Income Inequality and Economic Growth: Evidence from American Data

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Abstract

Cross-country studies have found a negative relationship between income inequality and economic growth. The main problem with the cross-country analyses is the poor quality of the data on income distribution. This paper tests the robustness of the cross-country results to the use of a more accurate cross-state data-set. Data from the US states confirm the negative relationship between income inequality and growth. The same data-set is used to run structural estimations aimed at testing several possible channels linking inequality to growth. Although the results are not as strong as in the case of the reduced form estimations, the paper finds some evidence in support of a fiscal channel linking inequality to growth.

JEL Codes: D31, E62, P16, O41, I22.
Keywords: Inequality, Endogenous Growth, Political Economy.

In 1960 the Philippines and South Korea had about the same standard of living, as measured by their per capita GDPs of about \$640 US 1975. The two countries were similar in many other respects... From 1960 to 1988, GDP per capita in the Philippines grew at about 1.8 percent per year... In Korea, over the same period, per capita income grew at about 6.2 percent per year... (Lucas, 1993)

If one looks beyond the first moments, however, initial conditions were in fact quite different... the distribution of income was more unequal in the Philippines. The Philippines' Lorenz curve lay everywhere below that of Korea. The Gini coefficient was seventeen percentage points higher... Most strikingly, the ratio of the income share of the top 20% to the bottom 20%, or even to the bottom 40%, was about twice as large in the Philippines. (Bénabou, 1996b)

1 Introduction

The study of income distribution and its links with economic growth is a good example of fashion trends in economics. Already present in Ricardo's work, this topic was at the center of the economic debate in the 1960's. But, like the miniskirt, income distribution went out of fashion in the mid 1970's, and, for more than a decade, it found very little space in the academic literature. The 1990's, however, witnessed a resurgence of interest in the subject. The main reason for this renewed interest comes from the experience of the East Asian countries where (as illustrated in the passages quoted

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above) the low level of income inequality seems to have played an important role in explaining economic growth.[1]

The focus of the recent literature on this topic is to show how imperfect capital markets, pressure for redistribution, and socio-political instability can be the cause of a negative link between income inequality and growth. Despite the great success of the theoretical literature on this topic, the progress of its empirical side has been much slower. While the theoretical work provides a large series of explanations for the possible links between income distribution and growth, most of the empirical work consists of reduced form estimates of a standard Barro-style growth equation with an income inequality variable added to the right hand side. To the best of my knowledge, Perotti (1996) is the first attempt to test for the structural relationships described by the various theoretical models. One key issue with the existing empirical literature concerns data quality. Reliable data on income distribution exist only for a very small set of countries and large cross-country analyses often make use of low quality income distribution data.

This paper builds an income distribution data-set for the 48 states of the continental US, and uses it to explore the links between inequality and growth. The purpose of the paper is twofold. First, to use more accurate distributional variables to test the robustness of the cross-country studies which have found a negative relationship between inequality and growth. Second, to go beyond the reduced form analysis of these links. The main aim of the paper is to test for the presence of the *fiscal channel* described by, among others, Bertola (1993), Alesina and Rodrik (1994), and Persson an Tabellini (1994). An attempt to test for what Perotti (1996) calls the *endogenous fertility channel* is also made.

This paper finds strong evidence in support of a negative relationship between income inequality and growth. Both the direction of the link and its magnitude corroborate the results of the various cross-country studies surveyed by Bénabou (1996b).[2] I also find that inequality is positively correlated with tax progressivity and that tax progressivity is negatively correlated with economic growth. The latter is a new result. In fact, all previous empirical studies failed to find any significant relationship between fiscal variables and inequality and, at the same time, found a positive correlation between taxation and growth. The empirical analysis also supports the idea (suggested by Bénabou, 1996a, 1996b) that taxation is positively correlated with political participation.

The last part of the paper finds that inequality is positively correlated with teen pregnancy which, in turn, decreases college enrollment. Given the well-established negative relationship between education and growth, this can be seen as a result supporting the endogenous fertility channel.

The paper is organized as follows: Section 2 briefly discusses the related literature; Section 3 illustrates the costs and benefits of using regional data, discusses the methods used in deriving the income distribution data-set, and compares the cross-state variability with the cross-country variability; Section 4 briefly describes the evolution of the income distribution in the US and presents some evidence for cross-state convergence in income distribution; Section 5 presents the results of the reduced form estimates of an equation that links income distribution to economic growth and tests the robustness of these estimates to various specifications of the growth regression; Section 6 tests for the mechanisms linking inequality to growth; Section 7 concludes.

2 Literature Survey

Until recently, Kaldor's (1956) two-sectors model was the classical reference in the discussion of the links between income distribution and growth. In this model, inequality in the *functional* distribution of income is positively associated with growth. In the last few years, with the introduction of credit rationing and political economic models, income distribution has became again central in the analysis of economic growth. This new emphasis on income distribution has moved from the *functional* distribution of income to the *personal* distribution of income. This section surveys both the theoretical and empirical literature on this topic

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[1] This is well documented in the *East Asian Miracle,* World Bank (1993).

[2] This was the *status quo* at the time this paper was first circulated. Since then at least three papers (Partridge, 1997, Forbes, 1997 and Li and Zou, 1997) questioned, by using new data-sets and techniques, the presence of such a negative relationship.

A. Theoretical literature

To survey the most recent literature on income distribution and growth I will use the classification adopted by Perotti (1996). According to this classification, the literature can be divided into four groups: (i) Endogenous fiscal policy; (ii) Socio-political instability; (iii) Imperfect capital markets and investment in education; and (iv) Endogenous fertility.

Endogenous Fiscal Policy. The papers that try to join the theory of endogenous growth with endogenous fiscal policy models can be further divided into two groups. Those belonging to the first group (Alesina and Rodrik, 1994, Bertola, 1993, Krussell, Quadrini, and Rios-Rull, 1997, Perotti, 1993, and Persson and Tabellini, 1992, 1994) are inspired by the seminal work of Meltzer and Richard (1981). Meltzer and Richard study an economy composed by heterogeneous individuals who have different productivities and levels of income. The government levies a proportional tax and redistributes the tax revenue to everybody in equal amounts. Taxation is decided by the median voter and, since the income distribution is assumed to be skewed to the right (*i.e.*, the median voter's income is lower than the average income), high inequality causes high tax rates. Since taxation and redistribution are assumed to be distortionary, for investment, these authors predict a negative relationship between growth and inequality.

The second group of models (Acemoglu and Robinson, 1996, Bénabou, 1996a, 1996b, Bourguignon and Verdier, 1996) originate from the empirical failure of the first group of models. These authors consider a more complex interaction between income distribution and growth. Most of these models build on the evidence (documented by Perotti, 1996) of a positive correlation between fiscal policy variables and growth and show that, under certain conditions, less equal societies produce a lower level of, growth-enhancing, redistribution. Their reduced form is therefore identical to the one of Persson and Tabellini (1994) and Alesina and Rodrik (1994) (*i.e.*, a negative correlation between growth and inequality) but the structure is the opposite.

Chang (1998) uses a bargaining model in which two political parties negotiate the level and allocation of taxes. The political parties represent social classes which have different preferences about growth and redistribution. Chang shows that his model is consistent with the cross-country evidence of a negative relationship between inequality and growth. His approach differs from the ones discussed above in the fact that there is no clear causal relationship between inequality and growth. because both variables are endogenously determined by the outcome of tax bargaining. In this setting lump-sum redistribution does not necessarily increase growth.

Socio-political instability. According to this approach (Benhabib and Rustichini, 1996, Grossman and Kim, 1996, Bénabou, 1996b), inequality is positively correlated with socio-political instability (violent protests, assassinations, coups, etc.) because the very poor may be tempted to engage in predatory activity at the expense of the rich or the middle class. At the same time, a high level of political instability poses threats to property rights and, by increasing uncertainty, discourages investment and reduces growth.

Imperfect capital markets and investment. Banerijee and Newman (1991), Aghion and Bolton (1992), and Galor and Zeira (1993) study the interaction among income inequality, imperfect capital markets, and investment decisions. These papers use risk averse individuals and moral hazard as sources of capital market imperfection. They find that inequality reduces the share of agents able to invest in physical or human capital and therefore is negatively correlated with growth. Galor and Zeira (1993) show that, if there are fixed costs in education, poor households will be caught in a poverty trap and inequality will persist generation after generation.

Endogenous fertility. Using a representative agent framework, Barro and Becker (1988) and Becker, Murphy, and Tamura (1991) show how households face a trade-off between the *quality* and *quantity* of their offsprings. In this setting, wealthier households will have lower fertility rates and a higher investment in education than poorer households. Dahan and Tsiddon (1998) provide the first attempt to study the interactions among fertility, education, and income distribution. In their paper the causality goes from development to income inequality. It is shown that in the early phases of development fertility and inequality increase together. In more advanced countries (or at later stages of development), fertility decreases, investment in human capital increases, and inequality declines. Perotti (1996) argues that these models can be used to generate the prediction that a decrease in inequality would cause a decrease in fertility and therefore an increase in investment in human capital and growth.

B. Empirical studies

Despite the vast and continuously growing theoretical literature on income distribution and growth, empirical research on this topic has moved at a much slower pace. Data availability and the difficulty of finding measures of redistribution that are comparable across countries are the main obstacles to the development of an empirical literature on this topic.

Persson and Tabellini (1994) and Alesina and Rodrik (1994) test the reduced form equations of their models and find a negative relationship between income inequality and growth. Persson and Tabellini also show that this relationship is stronger in democracies than in dictatorships and claim that this provides indirect evidence for the fiscal policy approach.

In his 1996 survey, Bénabou (1996b) concludes that all the regressions deliveres the consistent message that inequality is harmful for growth. A first challenge to this view comes from Deininger and Squire (1996) who, using a high quality data-set, fail to find a statistically significant negative relationship between income inequality and growth.[3] It is not clear if this result is determined by the quality of the data or by the fact that the data-set used covers a small sample of countries. Later work by Forbes (1997) seems to indicate that, if one controls for country specific factors, it is possible to find a positive relationship between inequality and medium term growth. Similar results are found by Li and Zou (1997) who show that, when 5-years growth episodes are considered, the relationship between inequality and growth becomes positive.

Partridge (1997) addresses the data quality issue by using high-quality data for the American states.[4] Using 10-year growth episodes, he finds a positive correlation between the income share of the middle class and economic growth, but he also finds a positive correlation between inequality (measured by the Gini index) and growth. One of the main messages of Partridge's (1997) work is that different measures of inequality can convey very different messages.[5]

One critique that can be moved to Partridge (1997), Forbes (1997), and Li and Zou (1997) is that, while most theoretical models emphasize the relationship between inequality and long-run growth, these latter studies analyze the link between inequality and medium or short-term growth.

Very few studies go beyond the reduced form analyses described above. Alesina and Perotti (1996) and Alesina *et al.* (1996) present empirical evidence for the inequality, socio-political instability, and growth connection. Partridge (1997) shows that in the U. S. there is a negative correlation between income share of the middle class and employment in the public sector and that inequality is positively correlated with higher levels of welfare payments.

