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Inequality and Economic Growth: The Empirical Relationship Reconsidered in the Light of Comparable Data

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Abstract: All of the recent empirical work on the relationship between income inequality and economic growth has used inequality data that are not consistently measured. This paper argues that this is inappropriate and shows that the significant negative correlation often found between income inequality and growth across countries is not robust when income inequality is measured in a consistent manner. However, evidence is found of a significant negative correlation between consistently measured inequality of expenditure data and economic growth for a sample of developing countries.

Keywords: Income inequality, Distribution of expenditure, Economic growth

JEL Classification: O4

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1. Introduction

Whether income inequality reduces economic growth is an issue that has been explored in many empirical studies over the last decade or so. Many studies find that there is a negative correlation between income inequality and economic growth. This paper will argue that these studies need to be interpreted with a great deal of caution, as they measure inequality in an inconsistent manner.

Inequality can be measured using data on gross income, net income or expenditure. In addition, the unit of measurement can be the individual or the household. A priori, we would expect to obtain quite different measures of inequality, depending on which of these classifications are used. It follows that in empirical work it is important to use consistently measured data that are not, for example, based on gross income for some countries and based on expenditure for others. Unfortunately, due to a lack of comparable data, this is exactly what previous researchers, through no fault of their own, have been forced to do. Some researchers (eg Barro, 2000) suggest that mixing different classifications of data together does not affect the results. The results obtained in this paper, using a recently compiled data set with more observations, suggest that it does. Other studies (eg Perotti, 1996; Deininger and Squire, 1998) transform the data in order to try and make them more comparable. It will also be shown that different results are obtained if the data are measured consistently, rather than performing such transformations.

Section 2 will review the theoretical arguments as to why inequality is likely to affect economic growth. The discussion will bring out the fact that for one of these arguments it is the distribution of gross income that is relevant, but that for the other arguments it is the distribution of net income or expenditure that matters. This is something that should be kept in mind when conducting empirical work, but that has tended to be ignored in the past. The fact that most of the arguments are more likely to apply in the long run, rather than the short run, will also be discussed. Section 3 will analyse in more detail the problems with the way income inequality data have been used in previous empirical work. In Section 4 a standard cross-country growth regression, including income inequality as an explanatory variable, will be estimated in order to assess the sensitivity of the results to how income inequality is measured. Section 5 will conclude.

2. Why would we expect inequality to affect economic growth?

Traditionally there are two main arguments as to why income redistribution, to achieve a more equal distribution of income, will reduce the rate of economic growth. The first is that redistribution is typically accompanied by a progressive income tax structure, which has an adverse effect on incentives. This in turn is likely to reduce investment and lead to a reduced work effort. The second argument is that as those on high incomes tend to have a higher savings rate than those on low incomes, redistribution will reduce the rate of savings, and hence investment and growth.

There are four main arguments in the literature as to why income inequality will be harmful for economic growth. These arguments have been clearly summarised by Perotti (1996). The first argument is that an unequal distribution of income will lead to pressure for redistribution through distortionary taxes, hence reducing growth. Perotti is not explicit about this, but it is presumably an unequal pre-tax (or gross) distribution of income that is potentially bad for growth. Observing an equal after-tax distribution of income may simply mean that redistribution via progressive taxation, as discussed in the previous paragraph, has already taken place. If this argument is to be tested empirically then data on pre-tax income should be used, however Perotti uses data on the distribution of both the pre-tax and the post-tax distribution of income.[1] In fact, if data on the post-tax distribution of income are used a positive relationship between inequality and growth would be expected, assuming that countries with a more equal distribution of after-tax income have higher rates of redistribution and also assuming that redistribution does affect incentives.[2] Another point not discussed by Perotti is that the hypothesised negative relationship between inequality and growth is more likely to hold in the long run, rather than the short run. This is because there is likely to be a considerable time lag between an increase in inequality, mounting pressure for more redistribution, and for redistribution to then take place.

[1] Perotti is not explicit about whether the data he uses are for gross income, net income or expenditure. Two thirds of the data in the Deininger and Squire (1996) data set for the 1950s and 1960s (which includes some of the data used by Perotti) are for gross income. The remainder are for net income or expenditure.

[2] In effect, if data on the distribution of after-tax (or net) income are used, this hypothesis collapses to the argument, discussed in the previous paragraph, that redistribution distorts incentives and hence growth.

The second argument is that inequality may lead to sociopolitical instability, which will in turn reduce investment and hence growth. Again, this is more likely to occur in the long run, with it taking some time for inequality to lead to political instability (although the effect of instability on investment and hence growth may well be more immediate). The third argument is that in the presence of imperfect capital markets inequality will reduce investment in human capital, which will in turn reduce growth. This is also likely to be a long-run, rather than short-run, phenomena. The fourth and final argument is that as inequality increases, fertility is likely to rise and human capital investment fall, both reducing growth. Again, there may be significant time lags involved. Note that with these last three arguments it is not so much the distribution of gross income that is important, but the distribution of net income or expenditure that is likely to be relevant. This should be taken into account when testing these hypotheses empirically.

It is important to note that the arguments as to why redistribution of income (leading to a more equal distribution of income) may be harmful for growth may apply in the short run, as well as the long run, as it may not take long for redistribution to affect both incentives and savings behaviour. By contrast, the arguments as to why inequality may be harmful for growth are likely to apply only in the long run. This is consistent with the fact that the three empirical studies that focus on the short-run relationship (Li and Zou, 1998; Forbes, 2000; Deininger and Olinto, 2000) find a positive partial correlation between inequality and growth, whereas studies which use data over a longer time span tend to find a negative partial correlation between inequality and growth.[3] Alesina and Rodrik (1994), Birdsall, Ross and Sabot (1995), Sylwester (2000) and Easterly (2000) all obtain a negative partial correlation between income inequality and economic growth. Barro (2000) finds evidence of a negative relationship for poor countries, but a positive relationship for rich countries.[4] In contrast, Perotti finds evidence of a negative correlation between inequality and growth, with some suggestion that the correlation may be insignificant for poor countries. Persson and Tabellini

[3] Forbes acknowledges that she is looking at the short-run relationship, whereas most other studies are concerned with the long run. Her reason for arguing this is that she uses panel data for periods of only five years, whereas most of the other studies use cross-country data looking at growth over a period of about twenty-five years. Like Forbes, Deininger and Olinto (2000) and Li and Zou (1998) use panel data for five year periods, whereas Barro (2000) uses panel data for ten-year periods.

[4] It is also of interest to note that the other three panel data studies include a large number of observations for high-income countries. Therefore, the positive coefficient on income inequality in these studies could, in part, be due to the sample of countries.

(1994) find a negative correlation for democracies only, whereas Clarke (1995) obtains a negative correlation for both democracies and non-democracies. Deininger and Squire (1998) and Castelló and Doménech (2001) obtain a negative coefficient, but this becomes insignificant once continental dummies are included in the regression equation.[5] Keefer and Knack (2000) find evidence of a negative correlation between income inequality and growth, but this correlation becomes insignificant once a measure of property rights is included as a control variable.

