	0.336
Italy				0.306	0.289	0.342
Luxembourg				0.237	0.240	0.235
Mexico					0.467	0.496
Netherlands			0.260	0.256	0.266	0.253
Norway			0.223	0.233	0.231	0.238
Poland				0.271	.0274	0.318
ROC Taiwan			0.267	0.269	0.271	0.277
Russian Federation					0.393	0.447
Spain			0.318	0.311	0.303	
Sweden	0.260	0.215	0.197	0.218	0.229	0.221
Switzerland			0.309	0.308	0.307	
United Kingdom	0.267	0.268	0.270	0.303	0.336	0.344
United States		0.318	0.301	0.335	0.336	0.355

A few countries' experiences are now discussed in more details[10]. The fall and rise in the Gini coefficient in the US between 1975 and 1980, and 1980 and 1985 respectively actually reflects both ends converging and then diverging simultaneously. However the apparent inequality stability between 1985 and 1990 hides an increase at the top end of the distribution compensated for by a decrease in bottom end inequality. Both ends diverge again from 1990 to 1995. In Canada, the sustained reduction in bottom inequality over the entire period is responsible for the steady decrease in the Gini coefficient up to 1990, while from 1990 to 1995 the continued reduction in the 50/10 ratio was more than compensated for by an increase in the top ratio.

Graph 3.1: Evolution of the 90/50 and 50/10 ratios in Sweden and UK, 1970-1995



In the UK[11], the crossing of the top and bottom ratio lines between 1970 and 1975 resulted in a stable Gini coefficient over this period, while the subsequent increase in overall inequality from 1975 to 1995 is due to both ends of the distribution diverging, and to a top increase more than

[10] In this section, for simplicity of exposition, the term top end inequality is used to describe the 90/50 percentile ratio and the term bottom end inequality refers to the 50/10 percentile ratio, unless otherwise specified.

[11] Material from UK 1986, 1991, 1995 data included in the LIS database is Crown Copyright; it has been made available by the Office for National Statistics through the ESRC Data Archive; and has been used with permission. Neither the Office for National Statistics nor the ESRC Data Archive bear any responsibility for the analysis or the interpretation of the data reported here.

offsetting a reduction in bottom inequality over the last five years in the sample, see graph 3.1. The sharp decrease in income inequality in Sweden between 1970 and 1980, shown by a Gini coefficient dropping from 0.26 to 0.197, is the outcome of both ends converging and, especially, to the lower end of the distribution catching up. During the two subsequent periods, the Gini increase is once due to a rise in bottom and once in top end inequality, see graph 3.1.

Table 3.2 Different income inequality indices, by ascending order of the Gini coefficient, 1995

	Aggregate measures		Top inequality measures			Bottom inequality measures		
Country	Gini LIS	90/10	95/80	90/75	90/50	50/20	50/10	40/10
Sweden	0.221	2.610	1.354	1.256	1.560	1.330	1.669	1.538
Finland	0.226	2.690	1.354	1.245	1.590	1.403	1.687	1.529
Luxembourg	0.235	2.920	1.465	1.327	1.730	1.422	1.689	1.495
Norway	0.238	2.830	1.344	1.243	1.570	1.453	1.801	1.632
Netherlands	0.253	3.150	1.343	1.273	1.730	1.475	1.823	1.621
Czech Rep.	0.259	3.01	1.466	1.320	1.790	1.399	1.686	1.506
Belgium	0.260	3.200	1.433	1.300	1.740	1.480	1.841	1.632
Germany	0.261	3.180	1.485	1.304	1.740	1.456	1.834	1.635
Denmark	0.263	3.183	1.348	1.240	1.630	1.581	1.957	1.711
Austria	0.277	3.730	1.395	1.299	1.790	1.560	2.079	1.829
ROC Taiwan	0.277	3.380	1.522	1.346	1.890	1.468	1.787	1.591
Canada	0.285	3.870	1.432	1.327	1.850	1.584	2.097	1.841
France	0.288	3.540	1.551	1.379	1.910	1.480	1.856	1.653
Australia	0.311	4.330	1.441	1.335	1.950	1.755	2.225	1.907
Poland	0.318	4.040	1.563	1.360	1.890	1.576	2.136	1.879
Hungary	0.323	4.190	1.690	1.480	2.090	1.514	2.005	1.782
Israel	0.336	4.860	1.549	1.402	2.100	1.742	2.317	1.939
Ireland	0.336	4.391	1.610	1.402	2.072	1.708	2.119	1.783
Italy	0.342	4.770	1.536	1.353	2.020	1.714	2.364	1.959
UK	0.344	4.570	1.625	1.397	2.100	1.738	2.177	1.820
US	0.355	5.850	1.599	1.411	2.150	1.861	2.726	2.281
Russia	0.447	9.390	1.899	1.638	2.820	2.009	3.329	2.716
Mexico	0.496	10.966	2.380	1.883	3.370	2.125	3.253	2.614

To give an idea of how levels of inequality compares across countries, table 3.2 shows several measures of overall, top and bottom inequality for the countries present in the sample at the last year of observation, in 1995. This table also illustrates how aggregate inequality measures can summarize in the same way very different distributions, where inequality is placed rather at the top end in one case or at the bottom end in another. This brings us back to the measurement issue. The fact that top and bottom inequality rankings could differ depending on which measure is considered underlines again the difficulty in choosing the best way of measuring levels of inequality.

