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Does the Profile of Income Inequality Matter for Economic Growth?:

Distinguishing Between the Effects of Inequality in Different Parts of the Income Distribution

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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 suggest that inequality at the top end of the distribution is positively associated with growth, while inequality lower down the distribution is negatively related to subsequent growth. These findings highlight potential limitations of an exploration of the impact of income distribution on growth using a single inequality statistic. Such specifications may capture an average effect of inequality on growth, and mask the underlying complexity of the relationship.

Keywords: growth, inequality, income distribution, Gini coefficient

JEL classification: O4, D3

1. Introduction

The recently increasing availability of income distribution data has led to a growing empirical literature regarding the influence of income inequality on economic performance. Traditionally, the empirical analysis of this relationship has entailed estimating a coefficient on a single inequality statistic in a growth regression, alongside other explanatory variables. Theoretical models, however, suggest that inequality can both facilitate and retard growth. An examination of this literature (see Section 2) further reveals that most of the positive mechanisms can be linked to inequality at the top end of the distribution while many of the detrimental effects can be traced to bottom end inequality, or relative poverty. The current study therefore suggests a new way of taking into account the complex influence of inequality on economic growth that accounts separately for inequality in different parts of the income distribution, namely at the top and bottom end of the distribution.[1] The empirical results support the main hypothesis that inequality at the top and bottom ends of the distribution have different effects on growth, and implies that inference based on a single

1 Although more general specifications could also be considered, the basic distinction between top end and bottom end inequality should be seen as a starting point in the discussion regarding the empirical evidence on the profile of the income distribution and growth.

summary statistic, such as the Gini coefficient, could be misleading as it might reflect an average of these two offsetting effects.

Early empirical studies tended to support the conjecture that overall income inequality and growth are inversely related; see Bénabou (1996) for a review of these studies. Yet these observations, based on cross-section data, appeared to be quite sensitive to the inclusion of regional dummies, and to sample selection (e.g. Perotti, 1996). With the increasing availability of panel datasets, and the Deininger and Squire (1996) dataset in particular, it has become possible to reduce the measurement error in inequality statistics, to control for unobserved time-invariant heterogeneity between countries, and to use panel techniques to mitigate endogeneity concerns. Based on the Deininger and Squire (1996) dataset, some papers report a positive effect of overall income inequality on subsequent economic growth, using a diverse sample of developed and developing countries (see Li and Zou, 1998; Forbes, 2000). In the analysis of Barro (2000), however, inequality appears to encourage growth only within rich countries, and to slow it down in poorer countries. Moreover, allowing for non-linearity of the effect of inequality suggests that a change in inequality *in any direction* may be detrimental to growth (Banerjee and Duflo, 2003).

Although none of the papers mentioned have specifically focused on the shape of the distribution, the importance of the middle class emerges from several papers using the middle quintile share (e.g. Alesina and Perotti, 1996; Easterly, 2001). Furthermore, in response to concerns regarding data quality and comparability, some studies have focused on US data for individual states. With a cross-sectional approach, Partridge (1997) finds, simultaneously, a positive coefficient for the Gini index and a positive coefficient for the middle quintile share. Panizza (2002), in contrast, uses panel data techniques and only reports a negative impact of inequality on growth.[2]

The debate continues in the empirical literature as to whether the ultimate effect of overall income inequality on growth is positive, negative, or not significant. Nevertheless, it seems that studies' conclusions depend notably on the econometric method employed, and the data considered. This study looks at a broader question and investigates whether inequality in different parts of the distribution have different influences on subsequent economic growth, following the implications of theoretical literature. The central hypothesis—that top end inequality encourages growth while bottom end inequality retards growth—is explored using a standard growth model and a set of explanatory variables to control for inequality at the top and the bottom ends of the income distribution simultaneously. A system GMM estimation undertaken on a sample of industrialized countries, using data from the Luxembourg Income Study, indicates that inequality at different parts of the distribution does have different implications for growth, i.e. that the *profile* of inequality is also an important determinant of economic growth. Top end inequality appears to have a positive effect on growth while inequality further down the income distribution appears to be inversely related to growth.

2 Several studies have also looked at the reverse causation: how growth affects inequality and specific parts of the distribution in particular, e.g. Dollar and Kraay (2002).

The paper is organized as follows: Section 2 examines why we could expect the shape of the income distribution to matter for growth, according to the theoretical literature. Section 3 presents the data on income distribution. The model used for the estimations, the econometric method and the regression results are discussed in Section 4. Section 5 assesses the findings of the analysis and concludes.

2. Theoretical Reasons Why the Profile of the Income Distribution Should Matter

As is already well established by the theoretical literature, the income distribution exhibits a complex multi-dimensional relationship with economic growth. Although this paper focuses on one direction of the interaction—the impact of income inequality on growth—the various transmission channels that have been identified reveal an intricate picture. The story can be summarized by saying that inequality has both an inhibiting and a stimulating influence on economic performance, and that different theoretical mechanisms tend to focus on different aspects of the distribution. This section consequently considers how several mechanisms can be linked to specific parts of the income distribution, to better understand how the shape of the distribution might matter.

2.1. Budget Constraint, Savings and Investment

At the top of the distribution, individuals are wealthy enough to implement their investment plans, or have access to capital markets if they wish to borrow. Access to private funds is especially relevant in the presence of market imperfections or initial set-up costs. These individuals might also represent the main source of savings in the economy especially if, as in some of the Keynesian literature, the marginal savings rate is increasing with income, or if the propensity to save is higher on income from capital than on income from wages. Larger investors might also be more able to spread the risk of their investments and could receive a higher rate of return. These factors imply that higher inequality at the top end of the distribution may promote economic growth, as it boosts funds available and investment.[3]

Nevertheless, this process associated with the better off could be offset, 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, leading to high bottom end inequality (see e.g. Galor and Zeira, 1993; Aghion and Bolton, 1997). Even in the presence of trickle down, bottom end inequality remains a relevant concept so long as credit constraints apply. As a result of limited funds, some individuals will not be able to exploit their skills and talents, and fewer productive investments will be undertaken, or at a sub-optimal level (for example in education, see Galor and Moav, 2004).