Perotti (1996) is a serious attempt to estimate the structural equations of the theoretical models described above. Perotti's main results can be summarized as follows. First, there is a robust negative relationship between income distribution and growth. Second, it is not possible to separate a democracy effect from an income effect; therefore, it is not possible to claim that the relationship between inequality and growth is stronger in democracies. Finally, the structural estimations support the socio-political instability approach and the channel that goes through education and fertility decision. No support is found for the fiscal policy approach. In fact, Perotti finds no correlation between inequality and redistribution and finds a *positive* correlation between redistribution and growth. This latter result contradicts Easterly and Rebelo's (1993) previous finding of a negative relationship between these two variables. The main problems with Perotti's tests relate to data quality and to the identification of appropriate measures of redistribution. These problems will be discussed in greater detail in the next section.

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[3] They do find a negative relationship between inequality in land distribution and growth.

[4] His approach differs from the one of this paper because, while I address log-run growth episodes, his short panel forces him to concentrate on 10-year growth episodes.

[5] This is also the message of the cross-country study of Székely and Hilgert (1999).

3 The Data

As discussed in the previous section, most of the empirical papers that study the relationship between distribution and growth suffer from two main problems:

1. They use low quality data on income distribution. Platt (1989) points out that many of the official statistical aggregates used by economists are not reliable, lack rigorous theoretical backing, and are not comparable over time or space. Moll (1992) shows that the problem is particularly serious for income distribution data. The main problems consist of the different methods of data collection and aggregation, small sample size, and inadequate treatment of the informal sector. Fields (1989) surveys data on income distribution and poverty for 70 developing countries and finds that only 35 countries have data that meet some minimal criteria of reliability and comparability. Atkinson and Brandolini (1999) and Székely and Hilgert (1999) criticize the high quality data-set compiled by Deninger and Squire (1996).

2. Instead of trying to identify the structural links between income distribution and growth, they only test reduced form equations (the exception is Perotti, 1996). The reasons why these papers do not go beyond reduced form analysis is well expressed by Persson and Tabellini:

   > "Taxation in our model need not to be taken literally. Taxation can be either explicit or implicit, and many other policies are similar, in that they affect the incentives for productive accumulation and entail a redistributive component. Most important among general policies are probably some aspects of the regulatory system: patent legislation and enforcement of intellectual and general property rights. Most important among sectoral policies are probably trade, industrial, and sectoral policies, and sectoral regulations....These various general and sectoral policies are going to be hard to measure in a satisfactory way across countries (Persson and Tabellini, 1992)."

A. The rationale for using regional data

A possible solution to both problems consists in using regional data. Blanchard (1991) points out that macroeconomists have rediscovered regional economics because the comparison of regions offers a much better controlled experiment than the comparison of countries. In particular, the experience of the American states represents a very important source of data for studying the determinants of long run growth. In two seminal papers, Barro and Sala-i-Martin (1991, 1992a) use data on American states, European regions, Japanese prefectures, and Canadian provinces to test for long-run convergence. Barro and Sala-i-Martin (1992b), use regional data to study the empirical determinants of net migration across US states and Japanese prefectures. Benhabib and Spiegel (1992) use US regional data to test for the role of human capital in economic development. Ciccone and Hall (1996) use US states data to explain the factors that link productivity to industrial density.

The reasons for the success of cross-state studies reside in the fact that the use of regional data solves some of the typical problems of cross-country regressions. The data are of good quality and are comparable across states. Furthermore, regression analysis presupposes that the data are sampled from a single population.[6] This assumption is more plausible for regional studies than for large cross-country samples.

For this paper's purpose of testing the links between inequality and growth, data on American states have some additional advantages: while sharing most of the regulations that are difficult to quantify and compare across countries, the American states have different levels of taxation and transfer policies (Partridge, 1997). This is the ideal setting for investigating the presence of a fiscal channel linking inequality to growth.

There are, however, some problems in using this data-set. The most important relates to the low variability of income distribution across states. The next subsection studies this problem in greater

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[6] Harberger (1987) asks "What do Thailand, the Dominican Republic, Zimbabwe, Greece, and Bolivia have in common that merits their being put in the same regression analysis ?"

detail. Another problem is that in the US most of redistribution and taxation is done through the federal government and therefore, even if a fiscal channel exists, it may not be possible to uncover it by using state level data.

B. Measuring inequality

The distributional variables were built using adjusted gross income data from the annual reports, *Statistics of Income, Individual Income Tax Return* (SOI), published by the Internal Revenue Service. The SOI data were used to compute Gini indices and break up the population in quintiles for 1920, 1930, 1940, 1950, 1960, 1969,[7] and 1980. The SOI data are based on pre-tax adjusted gross income. They include capital gains but exclude interest on state and local bonds and most transfer income. This is an optimal source of data for at least three reasons: (i) since tax evasion is not a big problem in the United States, data on taxation are likely to be more accurate than the data of other surveys (such as the Census and the CPS); (ii) most theoretical models link economic growth to pre-tax and transfer income distribution; and (iii) pre-tax data show more variability than after tax data. The biggest problem with this data-set is that it does not capture the income of the people who are not required to fill out a tax return. The censoring at the lower end of the distribution may explain the low correlation between the Gini index computed with Tax data and the Gini index computed with Census data. Panizza and Sandy (1998) show that this correlation oscillates between 0.22 and 0.42.

The SOI data are grouped in income classes. For each income class, SOI reports the number of individuals and their total income. It is therefore necessary to use an approximation technique to estimate the Gini index and to divide the population into quintiles.

The Gini index was computed by using a simple linear approximation to the Lorenz curve. It is well known that this method systematically understates inequality. However, Gastwirth (1972) shows that if the number of groups is large enough the error is small.

An interpolation method was used to break down the population into quintiles. Because of the large number of indices to compute (5 quintiles for 48 states for 7 years yield 1680 data points), the method needed to be both accurate and simple. The split histogram method suggested by Cowell (1995) has both characteristics. Cowell (1995) computes various inequality indices using the split histogram method to interpolate data from the *Statistics of Income* and finds this method to be very robust. Technical details on the derivation of the quintiles are provided in the appendix.

Some cross-country studies use the Gini index as a measure of income distribution (this is the variable used by Alesina and Rodrik, 1994). This choice is often due to data availability. In fact, no theoretical model makes an explicit reference to this index. Furthermore, the Gini index is a good measure of income inequality only if there is no Lorenz crossing. Both Persson and Tabellini (1994) and Alesina and Rodrik (1994) make use of the median voter theorem. In these models redistribution and growth depend on the distance between the income of the median voter and the average per capita income.

The ideal distributional variable to test these models would then be the relative position of the median voter. Unfortunately, this statistic cannot be calculated with sufficient precision. A measure of inequality that provides a good approximation to the relative position of the median voter is the income share of the third quintile. It is possible to show that the position of the median voter is a function of the income share of the third quintile plus the shape of the income distribution within the third quintile. Information on the latter is necessary to determine the exact position of the median voter, but, for any inter-quintile distribution, the higher the income share of the third quintile the higher (relative to the average income) the income of the median voter, regardless of the characteristics of the other quintiles.[8]

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[7] 1969 data were used instead of 1970 data because a change in the reporting procedure greatly reduced the number of reporting individuals in 1970.

[8] By assuming that the within-quintile income distribution is not skewed, it is possible to show that there is a perfect correspondence between the income share of the third quintile and the relative position of the median voter. In particular, the income of the median voter will be higher (lower) than average income if the income share of the third quintile is higher (lower) than 20%. Let Y be total income, $\bar{Y}$ average income, $\bar{Y}_s$ the average income of the s^{th} quintile and Y_s the income share of the s^{th} quintile. $Y_s = \frac{\frac{100}{5} n\bar{Y}_s}{Y} = \frac{20\bar{Y}_s}{\bar{Y}}$, therefore $Y_s > 20 \Rightarrow \bar{Y}_s > \bar{Y}$. This result will not hold if the within-quintile distribution is skewed (because it would be impossible to establish a correspondence between the income of the median voter and average income of the third quintile).

Table 1: Cross-country data. Income distribution and income per capita (all the variables are measured around 1960. Income per capita is in 1980 prices)

	Gini	3rd quintile		3rd+4th quintiles		Income per capita	
Min.		7	Gabon	22.5	Kenya	208	Tanz.
Max.	0.62	18.8	DK	42	DK	7380	USA
Av.	0.448	13		34.2		2190	
Norm. Stdev.	0.18	0.19		0.156		0.85	

By using two different measures of inequality Partridge (1997) obtains contradictory results. On the one hand, he finds a positive correlation between the income share of the third quintile and growth, indicating that inequality is harmful for growth. On the other hand, he finds a positive correlation between the Gini index and growth, indicating that inequality is growth enhancing. Similar results are found by Székely and Hilgert (1999) who show that the relationship between inequality and growth is sensitive to the measure of inequality used in the regression. In this paper, I follow Persson and Tabellini (1994) and use the income share of the third quintile as the main distribution variable. I also show that the results of a negative correlation between inequality and growth are robust to the use of other distributional variables.

While the income share of the third quintile is the best variable to test for the presence of a fiscal channel, the models that emphasize the role of education and fertility concentrate on the behavior of the poorest part of the population. In this case the appropriate distribution measure would be the income share of the first quintile, or the number of people (or families) living below the poverty line. The problem with the latter measure is that the poverty line is uniform across the US therefore the number of people below the poverty line in a given state is highly correlated with the income per capita of that particular state. Hence, I use the ratio of the income share of the first and fifth quintiles ($Q1/Q5$) to capture the difference between the richest and poorest sections of the population.

C. Variability of the data

The well known large cross-country differences in the levels of income inequality justify the empirical work of Perotti (1996), Alesina and Rodrik (1994), and Persson and Tabellini (1994). If cross-state data are to provide more information than cross-country data, it is necessary to make sure that there are different patterns of inequality and income growth across states. This subsection compares the variability of cross-state data with the variability of cross-country data. The results are reported in Tables 1, 2, 3, 4, and 5.

Table 1 contains the summary statistics of the data-sets used by Alesina and Rodrik (1994), Perotti (1996), and Persson and Tabellini (1994). To compare the variability of the cross-state data-set used in this paper with the cross-country variability I normalize the standard deviations (σ_x/μ_x) of the distributional variables and of the level of per capita income. As expected, the cross-country data have larger variability but the differences are not as dramatic as one would think. The cross-country normalized standard deviation for the income share of the 3rd quintile is 0.19. The cross-state normalized standard deviations range from 0.053 (for the year 1980) to 0.13 (see Table 2). If 1980 is excluded, the normalized standard deviations for the cross-state data-set are always at least one fourth (often greater than one third) of the cross-country standard deviation. In two decades (1930 and 1960), the cross-state normalized standard deviations are greater than half the cross-country estimates. The non-trivial variability of the income share of the third quintile is also illustrated by Figure 1.