In general, in this table, the Benelux and Scandinavian countries tend to display the lowest overall income inequality levels, while some of the Eastern European countries, the UK, the US and Mexico are located at the other end of the spectrum, in terms of overall inequality. In 1995, Sweden the country with the lowest Gini coefficient is also placed among the countries with the least bottom inequality. However, we can find many countries located apart in the table with the same type of top or bottom inequality. This can be said for France and Belgium with respect to bottom end inequality, for example, and for Taiwan and Poland and top end inequality. A more in-depth description of the evolution of inequality between and within the countries in the LIS dataset can be found in Atkinson et al. (1995) and in Gottschalk and Smeeding (1997).

4. Empirical analysis

4.1. The model

This analysis follows the 5-years panel data growth model developed in several recent papers (Forbes 2000, Caselli et al. 1996, Bond et al. 2001). The choice of a 5-year growth structure has essentially been dictated by the infrequent availability of data on income distribution. Specifically, the 5-year growth rate evolves as follows:

$$y_{it} - y_{i,t-1} = (\alpha - 1) y_{i,t-1} + \beta X_{it} + u_{it} \quad (1)$$

Where t corresponds to a 5-year period starting in the year t and i denotes a particular country. y_{it} is the log of real GDP per capita. u_{it} is an error term including an unobserved country-specific effect, n_i , and a time-specific effect, h_t. The vector X_{it} contains current and lagged values of several explanatory variables. This set of controls includes both a top and bottom of distribution inequality measures to account separately for the impact of both ends of the distribution, measured in *t-1*. The other explanatory variables are: an average investment rate dated t, measured over the 5 years starting in *t-1*[12] and the average years of schooling in the population measured in *t-1*. The sample covers 25 countries that are observed for at least two consecutive 5-year-periods, or for all the years, between 1975 and 2000.

Income is measured by the log of real GDP per capita in 1995 USD. All income data is from the World Bank CD-Rom 2001 and GDP per capita in 2000 was taken from the World Bank website, except for Taiwan, Germany and Poland due to restricted availability of the data required in this source. Income data for Taiwan come from the National Statistics website of Taiwan ROC at http://www.stat.gov.tw/. Income data for Poland come from the Economist Intelligence Unit (EIU) website and income data for Germany was taken from the International Financial Statistics CD-Rom version, IMF 1.1.54. The German income series concerns West Germany until 1990 and relates to reunited Germany since 1991. This follows the construction of the inequality data series.

[12] For example: investment labelled 2000 is measured by the average investment between 1995 and 1999.

Inequality statistics are computed from the Luxembourg Income study, as described in section 3. Several ratios of income percentile as well as quintile share ratios on either side of the median are considered for top and bottom end inequality. Overall inequality is measured by the Gini coefficient and the 90/10 ratio.

Investment dated t is measured by the average share of gross domestic fixed investment in GDP over the five years starting at and including t-1. Investment data comes from the World Bank CD-Rom 2001 except again for Taiwan ROC, Ireland and Germany. Taiwanese data on gross domestic fixed investment come from the National Statistics website of Taiwan ROC at http://www.stat.gov.tw. Data for Germany are from the International Financial Statistics CD-Rom, IMF version 1.1.54. The German investment series relates to West Germany until 1990 and to unified Germany after 1991. Data for Ireland come from the Economist Intelligence Unit.

Education is measured by the average years of schooling in the population aged 25 and over. The data come from the Barro and Lee (2000) dataset. Data for Luxembourg were not available, so the education data of the Netherlands is used for Luxembourg instead.

4.2 Estimation technique

This model is dynamic by construction and this becomes evident when rewriting equation (1) as

$$y_{it} = \alpha y_{i,t-1} + \beta X_{it} + u_{it} \qquad (2)$$

It is a well-known fact that the OLS and Within-groups techniques will provide a biased estimate of the coefficient on the lagged dependent variable. The coefficients of the other explanatory variables may end up being biased as well, as a result of their correlation with the lagged depend variable. For this reason, it is important to find a way of estimating the full set of coefficients consistently.

This bias on the lagged dependent variable will be positive in the OLS case, as a result of the correlation between the individual effect and the lagged dependent variable (Hsiao 1986). The

Within-groups estimator will suffer from a downward bias in panels with a small number of time periods (Nickell 1981). These two estimates nevertheless suggest upper and lower bounds within which the true value of the estimate is likely to lie[13] (Sevestre and Trognon 1996).

Some papers (Forbes 2000, Caselli et al. 1996, for example) have employed the first-difference GMM technique developed notably by Arellano and Bond (1991) to account for the lagged structure of the model. In brief, this method implies taking the first-difference of the equation, to eliminate the time-invariant individual effects n_i, and then using sufficiently lagged values of y_{it} or other variables as instruments for the first differences, $(y_{i,t-1} - y_{i,t-2})$ and $(x_{it} - x_{i,t-1})$. The consistency of this estimator hinges on the absence of serial correlation in the disturbances. In that case, the first-differenced residuals are expected to show some negative first-order serial correlation but should not display any second-order serial correlation. A first- and second-order serial correlation tests are reported as *m1* and *m2* in the results tables.

However, as demonstrated by Bond, Hoeffler and Temple (2001) in the growth model context, because GDP per capita series tend to be very persistent over time the instruments, i.e. lagged values of y_{it} in levels, are likely to be only weakly correlated with the first-differences. Under these conditions, the first-difference GMM estimator will still be consistent when T is fixed and N is large. But, especially when T is small, the estimated coefficients can suffer from a severe finite sample bias as a result of weak instruments. The ensuing bias for the coefficient on the lagged dependent variable is expected to be downwards, in the same direction as that of the Within-groups estimator (Blundell and Bond 1998, Blundell et al. 2000).