In summary, most of the existing studies focus on growth over a long time span and, therefore, are estimating the long-run effect of inequality on growth. The arguments suggesting that inequality is harmful for growth are more likely to apply in the long run than are the arguments suggesting redistribution is harmful for growth. It is also important to note that three out of four of the theoretical arguments predicting a negative correlation (and both of the arguments predicting a positive correlation) refer to the distribution of income after redistribution has taken place. Data on the distribution of net income or the distribution of expenditure are therefore the most appropriate to use in empirical work. The next section will discuss in detail the data problems that pertain to the existing empirical literature.

3. Problems with the existing empirical work on income inequality and economic performance

The major argument of this paper is that all of the existing empirical work on the effect of income inequality on economic growth suffers from potentially serious data problems. The first problem is that of data quality. It is often argued that studies predating the release of the Deininger and Squire (1996) data set include data of dubious quality. Such studies include Persson and Tabellini (1994), Alesina and Rodrik (1994), Clarke (1995), Birdsall, Ross and Sabot (1995) and Perotti (1996).

Deininger and Squire (1996) compile a data set based on existing surveys of the distribution of income and expenditure. To be included in Deininger and Squire’s “high quality” data set, the data have to meet three main criteria. The data must be based on household surveys,

[5] Perotti finds that the inclusion of continental dummy variables reduces both the coefficient and the t-statistic on the distribution of income. However, the distribution of income remains significant at the ten percent level.

rather than estimates derived from national accounts statistics; the population covered must be representative of the whole population rather than covering, for example, the urban population or wage earners only; and the measure of income or expenditure must include income from self employment, nonwage earnings, and nonmonetary income. Deininger and Squire consider 2,600 observations, but only 682 qualify to be included in their "high quality" data set. Many of the observations that do not satisfy their "high quality" criteria have been included in the studies mentioned above. Persson and Tabellini, for example, use income distribution data compiled by Paukert (1973). However, Paukert acknowledges that many of the data are "of rather doubtful value" (Paukert, 1973, p.125). Deininger and Squire (1998) note that only 18 of the 55 observations in the Paukert data set meet their minimum criteria. Studies which use the more reliable "high quality" Deininger and Squire data in growth regressions include Deininger and Squire (1998), Li and Zou (1998), Rodrik (1999), Forbes (2000), Barro (2000), Keefer and Knack (2000), Banerjee and Duflo (2000), Deininger and Olinto (2000) and Castelló and Doménech (2001).[6]

The more recent empirical work which uses the Deininger and Squire data set is, in one respect, an improvement on what came before. However, another potentially serious data problem is that virtually all of the previous empirical work examining the effect of the distribution of income/expenditure on economic growth (eg Alesina and Rodrik, 1994; Clarke, 1995; Birdsall, Ross and Sabot, 1995; Perotti, 1996; Deininger and Squire, 1998; Forbes, 2000; Barro, 2000; Banerjee and Duflo, 2000; Keefer and Knack, 2000; Easterly, 2000; Deininger and Olinto, 2000; Sylwester, 2000; Castelló and Doménech, 2001) has failed to measure the distribution of income/expenditure in a consistent manner.

Gini coefficients can be calculated either for the distribution of income before tax, the distribution of income after tax, or the distribution of expenditure. In addition, the unit of measurement can be the individual or the household. It is important when making cross-country comparisons that like is being compared with like, as a priori we would expect the distribution of income before tax to be less equal that the distribution of income after tax, as long as the tax structure in a given country is progressive. We would also expect the distribution of expenditure to be more equal than the distribution of income (measured either

[6] Easterly (2000) and Sylwester (2000) make us of all the data included in the Deininger and Squire data set, including those omitted from the "high quality" category.

before or after tax) if individuals or households smooth their expenditure over their life times. In addition, given that in developing countries most households contain a large number of children with zero or low incomes, we would expect the distribution of income to be more equal for households, than for individuals.

Making cross-country comparisons of the distribution of income/expenditure which mix these different measures together is not likely to provide much useful information. However, this is precisely what is done in the existing literature. This is not a criticism of those conducting this research, many of who are aware of the problem, as at the time insufficient comparable data existed to measure the distribution of income in a comparable manner. Some researchers have attempted to get around this problem by transforming the data to make them more comparable. These transformations are an improvement on doing nothing, but it will be argued that this is less satisfactory than using comparably measured data. Studies which do not transform the data include Alesina and Rodrik (1994), Clarke (1995), Birdsall, Ross and Sabot (1995), Rodrik (1999), Easterly (2000), Keefer and Knack (2000), Sylwester (2000) and Castelló and Doménech (2001).

The first study to transform the data is Perotti (1996), who measures the distribution of income as the income share of the middle class (MID), where the middle class is defined as the third and fourth quintiles of the income distribution. Perotti is aware of the fact that individual and household data are not comparable, and transforms the data in the following manner. He calculates the average MID based on personal income data ($avMID_{IND}$) and the average MID based on household data ($avMID_{HSLD}$) "where the average is taken over all years and countries for which data on MID organised by households and individuals are available." (p.156) For countries that only have data on the distribution of individual income he multiplies MID_{IND} for country i by ($avMID_{HSLD}$)/ ($avMID_{IND}$).[7, 8] This transformation is a useful attempt to make the data more comparable, but it implicitly assumes that the relationship between individual and household measures of the distribution of income is relatively stable across countries and time. Even if the transformation is accepted as valid, the

[7] Perotti uses the same methodology to convert data based on "income recipients" (those with an income) and "economically active persons" (those of working age) to data based on households. Note that data based on either of these two categories are not included in the Deininger and Squire "high quality" data set as they are unrepresentative of the whole population.

[8] Perotti (1996, p.157) notes that his empirical results are not altered in any way if non-adjusted data are used.

problem remains that data on the distribution of gross income, net income and expenditure are being treated as comparable.

In the Deininger and Squire data set the average difference between expenditure based Ginis and gross income Ginis is 6.6 percentage points, for countries that have data on both. This has led Deininger and Squire (1998), Li and Zou (1998), Banerjee and Duflo (2000), Keefer and Knack (2000) and Forbes (2000) to add 6.6 to expenditure based Gini coefficients to transform them into gross income based Ginis. This approach may be valid if there is relatively little deviation around the mean difference of 6.6, but unfortunately this is not the case. Deininger and Squire (1996) report that the range of values is between –3 (for Bangladesh in 1973) and 20 (for Tanzania in 1969). They also report that the gap between expenditure and income based Ginis is narrowing over time.

Whereas it has become traditional to transform expenditure data into gross income data, it has become equally as traditional not to worry about the distinction between pre-tax and post-tax data and household versus individual data.[9] This is due to the fact that in the Deininger and Squire data set, for countries with data on both household and individual income, the average difference in Gini coefficients is only 1.7 percentage points. For pre-tax and post-tax data the difference is 2.7 percentage points. Again, these averages are likely to mask significant deviations around the means. For example, Deininger and Squire (1996) note that for Sweden in 1981 the Gini coefficient is 5 percentage points higher when measured pre-tax, rather than post-tax. This difference is hardly insignificant.