3 This positive dynamic is reinforced if rich people's investments create a positive externality in the economy that increases the productivity of subsequent investments, e.g. Perotti (1993), Galor and Tsiddon (1996).

2.2. *Incentives, Effort and Innovation*

In an economic structure where ability is rewarded, effort, productivity and risk-taking will also be encouraged, generating higher growth rates as well as income inequality as a result. In such an environment, we can expect a higher level of income mobility as talented individuals have incentives to seize the higher returns of their skills. A concentration of talented and skilled individuals in the upper income ranks (in advanced technology sectors) is also conducive to technological progress, and therefore to growth (e.g. Galor and Tsiddon, 1997; Hassler and Mora, 2000).

Positive incentives can induce greater effort in all parts of the distribution. Thus, a greater level of inequality at the bottom end of the distribution might reflect such an incentive structure or a downwardly flexible wage system. However, at lower wages in particular, these productive effects are likely to be counterbalanced by workers' feelings of frustration and unfairness, see e.g. Akerlof and Yellen (1990) on the fair wage-effort hypothesis.

2.3. *Crime, Rent Seeking, and the Balance of Power*

In many theoretical and empirical papers, income or wage inequality and poverty appear to be recurrent explanatory factors, among other explanations, for crime, for victimization and for homicide (e.g. Kelly, 2000; Fajnzylber et al., 2002). The increased risk due to insecurity, in turn, unfavorably affects investment decisions, and growth as a result (e.g. Alesina and Perotti, 1996). Anti-social behavior is usually linked to poverty and thus to bottom end inequality, it may, however, also arise due to top end inequality. When income inequality is reflected by political polarization, the rich or ruling elite might prevent the implementation of pro-poor and other productive polices, like spending on human capital or infrastructure, appropriate the country's resources and subvert the legal and political institutions by rent-seeking and corruption (e.g. Easterly, 2001; Glaeser et al., 2003).

Furthermore, high overall inequality might result in social unrest and political instability, when both ends of the distribution are tempted to expropriate the opposing end (e.g. Bénabou, 1996). The link between political instability, inequality and growth appears in numerous empirical studies, e.g. Alesina and Perotti (1996), Easterly (2001).

2.4. *Taxation and Redistribution*

Redistribution, via a median voter mechanism for example,[4] is likely to have an ambiguous effect on growth.[5] Assuming more inequality means increased taxation,

4 Note that the standard median voter redistribution model focuses on the difference between the median and mean income. This is a measure of skewness rather than inequality per say.

5 See for example, Persson and Tabellini (1994), Perotti (1996) for empirical support.

the negative incentive effect on taxed agents at the top can be compensated by the productive impact of poor agents' relaxed credit constraints, of government public spending[6] (e.g. Perotti, 1993; Bénabou, 1996; Aghion and Bolton, 1997) or of reduced instability (Alesina and Perotti, 1996).[7]

2.5. Overall Inequality and the Shape the Income Distribution

The review presented above emphasizes how inequality at different parts of the income distribution can affect growth differently, with top end inequality more relevant for some of the mechanisms considered by the theoretical literature and bottom end inequality more relevant for others. These alternative mechanisms suggest that controlling for the effect of inequality on growth with a single distributional statistic may be unduly restrictive. Hence, the importance of looking at the shape of the income distribution more generally. This paper proposes a first step to allow for the diversity of pathways through which inequality can affect growth—one that takes into consideration the fact that many of the positive effects from inequality can be associated with the upper end of the distribution, while the reverse is true of inequality at the bottom end.

The ultimate effect of inequality on the economy, as considered by the current study, will consequently depend on the relative strengths of the positive and negative influences that are identified. In theory, this balance is unlikely to be independent of the overall level of inequality, see e.g. Banerjee and Duflo (2003). For example, at high disparity levels, the negative influence of inequality on growth might dominate due to a greater prevalence of social unrest, break down of law and order, rent-seeking and corruption.[8] Additionally, several theoretical papers have discussed how different levels of inequality may be conducive to growth at different levels of development. [9] From this perspective, the current paper attempts to identify aspects of the shape of the income distribution that are most beneficial to growth, in a linear way, and in countries where average income is relatively high. The question of how the profile of inequality might be linked empirically to growth in poorer countries is related, though potentially quite different, and remains a subject for further research.

6 Another documented outcome of high inequality, especially top end inequality, is reduced social solidarity with the rich trying to pull out of publicly funded programmes, like health care and education, in favor of private provision, see Schwabish, Smeeding and Osberg (2003). They find that top end inequality, measured by the 90/50 percentile ratio, has a strong negative impact on social expenditures while bottom end inequality, measured by the 50/10 ratio, has a small positive effect.

7 As discussed in Barro (2000), in a country where high levels of redistribution are taking place, however, top and bottom end inequality will tend to be lower than in a country where there is no active redistribution policy. High top end inequality could consequently reflect low redistribution levels, which might be accompanied by fewer distortions on investment incentives.

8 Other factors might be considered here, e.g. national preferences for inequality, perceived inequality levels, or the strength of political institutions.

9 For theoretical papers that consider this issue see e.g. Perotti (1993), Galor and Moav (2004), also Barro (2000) for related empirical evidence.

3. Income Distribution Data

The consequences of mismeasurement and poor comparability of inequality statistics, across countries and over time, have been a serious concern in this empirical literature. Researchers have, however, also been constrained by data scarcity. In this context, the introduction of the Deininger and Squire (1996) dataset was an important improvement in the quantity and quality of income distribution data available. Nonetheless, as pointed out by Atkinson and Brandolini (2001), and even for the OECD countries, differences in data coverage, income definition and construction methods could raise serious comparability issues, not only across countries but also over time. In order to reduce measurement error further, this study considers income distribution data from the Luxembourg Income Study (LIS). Opting for this dataset means a significant improvement in data quality and comparability, as described below, but at the expense of sample size.

3.1. Description of the Dataset

The LIS dataset offers several advantages as compared to other datasets. First, it provides income information coming from household surveys,[10] with a high degree of cross-national and over time comparability.[11] 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, [12] 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 Atkinson, Rainwater and Smeeding (1995), or the LIS website.