Therefore, when the series is highly persistent another estimator with better finite sample properties in this context has been suggested: the so-called system GMM estimator (Bond et al. 2001, Blundell and Bond 1998). The system GMM estimator can be seen as an extended

[13] These results have been demonstrated assuming that the other explanatory variables are exogenous and uncorrelated with the individual effect. However, the OLS-Within-groups bound can still provide helpful warning bounds when the explanatory variables are not exogenous (Bond et al. 2001).

version of the first-differenced GMM estimator. It is computed by combining moment conditions for the equations in first-differences instrumented by suitably lagged variables in levels, together with additional non-redundant moment conditions provided by the equations in levels, where the instruments are suitably lagged first-differences. A further assumption for the system GMM estimator requires the first-differences of y_{it} and x_{it} to be uncorrelated with the individual effect n_i in order to be used as instruments in the level equations. This assumption will be valid, in particular, under the mean stationarity of the y_{it} and x_{it} processes. As pointed out by Bond et al. (2001), even if mean stationarity of investment rates does not seem to be an unreasonable supposition, the same suggestion can hardly be justified for a GDP per capita series. But, assuming common technical progress across countries in the sample, the inclusion of time dummies to capture these common time trends will allow the first-differenced GDP series to meet the requirement (Bond et al. 2001).

The Sargan test of overidentifying restrictions did not reject the validity of all reported instrument sets but, as demonstrated by Bowsher (2002), the test may lose its power and fail to reject the null hypothesis that the instruments are valid, when the sample size is small. Hence, this test is not reported. See Appendix B for a comparison of estimation results using the different techniques.

4.2.1 Instrument set

Given the restricted size of the sample, the instrument set chosen in this paper is rather parsimonious. For equations in first-difference, only the second lag of y_{it} is used as instruments for the lagged dependent variable. Education dated t-1 is treated as exogenous as the stock of education in a country measured by the average year of schooling in the population is expected to vary only slowly over time. The education variable turns out to be usually insignificant in the regressions whether considered exogenous or predetermined. Investment is regarded as predetermined due to restrictions on investment data in some countries of the sample. This means that investment labelled *t* is considered to be uncorrelated with the shock in period t, but not with the shock in $t\text{-}1$[14]. If, however, investment is believed to be endogenous, implying that investment labelled t is correlated with both shocks in $t\text{-}1$ and t, instruments should be lagged one period further. There might however be a trade-off between allowing more flexibility in the choice of instrument by treating investment endogenous and getting a weaker correlation between the instruments and the variable to be instrumented. This situation might be expected with Eastern European countries where growth rates of the 1990s would be explained by investment rates of the early 1980s in that case. Nevertheless, the results of interest in this study appear to be robust to the assumption of endogeneiety of investment, see appendix C. Finally, following Forbes (2000) income inequality is considered as endogenous.

For the level equations, only the lagged dependent variable and investment are included in the instrument set. Besides being an attempt to minimize the size of the instrument set, the exclusion of the inequality and education variables from the levels equations allows for a correlation between these first-differenced series and the individual effects n_i. Therefore, unless otherwise specified, the instrument set of the System GMM estimations consists of: for the first-difference part, $\ln(y_{t-2})$, Invest_{t-1}, $\Delta\text{AvgYrsSchool}_{t-1}$, and Inequality variables_{t-2} ; the additional instrument set for the level part comprises $\Delta\ln(y_{t-1})$ and ΔInvest_t.

4.3 Results

Estimations were obtained using DPD98 for Gauss provided by Arellano and Bond (1998), and available at: www.ifs.org.uk/staff/steve_b.shtml. Results reported are first-step estimates given that the large differences in variance between the first- and second-step estimates suggest the presence of heteroscedasticity[15]. In this case, inferences based on first-step estimator are more reliable, Arellano and Bond (1998).

[14] For example, investment labelled 2000 is the average investment over the period 1995 to 1999 and is assumed to be correlated with the shock in 1995 but not with the shock in 2000.

[15] The first- second-step estimators differ in their weighting matrix. The first-step weighing matrix is composed of 2s on the diagonal, –1s on each side of the diagonal and zeros everywhere else. The second step matrix is based on the residuals from an initial consistent estimation. When errors are independent and homoscedastic across units and over time, the estimated coefficients are asymptotically equivalent.

All System GMM estimations of the paper contain a set of time dummies; dummies were grouped or deleted depending on their statistical significance. The aim of this approach is to limit the number of non-significant coefficients to be estimated, without affecting the conclusions of the study. See appendix C for a comparison of the results when all time dummies are included separately.

The results of the growth model estimations using the System GMM estimator are reported in table 4.1. In columns 1-3, inequality measured either by the Gini coefficient, the 90/50 or 50/10 percentile ratios does not appear to be significantly related to economic growth in the subsequent 5-year period. However, when both top and bottom end inequality measures are used at the same time, their coefficients move away from zero - in the positive direction for the 90/50 coefficient and in the negative direction for the 50/10 coefficient. And, both coefficients become statistically significant at the 10 percent level, see column 6. Evidence from other top and bottom inequality measures combined further supports this relationship, regressions 9 – 11. The same conclusion emerges using quintile share ratios instead of percentile ratios, in the last column.