Barro (2000), who uses data from Deininger and Squire (1996), supplemented by additional observations that he argues are of high quality, combines data on net income, gross income and expenditure, and also combines data based on households and individuals. He notes that he did try transforming the data to take account of whether the data are for net or gross income or expenditure and whether they refer to individuals or households and this "turns out to have little consequence for the estimated effects of inequality on growth and investment."(p.17). However, Barro gives no details of how the data were transformed, nor

[9] The two exceptions are Perotti (1996) and Lundberg and Squire (1999). Perotti transforms individual to household data in the manner described above. However, Perotti does not transform pre-tax into post-tax data. Lundberg and Squire convert all data to individual expenditure data, following the methodology described below.

does he elaborate further on how sensitive the results were. The fact that transforming the data has "little consequence" for the results could simply mean that the transformations are imperfect. Deininger and Squire (1998) note that their results are not significantly different if 6.6 is added to expenditure Ginis to transform them to gross income Ginis or not.

One paper which attempts to deal with all of the possible measurement inconsistencies outlined above, in a slightly different context, is Lundberg and Squire (1999). This paper simultaneously estimates the determinants of income inequality and economic growth, but without including income inequality in the growth regression. Strictly speaking, therefore, this is not a study on the effect of income inequality on growth. Lundberg and Squire transform the various different categories of inequality data in an attempt to make them all comparable to individual expenditure data. Their methodology involves running a fixed effects regression with the measured Gini coefficient as the dependent variable and with dummy variables for gross income, net income, other income and household-level data as the explanatory variables (the omitted categories are individual-level and expenditure-based data). The coefficients obtained for these dummy variables, all of which are significant, are then used to convert the data into individual expenditure data. Their results suggest that to make this conversion 2.096 should be subtracted from Ginis based on gross income, 3.127 subtracted from Ginis based on net income, 5.762 subtracted from Ginis based on other income and 3.171 added to Ginis based on household data. Like the Perotti and Deininger and Squire transformations, this methodology assumes that the relationship between the different categories of income/expenditure is constant across countries and across time, which is a heroic assumption to make. [10]

Atkinson and Brandolini (1999), in a paper which critiques the Deininger and Squire (1996) data set, particularly with respect to the OECD countries, caution against such adjustments, arguing "[i]n our view, the solution to the heterogeneity of the available statistics is unlikely to be the simple additional or multiplicative adjustment. In order to assess differences in income distribution across countries, what is needed is a data-set where the observations are as fully consistent as possible." Deininger and Squire (1996, p.581) appear to agree, when

[10] Note that these results lead to the counter intuitive conclusion that gross income is more equally distributed than net income. As the authors point out, this either means that taxes and transfers are regressive, or that countries that would have a more equal distribution of income, if it were measured consistently, tend to have Gini coefficients based on gross income. The former seems unlikely, while the latter calls into question the

they argue that “[m]ethodologically, the most justifiable way to ensure cross-country comparability of inequality measures is to use only measures that are defined consistently.” The only reason they do not do this is because they would end up with a very small data set. Deininger and Squire (1996, p.582) also argue that “[i]t would be prudent to examine whether [empirical results using income distribution data] hold for (a) the raw data, (b) data that have been adjusted for differences between expenditure and income-based coefficients, and (c) data consistently based on a common definition.” The World Income Inequality Database (WIID), compiled by the United Nations University/World Institute for Development Economics Research (1999), contains sufficient data that are measured consistently that it is now possible to proceed with (c) using cross-country data. This database extends the Deininger and Squire data set and is more comprehensive, including approximately twice as many data points. By only making use of data labelled as being “reliable” and which apply to the whole population it is possible to obtain a subset of this data which meet the same “high quality” criteria as those adopted by Deininger and Squire.

In summary, due to data limitations, the vast majority of the existing empirical literature on the effect of income inequality on economic growth does not measure income inequality in a consistent manner. Persson and Tabellini (1994) is the only study that uses consistently measured data, but much of the data are of questionable accuracy. Some attempts have been made to transform the data to make them more comparable, but these transformations are less satisfactory than using consistently measured data. Barro (2000) and Deininger and Squire (1998) both argue that transforming the data makes little difference to the results, but this may simply call into question the validity of the transformations. This paper will test whether results that hold for the raw data are robust when the data are transformed in the manner of Deininger and Squire and Perotti, and, more importantly, whether these results are robust when the data are measured consistently.[11]

validity of the transformation.

[11] The focus is on assessing the usefulness of the Perotti and Deininger and Squire transformations, rather than the Lundberg and Squire transformation, as data based on the latter have yet to be included in a growth regression. The Deininger and Squire transformation, on the other hand, has been used extensively in the literature, with the Perotti transformation being used in one influential study.

4. Estimating the effect of income inequality on economic growth using consistently measured data

4.1 The empirical model and data

The purpose of this paper is to test whether the results found in the existing empirical literature are robust to measuring the distribution of income in a consistent manner. For the sake of comparability, it therefore seems desirable to estimate an equation as close as possible to that employed in the existing literature. Many of the existing studies estimate a Barro-style growth regression such as that given in equation (1)

$$(1)\qquad \text{Growth}_i = \text{Constant} + \beta_1\text{GDP}_i + \beta_2\text{MSE}_i + \beta_3\text{FSE}_i + \beta_4\text{PPPI}_i + \beta_5\text{Ineq}_i + e_i$$

where Growth is the growth rate of GDP per capita, GDP is income per capita in the base year, MSE is average years of male secondary schooling in the base year, FSE is average years of female schooling in the base year, PPPI is the PPP value of the investment deflator relative to that in the United States in the base year, Ineq is income inequality, measured as close to the base year as possible, and e_i is the country-specific error term. PPPI is included as a proxy for price distortions within the economy. Perotti (1996) estimates equation (1) and Forbes (2000) estimates a panel data variant of equation (1), but with the initial income term logged.[12] An equation reasonably similar to (1) is estimated by Barro (2000), Deininger and Squire (1998), Clarke (1995), Alesina and Rodrik (1994), Birdsall, Ross and Sabot (1995), Li and Zou (1998), Deininger and Olinto (2000), Keefer and Knack (2000) and Castelló and Doménech (2001). As well as including income inequality as an explanatory variable, Deininger and Squire (1998) and Deininger and Olinto (2000) also include the distribution of land as an explanatory variable and Castelló and Doménech include educational inequality. These proxies for the distribution of *wealth* are not subject to the data problems for the distribution of *income* discussed in this paper. Forbes and Deininger and Olinto use five-yearly panel data and a generalised method of moments (GMM) estimator, whereas Li and Zou use five-yearly panel data and both fixed and random effects estimators. All the other studies use cross-country data over a reasonably long time span, except for Barro who uses

[12] The vast majority of empirical studies which include base-period income per capita either take the natural logarithm of this variable, or include base-period income per capita squared. Perotti is somewhat of an outlier in measuring base-period income per capita in levels.

ten-yearly panel data. Cross-country data will be used in this paper for two reasons. The first is for comparability with the existing literature, the majority of which uses cross-country data. The second is the more practical reason that sufficient comparable data are not available in the WIID data set to conduct meaningful panel-data analysis.