Although the reporting of income sources is becoming more and more comprehensive over time, several components of income are still excluded from the household disposable income on which the inequality measures are based. For example, non-cash benefits from housing, medical care or education, the imputed value of

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10 Most surveys were conducted through interviews. In some surveys however household income data was collected from administrative records or from a combination of both sources. Surveys for the US before 1991 comprise a 10% random sample from the full household survey. For Germany in the GSOEP years (from 1985 onwards) 90% of the sample is included, but the correcting household weights provided should mitigate a potential resulting sample bias. The other surveys consist of the full sample.

11 These surveys conducted in different countries for different purposes are made comparable through a "lissification" process. In other words, the original datasets are reorganized, if necessary, to correspond to the LIS coding and variable structures. For more information see: www.lisproject.org.

12 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.

owner-occupied housing, in-kind earnings,[13] realized capital gains/losses and indirect and property taxes are not included. Finally, this dataset allows direct access to raw income data on individual households. Access to raw data gives the advantage of increased precision in the calculation of inequality measures since they are based on a larger number of data points. In addition, it provides a greater flexibility in the choice of inequality measures and, importantly, uniformity and comparability in the computation of inequality indices across countries and over time.

3.2. Computation of Inequality Measures

This paper follows the standardization proposed by LIS for the computation of inequality measures[14] as follows: inequality indices are based on the individual equivalised income defined as the household annual net disposable income divided by an equivalence scale S^{ε}, where S is the number of persons in the household and ε is the equivalence elasticity set to 0.5.[15] All households surveyed and all their members are included. The inequality measures also include a correction for the sample bias using person weights. The extreme bottom of the distribution is recoded at 1 % of equivalised mean income and the extreme top at 10 times the median of non-equivalised income. Missing values and zero incomes have been excluded.

The point dividing the top and bottom of the income distribution is arbitrarily set at the median. Thus, ratios of income percentiles 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, which is the ratio of the equivalised individual median income to the 10th percentile equivalised individual income. Other bottom end inequality indices that have been considered include the 50/20 and 40/10 ratios, and similarly the 90/75, 95/80 and 90/50 ratios for top end inequality. These measures give an indication of the relative distance between the two points considered, at the top or bottom end of the distribution. They are easy to compute but are obviously not perfect and the top or bottom inequality ranking of countries might change depending on which ratio is considered. Also, these indices are sensitive to mismeasurement at the percentiles considered, though they do avoid the more common problem of mismeasurement at both extremes of the distribution. As a crosscheck, top and bottom quintile

13 In-kind earnings are included in the household disposable income of Mexico as this information is available in these surveys, and is likely to be an important source of income in that case.

14 See Atkinson, Rainwater and Smeeding (1995) for detailed discussion on LIS methodology and procedures, and notably how LIS data compare with national studies.

15 The square root of the number of persons in the household is a commonly used equivalence scale. However, the equivalence elasticity ε can be chosen to vary between 0 (perfect economies of scale) and 1 (no economies of scale). Inequality statistics are sensitive to the choice of the equivalence scale as discussed in several papers, e.g. Coulter, Cowell and Jenkins (1992), see also Buhmann et al. (1988) for sensitivity analysis based on LIS data. The sensitivity of the current findings to the value judgment implicit in the equivalence scale used remains an issue for further research.

share ratios have been used instead: Q5/Q3 for top end inequality and Q3/Q1 for bottom end inequality.

3.3. Selection of Household Surveys

This study considers a 5-year growth model in a selection of countries where the availability of this detailed 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; see Table 5 for details.

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.[16] 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 until 1990 and to reunited Germany thereafter; data for Austria in 1995 does not include self-employment income.

3.4. Some Summary Statistics

The Gini coefficients of the surveys included in the analysis are reported in Table 1. 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 distributions.[18] For example, in the UK, a compression at the top end and a widening of inequality at the bottom end, between 1970 and 1975, resulted in a stable Gini coefficient over this period. The subsequent increase in overall inequality from 1975 to 1995 is due to both ends of the distribution diverging, and to a top end increase more than offsetting a reduction in bottom end inequality over the last five year period. In Canada, the sustained reduction in bottom end 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 bottom ratio was more than compensated for by an increase in the top ratio. A more in-depth description of the

16 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. 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.

18 This discussion refers to the 90/50 ratio for top end inequality, and 50/10 ratio for bottom inequality.

Table 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	
Finland				0.209	0.210	0.226
France			0.293	0.298	0.287	0.288
Germany	0.271	0.264	0.244	0.268	0.257	0.273
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					0.274	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[17]	0.267	0.268	0.270	0.303	0.336	0.344
United States		0.318	0.301	0.335	0.336	0.355

[17]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.

evolution of inequality between and within the countries using the LIS dataset can be found in Atkinson, Rainwater and Smeeding (1995) and in Gottschalk and Smeeding (1997).

4. Empirical Analysis

4.1. The Model

This analysis follows the 5-year panel data growth model developed in several recent papers, with a lagged income variable to account for convergence (e.g. Caselli, Esquivel and Lefort, 1996; Li and Zou, 1998; Forbes, 2000; Bond et al., 2001). The 5-year structure of the model has been dictated by the limited data availability on the distribution of income, and also allows for comparison with other studies in the literature. 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 and $t-1$ correspond to observations 5 years apart and i denotes a particular country. y_{it} is the log of real GDP per capita, u_{it} includes an unobserved country-specific effect n_i, a time-specific effect h_t, and an error term v_{it}. The vector X_{it} contains current or lagged values of several explanatory variables. This set of controls includes inequality measures, both at the top and at the bottom end of the distribution, measured at t–1; the average years of schooling in the population in year t–1 as a measure of human capital; and an average investment rate dated t and measured over the 5 year period ending in t.[19] A complete description of the data and descriptive statistics are given in the Appendix and Table 6.

Although usually referred to as growth models, the type of neoclassical growth model on which this specification is based explains the long-term steady state level of income.[20] In this framework, a change in one of the explanatory variables will shift the long-run steady state level of income and will affect the growth rate only while on the convergence path to the new equilibrium level.[21] As such, a permanent change in income inequality will influence the growth rate in the short term, conditional on the initial level of income, but will have no permanent consequences for the growth rate once the new steady state is reached. Therefore, shifts in the explanatory variables have a short-term effect on growth and a long-term influence on the level of income. Nevertheless, as pointed out by Barro (2000), given that it can take a long time to reach the new steady state, the 'short-term' effects on growth can be quite enduring.