These results suggest that top and bottom inequality variables generate opposite effects, and as a consequence, their coefficient ends up being pulled towards zero when either one or the other is the sole inequality measure in a regression. When together, their standard error rises (reflecting a high level of inter-correlation) and each coefficient moves away from zero in opposite directions, becoming significant. This pattern could fit an omitted variable bias story quite well. The same picture holds for the Gini coefficient. The coefficient becomes significantly negative when the top of the distribution is controlled for in regressions 4 and 7, while its coefficient shifts significantly in the positive direction when a bottom inequality measure is included instead, see regressions 5 and 8. This leads to the suggestion that the Gini coefficient is insignificant as a result of acting as a proxy for both the positive and negative effects of the top and bottom end inequality respectively.

Table 4.1: Regression analysis with top end and bottom end inequality measures

Regressions	Gini only	90/50 only	50/10 only	Gini and top	Gini and bottom	**Top and bottom**	Alternative specifications					
$\ln(y_{t-1})$	-0.1000***	-0.1042***	-0.1030***	-0.1438***	-0.1032***	**-0.1315*****	-0.1482***	-0.0927***	-0.1094***	-0.1681***	-0.1188***	-0.0984***
	(0.0268)	(0.0327)	(0.0284)	(0.0398)	(0.0334)	**(0.0415)**	(0.0421)	(0.0317)	(0.0480)	(0.0493)	(0.0394)	(0.0363)
Invest $_t$	0.0320***	0.0302**	0.0343***	0.0352**	0.0268**	**0.0290*****	0.0210*	0.0299***	0.0249	0.0201*	0.0316***	0.0280**
	(0.0161)	(0.0160)	(0.0146)	(0.0181)	(0.0146)	**(0.0141)**	(0.0134)	(0.0141)	(0.0178)	(0.0135)	(0.0141)	(0.0143)
AvgYearSchool$_{t-1}$	-0.0296	-0.0394	-0.0075	-0.0187	0.0022	**0.0080**	-0.0352	0.0028	-0.0031	-0.0107	0.0073	-0.0127
	(0.0454)	(0.0478)	(0.0454)	(0.0441)	(0.0495)	**(0.0479)**	(0.0460)	(0.0514)	(0.0444)	(0.0456)	(0.0495)	(0.0428)
Gini $_{t-1}$	0.7053			-6.5466**	4.9244**		-3.7418***	4.4466**				
	(0.9391)			(3.3578)	(2.7774)		(1.8275)	(2.6455)				
90/50 $_{t-1}$		0.1966		1.2116***		**0.7904*****					0.7215***	
		(0.1510)		(0.4693)		**(0.3673)**					(0.3538)	
95/80 $_{t-1}$							1.3474***		1.4246***			
							(0.4429)		(0.6328)			
90/75 $_{t-1}$										1.3785***		
										(0.5715)		
Q5/Q3												0.4336***
												(0.1830)
50/10 $_{t-1}$			-0.0122		-0.6455**	**-0.6152****				-0.4423**		
			(0.1046)		(0.3745)	**(0.3352)**				(0.2179)		
50/20 $_{t-1}$									-1.2006**			
									(0.6168)			
40/10 $_{t-1}$								-0.7568*			-0.7229**	
								(0.4693)			(0.4217)	
Q3/Q1												-0.3649*
												(0.2265)
Wald joint test[1]	-	-	-	0.009	0.208	**0.079**	0.004	0.243	0.078	0.051	0.102	0.049
m1	-2.452	-2.463	-2.477	-2.539	-2.696	**-2.687**	-2.646	-2.645	-2.486	-2.808	-2.660	-2.483
m2	-0.151	-0.267	-0.009	-0.424	-0.645	**-0.905**	-0.539	-0.720	-0.358	-0.848	-0.968	-0.595

25 countries, 91 observations, time dummies set, robust std errors in parenthesis. The dependent variable is $\Delta\ln(y_t)$ where t - (t-1) is a 5-year period. For each country, growth periods considered are all or at least 2 subsequent 5-year periods, between 1975 and 2000. [1] p-value reported, Wald joint test on the two inequality variable coefficients in the regression. ***, **, * indicates that the coefficient is significantly different from zero at the 5, 10, and 15 percent significance levels, respectively.