Data on output per capita in 1960 and 1990 are taken from the Penn World Tables version 5.6. The variable used is real output per capita, calculated using the chain index. Data on PPPI in 1960 are from the Barro and Lee (1994) data set. Data on male and female average years of secondary schooling for the population aged 15 and over are from the Barro and Lee (2000) data set. Inequality is proxied by the Gini coefficient, with data being taken from the WIID data set. Only observations labelled as being of "reliable" quality and applying to the whole population are used. The Gini data are for the period 1960 to 1970, with the data being taken for the closest possible year to 1960.[13] The Gini coefficient is chosen as the measure of inequality, because the data are more readily available than for other possible measures and for comparability with the existing literature.[14] However, as noted by Lundberg and Squire (1999), it should be kept in mind that the Gini coefficient is a summary statistic that does not convey any information about the shape of the Lorenz curve. For example, it is possible for the relative incomes of the poor and rich to change, without changing the aggregate Gini coefficient.

4.2 The implications of using consistently measured gross income data

The first column in Table One gives the results obtained when estimating equation (1) using the WIID data for all six possible income/expenditure categories (as listed in footnote 13), without performing any transformations. Combining the different categories of income/expenditure and not transforming the data is the same approach as that of Alesina and Rodrik (1994), Clarke (1995), Birdsall, Ross and Sabot (1995), Rodrik (1999), Easterly (2000), Keefer and Knack (2000), Barro (2000), Sylwester (2000) and Castelló and

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[13] If there were two or more observations per country for the same year then preference was given to gross individual income data, then gross household income data, then net individual income data, then net household income data, then individual expenditure data, then household expenditure data. If there were still two or more observations for the same year, then an average was taken.

[14] All the existing studies discussed in this paper measure income inequality using the Gini coefficient, except for Perotti, who measures inequality as the income share of the third and fourth quintiles.

Doménech (2001). Initial testing suggested some problems with heteroscedastiticy, therefore for all regressions reported in this paper the t-statistics are calculated using White's (1980) heteroscedasticity-consistent standard errors. In column (i) male schooling is significant and

Table One: Income Inequality and Economic Growth

Dependent Variable: Growth in income per capita: 1960-90

	(i)	(ii)	(iii)	(iv)	(v)
Constant	1.678**	1.631**	1.835**	25.873	-0.018
	(4.01)	(3.90)	(3.98)	(0.56)	(-1.37)
GDP	-0.00003	-0.00003	-0.00004	0.00001	-0.002†
	(-0.95)	(-0.89)	(-1.08)	(0.34)	(-1.77)
MSE	0.406†	0.433†	0.364	0.395	0.031**
	(1.78)	(1.91)	(1.59)	(1.29)	(4.05)
FSE	-0.342	-0.375	-0.309	-0.316	-0.025**
	(-1.39)	(-1.53)	(-1.24)	(-0.90)	(-3.06)
PPPI	-0.384	-0.400	-0.368	-0.639*	-0.002
	(-1.49)	(-1.53)	(-1.38)	(-2.49)	(-0.30)
Ineq	-0.017*	-0.016†	-0.020*	-0.013	0.118**
	(-2.08)	(-1.94)	(-2.19)	(-0.54)	(2.84)
N	40	40	40	27	67
R^2	0.29	0.28	0.31	0.24	0.30
LM	0.911	0.813	1.346	0.292	
RESET(2)	0.060	0.008	0.540	2.843	
RESET(3)	2.116	1.359	2.125	5.805*	
RESET(4)	1.630	1.238	1.440	4.087*	

All variables are as defined in the text and N is the sample size. Column (i) gives the results when data for all six income/expenditure classifications are used without any transformations being performed. Column (ii) gives the results when the Perotti transformation is applied to the data and column (iii) gives the results when the Deininger and Squire transformation is applied to the data. Column (iv) gives the results when data on the distribution of gross individual income only are used. Column (v) reproduces the results from Perotti (1996). For column (v) standard t-statistics are given in parentheses. For all other columns in the table, asymptotic t-statistics based on heteroscedasticity-consistent standard errors are reported. **, * and † indicate significance at the 1%, 5% and 10% level respectively, on the basis of two tailed tests. LM is the Lagrange multiplier test for normality of the residuals and is chi-squared distributed, with the null hypothesis of normally distributed residuals. The RESET tests for model mis-specification are F-distributed, with the null hypothesis of correct model specification.

positive at the ten percent level and the Gini coefficient is significant and negative at the five percent level. This significant negative coefficient on income inequality is consistent with that typically found in the literature. It is of interest to see how sensitive the results are to performing the Perotti transformation to convert individual income distribution data into household data. The results obtained when this transformation is performed are reported in column (ii). The correction factor of 0.97 was calculated by making use of all available distribution data over the period 1960 to 1970. The results in column (ii) are similar to those in column (i), although note that the Gini coefficient has a slightly lower t-statistic. In column (iii) the Deininger and Squire transformation, of adding 6.6 to all expenditure based Ginis, is applied, but the Perotti transformation is not. The only significant variable is the Gini coefficient. The coefficients and t-statistics on the income inequality variable do not appear to be particularly sensitive to applying either the Perotti or Deininger and Squire transformations. The coefficient on income inequality is negative, with a similar point estimate and t-statistic, irrespective of whether the transformations are applied or not.

The key question posed by this paper is what happens to the negative partial correlation between income inequality and economic growth if the inequality data are measured on a consistent basis. For the period 1960 – 1970, the category with the largest number of observations is gross individual income. Ideally, data on net income or expenditure would be used, as most of the arguments as to why income inequality will affect economic growth refer to the distribution of income after redistribution has taken place. Unfortunately, using such data would give a much smaller data sample for the 1960s. However, it is possible to obtain data for a reasonable number of countries for individual expenditure for the 1980s and 1990s, and this will be explored later in the paper. For the moment base-period data will be used to maintain consistency with the existing literature.

Column (iv) gives the results when only gross individual income distribution data are used. This reduces the sample to 27 countries. Note that the Gini coefficient is now insignificant (with a t-statistic of only –0.54). The only significant variable is PPPI, a variable that was not significant in any of the previous regressions. It should be noted that two out of the three RESET tests suggest there may be a problem with model mis-specification. The fact that the Gini coefficient is insignificant suggests that once the distribution of income is measured on a consistent basis, using gross income data, there is no significant partial correlation between the distribution of income and economic growth for the sample of countries included in column (iv). Deininger and Squire (1996) noted that transforming the data was not as ideal as using consistently measured data. The results reported in Table One confirm that using only consistently measured data gives different results to transforming the data. Another possibility, explored more fully below, is that the empirical results are highly sensitive to the sample of countries included in the regression equation.

For the sake of comparison, the results obtained by Perotti (1996) are reported in column (v)[15]. The relevant comparison is with column (ii), where the Perotti transformation is applied. For Perotti's results, base-period income per capita has the expected negative sign and is significant at the ten percent level. Male and female schooling are both significant at the one percent level, with male schooling being positive and female schooling negative. The negative coefficient on female schooling is counter to expectations, but is consistent with Barro and Lee (1994) and subsequent work by Robert Barro and his colleagues (for example, Barro and Sala-i-Martin, 1995; Barro, 1996).[16] PPPI is insignificantly different from zero. Income equality, as measured by the income share of the third and fourth quintiles, is positively correlated with growth.