Perotti (1996) uses the income share of the third and fourth quintiles because this variable is highly correlated with the income share of the third quintile and is less sensitive to measurement errors. Furthermore, this measure should capture the idea of "middle class" which is relevant in some of the theoretical models. Table 3 shows that the cross-state variability of the income share of the third and fourth quintiles ranges from 0.04 to 0.12. The corresponding value for the cross-country data is 0.156. Also here the variability of the cross-state data-set is often greater than one third of the cross-country variability and, in four decades (1920, 1930, 1940, 1960), close to or greater than

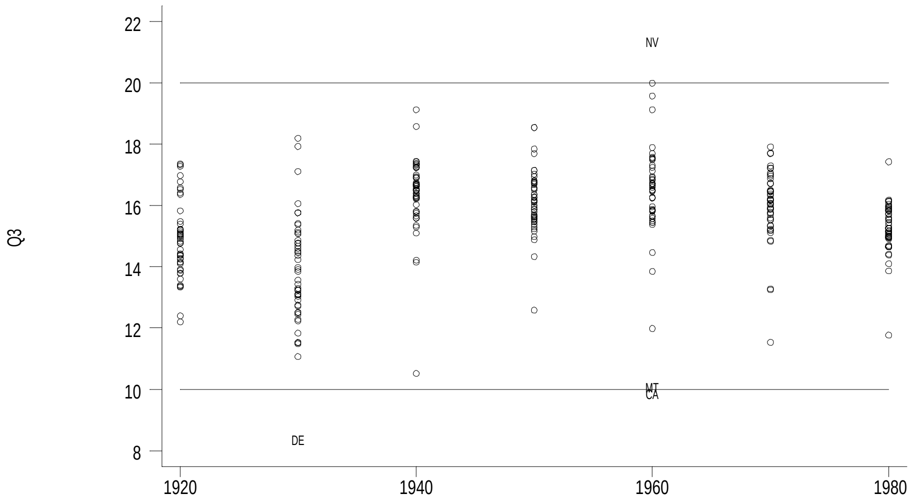

Figure 1: Income Share of the 3rd Quintile. Various Years

Table 2: Cross-state data. Income share of the third quintile

	1920		1930		1940		1950	
Min.	12.18	NY	8.21	DE	10.51	DE	12.57	DE
Max.	17.35	NV	18.20	ND	19.13	NM	18.55	WA
Av.	14.84		13.84		16.36		16.12	
Norm. Stdv.	0.083		0.13		0.076		0.063	
	1960		1970		1980		1920-80	
Min.	9.72	CA	11.52	DE	11.77	TX	8.21	
Max.	21.23	NV	17.91	NH	17.42	CT	21.23	
Av.	16.31		15.97		15.24		15.52	
Norm. Stdv.	0.123		0.074		0.053		0.104	

Table 3: Cross-state data. Income share of the third and fourth quintiles

	1920		1930		1940		1950	
Min.	28.74	NY	20.68	DE	23.7	DE	30.36	DE
Max.	38.36	NV	42.73	ND	42.54	NM	41.19	MN
Av.	33.82		33.19		36.95		38.22	
Norm. Stdv.	0.07		0.12		0.07		0.05	
	1960		1970		1980		1920-80	
Min.	24.36	MT	32.05	DE	36.75	FL	20.68	
Max.	45.31	NV	44.91	NH	46.12	CT	46.12	
Av.	40.09		40.84		40.40		37.62	
Norm. Stdv.	0.09		0.05		0.04		0.105	

Table 4: Cross-state data. Gini index

	1920		1930		1940		1950	
Min.	0.22	WY	0.32	ID	0.31	ID	0.30	GA
Max.	0.46	NY	0.64	DE	0.58	DE	0.53	DE
Av.	0.34		0.44		0.36		0.41	
Norm. Stdv.	0.17		0.07		0.06		0.05	
	1960		1970		1980		1920-80	
Min.	0.40	UT	0.42	MA	0.40	CT	0.22	
Max.	0.67	MT	0.49	DE	0.52	SD	0.67	
Av.	0.44		0.46		0.47		.42	
Norm. Stdv.	0.04		0.03		0.05		0.14	

half of the cross-country variability.

Table 4 contains the Gini index data. The variability of this index is slightly lower than the variability of the third and fourth quintiles but it is often greater than one fourth of its cross-country variability.

These results are quite remarkable considering the significant differences between the two data-sets. While the cross-state data-set uses high quality and homogeneous data, the cross-country data-set is derived from surveys that: (i) are subject to wide measurement errors (especially in developing countries); (ii) are based on different concepts of recipient units (some use individuals other households); and (iii) do not have homogeneous coverage (some surveys are limited to urban areas). Hence, even if the two populations had the same underlying variability, we expect to find a higher variability in the cross-country data-set as it is subject to a higher measurement error.

Income per-capita is an explanatory variable used in all cross-country and cross-state studies (*e.g.* Barro and Sala-i-Martin, 1992). How does the variability of cross-country per capita income compare to its cross-state variability? The normalized standard deviation for cross-country per-capita income in 1960 is 0.850; the corresponding cross-state standard values range from 0.31 to 0.528 (for the pooled sample). If the pooled sample is excluded, the cross-state variability is always less than half of the cross-country variability and, from 1950 on, always less than one fourth of the cross-country variability.

Although the variability in cross-state inequality is smaller that the variability in cross-country inequality, the differences between these two data-sets are similar to the differences between the cross-country and cross-state variability in per capita income. Since data on cross-state per capita income have been successfully used in many empirical studies, the evidence presented above provides strong support for using cross-state data on inequality.

Table 5: Cross-state data. Income per capita (1980 prices)

	1920		1930		1940		1950		
Min.	1147	MS	980.19	MS	1247	MS	2651	MS	
Max.	4184	NY	5054	NY	5958	DE	6962	DE	
Av.	2491		2653		3132		4833		
Norm. Stdv.	0.3102		0.3786		0.3551		0.2182		
	1960		1970		1980		1990		1920-80
Min.	3443	MS	5503	MS	6868	MS	7926	MS	980
Max.	8109	CT	10702	CT	12170	CT	16032	CT	12170
Av.	5855		7999		9391		11088		5193
Norm. Stdev.	0.1929		0.1583		0.1397		0.1587		0.528

4 Evolution of Income Distribution in the US Regions

By dividing the 48 continental US states into four Census regions it is possible to observe some convergence in the evolution of their income distribution. In 1980, for almost all quintiles, the deviation from the national average was close to zero (Panizza, 1997, presents preliminary evidence for convergence in income distribution). The inequality indices for the Northeast and the West moved in opposite directions. Before 1950, the Northeast was characterized by very high inequality with low income shares of the first, second, third, and fourth quintiles and a very high income share of the fifth quintile. The opposite was true for the West which, until 1950, was characterized by relatively high income shares of the first four quintiles. The income shares of the five quintiles were quite stable in the South and the Midwest. The South has been characterized by a level of inequality slightly above the national average, and the Midwest by a level of inequality slightly below the national average. In the South, the income shares of the third and fourth quintiles are much lower than the national average, a sign of the relative poverty of the middle class.

The states grouped in the four Census regions are far from being homogeneous. It is possible to obtain more information by using the 8 Census divisions. This finer partition shows that the New England and Mideast states have the same trend as the Northeast.[9] The Great Lakes and the Plains follow opposite patterns; this contributes to the flatness of the Midwest trend. The most important piece of information obtained analyzing the Census divisions is the very high level of inequality of the Mideast. For this group of states, the income share of the fifth quintile is always above the US average while the income share of the third and fourth quintiles is always below the US average.

The evolution of the income distribution of the single states illustrates that the Mideast pattern is driven by the behavior of New York and Delaware. All the states in this region exhibit a higher than average level of inequality. Maryland, New Jersey, and Pennsylvania however, have shown some convergence toward the national average (especially in the income share of the first and second quintiles). New York and Delaware, instead, are characterized by very low income shares of the first four quintiles.

I am not aware of any study that decomposes state level inequality indices using tax data. Some authors have calculated inequality indices using household surveys. Betson and Haveman (1984) compute state-level Theil inequality indices for 1975. Their measure of inequality is not directly comparable to the measure used in this paper for three reasons: (i) they use a different inequality index; (ii) they use a different specification of income recipient (households instead of individuals); and (iii) they use a different data-set (the 1975 survey on income and education). Even with these differences, Betson and Haveman find results similar to the one obtained using the data from the SOI; in 1975, the Southern states had the most substantial levels of inequality and the states in the Midwest had the lowest. Betson and Haveman also analyze the role of transfers in reducing inequality within regions. They find that, in the period from 1967 to 1979, transfers were very high in the Northeast and Midwest, but very low in the West. It is interesting to note that in the same period pre-transfer inequality (measured using tax data) was decreasing in the Northeast and increasing in the West. It is possible that these transfers helped some families to exit from the poverty trap illustrated by Galor and Zeira (1993). This could also explain the role of transfers in the convergence of the inequality indices among regions.

5 Reduced Form Estimates

This section of the paper tests for the presence of a correlation between inequality and economic growth. Alesina and Rodrik (1994), Persson and Tabellini (1994), Perotti (1996), and many other authors (see Bénabou 1996b for a complete survey) estimate reduced forms of cross-country models and find a negative relationship between inequality and growth. Deininger and Squire (1996) find that only inequality in land distribution is strongly correlated with growth. Forbes (1997) and Li and Zou (1997) find a positive relationship between inequality and short-term growth.

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[9] The inclusion of two extra states (Maryland and Delaware) reinforces the trend that characterizes the Northeast. This is a sign that Delaware and Maryland are economically closer to the Northeast than to the South.

The main problem with the existing empirical work is the poor quality of the cross-country data on income distribution. This section shows that the finding of a negative relationship between inequality and growth is robust to the use of a higher quality data set. To devise a test for the presence of a relationship between growth and inequality one needs to consider the following issues:

1. *What is the correct specification of the model?* In this paper, the analysis starts with a very simple and widely accepted specification of the reduced form and then studies the sensitivity of the results to the inclusion of a set of variables that are likely to be correlated with both income distribution and growth.
2. *What income distribution variable should be used?* Income distribution is measured in four ways: (i) income share of the third quintile ($Q3$); (ii) income share of the third and fourth quintiles ($Q3+Q4$); (iii) income share of the first quintile divided by the income share of the fifth quintile ($Q1/Q5$); and (iv) Gini index ($GINI$).
3. *What is the optimal length of the growth period to be examined?* Most papers test for the factors determining long run growth by studying growth over either twenty or thirty-year periods. Forbes (1997) and Li and Zou (1997) consider a panel of five-year growth episodes. In this paper I present results for ten, twenty, and thirty-year periods, but I will not make any attempt to estimate the effect of inequality on five-year growth episodes.
4. *Is it better to use a simple cross-state model or a panel?* Wherever possible a panel data-set is used. This is a natural choice because, besides increasing the number of observations, the panel data-set makes the cross-state data more comparable with the cross-country data. The per-capita income of Mississippi in 1930 ($980) was similar to the 1960 per-capita income of many developing countries.[10] Furthermore, the extreme values, the averages, and the normalized standard deviations of all the distribution variables for the pooled data-set are similar to the respective cross-country values.

   Another advantage of using the panel is the possibility of running fixed effect estimations. One problem that afflicts most cross-sectional regressions is the omitted variable bias. The fixed effect estimations used in this paper allow to control for unobservable state characteristics and remove any bias that would result from the correlation of these unobserved characteristics with the explanatory variables. Results for simple (non-pooled) cross-state regressions are also presented.