In the current context, the smooth adjustment to the new long-term level of income is, however, influenced by the 5-year lag structure imposed by data restrictions. This dynamic structure forces the adjustment process, following a change in explanatory variables, to start almost immediately, i.e. within the first five years. Arguably, the economy might react much more slowly to changes in variables like income inequality. That is, following the theoretical literature, a shift in income inequality might take more than five years before its consequences are first evident in the economy. This proposition should ideally be tested by relating growth to much longer lags of the inequality measures. The currently available dataset however does not allow for this type of investigation. It is therefore acknowledged that the short-term effect on growth might be affected by the 5-year specification imposed. It is hoped, however, that in spite of this restrictive dynamic structure, the longer term effect on the level of income will be adequately captured.

It should also be noted that the estimated coefficient on a variable in this model reflects its effect on income, given the other controls included in the regression.

19 E.g. investment labeled 2000 is measured by the average investment rate between 1996 and 2000.

20 See also Barro (2000) for more discussion.

21 In the first period, a change in X_{it} will affect the level of income by a magnitude of β, but the long-run effect on the steady state level of income is given by $\beta/(1-\alpha)$.

For example, the estimated coefficient on inequality tells us about the partial effect of inequality on income holding investment and education constant, which is unlikely to be equivalent to the overall effect of inequality on income as both education and investment could be affected by a change in inequality. However, excluding these two variables from the analysis would increase the risk of an omitted variable bias, especially if they are correlated with inequality. Also, this specification cannot take into account the cross-country transfers arising from inequality. For example, inequality in one country can affect the growth process in another through resulting labor policies. Equally, the present reduced form analysis is not very informative regarding the different channels through which inequality might affect income. This remains an issue for further research.

4.2. Estimation Technique

The usual OLS and within-groups methods for panel data are unlikely to be appropriate in the current analysis. Specifically, omitted variable bias is likely to affect the OLS coefficient estimates, due to the presence of unobserved country-specific influences, n_i. Although this concern can be addressed by using the within-groups estimation technique, neither method would allow for the potential endogeneity of the variables or measurement errors. The model considered here is dynamic by construction, and can be rewritten as:

$$y_{it} = \alpha y_{i,t-1} + \beta X_{it} + n_i + h_t + v_{it} \tag{2}$$

which highlights the presence of a lagged endogenous variable.[22] It is well-known that the OLS and within-groups techniques provide biased estimates of the coefficient α on the lagged dependent variable described by Equation (2). The bias on the lagged dependent variable will typically be positive in the OLS case, as a result of the correlation between the individual effects and the lagged dependent variable. The within-groups estimator will tend to suffer from a downward bias in panels with a small number of time periods (see e.g. Bond et al. (2001) for discussion). Furthermore, the coefficients of the other explanatory variables may also be biased as a consequence of their correlation with the lagged dependent variable.

To address the issue of omitted variable bias and to account for endogeneity, some studies have employed the first-difference GMM technique developed notably by Arellano and Bond (1991); see e.g. Caselli et al. (1996), Forbes (2000), Panizza (2002). The differencing of the model removes the unobserved time-invariant effects n_i, and appropriate instruments can then control for endogeneity and measurement error. This method implies taking the first-difference of Equation (2):

$$(y_{it} - y_{i,t-1}) = \alpha(y_{i,t-1} - y_{i,t-2}) + \beta(X_{it} - X_{i,t-1}) + (h_t - h_{t-1}) + (v_{it} - v_{i,t-1}) \tag{3}$$

22 This representation also confirms that the usual empirical growth model in (1) is in fact a dynamic model for the level of y_{it}, when $\alpha \neq 1$.

and then using sufficiently lagged values of y_{it} and X_{it} as instruments for the first-differences, $(y_{i,t-1} - y_{i,t-2})$ and $(X_{it} - X_{i,t-1})$ in (3).[23] However, the differencing procedure may discard much of the information in the data since the largest share of the variation in income, and income inequality statistics in particular, is cross-sectional, as discussed in several studies; e.g. Li, Squire and Zou (1998), Barro (2000) and Dollar and Kraay (2002). As a result, it is not clear that relying solely on the limited within country information is the best option. The restricted time-series variation in the data might make it difficult to estimate the coefficients with any precision (Dollar and Kraay, 2002).

This study consequently focuses on the system GMM estimator developed by Arellano and Bover (1995) and Blundell and Bond (1998).[24] The system GMM estimator can be seen as an extended version of the first-differenced GMM estimator that provides a way of retaining some of the information in the equations in levels. Provided the additional instruments used are valid, then the system GMM estimator tends to have better finite sample properties compared to the first-differenced GMM estimator, since it exploits the time-series information available more efficiently. This is likely to be particularly important when considering variables that are highly persistent; see Blundell and Bond (1998, 2000), and Bond et al. (2001). An analysis of the inequality data used in this study confirms the concerns raised by previous studies: between 87 and 90% of the variation in the inequality statistics is cross-sectional, (see Table 7 for details). As a result, the cost of controlling for the country-specific omitted variable bias, in terms of reduced precision of parameter estimates, is likely to be high and it is thus important to exploit the remaining information as efficiently as possible. In this context, the system GMM estimator is expected to provide more precise and less biased estimates than the first-differenced GMM estimator.

In brief, the system GMM estimator is computed by combining moment conditions for the equations in first-differences—Equation (3)—using suitably lagged variables as instruments, with additional moment conditions for the equations in levels — Equation (2) — where the instruments are suitably lagged values of $(y_{i,t-1} - y_{i,t-2})$ and $(X_{it} - X_{i,t-1})$, provided these first-differences are uncorrelated with the country-specific effects n_i.[25] Therefore, the instrument matrix is also com-

23 In order to get a consistent estimator for α and β, instruments should be correlated with the first differences $(y_{i,t-1} - y_{i,t-2})$ and $(X_{it} - X_{i,t-1})$ respectively, but not with the differenced error term $(v_{it} - v_{i,t-1})$. Different lagged values of the variables should be used as instruments depending on the degree of endogeneity in the variables. If a variable labeled t is considered to be predetermined, that is, uncorrelated with the shock in period t, but not with the shock in $t-1$, values lagged one period and further can be used as instruments. If, however, the variable is believed to be endogenous, implying that it is correlated with the shock in period t, only instruments lagged two periods and further can be used as instruments. See e.g. Bond, Hoeffler and Temple (2001) for discussion.