There are many possible reasons for the difference between the results in column (ii) and Perotti's. The first is that Perrotti has data for many more countries, which is most likely due to the fact that he makes use of some data not considered of high enough quality to be labelled as "high quality" in the Deininger and Squire (1996) data set or as "reliable" in the WIID data set. Another possibility is that Perotti uses income inequality data from outside the period 1960 to 1970. Perotti takes data from as close as possible to 1960, but does not discuss the time span of the data. Note also that Perotti measures income inequality using data on the income share of the third and fourth quintiles, whereas this paper uses the Gini coefficient. However, Forbes (2000), when comparing her results to Perotti's, finds that the results are not highly sensitive to whether inequality is measured as the share of the third and fourth quintile or as the Gini coefficient. Another difference between the current work and Perotti's

[15] Note that Perotti's dependent variable is the average annual growth rate in income per capita. The dependent variable in this paper is the growth rate over the period 1960-1990 (measured as the log change in income per capita). Therefore, the coefficients in this paper need to be divided by 30 to make them comparable with Perotti's. However, in the discussion which follows, the focus is on the signs of the coefficients and the level of statistical significance, rather than on the magnitude of the coefficients.

[16] Stokey (1994) and Lorgelly and Owen (1999) argue that the negative coefficient on female schooling is not robust if Hong Kong, Singapore, Taiwan and South Korea are omitted from the data sample. Knowles, Lorgelly and Owen (2001) show that in the context of an augmented Mankiw, Romer and Weil model, that female schooling is negatively correlated with growth if measured in the base period, but positively correlated with growth if it is averaged over the period 1960-90 (which is consistent with their model).

is that different vintages of the Barro and Lee education data are used. Perotti uses Barro and Lee's (1993) data and focuses on average years of schooling of those aged 25 and over. In this paper Barro and Lee's (2000) data set is used and the data are for the average years of schooling of those aged 15 and over. Note, however, that Knowles, Lorgelly and Owen (2001) find that, in the context of an augmented Mankiw, Romer and Weil model, the coefficients on the human capital variables are not sensitive to using different vintages of the Barro and Lee data set.[17] Another difference is that this paper focuses on growth over the period 1960-90, whereas Perotti was looking at the period 1960-85.

Despite the differences between this study and Perotti's, it is surprising that in columns (i) – (iv) that few of the control variables are significant, compared to Perotti's results. The most likely explanation for this is that Perotti's data sample is larger. The countries included in the current work are listed in Appendix Table One. Note that there are only two African countries (and only one Sub-Saharan African country) included in the sample. Perotti's sample, by contrast, includes six Sub-Saharan African countries. Schooling levels were typically low in Sub-Saharan Africa in 1960, so it could be that only having a small number of these countries reduces the natural variation in the data, hence rendering these variables insignificant.

4.3 The role of influential observations and outliers

The fact that PPPI becomes significant in column (iv), when the sample is reduced, also suggests that the results are sensitive to the sample of countries used. This raises the possibility that some of the countries included in columns (i)-(iii) are either influential observations or outliers.[18] To identify potentially influential observations, the RSTUDENT, or studentised residual, statistic was calculated for each of the observations for the results presented in column (i). Using the cut-off of an absolute value of 2 suggested by Belsley, Kuh and Welsch (1980) only Taiwan is identified as influential (Bolivia with a studentised residual of –1.96 is close). Countries identified as having high leverage, on the basis of the h_i

[17] Knowles, Lorgelly and Owen compare the Barro and Lee (1996) data set (using data for the population aged 15 and over) with the Barro and Lee (1993) data set (which reports data for the population aged 25 and over).

[18] Temple (1998) and Lorgelly and Owen (1999) show that the results from cross-country growth regressions can be sensitive to the presence of outliers and/or influential observations. By contrast, in the context of growth regressions including inequality, Perotti and Forbes both find their results are robust when potential outliers are omitted from the data sample.

statistic (using the cut-off value of 2k/n suggested by Belsley, Kuh and Welsch) are the USA, Bolivia, and Korea. These four countries are also identified as influential observations and/or outliers for the results reported in columns (ii) and (iii). Of these four countries, two (Taiwan and Korea) do not have data on gross individual income, so are not included in the results reported in column (iv). For the results reported in column (iv), Bolivia, Japan and Korea are identified as being influential, on the basis of the RSTUDENT statistic, and the USA and Korea are identified as being outliers by the h_i statistic.

Stokey (1994) argues that Hong Kong, Singapore, Taiwan and South Korea are outliers in Barro-style regressions including base-period male and female education. Lorgelly and Owen (1999) have also shown that Barro and Lee's (1994) empirical results are not robust to the omission of these four countries. Of these four countries, only Taiwan and South Korea are included in the sample, and both are identified as either being influential observations or as outliers. Stokey also suggests that the education data for Bolivia contain errors, which may explain why Bolivia is consistently identified as an outlier in the empirical results presented in this paper.[19]

If observations are influential and/or outliers due to the fact that they contain data errors, and if those errors can not be easily corrected, then it is sensible to exclude those observations from the sample. It makes sense, therefore, to omit Bolivia. However, if particular observations are influential due to natural variation in the data it is not so clear that they should be omitted. It is informative, however, to know how sensitive the results are to the exclusion of a small set of countries, particularly where parameter heterogeneity is of concern. For this reason, the results with the influential observations and outliers omitted are reported in Table Two. PPI is now significant in all columns; it was previously only significant in column (iv) of Table One. However, the main point to note is that income inequality is no longer significant in any of the regressions, once a small group of countries is omitted from the data sample. This suggests that the insignificance of income inequality in

[19] In Barro and Lee's (1993) data set, which applies to the population aged 25 and over, male schooling for those aged 25 and over in Bolivia was 1.2 in 1960, 1.9 in 1965 and then 1.5 from 1970 to 1980. Stokey (p.53) argues that this "behaviour is completely implausible for a stock variable describing the entire adult population". In the Barro and Lee (2000) data set, which is used in this study, the average years of male schooling for those aged 15 and over also behaves strangely. Average years of male schooling in Bolivia is 2.309 years in 1960. It then falls steadily over time and is only 1.162 years in 1990. Bolivia is not the only country for which male average years of secondary schooling is lower in 1990 than 1960: this also happens for Mozambique, Rwanda, Afghanistan and Austria.

column (iv) of Table One could be due to sample selection, rather than whether the data are measured consistently or not. Unfortunately it is not obvious how to discriminate between these two possible explanations, as reestimating the regressions in columns (i) – (iii) for the same sample as column (iv) would also mean using only consistently measured income distribution data. The finding that the results are sensitive to outliers is in contrast to the work of both Perotti and Forbes, who both find that their results are robust when potential outliers are omitted.