The rest of the section is organized as follows. A simple regression linking inequality to growth is first analyzed. The robustness of the results to outliers is then checked. The section concludes with a sensitivity analysis to check whether the results are driven by the fact that inequality captures the effect of other variables correlated with both growth and inequality.

5.1 Basic Reduced Form Regressions

I start with a simple specification of the model. To avoid direct reverse causation, I adopt the standard practice of measuring inequality at the beginning of each growth period. The specification for the panel reduced form regression is the following:

$$GROWTH_{(t,t+n),\ i} = \alpha_i + \beta y_{t,i} + \gamma DISTR_{t,i} + \theta \mathbf{Z}_i + \varepsilon_{t,i}, \tag{1}$$

α_i is a state specific intercept, y is the log of initial income, $DISTR$ a variable capturing income distribution, and $\mathbf{Z}$ a vector of dummies for different decades. Annual growth is measured over periods of ten ($G10$), twenty ($G20$), and thirty ($G30$) years.[11]

The expected signs for $Q3$, $Q3+Q4$, and $Q1/Q5$ are positive, while the expected sign for the Gini index is negative. Tables 6 and 7 reports the coefficients and t statistics attached to initial

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[10] For instance: Brazil $991, Bolivia $882, Honduras $748, Paraguay $991, Sri Lanka $974, Philippines $874, Cote d'Ivoire $743, Zambia $740.

[11] Since the data-set ends in 1995, the last observations of the panel are for growth periods over 15 and 25 years.

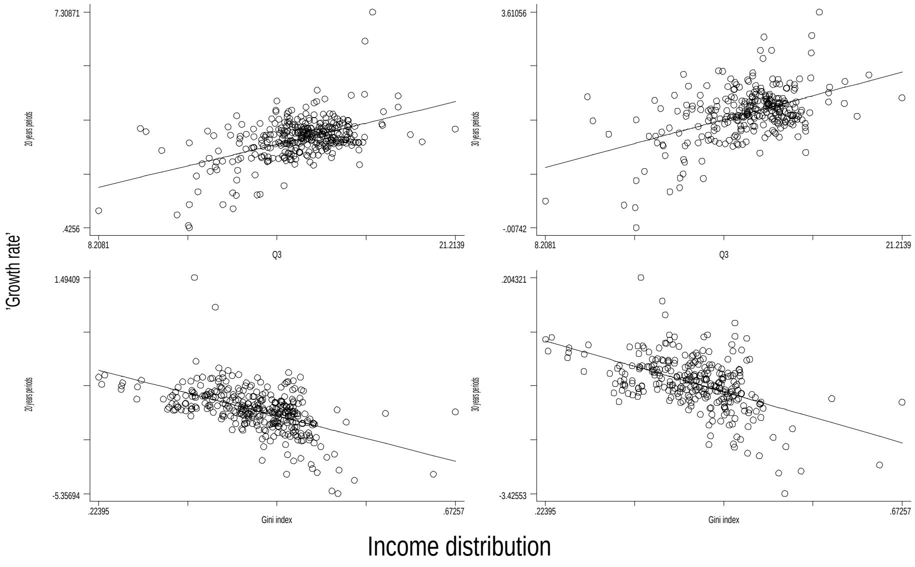

Figure 2: Growth and Inequality

Table 6: Basic Panel Regressions. Ten and Twenty-year Growth Episodes

	Ten-Year Growth Episodes				Twenty-Year Growth Episodes (1930, 1950, 1970)			
y	-3.51	-3.45	-3.62	-3.49	-3.33	-2.95	-3.82	-3.49
	(-8.18)*	(-7.91)*	(-9.12)*	(-8.34)*	(-6.48)*	(-5.67)*	(-8.59)*	(-6.62)*
$Q3$	0.09				0.35			
	(2.07)*				(5.65)*			
$Q3+Q4$		0.05				0.22		
		(2.23)*				(6.34)*		
$Q1/Q5$			7.70				26.85	
			(3.446)*				(6.48)*	
$Gini$				-3.71				-11.04
				(-2.56)*				(-4.93)*
F	91.15	91.46	95.28	92.76	321.3	344.6	350.9	304.9
R^2	0.67	0.67	0.67	0.67	0.85	0.85	0.85	0.85
N. Obs.	334	334	333	336	142	142	141	144

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%.

income and inequality.[12] Figure 2 shows the correlation between $Q3$ and $GROWTH$ and $GINI$ and $GROWTH$ (in the graph $GROWTH$ is controlled for all the other independent variables).

The regressions fit the data fairly well. The R^2s are often above 0.8, the values for the F statistics are high, and the coefficients attached to the inequality indices have always the right sign and are often statistically significant at the 1% level (if we exclude the second part of Table 7, they are always significant at least at the 5% level).

Table 7 shows that the relationship between inequality and thirty-year growth is not stable. I find a strong link between these two variables when I consider growth episodes staring in 1930 and 1960, but when I consider periods starting in 1940 and 1970, I find that only the income share of the third quintile is significantly associated with growth.

Are the coefficients of Tables 6 and 7 *economically* significant? Table 8 shows the standardized impact of inequality on annual growth. If $Q3$ increases by one standard deviation annual growth will increase by 0.6 percent when twenty-year growth episodes are considered and by approximately 0.1 percent when growth is computed over ten or thirty-year periods. These results are not very different from the findings of the cross-country studies; the latter show that if $Q3$ increases by one standard deviation, growth increases by about half a percentage point (Persson and Tabellini, 1994,

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[12] The coefficients attached to the decade dummies are available upon request.

Table 7: Basic Panel Regressions. Thirty-year Growth Episodes

	1930 and 1960 Panel				1940 and 1970 Panel			
y	-3.11	-3.00	-3.09	-2.91	-1.80	-1.81	-2.00	-1.90
	(-8.44)*	(-7.58)*	(-10.44)*	(-7.81)*	(-8.32)*	(-7.93)*	(-9.42)*	(-8.81)*
$Q3$	.06				0.08			
	(1.97)*				(2.12)*			
$Q3 + Q4$		0.04				0.04		
		(2.01)*				(1.61)		
$Q1/Q5$			7.74				2.40	
			(4.14)*				(1.1)	
$Gini$				-2.93				-0.77
				(-2.68)*				(-0.62)
F	283.9	284.9	365.3	304.1	193.7	185.3	177.7	183.3
R^2	0.86	0.87	0.86	0.87	0.62	0.61	0.61	0.63
N. Obs.	96	96	96	96	94	94	93	96

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%.

Table 8: Economic Impact of Inequality.

	G10	G20	G30 (1930-60)	G30 (1940-70)
$Q3$	0.14	0.60	0.13	0.09
$Q3 + Q4$	0.20	0.91	0.20	0.12
$Q1/Q5$	0.44	0.86	0.26	0.13
Gini	-0.22	-0.47	-0.14	-0.04

Perotti, 1996).

It has already been argued that the pooled data-set has many advantages over the simple cross-section sample. Unfortunately, it is not possible to use the pooled data-set for the sensitivity analysis and for the structural estimations. It is then interesting to look at the cross section results for different growth periods. This is done by estimating the following regression:

$$GROWTH_i = \alpha + \beta Y_i + \gamma DISTR_i + \delta \mathbf{X}_i + \varepsilon_i. \tag{2}$$

As in the pooled regression case, Y is initial income, $DISTR$ a distribution variable, $\mathbf{X}$ is a vector of regional dummies, and $GROWTH$ is the average growth rate over twenty and thirty-year periods. All the right-hand-side variables are measured at the beginning of the growth period. Table 9 reports the coefficient estimates attached to the distribution variables for different growth periods and starting points (Table 9 summarizes the results of 58 regressions by reporting only the regressions' R^2 and the coefficients and t statistics for the inequality variables).

Although the results are not as strong as those of the pooled model, the cross-section analysis still supports the presence of a negative relationship between growth and inequality. The income share of the third quintile has often a significant positive coefficient when used as explanatory variable for growth over a twenty-year period and in three decades is related to growth over a thirty-year period. Another variable that is strongly correlated with growth is the income share of the third and fourth quintiles. The results are, however, mixed for the other measures of income distribution. In most cases, they have the right sign, but they are often insignificant, especially when used to explain growth over a period of thirty years.

None of the variables contributes to explaining growth when the starting point is either 1920 or 1950. The most plausible explanation for the 1920's result is that the great depression affected different states in different ways, and this probably explains most of the growth pattern for the 1920-1940 period.[13] This would also explain the very low values of $\bar{R}^2$ that characterize the 1920-40 regressions. Another possible explanation is linked to the poor quality of the data for 1920, when only a small fraction of the US population was required to fill out a tax report. The 1950 results are more puzzling; all the coefficients attached to the income distribution variables have the right sign, but none of them is statistically significant. A possible explanation for the 1950 estimates could be the post World War II structural adjustment.

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[13] For the period 1920-1940, I find a positive, but not statistically significant, relationship between growth and inequality. For this period, even the coefficient attached to initial income (a variable that is usually highly correlated to subsequent growth) is not statistically significant.

Table 9: Cross section results

	G1920-40	G1930-50	G1940-60	G1950-70	G1960-80	G1970-90	G1980-95
Q3	-0.00011	0.41	0.13	0.048	0.048	0.09	0.28
	(-0.87)	(4.7)***	(2.06)**	(1.22)	(2.70)***	(2.24)**	(3.08)***
$\bar{R}^2$	0.1	0.86	0.75	0.79	0.8	0.57	0.44
Q3+Q4	-0.0006	0.19	0.03	0.024	0.033	0.07	0.05
	(-0.97)	(4.43)***	(0.79)	(1.04)	(3.76)***	(2.45)***	(1.23)
$\bar{R}^2$	0.12	0.86	0.73	0.79	0.83	0.58	0.37
Q1/Q5	-0.18	17.98	-0.35	4.59	5.82	-2.97	17.46
	(-0.49)	(3.17)***	(-0.12)	(0.89)	(2.97)***	(0.39)	(3.15)***
$\bar{R}^2$	0.1	0.83	0.73	0.78	0.81	0.5	0.48
Gini	0.009	-8.6	1.21	-0.95	-0.56	2.86	-8.19
	(-0.3)	(-2.67)***	(0.69)	(-0.68)	(-0.59)	(0.97)	(-2.41)**
$\bar{R}^2$	0.1	0.82	0.73	0.78	0.77	0.54	0.43

	G1920-50	G1930-60	G1940-70	G1950-80	G1960-90	G1970-95
Q3	0.00034	0.15	0.086	0.006	0.025	0.066
	(-0.58)	(3.07)***	(2.11)**	(0.19)	(1.45)	(1.94)*
$\bar{R}^2$	0.67	0.89	0.81	0.82	0.61	0.59
Q3+Q4	0.00009	0.07	0.03	0.006	0.021	0.051
	(-0.32)	(2.77)***	(1.19)	(0.34)	(2.45)***	(2.09)**
$\bar{R}^2$	0.67	0.89	0.79	0.82	0.66	0.59
Q1/Q5	0.004	4.08	0.57	4.99	3.21	-2.32
	(-0.28)	(1.33)	(0.28)	(1.23)	(1.67)	(0.37)
$\bar{R}^2$	0.67	0.87	0.79	0.83	0.64	0.53
Gini	-0.005	-2.63	0.28	-0.38	-0.88	2.06
	(-0.35)	(-1.57)	(0.24)	(0.34)	(-1.02)	(0.86)
$\bar{R}^2$	0.67	0.87	0.79	0.82	0.63	0.57

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%.