24 The system GMM estimator has also been used in the study of Dollar and Kraay (2002), following similar concerns, although they look at the reverse causality of the inequality-growth relationship.

25 Note that there are no restrictions regarding the format of the variables that can be used as instruments in the first-differenced equations (3), so long as they are uncorrelated with the

posed of two distinct parts: one part with the lagged variables as instruments for the first-differenced equations, and the other part with the lagged variables (in first-differences) as instruments for the equations in levels. For a discussion of this estimator in the context of empirical growth models, see Bond et al. (2001).

The validity of the instruments used for the first-differenced equations depends principally on the absence of serial correlation in the disturbances v_{it}. In that case, the first-differenced residuals are expected to show negative first-order serial correlation but should not display any second-order serial correlation. Tests for first- and second-order serial correlation are reported as m1 and m2 in the results tables. Serial correlation does not appear to be a problem in this analysis. A key additional assumption for the system GMM estimator requires the first-differences of y_{it} and X_{it} to be uncorrelated with the individual effects n_i in order for the first-differences to be valid instruments in the levels equations. This assumption is guaranteed to be valid if the y_{it} and X_{it} series have constant means over time for each country, after removing common time trends. Given the limited size of our sample, the instrument set chosen in this paper is rather parsimonious. A Sargan test of overidentifying restrictions did not reject the validity of any of the instrument sets considered but, as demonstrated by Bowsher (2002), the test may have low power to reject the null hypothesis, that the instruments are valid, when the sample size is too small. Therefore, Hausman tests were also implemented to test the exogeneity assumptions imposed on the explanatory variables.

In the instruments for the first-differenced equations, we use the second and third lags of the dependent variable y_{it}, which is necessarily endogenous. The education and income distribution variables, measured at the beginning of each five-year period (see Equation (1) and its description), are treated as predetermined. This implies that the first-difference, dated t-1, of each of these variables, is available as a potential instrument. Hausman tests did not reject the inclusion of the first-difference of these variables in the instrument set for the first-differenced equations.[26] A priori, it is not obvious whether investment dated t should be treated as predetermined and instrumented with its first lag, or as endogenous and instrumented with its second lag. Empirically, the hypothesis that investment is predetermined was not rejected.[27] Therefore, the default

differenced error term $(v_{it} - v_{i,t-1})$. In other words, suitably lagged variables in levels and/or in first-differences could be used as instruments for the equations in first-differences. For the equations in levels (2), however, suitable instruments must be orthogonal to the country effects n_i. This rules out using lagged levels of any variables that are correlated with the country effects, but may allow the use of lagged first-differences of such variables.

26 The tests are reported for the baseline sample, i.e. the sample excluding Eastern European countries as discussed below, and for the specification considered in column 6 of Table 2 (with the joint inclusion of the top and bottom end inequality measures). We focus on the coefficients on the variables for which exogeneity is being tested. For example, when we exclude the first lags of education and our two inequality measures from the instrument set, we test the null hypothesis of no change in the coefficients on these three variables. This joint hypothesis is not rejected with a p-value of 0.374. The null hypotheses of no change in these individual coefficients are also not rejected, with p-values of 0.661 on the education coefficient, and p-values of 0.762 and 0.382 on the top end and bottom end inequality coefficients respectively.

27 With a p-value of 0.330 on the coefficient on the investment variable.

instrument set that we use for the first-differenced equations consists of: y_{t-2} and y_{t-3}, ΔAvgYrsSch$_{t-1}$, ΔInequality variables$_{t-1}$ and Invest$_{t-1}$.

To be valid instruments for the equations in levels, the first-differenced explanatory variables have to be uncorrelated with the individual effect n_i. It is also possible for lagged first-differences of the dependent variable to be uncorrelated with the individual effect and used as an instrument, but as further discussed in Blundell and Bond (2000) this would require the first-differences of all the other explanatory variables to be uncorrelated with the individual effect n_i.

The explanatory variables are considered in turn. The inclusion of first-differenced investment in the instrument set for the levels equations is not rejected, nor is education.[28] When including the first-differences of the top and bottom end inequality measures in the instrument set for the levels equations, the hypothesis that they are both valid is rejected,[29] but a test does not reject the validity of including only the first-differenced bottom end inequality variable.[30] Consequently, in the baseline analysis, the first-differences of neither of these inequality variables are used as instruments for the equations in levels, but the inclusion of first-differenced bottom end inequality is considered in the sensitivity analysis.[31] Therefore, unless otherwise specified, the default instrument set for the levels equations comprises: ΔInvest$_t$ and ΔAvgYrsSch$_{t-1}$.

4.3. Results

The whole sample covers 25 countries, including a set of Eastern European countries, observed for at least two consecutive 5-year-periods. Following the discussion in Section 4.1, however, it could be argued that the Eastern European countries were not close to a long-term steady state path during the period of observation but rather in transition. These countries are therefore excluded from the baseline analysis and considered only in the sensitivity analysis. The baseline sample thus comprises 21 countries, observed for at least two consecutive 5-year-periods, or for all the years, between 1975 and 2000.

Compared to other empirical studies based on a larger sample of developed and developing countries, the current sample is rather small. However, its greater degree of homogeneity may reduce the impact of biases from time-varying omitted variables. In fact, the present sample only includes wealthy democratic countries. This feature of the data should ensure a rather similar evolution of several controls that have been considered in the growth literature such as demographic variables (e.g. fertility rates, life expectancy), political variables (e.g. democracy index, rule of law) and other economic variables (such as the level of financial development). All of these factors are likely to affect the growth process and might be correlated with income inequality.

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28 With a p-value of 0.437 on investment, and a p-value of 0.908 on education.

29 With p-values of 0.012 on bottom end inequality, and 0.0004 on top end inequality.

30 With a p-value of 0.301 on bottom end inequality.

31 Joint tests for the inclusion of both education and investment (and bottom end inequality), in first-differences, as instruments for the equations in levels, were not rejected.