Table Two: Influential Observations and Outliers Omitted

Dependent Variable: Growth in income per capita: 1960-90

	(i)	(ii)	(iii)	(iv)
Constant	1.283**	1.242**	1.343**	7.230
	(3.66)	(3.55)	(3.52)	(0.20)
GDP	-0.00003	-0.00003	-0.00003	0.00003
	(-0.88)	(-0.85)	(-0.93)	(1.03)
MSE	0.531	0.551†	0.521	0.064
	(1.60)	(1.69)	(1.57)	(0.27)
FSE	-0.424	-0.445	-0.417	-0.031
	(-1.19)	(-1.27)	(-1.17)	(-0.11)
PPPI	-0.584*	-0.599*	-0.576*	-0.880**
	(-2.07)	(-2.11)	(-2.03)	(-3.14)
Ineq	-0.007	-0.006	-0.008	-0.003
	(-0.92)	(-0.79)	(-1.01)	(-0.17)
N	36	36	36	23
R^2	0.278	0.274	0.280	0.443
LM	1.508	1.460	1.601	0.785
RESET(2)	0.196	0.091	0.517	0.492
RESET(3)	1.416	1.129	0.949	5.241*
RESET(4)	1.029	0.783	0.646	3.455*

See notes to Table One.

To further explore the possibility that sample selection is behind the lack of significance of the inequality coefficient in column (iv) of Table One, compared to the results in columns (i) – (iii), it is worth analysing which countries are omitted once the distribution of income is measured consistently (column (iv)). If these countries have something in common, other than how inequality is measured, then this may help explain the insignificance of the inequality variable in column (iv) of Table One. Appendix Table One provides information on how the distribution of income/expenditure is measured for each of the 40 countries included in columns (i) – (iv). Note that in the results reported in column (iv) an additional three countries have data on gross individual income.[20] It is not obvious that the countries omitted from column (iv) have anything in common that should markedly change the results. However, it is worth noting that the Latin American countries, which typically have high Gini coefficients, tend to have individual gross income distribution data, the very data that we would expect to give the highest Gini coefficient. This may exaggerate the degree of income inequality in these countries, relative to countries where inequality is measured differently. This is an interesting point, as it has become somewhat of a stylised fact that income inequality is high in Latin America.

4.4 The implications of omitting education

The results obtained so far include both male and female schooling as explanatory variables. However, one of the standard arguments as to why income inequality will reduce growth is that high income inequality is associated with low educational attainment. Income inequality may, therefore, still affect growth indirectly through it's effect on education. Including education as a control variable means that this indirect effect will not be picked up. It is therefore informative to check how sensitive the results are to the omission of the education variables.[21] Table Three gives the results, without excluding influential observations, when male and female education are omitted from the data sample. The main point to note is that the t-statistics on the income inequality variable are higher in columns (i) – (iii) than when the education variables were included (Table One). However, once income inequality is measured consistently in terms of gross individual income distribution data, income inequality again becomes insignificant. Note, however, that the Lagrange multiplier test suggests that the errors may not be normally distributed, making inference problematic.

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[20] These three countries (Pakistan, Korea and Norway) all have data for gross individual income in the 1960s. However, they also have data for another category of income/expenditure for a year closer to 1960, meaning this data (and not the gross individual income distribution data) were used for the results reported in Table One. This was due to the desire to use data for as close as possible to 1960.

[21] Deininger and Squire (1998) also omit education from their regression equation for the same reason.

Table Three: Income Inequality and Economic Growth: Education Variables Omitted

Dependent Variable: Growth in income per capita: 1960-90

	(i)	(ii)	(iii)	(iv)
Constant	1.879**	1.842**	1.989**	23.349**
	(4.44)	(4.32)	(4.42)	(0.54)
GDP	-0.00003	-0.00003	-0.00004	0.00002
	(-1.36)	(-1.34)	(-1.55)	(1.37)
PPPI	-0.286	-0.289	-0.259	-0.710**
	(-1.38)	(-1.36)	(-1.16)	(-4.79)
Ineq	-0.020**	-0.019*	-0.022**	-0.011
	(-2.63)	(-2.49)	(-2.65)	(-0.52)
N	43	43	43	29
R^2	0.242	0.226	0.248	0.332
LM	0.715	0.722	0.957	6.229**
RESET(2)	0.360	0.439	0.157	0.509
RESET(3)	0.221	0.251	0.114	0.415
RESET(4)	0.460	0.673	0.120	0.685

See notes to Table One.

As previously discussed, the main results reported in Table One were not robust when a small group of outliers and/or influential observations were omitted from the data sample. In particular, income inequality became insignificant. It therefore seems important to check how robust the results in Table Three are to the exclusion of influential observations and/or outliers. The results obtained when the relevant countries[22] are omitted from the sample are reported in Table Four.

[22] For the results in column (i) Madagascar, Japan and Korea were found to be influential observations on the basis of the RSTUDENT statistic and Egypt, Madagascar and the USA were found to have high leverage. For the results in column (ii) Madagascar and Taiwan were found to be influential and Egypt, Madagascar and the USA were found to have high leverage. For the results in column (iii) Egypt, Madagascar and Taiwan were found to be influential and Egypt, Madagascar and the USA were found to have high leverage. For the results in column (iv) Japan and Korea were influential and Madagascar and the USA were found to have high leverage.

Table Four: Income Inequality and Economic Growth: Education Variables and Influential Observations and/or Outliers Omitted

Dependent Variable: Growth in income per capita: 1960-90

	(i)	(ii)	(iii)	(iv)
Constant	1.357**	1.433**	1.581**	29.164
	(3.98)	(4.04)	(4.10)	(0.78)
GDP	-0.00001	-0.00001	-0.00002	0.00003
	(-0.50)	(-0.61)	(-0.85)	(1.64)
PPPI	-0.289	-0.270	-0.242	-0.650*
	(-1.10)	(-1.03)	(-0.91)	(-2.49)
Ineq	-0.014	-0.012†	-0.015*	-0.014
	(-1.55)	(-1.70)	(-1.97)	(-0.76)
N	38	39	39	25
R^2	0.131	0.122	0.146	0.261
LM	1.183	0.615	0.880	0.597
RESET(2)	0.057	0.207	0.030	4.767*
RESET(3)	1.035	1.255	1.429	3.222†
RESET(4)	1.890	1.619	0.927	4.346*

See notes to Table One.

In contrast to the results reported in Table Two, we no longer find that income inequality is always insignificant once countries suspected of being influential observations and/or outliers are omitted from the data sample. When the Perotti transformation is applied (column (ii)), income inequality becomes significant at the ten percent level. When the Deininger and Squire transformation is applied to the data (column (iii)) income inequality is significant at the five percent level (although only just). However, once only consistently measured data are used (column (iv)), income inequality again becomes insignificant. It should be noted, however, that the RESET tests suggest that model mis-specification is a potential problem in column (iv). With this caveat in mind, the results presented in Table Four confirm that it does make a difference how the distribution of income is measured, even once influential observations and/or outliers are omitted from the data sample. This suggests that empirical work which combines different income/expenditure classifications has to be interpreted with some caution. The problem is not resolved by transforming the data in either the manner of Perotti or Deininger and Squire. Performing the Deininger and Squire transformation is meant to transform expenditure data into gross income data. When this transformation is performed, it appears that there is a significant correlation between income inequality and growth. However, when consistently measured gross income data are used, there is no evidence of a significant correlation at all. This calls the validity of the Deininger and Squire transformation into question. A similar argument can be made with regard to the Perotti transformation.