Table 4.2 Sensitivity analysis

Country/ies excluded	Whole sample	Sweden	Scandinavia	Benelux	ROC Taiwan	UK	Ireland	US	Mexico	Mexico	Russian Fed.	Poland	Eastern Europe
No countries remaining	25	24	21	22	24	24	24	24	24	24	24	24	21
Observations	91	85	75	81	87	85	88	86	89	89	89	88	82
$\ln(y_{t-1})$	-0.1315^{***}	-0.1275^{***}	-0.1247^{***}	-0.1243^{***}	-0.1302^{***}	-0.1422^{***}	-0.1277^{***}	-0.0985^{***}	-0.1387^{***}	-0.1742^{***}	-0.1330^{***}	-0.1124^{***}	-0.3081^{***}
	(0.0415)	(0.0434)	(0.0369)	(0.0427)	(0.0450)	(0.0444)	(0.0432)	(0.0406)	(0.0451)	(0.0543)	(0.0319)	(0.0509)	(0.0682)
$Invest_t$	0.0290^{***}	0.0236^{*}	0.0177	0.0259^{**}	0.0306^{***}	0.0290^{**}	0.0290^{***}	0.0238^{***}	0.0326^{***}	0.0238^{**}	0.0138	0.0337^{***}	0.0452^{***}
	(0.0141)	(0.0162)	(0.0238)	(0.0139)	(0.0147)	(0.0152)	(0.0142)	(0.0111)	(0.0148)	(0.0141)	(0.0101)	(0.0123)	(0.0097)
$AvgYearSch_{t-1}$	0.0080	0.0200	0.0411	0.0031	0.0027	0.0338	0.0043	-0.0292	0.0039	-0.0122	0.0285	-0.0053	0.0909^{**}
	(0.0479)	(0.0510)	(0.0607)	(0.0473)	(0.0509)	(0.0539)	(0.0457)	(0.0470)	(0.0438)	(0.0427)	(0.0332)	(0.0564)	(0.0478)
$90/50_{t-1}$	0.7904^{***}	0.7948^{***}	0.9227^{***}	0.8275^{***}	0.8109^{***}	0.9790^{***}	0.7419^{***}	0.7087^{**}	0.6608^{**}		0.6921^{***}	0.5349^{***}	
	(0.3673)	(0.3434)	(0.3811)	(0.3705)	(0.3809)	(0.3800)	(0.3409)	(0.3894)	(0.3814)		(0.3309)	(0.2460)	
$90/75_{t-1}$										1.2645^{***}			1.3936^{***}
										(0.5821)			(0.5166)
$50/10_{t-1}$	-0.6152^{**}	-0.6270^{***}	-0.8007^{***}	-0.6175^{**}	-0.6333^{**}	-0.8533^{***}	-0.5734^{**}	-0.5135^{*}	-0.4794^{*}	-0.3713^{**}	-0.4251^{*}	-0.4536^{**}	-0.4469^{***}
	(0.3352)	(0.3075)	(0.3726)	(0.3458)	(0.3422)	(0.3516)	(0.2932)	(0.3550)	(0.3013)	(0.1923)	(0.2894)	(0.2596)	(0.2230)
Wald joint test[1]	0.079	0.063	0.049	0.055	0.086	0.035	0.093	0.103	0.222	0.089	0.068	0.060	0.023
m1	-2.687	-2.578	-2.256	-2.718	-2.648	-2.704	-2.639	-2.545	-2.722	-2.809	-2.673	-2.300	-2.605
m2	-0.905	-1.178	-1.273	-0.586	-0.837	-0.763	-0.901	-2.044	-0.814	-0.865	-1.423	-0.273	0.161

Time dummies set included, robust standard errors in parenthesis. The dependent variable is $\Delta\ln(y_t)$ where t - (t-1) is a 5-year period. For each country, growth periods considered are all or at least 2 subsequent 5-year periods, between 1975 and 2000.

Eastern Europe in the sample includes: Hungary, Poland, the Russian Federation and the Czech Republic.

[1] p-value reported, Wald joint test on the two inequality variable coefficients in the regression.

***, **, * indicates that the coefficient is significantly different from 0 at the 5, 10, and 15 percent significance levels, respectively.

In table 4.2 the results are tested for their robustness to the exclusion of a country or a set of countries displaying either a very unequal or equal income distribution. Sweden and the Scandinavian countries in general, as well as the countries from the Benelux, tend to be regions where inequality is the lowest in the sample. By contrast, the UK, the US, Mexico and some countries from Eastern Europe have much higher levels of inequality, especially towards the end of the period. Taiwan, the only Asian country in the sample, is also excluded in column 5. Without Scandinavia or Eastern Europe the sample drops to 21 countries, but the top and bottom end inequality coefficients remain significantly positive and negative. Some other countries are also excluded for data quality reasons, e.g. a discontinuity in the household survey over the period, and the results are not affected either, see appendix D. Consequently, these findings do not appear to be driven by a specific country or set of countries. This is an important observation given the small size of the sample and the fact that a single country could have an important influence on the outcome of the analysis.

It can also be noted, that education exerts a significant and positive effect on the growth process when all Eastern European countries are excluded from the sample, see last column of table 4.2. This could be explained by the fact that education levels in Eastern European countries are quite high[16] while at the same time, these countries experienced on average a negative growth rate over that period compared to an average positive growth rate in the remaining of the sample. However, De la Fuente and Donenech (2000) have also pointed out to the quality of education data as an explanation for the lack of significance of human capital in growth regressions.

5. Discussion and conclusion

This study highlighted potential problems arising when seeking to identify the effect of income distribution on growth with an aggregate inequality index, like the Gini coefficient. The empirical analysis demonstrated that top end inequality is systematically positively related to subsequent

[16] Over the entire period, the average years of schooling among the Eastern European countries included in the sample is 9.5 compared to 8.89 in the rest of the sample.

economic growth while bottom end inequality has a negative influence on economic performance. These findings are robust across inequality measures and sample selections.

It follows that whether inequality has a positive or negative overall influence on growth depends on the relative importance of each type of inequality in a country. Effectively, for the same distance between the top and bottom of the distribution, one country could have inequality concentrated at the top and the other at the bottom, resulting in a different overall effect of inequality. The ideal shape for the income distribution seems, therefore, to be compressed at the bottom but not so restricted at the top. These results, nevertheless, do not imply that the negative effect of bottom end inequality can always be compensated for by more top end inequality. There might be an upper limit to overall inequality after which this relationship changes altogether. As already well acknowledged in the literature, when income inequality, or the concentration of economic power, also influences the allocation of political power, people on either ends of the distribution might have an incentive to expropriate individuals at the other end. The next period productivity ends up being lower as a result (e.g. Bénabou 1996, Benhabib and Rustichini 1996).