Table 2. System GMM estimations, analysis with top and bottom end inequality measures, baseline sample (excl. Eastern European countries).

No	Gini only 1	Top Only 2	Bottom only 3	Gini and top 4	Gini and bottom 5	Top and bottom 6	Gini, top and bottom 7
y_{t-1}	−0.2635***	−0.2432***	−0.2820***	−0.2366***	−0.2656***	−0.2475***	−0.2516***
	(0.0681)	(0.0658)	(0.0701)	(0.0623)	(0.0588)	(0.0572)	(0.0605)
Invest_t	0.0164***	0.0147**	0.0173***	0.0137*	0.0161***	0.0143**	0.0146**
	(0.0077)	(0.0080)	(0.0078)	(0.0086)	(0.0079)	(0.0085)	(0.0080)
AvgYrsSch_{t-1}	0.0414**	0.0408**	0.0484***	0.0456***	0.0580***	0.0559***	0.0572***
	(0.0213)	(0.0219)	(0.0205)	(0.0211)	(0.0271)	(0.0235)	(0.0268)
Gini_{t-1}	−0.0451			−1.2053***	1.3363		0.5349
	(0.6151)			(0.5154)	(1.4167)		(1.5998)
$90/75_{t-1}$		0.2031		0.8933***		0.6464	0.4438*
		(0.4138)		(0.4207)		(0.5241)	(0.3014)
$50/10_{\ t-1}$			−0.0736		−0.2319	−0.1574***	−0.1940
			(0.0551)		(0.1671)	(0.0742)	(0.1764)
p-value[1]	0.941	0.623	0.181	0.018	0.183	0.104	0.029
m1	−2.220	−2.296	−2.144	−2.079	−2.157	−2.100	−2.127
m2	−0.782	−0.826	−0.749	−0.818	−0.738	−0.794	−0.761

21 countries, 81 observations, first-step estimates reported, time dummies included, robust standard errors in parenthesis. The dependent variable is Δy_t where $t - (t-1)$ is a 5-year period.
[1]Wald (joint) test on the inequality variable coefficient(s) in the regression.
***, **, * indicates that the coefficient is significantly different from 0 at the 5, 10 and 15% significance levels, respectively.

All estimations were obtained using DPD98 for Gauss provided by Arellano and Bond (1998).[32] Results reported are first-step estimates given that the large differences in estimated standard errors between the first- and second-step estimates suggest the presence of heteroscedasticity. In this case, inferences based on first-step estimator are more reliable; see Arellano and Bond (1998). Time dummies are included in all regressions. Although usually not individually significant, time dummies are systematically jointly significant.

The results for the baseline growth model estimations, using the system GMM estimator, are reported in Table 2. Inequality measured either by the Gini coefficient, the 90/75 percentile ratio or the 50/10 percentile ratio does not appear to be significantly related to economic growth when only one of these measures is included in the specification (columns 1–3). However, a joint test indicates that these inequality measures are highly significant when all three are included together (column 7). This remains the case when the 50/10 percentile ratio is excluded from the specification (column 4), although other pairs of the inequality measures appear to be less informative (column 5–6).

32 available at: www.ifs.org.uk

On the basis of this sample and instrument set, it seems therefore that the combination of the Gini and a top end inequality measure (column 4) is more efficient at capturing the effects of inequality on growth, with the inequality variables jointly significant at 2%, than the combination of the top and bottom end inequality measures together, which are jointly significant at the 10% level only (column 6). The economic interpretation of the specification with the Gini index and a top end inequality measure can, however, be related to our earlier discussion. The distinctive positive influence from inequality at the top end of the distribution may reflect the beneficial mechanisms identified in the theoretical literature, like increased incentives, innovation or savings. Inequality outside that top range and lower down the income distribution—captured by the Gini coefficient once the 90/75 percentile ratio is controlled for—is negatively related to subsequent growth and may be associated with channels such as credit constraints to investment in human capital, increased crime and insecurity, or reduced work effort. These opposing effects from inequality at different parts of the income distribution can help explain why any single measure of inequality is not found to be significant when included on its own, given that the different inequality measures are positively correlated with each other.[33]

The choice of a preferred specification appears, however, to be sensitive to changes in the instrument set, as demonstrated in Table 3. When the first-difference of the bottom end inequality measure is added as an instrument for the equations in levels, the joint significance of both combinations (columns 2–3) becomes much more similar, at the 11 and 12% levels respectively. This sensitivity is likely to reflect the colinearity between the different inequality indices and the small number of observations. The sign pattern and other characteristics of the results discussed above are nevertheless robust to such changes in the instrument set, or to the inclusion of the Eastern European countries into the sample (Table 3, columns 4–6).

Results from Tables 2 and 3 thus indicate that inequality in different parts of the income distribution have different effects on growth and therefore that the profile of the income distribution matters for economic growth. We find a positive effect from inequality in the top quartile of the income distribution, and a negative effect from inequality further down the income distribution. These findings further suggest that a single inequality statistic is insufficient to capture the effects of inequality on growth and that a more flexible specification should be considered, over and above a specification with a single inequality index.

33 The sign pattern found in Table 2 is robust to replacing Invest_t by PPPI_{t-1} (price level of investment from the Penn World Tables, used as a measure of market distortion) and/or to replacing the average years of schooling in the population by male and female average years of secondary schooling, also dated $t-1$ (from the Barro and Lee dataset) — results not reported. These controls have been used in other studies, e.g. Perotti (1996), Forbes (2000). Similar results were obtained using other percentile ratios or combinations of ratios, e.g. the 95/80 and 90/50 ratios for top end inequality or the 50/20 and 40/10 ratios for bottom end inequality. Including quintile share ratios, Q5/Q3 and Q3/Q1 rather than percentile ratios for top and bottom end inequality, provided similar results — results not reported.

Table 3. Sensitivity analysis.