It is fair to conclude that, even with the caveats mentioned above, both the panel and cross-section analyses support the presence of a negative link between income inequality and economic growth.

5.2 Sensitivity Analysis

The results of the previous section seem too good to be true. The coefficients attached to the income distribution indices have values close to those found in cross-country studies; their t statistics are high, and the explanatory power of the various regressions is large. There are many reasons for expecting income distribution to have a much smaller effect on growth in the cross-state sample as opposed to the cross-country sample.[14] When one deals with cross-section data there is always the suspicion that the results may be driven by the presence of few outlying observations or may be distorted by the exclusion of relevant variables. This section explores how correcting for these problems would affect the results presented in Tables 6 and 7.

The role of outliers is analyzed by using a robust estimation method. The robust estimator used in this paper starts by running OLS, computes Cooks's D and excludes all the observations for which $D > 1$. Another regression is then performed, and the residuals are used to calculate White's weights which are used in a third regression. The program stops when the maximum change in weights drops below 0.01. At this point, the program starts using Beaton and Tukey's biweights until convergence. The results of the robust estimations are presented in Table 10 (this table summarizes the results of 12 regressions by reporting only the coefficients and t statistics for the inequality variables). It is interesting to note that the robust regression results for ten-year growth episodes are almost identical to the ones for the standard fixed effect estimates. When twenty and thirty-year growth episodes are considered the robust regressions yield lower coefficients and t statistics suggesting the presence of some important outlying observations. Even with these caveats the coefficients remain high and often statistically significant, suggesting the presence of a robust negative correlation between inequality and growth.

The regressions ran so far confirm the presence of a relationship between inequality and growth. Since their specifications are very parsimonious it is possible that the coefficients attached to the

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[14] Some of these reasons are: the high mobility of the factors of production; the role of the federal government; and the presence of some form of fiscal federalism.

Table 10: Panel Robust Regression.

	G10	**G20**	**G30**
$Q3$	0.09	0.17	0.06
	(2.23)*	(3.21)*	(1.7)
$Q3+Q4$	0.05	0.12	0.04
	(2.18)*	(3.71)*	(1.74)
$Q1/Q5$	8.80	20.25	7.70
	(4.09)*	(7.70)	(3.61)*
Gini	-0.04	-0.08	-0.03
	(-2.68)*	(-4.43)*	(-2.25)*

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%.

income distribution indices reflect the effects of other variables correlated with both income distribution and growth. To test for this possibility, Equation (1) is augmented with a set of regressors that are likely to be correlated with income distribution:

$$\begin{aligned} GROWTH_{(t,\ t+n),\ i} = \alpha_0 + \alpha_1 Y_{t,\ i} + \alpha_2 DISTR_{t,\ i} + \alpha_3 \mathbf{X}_i + \alpha_4 COLL_{t,\ i} + \\ + \alpha_5 HIGH_{t,\ i} + \alpha_6 METR_{t,\ i} + \alpha_7 OLD_{t,\ i} + \varepsilon_{t,\ i} \end{aligned} \tag{3}$$

Some of the variables included in Equation (3) are, according to the theories surveyed in the introduction, endogenous and will be treated in a more extensive way in the section that deals with the structural estimations. As argued in Perotti (1996), it is very important to distinguish between stocks and flows of human capital. $HIGH$ and $COLL$ are the percentage of adults with high school and college degree respectively; these variables should be a good proxy for the *stock* of human capital.[15]

Perotti (1996) points out that the regressions should be augmented with a measure of urbanization because urban areas are likely to have higher levels of both inequality and income. In Equation (3), $METR$ measures the fraction of the population that lives in metropolitan areas.

OLD is a demographic variable that measures the percentage of the population above 65 years of age. Since retired people have lower levels of both income and inequality, this variable is likely to be correlated with both growth and inequality. Furthermore, a higher number of retired people is likely to be positively linked to social security expenditure.

For most variables data for periods before 1960 are not available. It is therefore impossible to use panel regression without using overlapping growth periods. To avoid serial correlation, I only run simple cross-section regressions using twenty-year growth episodes starting in 1960 and 1970.[16]

The results of the sensitivity analysis are reported in Table 11. The negative relationship between inequality and growth is robust when the dependent variable is growth starting in 1970, but outliers seem to play a very important role when growth starting in 1960 is analyzed. The results of Table 11 are not robust to the use of different measures of income distribution. Table 12 summarizes the coefficients attached to the income distribution variables when inequality is measured by $Q3+Q4$, $Q1/Q5$, and $GINI$. As suggested by Table 9, $GINI$ does not enter in a significant way in the growth regression. The behavior of $Q1/Q5$ is the opposite of the behavior of $Q3$ and $Q3+Q4$. In fact, $Q1/Q5$ has an important role in explaining growth starting in 1960, but its t statistics drop noticeably when growth periods starting in 1970 are used.

Table 11 shows that the stock of human capital (measured as the percentage of college graduates) is positively correlated with growth in the 1970 regression while the level of urbanization and the age structure of the population do not affect growth.

5.3 Reduced Form Estimations: Conclusions

The first task of this paper was to test the robustness of the negative relationship between inequality and growth found in cross-country studies. The reduced form estimates strongly support such a relationship. The finding that the income share of the third quintile is positively correlated with

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[15] In the structural estimations I will use college enrollment as a proxy for *investment* in human capital.

[16] Thirty-year growth episodes are not studied because Table 9 shows that there is not a robust correlation between income distribution and growth over thirty-year periods.

Table 11: Sensitivity analysis

	1960		1970	
	OLS	Robust Reg.	OLS	Robust Reg.
Y	-0.00032	-0.00028	-0.00004	-0.00006
	(-8.145)***	(-9.08)***	(-0.684)	(-0.929)
Q3	0.046	0.004	0.119	0.12
	(2.486)***	(0.302)	(2.822)***	(2.671)***
South	0.419	0.473	-0.601	-0.586
	(3.351)***	(4.823)***	(-3.757)***	(-3.435)***
Midwest	0.202	0.193	-0.648	-0.585
	(1.905)*	(2.418)**	(-5.192)***	(-4.328)***
West	0.206	0.156	-1.102	-1.033
	(1.841)*	(1.845)*	(-7.660)***	(-6.723)***
COLL.	0.015	0.008	0.107	0.125
	(0.466)	(0.330)	(3.907)***	(3.765)***
HIGH	0.006	0.01	-0.052	-0.063
	(0.644)	(1.251)	(-4.043)***	(-3.870)***
METR.	0	0	0.001	0.002
	(-0.056)	(0.322)	(0.339)	(0.561)
OLD	0.004	-0.01	-0.008	0.024
	(0.731)	(-0.630)	(-1.492)	(0.959)
CONST.	3.384	3.808	1	0.866
	(7.550)***	(9.880)***	(1.105)	(0.888)
$\bar{R}^2$	0.83		0.71	
F	20	33.02	13.03	10.11
N. Obs	48	47	46	45

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%.

Table 12: Sensitivity analysis: Alternative measures of income distribution.

	1960		1970	
	OLS	Robust Reg.	OLS	Robust Reg.
Q3+Q4	0.34	0.108	0.68	0.63
	(3.81)***	(1.52)	(2.48)***	(2.077)**
$\bar{R}^2$	0.82		0.69	
Q1/Q5	9.83	4.76	8.17	13.8
	(3.77)***	(2.259)**	(1.058)	(1.646)
$\bar{R}^2$	0.82		0.63	
Gini	-0.696	-0.496	1.2	0.957
	(-0.702)	(-0.723)	(0.43)	(0.34)
$\bar{R}^2$	0.79		0.6	

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%.

subsequent growth has proven to be very robust to a wide variety of specifications of the model and testing methods. The result are more mixed when other indices of inequality are used.[17]

When this paper was originally written, the section on reduced form estimations was only meant to provide a robustness test for the cross-country findings of a negative link between inequality and growth. Checking for the true direction of the link between these two variables became more important after Partridge (1997), Forbes (1997) and Li and Zou (1997) found a *positive* correlation between inequality and medium-term growth. This paper shows that regional data strongly support the previous finding of a negative link between inequality and long-run growth. These results are of some importance because the data-set used in this paper is broader and is less likely to be affected by measurement errors than the data-set used in cross-country regressions. Furthermore, dealing with similar economies allows to implicitly control for a large set of variables that cannot be included in standard cross-country regressions.

The next section moves to the second task of this paper: the test of the structural relationship described by the models that study a fiscal channel linking inequality to growth.

6 Structural Form Estimates

To the best of my knowledge, Perotti (1996) is the only attempt to investigate the structural relationship between income distribution and growth. He identifies four channels through which income distribution can affect growth: (i) fiscal policy; (ii) imperfect capital markets; (iii) socio-political instability; and (iv) endogenous fertility. All four channels are characterized by the same reduced form: *growth is negatively affected by inequality.*[18] Perotti (1996) points out that the four channels are not mutually exclusive and therefore one should estimate them together and analyze their interactions. This task would require the estimation of a large system of equations. This is impossible to do with the small sample of American states used in this paper. Furthermore, since all the states have similar political institutions, it would be impossible to test for the socio-political channel using US data.

On the bases of these considerations, this section is mainly devoted to test for the presence of a fiscal channel. An attempt to measure the relationship among income distribution, fertility, and education is also made.

6.1 The Fiscal Policy Channel

The fiscal policy approach consists of a political and an economic mechanism. The former determines the economy's tax rate and the level of redistribution, the latter analyzes the effect of taxation and redistribution on growth. As mentioned in Section 2, the fiscal policy approach can be divided into two sub-groups. In the models that belong to the first group (Bertola 1993, Perotti 1993, Alesina and Rodrik 1994, and Persson and Tabellini, 1994) inequality is positively correlated with distortionary redistribution that, in turn, has a negative effect on growth. In the second group of models (Bénabou, 1996a, 1996b, Bourguignon and Verdier, 1996), the mechanism is the opposite: inequality is negatively correlated with growth-enhancing redistribution. The reduced forms of the two groups of models are the same, but the structures are the opposite.

To investigate the structural relationship between income distribution and growth I start by estimating the following model:

$$GROWTH_{70-90_i} = \alpha + \beta Y_{70_i} + \gamma DISTR_{70_i} + \delta FISC_{70-80_i} + \lambda \mathbf{X}_i + \varepsilon_i, \tag{4}$$

$$FISC_{70-80_i} = \beta_0 + \beta_1 Y_{70_i} + \beta_2 DISTR_{70_i} + \beta_3 VOTE_{70_i} + \beta_4 METR_{70_i} + \mu_i. \tag{5}$$

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[17] Especially the Gini index that, under some specifications, loses its explanatory power.

[18] One exception is Saint-Paul and Verdier (1993). Sometimes the theoretical models predict non-linearities in the relationship between growth and inequality. Perotti (1993), for instance, concludes that in very poor societies inequality might be growth enhancing. This is not a serious problem for the analysis of the US.