Redistribution policies in this context can have two potential effects on growth: a negative one that reduces top inequality and a positive one that restricts income differences at the bottom of the distribution. The ambiguous effect of redistribution has been documented in numerous theoretical papers, where the negative incentive effect on taxed agents can be counter-balanced by the productive impact of relaxed credit constraints and government public spending (e.g. Bénabou 1996, Perotti 1993, Aghion and Bolton 1997, Lee and Roemer 1998, Aghion et al. 1999). However in a country where high levels of redistribution are taking place, top and bottom end inequality will tend to be lower than in a country where there is no active redistribution policy. Therefore, high top end inequality could mean that less redistribution occurred in the first place and that fewer distortions were created on investment incentives (see Barro 2000).

It becomes difficult to disentangle the direct effect of inequality on growth from its indirect effect via ensuing redistribution policies, especially since taxation and other policies from earlier periods are likely to influence the ex-ante distribution of income. The question whether the top and bottom end inequality coefficients do or do not capture the effect of redistribution on growth should probably be tested in another way. This could be done, for example by incorporating taxation policy variables directly into the model.

Several theoretical papers have also discussed how different levels of inequality may be required at different levels of income to ensure continued growth in a country (e.g. Perotti 1993). How top and bottom end inequality might relate empirically to development or to economic growth in poorer countries remains to be explored.

Finally, the main limitation of this analysis is the size of the sample on which it is based. The system GMM estimator is also a technique that performs better in larger samples than that considered here. At the same time, this sample is fairly homogenous and consists only of democracies with high levels of income per capita, which should limit biases resulting from time-varying omitted variables. Also, this study does not take into account cross-country transfers arising from inequality. Inequality in one country can affect in growth another country through resulting labour policies, for example. As well, in this study it is assumed that the rich and unconstrained agents only invest in the country where they obtained their income.

This paper suggests one way of taking into account the shape of the income distribution as a determinant of economic growth. And, the results of the analysis support the proposition that the specific configuration, and not only the spread of the distribution, determines the effect of income inequality on a country's economic performance. Therefore, a shift in inequality where the rich are getting richer is expected to have a different outcome on growth than a shift where the disparity is increasing at the bottom of the distribution. The ultimate impact of inequality will depend on the relative importance of the positive and negative influences of top and bottom end inequality. The next step of this investigation should be to identify empirically or theoretically the different channels through which bottom and top end inequality may influence the growth process in an economy.

6. References

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Appendix A

Table A, List of surveys for the countries in the sample

Country	Surveys	1970	1975	1980	1985	1990	1995
Australia	Australian Income and Housing Survey			1981	1985	1989	1994
Austria	Austrian Microcensus				1987		1995
Belgium	Panel Survey of the Centre for Social Policy				1985	1992	1997
Canada	Survey of Consumer Finances	1971	1975	1981	1987	1991	1994
Czech Republic	Microcensus					1992	1996
Denmark	Income Tax Survey				1987	1992	1995
Finland	Income Distribution Survey				1987	1991	1995
France	The French Survey of Income from Income Tax for 1979 and Family Budget Survey for 1984, 1989 and 1994			1979	1984	1989	1994
Germany	Income and Consumer Survey (EVS) for 1973 and 1978, The German Transfer Survey for 1981 and the GSOEP for 1984, 1989 and 1994	1973	1978	1981	1984	1989	1994
Hungary	Hungarian Household Panel					1991	1994
Ireland	ESRI Survey of Income Distribution, Poverty and Usage of State Services for 1987, European Community Household Panel (ECHP) for 1995				1987		1995
Israel	Family Expenditure Survey			1979	1986	1992	1997
Italy	The Bank of Italy Survey (Indagine Campionaria sui Bilanci Delle Famiglie)				1986	1991	1995
Luxembourg	The Luxembourg Social Economic Panel Study "Liewen zu Letzebuerg"				1985	1991	1994
Mexico	National Household Survey on Income and Expenditure (Encuesta Nacional de Ingresos y Gastos de los Hogares)					1989	1994
Netherlands	Additional Enquiry on the Use of (Public) Services (AVO) for 1983 and 1987, Socio-Economic Panel (SEP) for 1991 and 1994			1983	1987	1991	1994
Norway	Income and Property Distribution Survey			1979	1986	1991	1995
Poland	Household Budget Survey				1986	1992	1995
R.O.C Taiwan	Survey of Personal Income Distribution, Taiwan Area			1981	1986	1991	1995
Russia	Russian Longitudinal Monitoring Survey					1992	1995
Spain	Expenditure and Income Survey			1980		1990	
Sweden	Income Distribution Survey (Inkomstfördelningsundersokningen)	1967	1975	1981	1987	1992	1995
Switzerland	Swiss Income and Wealth Survey for 1982 and Swiss Poverty Survey for 1992			1982		1992	
United Kingdom	The Family Expenditure Survey	1969	1974	1979	1986	1991	1995
United States	March Current Population Survey		1974	1979	1986	1991	1994