Sample	Baseline sample			Whole sample		
Col no.	1	2	3	4	5	6
Instrument set	b	b	b	default	default	default
y_{t-1}	−0.2627***	−0.2315***	−0.2379***	−0.2998***	−0.2785***	−0.2841***
	(0.0771)	(0.0722)	(0.0661)	(0.0822)	(0.0820)	(0.0725)
Invest_t	0.0166***	0.0138**	0.0146***	0.0304***	0.0279***	0.0261***
	(0.0069)	(0.0075)	(0.0074)	(0.0124)	(0.0120)	(0.0111)
AvgYrsSch_{t-1}	0.0427***	0.0464***	0.0571***	0.0447***	0.0535***	0.0587***
	(0.0210)	(0.0207)	(0.0220)	(0.0222)	(0.0232)	(0.0257)
Gini_{t-1}	−0.1836	−1.3885**		−0.1418	−1.5899***	
	(0.5649)	(0.7535)		(0.5464)	(0.7597)	
$90/75_{t-1}$		1.0168**	0.6932*		1.1110***	0.6823
		(0.5231)	(0.4698)		(0.5527)	(0.5180)
$50/10_{t-1}$			−0.1628***			−0.1566***
			(0.0799)			(0.0777)
p-value[1]	0.745	0.109	0.120	0.795	0.088	0.123
m1	−2.249	−2.090	−2.131	−1.875	−1.783	−1.955
m2	−0.792	−0.835	−0.812	−0.568	−0.591	−0.602

21 countries in baseline sample and 81 obs.; 25 countries in whole sample and 89 obs. Time dummies included; dummy for Eastern European countries added in whole sample analysis. First-step estimates reported. Robust standard errors in parenthesis. The dependent variable is Δy_t where $t-(t-1)$ is a 5-year period.
[1]Wald (joint) test on the inequality variable coefficient(s) in the regression.
***, **, * indicates that the coefficient is significantly different from 0 at the 5, 10 and 15 % significance levels, respectively.
Instrument set b: $\Delta 50/10_{t-1}$ added as an instrument for the equations in levels.

The next step in the sensitivity analysis is to test the robustness of the results to other estimation techniques. Table 4 reports results for three representative equations, estimated with OLS, within-groups and first-difference GMM. From the discussion in Section 4.2 we know that the OLS and within-groups results are likely to provide biased estimates in this case. Additionally, the within-groups and first-difference GMM estimator rely solely on the limited time-series variation in the data. Although endogeneity and measurement error are controlled for asymptotically in the first-difference GMM estimator, one indication that this estimator might suffer from a small sample bias in this application is that the estimated coefficients on the lagged dependent variable are very close to the within-groups estimates, which are likely to be subject to a serious downward bias, see Section 4.2.[34]

34 Some Monte Carlo experiments suggest that the bias on the lagged dependent variable does not affect the estimated values of other coefficients, see Judson and Owen (1999). An analysis on the current dataset in an earlier version of this paper showed, however, that the estimated coefficients on other explanatory variables are sensitive to the estimated coefficient on the lagged dependent variable in our specifications, especially when the bias on the lagged dependent variable is very large.

Nevertheless, the results in Table 4 reveal that the signs of the estimated coefficients on the top and bottom end inequality measures remain constant across the different estimation methods considered, although their statistical significance varies. In particular, while the within-groups and first-difference GMM methods both suggest that the positive effect of top end inequality is significant, OLS implies that the negative effect of bottom end inequality is significant. This pattern of results follows what has already been found in the literature, that the overall effect of inequality on growth is sensitive to the econometric technique used (see e.g. Panizza, 2002; Banerjee and Duflo, 2003). Methods that rely on the time-series variation in the data tend to indicate a positive effect of inequality on growth (e.g. Li and Zou, 1998; Forbes, 2000) while methods that rely on the cross-sectional information tend to indicate a negative effect (e.g. Persson and Tabellini, 1994).

Nonetheless, regardless of differences in the specific econometric method, the results in Table 4 still suggest that inequality at the top end and inequality further down the income distribution have different effects on the growth process. Additionally, when used alone, the Gini statistic is either reflecting the prevailing effect imperfectly (i.e. the negative effect of bottom end inequality when using OLS) or is insignificant (in all the other estimations and specifications considered in this analysis). This suggests that, with the current data, the Gini coefficient may not be adequately capturing any specific effect but reflecting an average of the different influences of income inequality on growth.

5. Discussion and Conclusion

Theoretical research has attributed the influence of inequality on growth to a diverse range of factors, some of which tend to stimulate while others inhibit economic activities. The central hypothesis of this paper is that the positive and negative influences of inequality on growth are mostly associated with inequality in different parts of the income distribution. Many of the positive mechanisms can be linked to inequality at the upper end of the income distribution, while many of the negative mechanisms are associated with inequality further down the distribution. The empirical analysis undertaken in section 4 supports this hypothesis for a sample of industrialized countries.

An important contribution of this study is to highlight the potential limitation of investigating the effect of income distribution on growth using a single inequality index. The findings reported here imply that a single inequality statistic is likely to capture a relatively unimportant average effect of inequality on growth, and mask the underlying complexity of the relationship. The results in this study suggest that growth is facilitated by an income distribution that is compressed in the lower part of the distribution, but not so at the top end. In this view, redistributive policies — such as progressive taxation and social welfare — are likely to facilitate growth through their impact on the bottom of the distribution, and to inhibit growth through their impact on the top of the distribution.

Table 4. Sensitivity analysis, cont. OLS, within-groups and first-difference GMM estimations, baseline sample.