4.5 The implications of using consistently measured expenditure data

The results obtained to date suggest that the negative relationship between income inequality and economic growth often found in cross-country studies is not particularly robust. The correlation has been shown to be insignificant once a small set of influential observations and/or outliers are omitted from the data sample. Although income inequality has been shown to be significant once the education variables are omitted from the regression equation, this correlation becomes insignificant once the distribution of income is measured in a consistent manner. However, the finding that inequality of gross income is not significantly correlated with economic growth does not necessarily mean that inequality of net income or expenditure will not be correlated with growth. Of the four hypotheses discussed in Section Two, only one relates to the distribution of gross income: the argument that an unequal distribution of income will lead to pressure for redistribution to take place.[23] To test the other three hypotheses, data on either net income or expenditure are required. The WIID data set contains data for very few countries of "reliable" quality for the distribution of net income. However, it does contain data for a reasonable number of countries on the distribution of expenditure.

Data on the distribution of personal expenditure are available for a sample of 30 countries, for which data for all other variables are also available, if data are taken from the period 1980-95. This is not ideal, as some of these data do not even correspond to the time period that growth

[23] Perotti (1996) tests each hypothesis individually by estimating the effect of inequality on redistribution, socio-political instability, education and fertility respectively. Perotti finds no evidence that countries with an unequal distribution of income had higher levels of redistribution, via progressive taxation or transfer payments.

is measured over, but ignoring the years 1991-95 significantly reduces the sample size.[24] The results obtained when the expenditure data are used are given in column (i) of Table Five. Male and female schooling are both significant, with the same signs obtained by Barro and Lee (1994) and Perotti (1996). Income inequality is significant at the ten percent level, suggesting that when the distribution of income is measured consistently and using data which take redistribution into account that higher levels of inequality are correlated with lower levels of economic growth.

Table Five: Inequality and Economic Growth: Results Using Expenditure Data

Dependent Variable: Growth in income per capita: 1960-90

	(i)	(ii)	(iii)	(iv)
Constant	1.071*	1.070*	1.383**	1.619
	(2.31)	(2.32)	(3.21)	(3.91)
GDP	-0.00006	0.00007	-0.0001	-0.0002
	(-0.54)	(-0.59)	(-0.89)	(-1.00)
MSE	0.953*	0.960*		
	(2.14)	(2.18)		
FSE	-1.28*	-1.228†		
	(-2.15)	(-1.93)		
PPPI	-0.124	-0.136	-0.209	-0.292†
	(-0.64)	(-0.66)	(-1.12)	(-1.80)
Ineq	-0.135†	-0.013†	-0.153*	-0.018**
	(-1.78)	(-1.73)	(-2.09)	(-2.58)
N	30	29	35	32
R^2	0.159	0.159	0.106	0.174
LM	0.362	0.400	0.797	0.546
RESET(2)	0.176	0.199	0.621	3.194†
RESET(3)	1.192	1.118	0.385	1.706
RESET(4)	0.913	0.850	0.489	1.304

See notes to Table One.

[24] Deininger and Squire (1998) note that there is little variation in the Gini coefficient over time. For the 44 countries in their data set that have four or more observations over time the average coefficient of variation is

The countries included in the data sample for the results reported in Table Five are listed in Appendix Table Two. Note that this sample of countries is very different than that included in Table One. The most obvious feature is that Portugal is the only industrialised country with data on the distribution of expenditure. There are also many more African countries and very few Latin American countries. Even though only three Latin American countries are included in the sample (Bolivia, Guyana and Peru) it is interesting to note that, when consistently measured expenditure data are used, the Latin American countries no longer stand out as having particularly high Gini coefficients, relative to other geographic regions. Several African countries, for example, have higher Gini coefficients. The inclusion of more African countries (that typically have low levels of education in 1960, thus providing more natural variation in the data) may help explain why both education variables are significant for this sample of countries. It is also worth noting that the significant negative coefficient on female schooling holds, even though none of the Asian Newly Industrialised Countires (NICs) are included in the data sample.[25] The fact that only one industrialised country is included in the sample means that these results should only be interpreted as applying to developing countries. This is particularly important in the light of Barro's finding that there is a negative correlation between inequality and growth for poor countries, but a positive correlation for rich countries.

No observations are identified as influential for the Table Five results on the basis of RSTUDENT. On the basis of h_i, only Bolivia is identified as being an outlier. The results obtained when Bolivia is omitted are reported in column (ii) of Table Five. Income inequality is still significant at the ten percent level, although the point estimate is somewhat reduced. The results obtained when education is omitted from the sample are given in column (iii) of Table Five. Income inequality is now significant at the five percent level. The Seychelles is identified as an influential observation on the basis of the RSTUDENT statistic and Mauritius and Iran were identified as having high leverage. The results obtained when these three countries are omitted are reported in column (iv). PPI becomes significant at the ten percent level and income inequality is now significant at the one percent level, although the point estimate of the coefficient is substantially reduced. These results suggest that there is a

only 0.03.

negative correlation between inequality and economic growth when consistently measured expenditure data, which take redistribution of income into account, are used. This result is robust when influential observations and outliers are omitted from the data sample. The correlation becomes more significant once education is omitted, in order to allow for the indirect effect of inequality on growth, via education.

The finding that there is only a significant correlation between inequality and growth once data that take the redistribution of income into account are utilised is an important one. The results obtained using gross income data suggest that there is no evidence to support the hypothesis that an unequal pre-tax distribution of income leads to pressure for distortionary transfers from the rich to the poor, which will in turn reduce the rate of growth. However, the results obtained using expenditure data do support the various hypotheses, summarised in Section 2, which suggest that inequality, measured after redistribution has taken place, will have a negative effect on the rate of economic growth. If these results are taken at face value, it would seem that, in the long run, high levels of inequality are associated with low levels of economic growth.

5. Conclusions

This paper has argued that treating inequality data based on gross income, net income, expenditure, and also individuals and households, as comparable is a mistake. However, this is precisely what past researchers have been forced to do due to a lack of comparable data. It has been shown that such empirical work is sensitive to whether the distribution data are measured consistently or not, and that transforming the data in the ways suggested by Perotti and Deininger and Squire does not adequately deal with the problem. This suggests that the existing empirical work needs to be interpreted with caution.

When consistently measured data on gross income are included in a cross-country growth regression there is no evidence of a significant correlation between inequality and economic growth. However, this should perhaps be of little surprise, as most of the arguments as to why inequality will affect growth relate to the distribution of income after redistribution, which can be measured by either net income or expenditure. When consistently measured

[25] Recall that Lorgelly and Owen (1999) found that female schooling became insignificant once the four NICs

expenditure data are used, there is evidence of a significant negative correlation between inequality and growth. Taking these results at face value, suggests that there is only a significant correlation between inequality and growth, once redistribution of income is taken into account.

Another point highlighted by the empirical work in this paper is that the estimates obtained in cross-country empirical work on economic growth are highly sensitive to the sample of countries included. It is therefore important in such work to report how sensitive the results are to the omission of influential observations and/or outliers.