Equation (4) is obtained by augmenting Equation (2) with a fiscal policy variable. The key assumption in the above system is that there is no feed-back from growth to fiscal policy. The system is therefore recursive and can be estimated with OLS. In Equation (4), fiscal variables measured in the decade starting in 1970 (except for the indices of tax progressivity that refer to 1977) are used to explain growth over the period 1970-1990 (panel data are not available for the fiscal policy variables).

Equation (5) includes the initial level of income to capture the idea that richer states can afford to spend and redistribute a higher share of their income (Wagner's Law). $VOTE$ measures political participation; this variable is included because redistribution should be positively correlated with political participation (Bénabou, 1996a, 1996b, Bourguignon and Verdier, 1996). $METR$ is the percentage of the population living in metropolitan areas. This variable is included because the residents of urban areas are often more politically active than residents of rural areas. When the dependent variable is expenditure on education and health, a demographic variable (AGE) is added to the regression.[19] When it is property taxes, a variable that measures home ownership (OWN) is included.

One of the most difficult task in testing Equations (4) and (5) is the identification of the appropriate fiscal policy variables. A test of the first group of models requires types of expenditure or taxation that are explicitly redistributive, while the second group of model requires the use of productive government expenditures. This paper uses the following variables: (i) four measures of state expenditure (total state current expenditure, state expenditure on education, state expenditure on welfare payments, and state expenditure on health care services); (ii) three measures of taxation (total state taxes, state income taxes, and state property taxes); and (iii) two indices of tax progressivity (the Kakwani and the Suits indices).[20]

Since most researchers have found that all states have *regressive* tax structures (Kiefer, 1991), the indices of tax progressivity are particularly useful. With a regressive tax system, the relationship between total taxation and inequality is no longer clear, but it should still be true that states with high levels of income inequality should have less regressive tax systems. Therefore the discussion will concentrate on the results obtained using the indices of tax progressivity. Results for the other fiscal policy variables will also be presented.

Table 13 reports the summary statistics for the various measures of state expenditures and state taxation (all the values are averaged over the decade starting in 1970). There are large inter-states differences in the levels of tax progressivity, income taxation, and property taxation.[21] On the expenditure side, there are large inter-state differences in the levels of expenditure on higher education, health care, and welfare. Although most of the fiscal policy indicators have relatively high variability, their absolute value is often very low.[22] Thus, they may have a very small effect on state-level growth.

The results of the estimation of Equation (4) are presented in Table 14. The first column reports the coefficient attached to $Q3$ obtained by estimating Equation (2). The other nine columns show the coefficients attached to both $Q3$ and the various fiscal policy variables. All the coefficients attached to the fiscal policy variables (with the exception of health care expenditure) have a negative sign consistent with the models that predict a negative relationship between redistribution and growth. Total state expenditure and the indices of tax progressivity are the only variables that have a significant role in explaining subsequent growth. The two measures of tax progressivity have high t

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[19] $YOUNG$ (percentage of the population below 21 years of age) is used when the fiscal variable is expenditure on education, and OLD (percentage of the population above 65 years of age) is used, when the fiscal variable is health expenditure.

[20] These indices were computed by Kiefer (1991) using the 1977 data-set put together by Phares (1980). The two indices are defined as follows: Kakwani index $K = C_t - G_b$, where C_t is the tax concentration index (computed as a regular Gini index with the distribution of taxes replacing the distribution of income) and G_b is the, pre-tax, Gini index. The Suits index is computed as a Gini index with the distribution of taxes replacing the distribution of income and the distribution of income replacing the distribution of the population.

[21] New Hampshire is the state with the most regressive tax system and Delaware the state with the least regressive system. Four states do not have income taxes, while income taxation is more than 4% of Wisconsin's personal income. Property taxes in Massachusetts are about six times higher than property taxes in Ohio.

[22] Average welfare expenditure, health care expenditure, and income taxation are less than 2% of state personal income. All other variables, with the exception of total state expenditure, are less than 10% of state personal income.

Table 13: Fiscal policy variables: Summary statistics.

Variable	Mean	Stand. Dev.	σ/μ	Min		Max	
Tot. Exp.	162.58	22.85	0.14	123.74	IN	219.82	VM
Educ.	64.74	11.07	0.17	45.12	CT	97.18	NM
Hig. Educ.	19.95	6.18	0.31	8.72	PA	38.39	UT
Welf.	20.43	6.96	0.34	8.88	AZ	36.93	MA
Health	12.05	3.37	0.28	7.36	ND	24.85	CT
Inc. Tax	18.55	11.63	0.63	0.00	NE, TX WA, WY	41.81	WI
Prop. Tax	42.25	15.07	0.36	12.93	OH	72.14	MA
Tot. Tax	98.76	12.03	0.12	76.65	OH	125.08	VM
Kakwani	-0.08	0.03	-0.33	-0.15	NH	0.001	DE
Suits	-0.07	0.03	-0.38	-0.14	NH	-0.02	DE

The values are in 1970 dollars for $1000 of state personal income.

Table 14: Fiscal policy variables and subsequent growth

		Fiscal Policy Variable Used in the Regression								
		T. Exp.	Educ.	Welf.	Health	I. Tax	P. Tax	T. Tax	Kakw.	Suits
Q3	0.092	0.065	0.081	0.091	0.097	0.086	0.088	0.08	0.04	0.053
	(2.10)**	(1.5)	(1.79)**	(2.09)**	(2.28)**	(1.98)*	(1.96)*	(1.79)*	(1.15)	(1.47)
FIS.		-0.046	-0.041	-0.005	0.017	-0.033	-0.003	-0.005	- 5.77	-5.6
		(-1.79)*	(-0.66)	(-0.82)	(1.45)	(-0.95)	(-0.46)	(-1.1)	(-3.7)***	(-3.7)***
$\bar{R}^2$	0.56	0.59	0.56	0.57	0.56	0.56	0.57	0.56	0.65	0.65

* Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%. Standard errors are adjusted by using White's weight.

statistics, they are highly significant, and increase the explanatory power of the regression by almost 20 percent. It is also interesting to note that, when the fiscal policy variable has a statistically significant coefficient, the coefficient attached to $Q3$ drops noticeably and loses its explanatory power.

The results of Table 14 are interesting because previous studies (in particular, Perotti, 1996) found the opposite: a *positive* correlation between fiscal policy variables and subsequent growth.

The results of the estimation of Equation (5) are reported in Table 15. In nine out of ten regressions, the coefficients attached to the income distribution variables have the negative sign predicted by Persson and Tabellini (1994) and Alesina and Rodrik (1994). Five of this nine regressions fit the data fairly well. For the remaining four regressions, the independent variables explain less than 5 percent of the variability of the fiscal policy measures. Again, the regressions that include the indices of tax progressivity are among those with the best fit. The coefficients of $Q3$ are statistically significant when the dependent variables are total state expenditures, state expenditures on education, Kakwani index of tax progressivity, and Suits index of tax progressivity. When the dependent variable is property taxation, $Q3$ is highly statistically significant, but with a *positive* sign.

In the five regressions with a better fit, the coefficients attached to the variables that measure political participation have the expected positive sign and are always statistically significant. This strongly supports Bénabou's (1996a, 1996b) idea that political participation is a key variable in determining redistribution.

These results support both the political and economic aspects of the fiscal policy approach. Three of the fiscal policy variables are, as predicted by the political mechanism, negatively correlated with the income share of the third quintile. The same variables are, as predicted by the economic mechanism, negatively correlated with subsequent growth.

Equations (4) and (5) assume that there is no feedback from growth to fiscal policy decisions. This assumption is particularly strong because the fiscal policy variables are averaged over a decade that overlaps with the first ten years of the growth period. Furthermore, the two indices of tax progressivity are computed for 1977. To control for the possibility of reverse causation, I use two-stage least squares to estimate the following system:

$$\begin{aligned} FISC_{1970-80_i} = \beta_0 + \beta_1 Y_{70_i} + \beta_3 DISTR_{70_i} + \beta_4 GROWTH_{70-90_i} + \\ \beta_4 VOTE_{70_i} + \beta_5 METR_{70_i} + \mu_i \end{aligned} \tag{6}$$

$$GROWTH_{1970-90_i} = \alpha_0 + \alpha_1 Y_{70_i} + \alpha_2 \mathbf{X}_i + \alpha_3 FISC_{70-80_i} + \varepsilon_i. \tag{7}$$

Table 15: Income distribution and fiscal policy variables.

	Dependent variable.								
	T.Exp.	Educ.	Welf.	Health	T. Tax.	I. Tax.	P. Tax.	Kakw.	Suits
Y	-0.006	-0.008	0.0002	-0.0001	0.001	0.001	0.008	4e-06	5e-06
	(-1.42)	(-3.0)***	(0.22)	(-0.11)	(0.55)	(0.46)	(4.5)***	(0.85)	(0.98)
Q3	-3.971	-3.306	-0.148	-0.746	-1.638	-1.952	4.284	-0.009	-0.006
	(-1.79)*	(-2.38)**	(-0.18)	(-1.25)	(-1.10)	(-1.36)	(2.8)***	(-2.4)**	(-1.98)*
Vote	0.574	0.527	0.056	-0.036	0.189	0.138	0.386	0.001	0.001
	(2.07)**	(2.8)***	(0.65)	(-0.96)	(1.27)	(0.98)	(3.4)***	(2.3)**	(2.24)**
Metr.	-0.144	0.125	0.09	0.008	-0.028	0.064	-0.295	-0.0001	-0.0002
	(-0.75)	(1.08)	(1.53)	(0.27)	(-0.33)	(0.64)	(-4.2)***	(-0.58)	(-0.92)
Age		0.042		-0.116					
		(2.5)***		(-3.0)***					
Own							-0.864		
							(-2.57)***		
Const.	252.691	145.961	12.746	27.093	109.007	32.392	-30.115	-0.001	-0.028
	(6.5)***	(5.7)***	(0.96)	(2.38)**	(4.1)***	(1.230)	(-1.27)	(-0.01)	(-0.45)
$\bar{R}^2$	0.16	0.29	0.04	0.046	0	0.021	0.63	0.21	0.16
N. Obs.	46	46	46	46	46	46	46	46	46

Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%. Standard errors are adjusted by using White's weights.

This model is similar the one estimated by Perotti (1996). The only difference between Equation (5) and Equation (6) is that the latter allows for a feedback from growth to fiscal policy decisions.

Equation (7) tests for the economic mechanism; a high value of the fiscal policy variable should be a predictor for low growth. This growth equation is similar to the one used in the reduced form regressions; the only difference is the inclusion of a fiscal policy variable in place of the income distribution measure. The system is identified by the exclusion of the regional dummies from the first equation and the exclusion of $Q3$, $VOTE$, and $METR$ from the second equation. The results of the 2SLS estimations are reported in Table 16.[23]

The regressions of Table 16 allow us to compute the magnitude of the fiscal channel. This can be done by multiplying the coefficient attached to $Q3$ by the coefficient attached to the fiscal policy variable. For the regressions of columns 1, 4, and 5, this magnitude is approximately 0.07. This is close to the total effect of inequality on growth obtained by estimating Equation (2) for the 1970-1990 period (0.09).