Appendix B

Table B, comparison of results with different estimators

Estimation Method	OLS	Within-groups	GMM First Difference					GMM system
				Lagged dep. variable value fixed at				
				- 0.2	-0.15	-0.10	-0.05	
Observations	91	66	66	66	66	66	66	91
$\ln(y_{t-1})$	-0.0561**	-1.0577***	-1.3597***					-0.1000***
	(0.0350)	(0.2094)	(0.3428)					(0.0268)
Invest_t	-0.0010	0.0480***	0.0289*	0.0552***	0.0558***	0.0564***	0.0570***	0.0320***
	(0.0074)	(0.0131)	(0.0180)	(0.0218)	(0.0226)	(0.0234)	(0.0243)	(0.0161)
$\text{AvgYrsSchool}_{t-1}$	-0.0217	0.0800***	0.1423**	0.1698***	0.1747***	0.1796***	0.1845***	-0.0296
	(0.0199)	(0.0378)	(0.0791)	(0.0829)	(0.0852)	(0.0876)	(0.0901)	(0.0454)
Gini_{t-1}	-0.4340	1.3602	6.7864***	1.5821	1.6848	1.7875	1.8902	0.7053
	(0.6071)	(1.0855)	(3.3777)	(5.5733)	(5.7981)	(6.0272)	(6.2600)	(0.9391)
m1	-1.711	-1.658	0.244	-2.245	-2.224	-2.204	-2.184	-2.452
m2	-1.228	0.323	-0.308	0.751	0.750	0.752	0.755	-0.151

The dependent variable is $\Delta \ln(y_t)$ where t-1 is a 5-year lag period. 25 countries, for each country, growth periods considered are all or at least 2 subsequent 5-year periods between 1975-2000.
***, **, * indicates that the coefficient is significantly different from 0 at the 5, 10, and 15 percent significance level respectively, robust standard errors in parenthesis, m1 and m2 refer to first and second order serial correlation tests

Time dummies:
OLS: 1975 and 80, 85, 90, 95, 2000; Within-groups and first differenced GMM: 1980, 85, 90, 95, 2000.
System GMM: 1975 and 80, 90 95 2000, see appendix C for discussion when all dummies are included separately

Instrument set: For GMM first-difference: $\ln(y_{t-2})$ and the next lag, Invest_{t-1}, Gini_{t-2}, $\Delta\text{AvgYrsSchool}_{t-1}$.
Additional instrument set for the level part of the system GMM: $\Delta\ln(y_{t-1})$ and ΔInvest_t

In the third column, the first-difference GMM estimate for the coefficient on the lagged dependent variable lies below the coefficient value obtained using the Within-groups estimator. As predicted by econometrics theory in this case, the coefficient obtained with the first-difference GMM technique appears to be biased downwards, suggesting a weak instrument bias. Notice that the significant and positive effect of the Gini coefficient on growth disappears when the lagged dependent variable is fixed at what is expected to be more reasonable values.

The lagged dependent variable coefficient obtained using the system GMM estimator lies between the OLS and within-groups bounds and is close to the value obtained in their study by Bond, Hoeffler and Temple (2001), on a different sample.

Appendix C

Table C, comparison of different assumptions, System GMM estimator

Regressions	More specifications			With all time dummies	
	1	2	2	4	5
$\ln(y_{t-1})$	-0.0920***	-0.1471***	-0.0324	-0.1429***	-0.0879
	(0.0277)	(0.0513)	(0.0493)	(0.0677)	(0.0838)
Invest $_t$	0.0314***	0.0216**	0.0501***	0.0253	0.0302***
	(0.0152)	(0.0125)	(0.0196)	(0.0181)	(0.0160)
$AvgYearSch_{t-1}$	-0.0273	-0.0261	0.0409	-0.0344	0.0167
	(0.0462)	(0.0457)	(0.0603)	(0.0451)	(0.0481)
Gini $_{t-1}$				-0.0593	
				(0.9094)	
90/10 $_{t-1}$	0.0298	-0.1329	0.4136***		
	(0.0338)	(0.1042)	(0.1271)		
90/50 $_{t-1}$		0.7251**			0.8939***
		(0.4261)			(0.4203)
50/10 $_{t-1}$			-1.5078***		-0.5962**
			(0.5497)		(0.3326)
Wald joint test[1]	-	0.088	0.002	-	0.090
m1	-2.439	-2.825	-2.452	-2.627	-2.732
m2	-0.138	-0.791	-0.275	-0.249	-0.867

25 countries, 91 observations, some time dummies included, robust standard errors in parenthesis. The dependent variable is $\Delta \ln(y_t)$ where t - (t-1) is a 5-year period. For each country, growth periods considered are all or at least 2 subsequent 5-year periods, between 1975 and 2000.

[1] p-value reported, Wald joint test on the two inequality variable coefficients in the regression.

***, **, * indicates that the coefficient is significantly different from zero at the 5, 10, and 15 percent significance levels.

Instrument set: for the first-difference part: $\ln(y_{t-2})$, Invest $_{t-1}$, inequality $variables_{t-2}$, $\Delta AvgYrsSchool_{t-1}$. Additional instrument set for the level part: $\Delta\ln(y_{t-1})$ and $\Delta Invest_t$

In columns 1-3, the same sign pattern holds when replacing the Gini coefficient by the 90/10 percentile ratio, see columns 1, 4 and 5 of table 4.1.

In columns 4, 5, and 10 all 6 time dummies were included separately; see col. 1 and 6 of table 4.1 for comparison with the smaller time dummy set. The smaller time dummy set comprises 4 dummies: one common dummy for both years 1970 and 1975, and one for 1985, one for 1990 and one for 1995.

Appendix C, cont.