Method	OLS	OLS	OLS	Within-groups	Within-groups	Within-groups	First-dif GMM	First-dif GMM	First-dif GMM
No	1	2	3	4	5	6	7	8	9
Observations	81	81	81	60	60	60	60	60	60
y_{t-1}	−0.0944***	−0.1003***	−0.0997***	−0.3902***	−0.3764***	−0.3754***	−0.4214***	−0.3771***	−0.3673***
	(0.0455)	(0.0424)	(0.0431)	(0.0421)	(0.0431)	(0.0420)	(0.0930)	(0.1010)	(0.0970)
Invest_t	0.0008	0.0005	0.0004	0.0087	0.0087	0.0087	0.0105	0.0108	0.0099
	(0.0023)	(0.0025)	(0.0025)	(0.0068)	(0.0069)	(0.0069)	(0.0111)	(0.0106)	(0.0108)
AvgYrsSch_{t-1}	0.0016	0.0086	0.0084	0.0312**	0.0325***	0.0321**	0.0386**	0.0420**	0.0349*
	(0.0068)	(0.0085)	(0.0078)	(0.0161)	(0.0164)	(0.0164)	(0.0216)	(0.0218)	(0.0219)
Gini_{t-1}	−0.5602**	0.0942		0.3854	0.0180		0.2481	−0.3148	
	(0.3258)	(0.4463)		(0.3167)	(0.4010)		(0.4469)	(0.4776)	
$90/75_{t-1}$			0.0273		0.3594*	0.3677**		0.5480***	0.4937***
			(0.1263)		(0.2406)	(0.1928)		(0.2672)	(0.2431)
$50/10_{t-1}$		−0.1109*	−0.1041**			−0.0034			−0.0987
		(0.0763)	(0.0561)			(0.0501)			(0.1057)
p-value[1]	0.086	0.117	0.117	0.223	0.142	0.147	0.579	0.112	0.124
m1	1.079	0.950	0.943	−2.375	−2.203	−2.221	−2.064	−2.083	−2.195
m2	−0.479	−0.460	−0.464	−0.886	−0.894	−0.891	−0.774	−0.809	−0.798

21 countries, time dummies included, first-step estimates reported for the first-difference GMM estimates, robust standard errors in parenthesis. The dependent variable is Δy_t where $t - (t-1)$ is a 5-year period.

[1]Wald (joint) test on the inequality variable coefficient(s) in the regression.

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

Instrument set for first-diff GMM: y_{t-2} and y_{t-3}, Invest_{t-1}, $\Delta\text{AvgYrsSch}_{t-1}$, and $\Delta\text{Inequality}_{t-1}$.

Table 5. 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
ROC 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 1982 and Swiss Poverty Survey 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

Table 6. Descriptive statistics.

	Baseline sample (excl. Eastern European countries), 21 countries				Whole sample, 25 countries			
	Variables in level		Variables in first-difference		Variables in level		Variables in first-difference	
Variables	Mean	Std	Mean	Std	Mean	Std	Mean	Std
y	9.9209	0.5302	0.1174	0.1011	9.7444	0.7272	0.1077	0.1200
Invest	21.1395	2.4869	−0.5405	2.4202	21.2926	2.7046	−0.4016	2.5638
AvgYrsSch	8.7379	1.5522	0.4188	0.5059	8.8064	1.5086	0.3858	0.5077
Gini	0.2815	0.0496	0.0043	0.0171	0.2844	0.0528	0.0070	0.0197
90/75	1.3303	0.0938	0.0060	0.0362	1.3368	0.0986	0.0115	0.0431
50/10	2.0006	0.3336	0.0199	0.1309	2.0139	0.3636	0.0362	0.1477

Income is observed for the period 1970-2000 and Investment between 1975 and 2000, where Investment labeled 1975 represents the average between 1971 and 1975. Education and inequality are observed between 1970 and 1995.

In the baseline sample there are 102 observations in level (81 in first-difference) for y. For the other variables there are 81 observations in level (60 in first-difference). In the whole sample there are 114 observations in level (89 in first-difference) for y. For the other variables there are 89 observations in level (64 in first-difference).

Table 7. Adjusted R^2 from regressions of income distribution statistics on time and country dummies.

	Baseline sample (excl. Eastern European countries), 21 countries, 81 obs		Whole sample, 25 countries, 89 obs	
Variables	Country dummies only	Time and country dummies	Country dummies only	Time and country dummies
Gini	0.881	0.911	0.876	0.915
90/75	0.900	0.924	0.878	0.916
50/10	0.873	0.883	0.874	0.891

The current analysis, however, cannot be used to determine which aspect of the distribution will dominate. This is because the magnitude of the estimated effects varies with the sample of countries, choice of instruments and estimation technique. The overall impact of inequality on growth may also depart from a linear aggregation of the two effects highlighted in this study. It may, for example, depend on the average income level. Other sub-parts or aspects of the income distribution, not identified in this study, could also contribute to the overall effect of inequality on growth, and remain to be investigated.

Additionally, if inequality at different parts of the distribution affects the growth process through separate channels, there is no reason to suppose that such effects will occur with a similar delay, as is imposed by the current specification. These effects could be important from a policy perspective. The short dynamic structure imposed by data limitations may also be giving undue weight to short-term fluctuations. Since data on inequality moves rather slowly, it would be useful to test the hypothesis using longer growth periods in order to be confident that the current findings are picking up long-term influences. Further analysis, using appropriate data, would be required to establish the effects of top and bottom end inequality in poorer countries.

Although some difficulties associated with the small sample size are mitigated by the fact that the sample is fairly homogenous (consisting only of democracies with high levels of income per capita), an important limitation of the current analysis is the size of the data sample that is used for estimation. The limited number of observations available restricts the type of investigation that can be undertaken. As more comparable data on household surveys becomes available, further research should help to disentangle some of the issues mentioned above.

For a better understanding of the overall effect of income inequality on growth as well as the role of policy in this context, it will also be important to study how income inequality influences the functioning of the economy, and not only outcomes such as income levels. That is, based on hints from the theoretical literature, a next step of this empirical investigation should be to identify the different channels through which inequality in different parts of the distribution may influence the growth process.

Appendix: Data Description

y: Income is measured by the log of real GDP per capita in 1995 USD. All income data is from the World Bank's World Development Indicators 2003, except for Taiwan. Income data for Taiwan come from the National Statistics website of Taiwan ROC at http://www.stat.gov.tw/. For Germany, income labeled 1970 is in fact income in 1971.

Invest: Investment dated t is measured by the average share of gross fixed capital formation in GDP over the five years ending in t. For example, investment labeled 2000 is measured by the average investment share between 1996 and 2000. Investment data comes from the World Bank's World Development Indicators 2003 except for Taiwan ROC. Taiwanese data on gross domestic fixed investment come from the National Statistics website of Taiwan ROC at http://www.stat.gov.tw. Investment dated 1990 for the Czech Republic is based on the 1990 value only; for Russia, investment dated 1990 is based on the values for both 1989 and 1990.

AvgYrsSch: 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.

Inequality statistics are computed from the Luxembourg Income Study, as described in section 3. Several ratios of income percentiles as well as quintile share ratios on either side of the median are considered for top and bottom end inequality.

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