The strongest support for the fiscal channel comes from the last two columns of Table 16. Both the Kakwani and the Suits indices of tax progressivity are negatively correlated with $Q3$ and growth. The Kakwani index has a significant coefficient in both regressions. In these last two columns, the effect of political participation disappears (both the coefficients and t statistics are very close to zero). The strong feedback from growth to the two indices of tax progressivity justifies the use of two stage least squares estimation.

Both measures of state expenditure are inversely correlated with the income share of the third quintile, but only expenditure on education has a (marginally) significant t statistic. The coefficients attached to the share of the population below 21 years of age and the share of the population living in metropolitan areas have significant t statistics when they are used to explain education expenditure.[24] $VOTE$ never plays a significant role in explaining state expenditure. Total spending has the expected negative sign and enters in a significant way in the growth regression, while expenditure on education has a marginally significant t statistic.

As in the OLS estimations, the equation for property taxation fits the data particularly well. The coefficient attached to $Q3$ is *positive* and statistically significant. The negative coefficient attached to OWN indicates a negative relationship between home ownership and property taxation.

Summarizing, with the exception of property taxation, all the regressions presented in this paper find a negative relationship between taxation or redistribution and growth. The results are particularly strong when fiscal policy is measured with the Kakwani index. It is also interesting to note that when some fiscal variables are included in the regression income inequality loses its correlation

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[23] The estimates for welfare and health care expenditure and income and total taxation are not reported. Their 2SLS estimates are very similar to the OLS estimates and confirm that these variables do not play a role either in the economic or the political mechanism. Including $Q3$ in Equation (7) produces results similar to those of Table 14.

[24] The results are robust to the use of expenditure on higher education and expenditure on primary education.

Table 16: Structural estimations: expenditure, taxation, and growth.(2SLS)

	T.Exp.	GG	Educ.	GG	P.Tax	GG	Kakw.	GG	Suits	GG
GG	0.061		-14.108		3.567		-0.029		-0.029	
	(0.01)		(-2.8)**		(0.68)		(-2.29)*		(-2.31)*	
Y	-0.006	0.000	-0.007	0.000	0.007	0.00	0	0.0001	0	0.0001
	(-1.29)	(-0.92)	(-3.2)**	(-0.24)	(3.6)**	(0.80)	(1.43)	(2.7)**	(1.57)	(2.37)*
Q3	-3.975		-2.639		3.997		-0.007		-0.005	
	(-1.45)		(-1.96)*		(3.0)**		(-2.32)*		(-1.5)	
Vote	0.575		0.286		0.445		0.00		0	
	(1.51)		(1.62)		(2.6)**		(0.59)		(0.52)	
Metr.	-0.144		0.182		-0.307		0		0	
	(-0.69)		(1.93)*		(-3.2)**		(-0.1)		(-0.43)	
South		-0.453		-0.193		-0.268		-0.071		-0.12
		(-2.27)*		(-1.05)		(-0.87)		(-0.41)		(-0.65)
M.West		-1.031		-0.723		-0.803		-0.394		-0.349
		(-5.3)**		(-4.3)**		(-4.7)**		(-1.98)*		(-1.50)
West		-0.593		-0.473		-0.852		-0.64		-0.584
		(-2.8)**		(-1.70)		(-4.9)**		(-3.8)**		(-3.0)**
T.Exp.		-0.017								
		(-2.5)***								
Young			0.051							
			(2.05)**							
Educ.				-0.021						
				(-1.74)*						
P. Tax						0.001				
						(0.14)				
Own					-0.794					
					(-2.16)*					
Kakw.								-11.237		
								(-3.1)**		
Suits										-13.517
										(-2.8)**
Const.	252.68	5.245	152.616	3.223	-35.311	1.495	0.005	-0.386	-0.022	-0.405
	(5.2)**	(3.4)**	(6.4)**	(3.0)**	(-1.1)	(2.7)**	(0.10)	(-0.51)	(-0.40)	(-0.49)
$\bar{R}^2$	0.14	0.37	0.32	0.49	0.62	0.52	0.37	0.3	0.53	0.48
N.obs	46	46	46	46	46	46	46	46	46	46

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5% and ** at 1%.

with subsequent growth. Furthermore, simple calculations show that the same fiscal policy variables explain almost completely the correlation between inequality and growth.

These findings represent a step forward with respect to the existing literature which has not been able to find any support for the fiscal policy channel. The benchmark is again Perotti (1996), who finds some support for the political mechanism but no support for the economic mechanism. In his regressions inequality is *weakly* associated with social security expenditure but the latter is *positively* correlated with growth.

The regressions presented so far are similar to those used by Perotti but the data are different. The cross-state regressions, by using high quality data and by implicitly controlling for a larger set of variables, unveiled a link between inequality and growth impossible to discover using cross-country data.

The political mechanism does not work when the fiscal variable is property taxation. The coefficient attached to $Q3$ is positive and statistically significant. A possible explanation for this puzzling result is that a large middle class provides a large tax base for property taxes. Home ownership is an important political variable for the determination of property taxes. One would expect that political support for low property taxation should be particularly strong in states where a large fraction of the population owns their homes. The negative coefficient attached to OWN strongly supports this idea. Therefore, the puzzling result of the property tax equation may not be so puzzling after all; $Q3$ is just not the right political variable.

6.2 Income Distribution, Fertility, and Education

Perotti (1996) tests for the presence of a fourth possible channel linking inequality to growth: endogenous fertility. According to this approach, investment in human capital is affected by fertility decisions that, in turn, are derived from the structure of income distribution. This problem has been studied, in a representative agent framework, by Barro and Becker (1988) and Becker, Murphy, and

Table 17: Fertility and school enrollment: Summary statistics.

Variable	Mean	Stand. Dev.	σ/μ	Min		Max	
Coll. Enr. Tot. 1970	35.31	8.01	0.23	19.95	SC	55.35	UT
Coll. Ent. Male 1970	20.76	4.82	0.23	11.85	SC	33.51	UT
Coll. Enr. Fe. 1970	14.56	3.28	0.23	8.10	SC	21.84	UT
Coll. Enr. Tot. 1980	38.19	7.37	0.19	25.16	GA	55.62	CA
Coll. Ent. Male 1980	18.56	3.57	0.19	12.43	GA	26.80	AZ
Coll. Enr. Fe. 1980	19.63	3.98	0.20	12.73	GA	29.30	WA
Coll. Enr. Tot. 1990	33.30	5.64	0.17	21.34	GA	45.88	RI
Coll. Ent. Male 1990	15.09	2.88	0.19	9.74	GA	22.30	UT
Coll. Enr. Fe. 1990	18.21	2.87	0.16	11.60	GA	24.71	RI
Fert. 1970	87.93	7.49	0.09	77.20	CT	114.50	UT
Fert. 1980	71.87	12.41	0.17	53.50	MA	123.00	UT
Teen Preg. 1970	13.70	3.38	0.25	8.11	NC	19.84	GA
Teen Preg. 1980	16.55	5.08	0.31	6.20	UT	28.00	MS

Tamura (1991). Similarly, Raut (1991) studies how the trade-off between education and fertility relates to the distribution of income. Dahan and Tsiddon (1998) explicitly investigate the interactions among fertility, inequality, and growth. They show that lower fertility is associated with a decrease in income inequality, an increase in investment in human capital, and hence growth. Perotti argues that these models generate the prediction that a decrease in inequality would cause a decrease in fertility and an increase in investment in human capital and therefore growth.

The relationship linking income distribution, investment in education, fertility decision, and economic growth is also studied in the context of models with imperfect capital markets. In such models, inequality prevents credit constrained individuals from investing in human capital.

In both frameworks, the link between inequality and growth goes through education. It is therefore necessary to find a variable to measure investment in education. Perotti (1996) measures investment in human capital by secondary school enrollment. College enrollment is probably a more appropriate measure for a rich country like the US.[25]

To measure fertility, I use two variables: (i) the fertility rate, measured as births per 1000 women with age between 15 and 44, and (ii) the rate of teenage pregnancy, that is measured as the number of births to mothers aged 11-19 divided by total births. This latter variable seems particularly useful because of its high interstate variability. Furthermore, teenage pregnancy should have a strong role in decreasing investment in human capital.[26] The summary statistics for the measures of fertility and education are reported in Table 17.

In light of the vast empirical evidence of a positive correlation between education and growth, I do not analyze the link between these two variables and immediately jump to the estimation of the following system:

$$TEEN_i = \alpha_0 + \alpha_1 Y_i + \alpha_2 COLL_i + \alpha_3 METR_i + \alpha_5 DISTR_i + \varepsilon_i. \tag{8}$$

$$ENROLL_i = \beta_0 + \beta_1 Y_i + \beta_2 TEEN_i + \beta_3 COLL_i + \beta_4 \mathbf{X}_i + \varepsilon_i. \tag{9}$$

Equation (8) includes a measure of the *stock* of human capital ($COLL$), income distribution and a measure of urbanization (urban areas are likely to have higher rates of teenage pregnancy). Equation (9) measures the effect of teen pregnancy on college enrollment (*i.e.*, on the investment in human capital).[27] The equation also includes a measure of the stock of human capital and the usual regional dummies. Equation (9), together with (8), form a block triangular system that can be estimated by OLS.

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[25] The cross-state variability of the secondary school enrollment is very low. College enrollment is measured as the number of people enrolled in college divided by the number of people aged 18-24.

[26] On one hand, it is very hard for teenaged parents to invest in their own education. On the other hand, it is likely that the quality of their children's education ends up being lower than average.

[27] The measures of college used are: (i) total college enrollment (TOT) measured in 1970, 1980, and 1990, plus its average over 1970-1990 ($AVTOT$); (ii) male college enrollment ($MALE$) measured in 1970, 1980, and 1990, plus its average over 1970-1990 ($AVMALE$); and (iii) female college enrollment (FEM) measured in 1970, 1980, and 1990, plus its average over 1970-1990 ($AVFEM.$). $Teen70$ is used as explanatory variable for college enrollment measured in 1970, 1980, and average college enrollment. $Teen80$ is used as an explanatory variable for college enrollment measured in 1980 and 1990.

Table 18: Income distribution and teenage pregnancy.

	Dependent variable.			
	Teen 1970	Teen 1980	Teen 1970	Teen 1980
Q3	-0.951	-2.352	-0.533	-1.872
	(-3.51)***	(-7.12)***	(-1.62)	(-5.22)***
Metr	0.06	0.137	0.03	0.099
	(2.34)**	(4.78)***	(1.38)	(3.18)***
Coll.	-0.053	-0.603	-0.182	-0.669
	(-0.37)	(-3.59)***	(-1.45)	(-4.96)***
Y	-0.002	-0.001	-0.001	0
	(-4.06)***	(-1.11)	(-1.06)	(0.55)
N.East			-1.804	0.445
			(-1.93)	(0.33)
South			3.345	4.095
			(2.55)***	(2.70)***
West			0.823	0.837
			(0.895)	(0.711)
Const.	41.021	58.253	25.705	42.249
	(8.67)***	(7.28)***	(3.53)***	(4.71)***
$\bar{R}^2$	0.32	0.45	0.46	0.48

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%. Standard errors are adjusted by using White's weight. All the explanatory variables are measured in 1970.