Table C cont., comparison of different assumptions, System GMM estimator

Regressions	Comparison when investment is considered endogenous Analysis on a sub-sample of 21 countries [2]				
	6	7	8	9	10
Instrument set	A	A	B	B	B, and all time dummies
$\ln(y_{t-1})$	-0.1247*** (0.0241)	-0.1660*** (0.0325)	-0.1484*** (0.0331)	-0.1703*** (0.0359)	-0.0970* (0.0648)
Invest $_t$	0.0212 (0.0150)	0.0248** (0.0135)	0.0265*** (0.0128)	0.0228** (0.0127)	0.0282** (0.0148)
AvgYearSch$_{t-1}$	0.0135 (0.0260)	0.0531 (0.0370)	0.0383 (0.0303)	0.0677*** (0.0312)	0.1009** (0.0552)
Gini $_{t-1}$	1.3637 (0.9950)		1.0014 (0.7011)		
90/50 $_{t-1}$		0.7485*** (0.3117)		0.5757*** (0.2604)	0.9196*** (0.4319)
50/10 $_{t-1}$		-0.5177** (0.2811)		-0.3797* (0.2444)	-0.4722** (0.2413)
Wald joint test[1]	-	0.041	-	0.036	0.103
m1	-2.526	-2.685	-2.528	-2.629	-2.660
m2	-0.091	-0.782	0.095	-0.722	-0.719

21 countries, 80 observations, some time dummies included, robust standard errors in parenthesis. The dependent variable is $\Delta \ln(y_t)$ where t - (t-1) is a 5-year period. For each country, growth periods considered are all or at least 2 subsequent 5-year periods, between 1975 and 2000.

***, **, * indicates that the coefficient is significantly different from zero at the 5, 10, and 15 percent significance levels.

[1] p-value reported, Wald joint test on the two inequality variable coefficients in the regression.

[2] excluding countries where investment lagged 2 periods was not available: the Netherlands, Spain, Czech Rep and Russian Fed.

Instrument set A, investment considered predetermined:
for the first-difference part: $\ln(y_{t-2})$, Invest $_{t-1}$, inequality variables$_{t-2}$, ΔAvgYrsSchool$_{t-1}$.
Additional instrument set for the level part: $\Delta \ln(y_{t-1})$ and ΔInvest $_t$

Instrument set B, investment considered endogenous:
for the first-difference part: $\ln(y_{t-2})$, Invest $_{t-2}$, inequality variables$_{t-2}$, ΔAvgYrsSchool$_{t-1}$.
Additional instrument set for the level part: $\Delta\ln(y_{t-1})$ and ΔInvest $_{t-1}$

Appendix D

Sensitivity analysis cont.

Country/ies excluded	France	Austria	Data on reunited Germany	Australia	Nether-lands	Switzer-land	Spain	Luxem-bourg
No countries remaining	24	24	25	24	24	24	24	24
Observations	87	88	89	87	87	88	88	88
$\ln(y_{t-1})$	-0.1279***	-0.1321***	-0.1260***	-0.1330***	-0.1262***	-0.1302***	-0.1272***	-0.1336***
	(0.0439)	(0.0414)	(0.0410)	(0.0430)	(0.0398)	(0.0400)	(0.0426)	(0.0436)
Invest $_t$	0.0290***	0.0284***	0.0287***	0.0297***	0.0284***	0.0280***	0.0279**	0.0269**
	(0.0138)	(0.0140)	(0.0135)	(0.0141)	(0.0143)	(0.0142)	(0.0144)	(0.0141)
$AvgYearSch_{t-1}$	0.0068	0.0088	0.0023	0.0108	0.0039	0.0080	0.0134	0.0101
	(0.0510)	(0.0473)	(0.0487)	(0.0480)	(0.0465)	(0.0475)	(0.0525)	(0.0481)
90/50 $_{t-1}$	0.8303***	0.8084***	0.7681***	0.7859***	0.7967***	0.7877***	0.7756***	0.8314***
	(0.3760)	(0.3754)	(0.3657)	(0.3694)	(0.3578)	(0.3633)	(0.3649)	(0.3721)
50/10 $_{t-1}$	-0.6523**	-0.6260**	-0.5931**	-0.6252**	-0.6082**	-0.6090**	-0.6215**	-0.6296**
	(0.3377)	(0.3417)	(0.3328)	(0.3386)	(0.3329)	(0.3344)	(0.3301)	(0.3455)
Wald joint test[1]	0.070	0.080	0.082	0.086	0.062	0.073	0.089	0.055
m1	-2.697	-2.700	-2.667	-2.606	-2.715	-2.684	-2.587	-2.660
m2	-0.392	-0.871	-0.522	-0.820	-0.613	-0.921	-1.013	-0.941

25 countries, 91 observations, some time dummies included, robust standard errors in parenthesis. The dependent variable is $\Delta\ln(y_t)$ where t - (t-1) is a 5-year period. For each country, growth periods considered are all or at least 2 subsequent 5-year periods, between 1975 and 2000.

[1] p-value reported, Wald joint test on the two inequality variable coefficients in the regression.
***, **, * indicates that the coefficient is significantly different from 0 at the 5, 10, and 15 percent significance levels, respectively.

In Column 3, data for Germany after 1990 is excluded.

Instrument set:
For the first-difference part: $\ln(y_{t-2})$, Invest $_{t-1}$, inequality $variables_{t-2}$, $\Delta AvgYrsSchool_{t-1}$.
Additional instrument set for the level part: $\Delta\ln(y_{t-1})$ and $\Delta Invest_t$