The empirical relationship between inequality and economic growth has received much attention over the last decade. Many studies have found evidence of a negative correlation between these two variables. However, these studies have used data that have not been measured in a consistent manner. This paper confirms that there is a negative correlation between inequality and growth across countries, but only when the focus is on inequality after redistribution has taken place. No evidence is found of a significant correlation between gross income and economic growth.

were omitted from the data sample.

References

Alesina, A., Rodrik, D., 1994, Distributive politics and economic growth, Quarterly Journal of Economics 109, 465-490.

Atkinson, A., Brandolini, A., 1999, Promise and pitfalls in the use of “secondary” data-sets: income inequality in OECD countries, Nuffield College Oxford, mimeo, available on the internet (http://www.nuff.ox.ac.uk/users/atkinson/).

Banerjee, A.V., Duflo, E., 2000, Inequality and growth: what can the data say?, NBER Working Paper No. 7793.

Barro, R.J., 1996, Democracy and growth, Journal of Economic Growth 1, 1-27.

Barro, R. J., 2000, Inequality and growth in a panel of countries, Journal of Economic Growth 5, 5-32.

Barro, R.J., Lee, J.-W., 1993, International comparisons of educational attainment, Journal of Monetary Economics 32, 363-394.

Barro, R.J., Lee, J.-W., 1994, Sources of economic growth, Carnegie-Rochester Conference Series on Public Policy 40, 1-46.

Barro, R.J., Lee, J.-W., 1996, International measures of schooling years and schooling quality’, American Economic Review 86, 218-223.

Barro, R.J., Lee, J.-W., 2000, International data on educational attainment: updates and implications,” NBER Working Paper No. 7911.

Barro, R.J., Sala-i-Martin, X., 1995, Economic Growth, McGraw-Hill, New York.

Belsley, D.A., Kuh, E., and Welsch, R.E., 1980, Regression Diagnostics: Identifying Influential Data and Sources of Collinearity, John Wiley, New York.

Birdsdall, N., Ross, D., Sabot, R., 1995, Inequality and growth reconsidered: lessons from East Asia, World Bank Economic Review 9, 477-508.

Castelló, A., Doménech, R., 2001, Human capital inequality and economic growth: some new evidence”, mimeo, available on the internet (http://iei.uv.es/~rdomenec/).

Clarke, G.R.G., 1995, More evidence on income distribution and growth, Journal of Development Economics 47, 403-427.

Deininger, K., Olinto, P., 2000, Asset distribution, inequality, and growth, The World Bank Development Research Group Working Paper No. 2375.

Deininger, K., Squire, L., 1996, A new data set measuring income inequality, World Bank Economic Review 10, 565-591.

Deininger, K., Squire, L., 1998, New ways of looking at old issues: inequality and growth, Journal of Development Economics 57, 259-287.

Easterly, W., 2000, The middle class consensus and economic development, The World Bank Development Research Group Working Paper No. 2346.

Forbes, K.J., 2000, A reassessment of the relationship between inequality and growth, American Economic Review 90, 869-887.

Keefer, P., Knack, S., 2000, Polarization, politics and property rights: links between inequality and growth", The World Bank Development Research Group Working Paper No. 2418.

Knowles, S., Lorgelly, P.K., Owen, P.D., 2001, Are educational gender gaps a brake on economic development? some cross-country empirical evidence, Oxford Economic Papers (forthcoming).

Li, H., Zou, H., 1998, Income inequality is not harmful for growth: theory and evidence, Review of Development Economics 2, 318-334.

Lorgelly, P.K., Owen, P.D., 1999, The effect of female and male schooling on economic growth in the Barro-Lee model, Empirical Economics 24, 537-557.

Lundberg, M., Squire, L., 1999, The simultaneous evolution of growth and inequality, mimeo.

Paukert, F., 1973, Income distribution at different levels of development: a survey of the evidence, International Labor Review 108, 97-125.

Perotti, R., 1996, Growth, income distribution, and democracy: what the data say, Journal of Economic Growth 1, 149-187.

Persson, T., Tabellini, G., 1994, Is inequality harmful for growth?, American Economic Review 84, 600-621.

Rodrik, D., 1999 “Where did all the growth go? external shocks, social conflict, and growth collapses, Journal of Economic Growth 4, 385-412.

Stokey, N., 1994, Comments on Barro and Lee, Carnegie-Rochester Conference Series on Public Policy 40, 47-57.

Sylwester, K. 2000, Income inequality, education expenditures, and growth, Journal of Development Economics 63, 379-398.

Temple, J., 1998, Robustness tests of the augmented Solow model, Journal of Applied Econometrics 13, 361-375.

United Nations University/World Institute for Development Economics Research, 1999, UNU/WIDER - UNDP World Income Inequality Database, Beta 3.

White, H., 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroskedasticity, Econometrica 48, 817-838.

Appendix Table One: Countries Included in Results Reported in Tables One and Three

Countries included in Table One	Gini	GI	GH	NH	EI
Senegal	56	*			
Tunisia	42.3				*
Costa Rica	50		*		
El Salvador	53	*			
Honduras	61.88		*		
Mexico	53	*			
Panama	48	*			
USA	34	*			
Argentina	42	*			
Bolivia	53	*			
Brazil	54	*			
Chile	44	*			
Colombia	62	*			
Ecuador	38	*			
Peru	61	*			
Venezuela	42	*			
Bangladesh	36.875		*		
India	32.59				*
Indonesia	33.3				*
Iran	41.88				*
Japan	39	*			
Korea	34.34		*		
Malaysia	48.3		*		
Pakistan	36.675		*		
Philippines	48	*			
Sri Lanka	44	*			
Taiwan	32.08		*		
Thailand	41.34		*		
Denmark	37	*			
Finland	46	*			
France	50	*			
Italy	40			*	
Netherlands	42	*			
Norway	37.52			*	
Spain	31.99		*		
Sweden	39	*			
Turkey	56		*		
UK	38	*			
Australia	32	*			
Fiji	46	*			

GI denotes data for gross individual income, GH denotes data for gross household income, NH denotes data for net household income and EI denotes data for individual expenditure.

Appendix Table Two: Countries Included in Table Five

Countries included in column (i)	Gini	Additional countries included in column (iii)	Gini
Algeria	38.73	Madagascar	43.44
Cameroon	49	Mauritania	42.53
Central African Rep	55	Morocco	39.2
Gambia	39	Nigeria	38.55
Ghana	35.54	Seychelles	47
Guinea-Bissau	56.12		
Kenya	54.39		
Lesotho	56.02		
Malawi	62		
Mauritius	38.16		
Rwanda	28.9		
Senegal	54.12		
Tunisia	42.13		
Uganda	40.78		
Zambia	47.46		
Zimbabwe	56.83		
Jamaica	40.37		
Bolivia	42.04		
Guyana	46.11		
Peru	41.59		
Bangladesh	28.85		
India	31.42		
Indonesia	32.71		
Iran	42.9		
Jordan	38.04		
Pakistan	31.15		
Philippines	40.86		
Sri Lanka	34.45		
Thailand	43.81		
Portugal	32.53		