Table 19: Teen pregnancy and college enrollment. (1970)

	Dependent variable.								
	Tot.70	Male70	Fem.70	Tot.80	Male80	Fem.80	Avtot	Avmale	Avfem.
Y 1970	0	0	0	0.002	0.001	0.002	0	0	0
	(-0.28)	(-0.48)	(-0.01)	(3.6)***	(2.32)**	(4.3)***	(0.51)	(-0.16)	(1.21)
Teen70	-0.668	-0.35	-0.318	-0.487	-0.225	-0.261	-0.558	-0.266	-0.292
	(-1.58)	(-1.39)	(-1.71)*	(-2.21)**	(-1.94)*	(-2.23)**	(-2.05)**	(-1.69)*	(-2.40)**
Coll70	0.717	0.466	0.252	0.306	0.221	0.085	0.451	0.301	0.15
	(1.83)*	(2.19)**	(1.36)	(1.24)	(2.12)**	(0.55)	(1.58)	(2.14)**	(0.99)
South	-6.509	-4.33	-2.18	-0.85	-1.59	0.74	-4.465	-3.136	-1.33
	(-2.16)**	(-2.41)**	(-1.72)*	(-0.56)	(-2.05)**	(0.91)	(-2.36)**	(-2.9)***	(-1.54)
N. E.	-3.103	-1.693	-1.41	-0.2	-0.533	0.334	-2.239	-1.375	-0.864
	(-1.91)*	(-1.76)*	(-1.74)*	(-0.09)	(-0.495)	(0.26)	(-1.19)	(-1.42)	(-0.89)
West	4.739	2.825	1.914	3.261	1.287	1.974	2.151	1.133	1.018
	(1.77)*	(1.83)*	(1.64)	(1.23)	(1.00)	(1.38)	(1.07)	(1.04)	(1.04)
Const.	40.892	24.06	16.833	21.227	13.29	7.937	36.976	20.129	16.847
	(4.2)***	(4.4)***	(3.9)***	(3.6)***	(4.5)***	(2.45)***	(6.0)***	(5.9)***	(5.8)***
$\bar{R}^2$	0.54	0.55	0.49	0.41	0.39	0.41	0.46	0.49	0.41
N. Obs.	48	48	48	48	48	48	48	48	48

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%. Standard errors are adjusted by using White's weight.

Table 18 shows a strong correlation between income inequality and teenage pregnancy. The income share of the third quintile (measured in 1970) is negatively correlated with teenage pregnancy in 1970 ($TEEN1970$) and 1980 ($TEEN1980$). As expected, the share of college graduates is inversely correlated with teen pregnancy, and states with a large share of the population living in metropolitan areas have a higher rate of teen pregnancy. The last two columns of Table 18 show that teen pregnancy is particularly high in the Southern states. After controlling for regional effects, the coefficients and t statistics attached to the income distribution variables drop noticeably.

Tables 19 and 20 show that teen pregnancy *predicts* changes in college enrollment. Both $TEEN70$ and $TEEN80$ explain future college enrollment, but are not correlated with contemporaneous values of college enrollment. The coefficients and the t statistics attached to $TEEN70$ are higher when the dependent variable is female enrollment. This fact supports the idea that teen pregnancy has a stronger effect on female education as opposed to male education.

To conclude, the results of Tables 19 and 20 support the first part of the endogenous fertility approach; inequality affects teen pregnancy which, in turn, decreases college enrollment.

Table 20: Teen pregnancy and college enrollment. (1980)

	Dependent variable.					
	Tot80	Male80	Fem.80	Tot90	Male90	Fem.90
Y 1980	0.002	0.001	0.001	0	0	0
	(2.8)*	(1.85)*	(3.5)***	(-0.552)	(-0.798)	(-0.262)
Teen 1980	0.087	0.001	0.085	-0.29	-0.149	-0.141
	(0.462)	(0.015)	’(0.885)	(-2.15)**	(-2.23)**	(-1.91)*
Coll 1980	-0.145	-0.052	-0.092	0.013	-0.014	0.027
	(-0.510)	(-0.422)	(-0.551)	(0.063)	(-0.134)	(0.250)
South	-4.065	-2.665	-1.4	-5.843	-3.16	-2.684
	(-2.4)***	(-3.2)***	(-1.528)	(-3.8)***	(-4.0)***	(-3.2)***
N. East	1.937	0.473	1.464	-2.154	-1.292	-0.862
	(0.752)	(0.397)	(1.010)	(-0.937)	(-1.138)	(-0.715)
West	3.331	1.531	1.799	-1.473	-0.501	-0.973
	(1.280)	(1.149)	(1.361)	(-0.776)	(-0.514)	(-0.985)
Const.	20.303	13.142	7.162	43.668	21.518	22.151
	(2.6)***	(3.3)***	(1.650)	(6.0)***	(5.6)***	(6.1)***
$\bar{R}^2$	0.3	0.29	0.32	0.23	0.28	0.17
N. Obs.	48	48	48	48	48	48

t statistics in parentheses. * Denotes a parameter which is statistically significant at 5%, ** at 2.5%, and *** at 1%. Standard errors are adjusted by using White's weight.

7 Conclusions

The purpose of this paper was twofold. First, to examine whether the negative relationship between inequality and growth, often found in cross-country studies, was robust to the use of a more accurate cross-state data-set. Second, to use the cross-state data to shed some light on the mechanisms linking growth to income distribution.

The reduced form estimates find a strong negative link between inequality and growth. The results are robust to different measures of income inequality and specifications of the model. The negative relationship between inequality and growth is present both in panel and simple cross-section estimates. The results are also robust to outliers.

Although the presence of a negative relationship between inequality and growth had already been detected in cross-country study, the results of this paper are interesting because they are based on high quality data. The low quality of the income distribution data is the main weakness of the existing cross-country studies. This paper is therefore useful in establishing that the cross-country results are robust to the use of more accurate measures of inequality. This finding is particularly interesting in the light of the recent papers (Partridge, 1997, Forbes, 1997, Li and Zou, 1997) that challenged the common wisdom of a negative relationship between inequality and growth.

The second part of the paper explores the structural relationship between inequality and growth. The analysis concentrates on two channels: fiscal policy and endogenous fertility. The results of the structural form estimates lead to the following conclusions:

1. Most of the fiscal policy variables are positively correlated with inequality. This result is particularly strong for the Kakwani index of tax progressivity.
2. All the fiscal policy variables are negatively correlated with subsequent growth. Again this link is particularly strong for the Kakwani index of tax progressivity.
3. The fiscal policy variables are often positively correlated with the level of political participation.
4. Inequality is positively correlated with teenage pregnancy which, in turn, is negatively correlated with college enrollment.

Points 1 and 2 above, indicate that the data support the fiscal policy channel as examined by Bertola (1993), Alesina and Rodrik (1994), and Persson and Tabellini (1994). The third point supports Bénabou's (1996a, 1996b) idea that political participation is a key variable in determining the direction of the relationship between inequality and redistribution. The fourth point shows that, by increasing teen pregnancy, inequality reduces college enrollment, this is in line with the predictions of the endogenous fertility channel.

The results of the structural form regressions should be read with some caution because of the impossibility of using panel data and the causality issue. Even with these qualifications, this paper uncovers a relationship between inequality and growth that had not been detected by the various cross-country studies previously undertaken.

The only attempt to investigate the structural relationship between inequality and growth (Perotti, 1996) found some support for the endogenous fertility channel but no support for the fiscal channel. While it is particularly difficult to find a unique variable measuring cross-country differences in the level of income redistribution, by implicitly controlling for a large set of variables, the cross-state analysis allows to identify a fiscal policy variable measuring redistribution. This variable is then used to show that, as predicted by the theory, redistribution is correlated with both growth and inequality.

Appendix

A Description of the split histogram method

This split histogram method suggested by Cowell (1995) was used to divide the population into quintiles. This method can be described as follows. Define $F(y)$ as the proportion of population with income less than or equal to y (the x axis in a Lorenz curve graph). Let $\Phi(y)$ be the proportion of total income received by those who have an income less than or equal to y (the y axis in a Lorenz curve graph). Let a_i be the lower limit of income class i, a_{i+1} its upper limit, and μ_i be the average income. Interpolation on the Lorenz curve may be performed as follows: between the observation i and $i+1$ the interpolated values of $F(y)$ and $\Phi(y)$ are:

$$F(y) = F_i + \int_{a_i}^{y} \phi_i(x)\, dx, \tag{10}$$

$$\Phi(y) = \Phi_i + \frac{1}{\bar{y}} \int_{a_i}^{y} x\phi_i(x)\, dx, \tag{11}$$

and the split histogram density function is:

$$\phi(y) = \begin{cases} \frac{f_i(a_{i+1}-\mu_i)}{(a_{i+1}-a_i)(\mu_i-a_i)}, & \text{for } a_i \le x < \mu_i \\ \frac{f_i(\mu_i-a_i)}{(a_{i+1}-a_i)(a_{i+1}-\mu_i)}, & \text{for } \mu_i \le x < a_{i+1} \end{cases} \tag{12}$$

B Data Sources

1. **Data on income and growth.** The data on nominal per capita personal income for the period 1929-1987 is available from the Bureau of Economic Analysis (1989) and from the Survey of Current Business. For the period 1880-1920, data can be found in Easterlin (1960). Real income (and real growth) is computed by dividing the nominal figures by the national values of the consumer price index. Following Watson (1992), the growth rate is computed by running least square regression of the log of income on time. One alternative to the data on state personal income (PSI) is the data on Gross State Product (GSP). GSP, like GDP, assigns the product to the state in which it has been produced; PSI, like GNP, assigns the product to the state in which the owners of the inputs reside. The quantitative difference between GSP and PSI is much bigger than the one between GDP and GNP because the American states are very open economies. I use data on PSI because data on GSP are only available starting in 1963. Barro and Sala-i-Martin (1992) show that the distinction between GSP and PSI is not very important for cross states regressions.

2. **Data on inequality.** The Gini index is computed using data on tax returns published by the Internal Revenue Service. The data, classified by state and size of adjusted gross income, can be found in the annual report *Statistics of Income, Individual Income Tax Return* (the data are not available for the period 1982-1986). It is possible to use the same data-set to measure the income share of the middle class (defined as the third quintile of the income distribution). Data on the number of people living below the poverty level are widely available (for instance in the *Statistical Abstract of the US*). Data on income distribution for families are published every ten years in the Census of the Population.

3. **Data on taxation.** These data are from the *Statistical Abstract of the US*, and the Bureau of Census, *State and Government Tax Collections.* The data on tax progressivity are from Kiefer (1991).

4. **Data on state expenditure.** The data on welfare expenditure and health expenditure are from the *Statistical Abstract of the US*, and from the Bureau of Census, *State and Government Finances.* The data on education expenditure are from the *Statistical Abstract of the US*, and from the Bureau of Census, *State and Government Finances.*

5. **Data on school enrollment.** These data are from the *Statistical Abstract of the US* and from US center for education statistics, *Digest of Education Statistics.*
6. **Data on political participation.** These data are from the *Statistical Abstract of the US*.

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