Growth and inequality effects on poverty reduction in Italy

Vincenzo Lombardo*

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Abstract

This paper deals with the evaluation of poverty sensitivity to growth and distributional changes in Italy, across its regions and over a three-decade period, spanning from 1977 to 2004. We use the "Survey on Household Income and Wealth" (SHIW) of the Bank of Italy to firstly construct growth incidence curves. After estimating the size income distribution, we evaluate the income and the inequality elasticities of poverty. Growth strongly determines the patterns of poverty; however, inequality appears to have strikingly characterized it as well. The difference between North, Centre and South can be due to the different income elasticity of poverty, which in turn depends on the initial conditions of inequality and level of development.

JEL: C14, C23, C46, I3, O52

1 Introduction

Along with the intensification of the research involved in understanding the microeconomic causes of poverty movements, macroeconomic aspects of poverty changes have stimulated a renewed interest. How are the gains of growth distributed to the poor? What are the effects of growth on poverty? Yet, what are the effects of distributional changes on poverty trends? These questions appear always more relevant in establishing poverty-reduction strategies.

It is largely recognized that economic growth is necessary to achieve poverty reduction; its impact on the poor depends, however, on how its benefits are distributed across the population. The more recent distributional dynamics

*Department of Economics, University of Naples "Parthenope", Naples–Italy. E-mail: vincenzo.lombardo@uniparthenope.it. I am grateful to Robert Eastwood for useful insights and for helpful supervision on early drafts of this research. I am indebted to Riccardo Marselli for helpful comments. Earlier versions of this paper have been presented at the INEQ Summer School on "Inequality: Mechanisms, Effects and Policies", Siena (Italy) – June, 2007 and at the DEFAP 4th International Workshop on "An opportunity for equality of opportunity", Milan (Italy) – December, 2007; I would thank all their participants. All remaining errors are mine.

have stimulated strong disputes on the effectiveness of policies growth-oriented only; inequality issues have entered into the growth-poverty nexus, because of both their direct and indirect effect - through the growth channel - on poverty. Given a mean income, lower inequality reduces *static* poverty; to the extent that economic growth is affected by inequality, or vice versa, poverty responsiveness depends also on inequality due to this latter link. Several other factors seem strikingly relevant in determining the extent to which growth can affect poverty; the level of development and the initial level of inequality are good candidates to explain the different outcomes of the growth process in terms of poverty reduction. There is a broad agreement in the literature that the more egalitarian the distribution of income the more powerfully income growth reduces poverty, and that the positive effect of lower inequality on poverty reduction is higher in richer countries.

Although most of the attention on these issues has been paid with reference to the developing world, several aspects of the recent trends in the advanced countries, in terms of low economic performance and increasing inequality, stimulate this paper on analyzing the impact of growth and inequality on poverty trends in Italy. The huge recession of the 90's, the recent distributional changes, describing Italy as one of the most unequal of the advanced countries [14], the strong dualistic structure of its economy resulting in high differentials in standards of living between northern, central and southern regions motivate the attention of this work on whether growth and inequality have influenced the poverty movements across the Italian regions and if so, to which extent.

Towards this end we use the "Survey on Household Income and Wealth" (SHIW) of the Bank of Italy drawn between the 1977 and the 2004 across the 20 Italian regions to evaluate the extent by which growth has contributed to poverty reduction and the degree by which poverty has responded to inequality changes as well. The analysis is based on semi-parametric and parametric approaches. Growth incidence curves [17] are firstly constructed to evaluate how the gains of growth have been distributed over time and across the Italian regions. After estimating the size of the income distribution to assess whether incomes were lognormal distributed, income and inequality elasticities of poverty are estimated. The study is conducted both over the long run (1977-2004) and splitting the sample in two sub-periods to evaluate how poverty has responded to growth and inequality in periods in which the country exhibited different economic performances; the first, since 1977 to 1991, characterized by a huge decrease in poverty rates, and the second - between the 1991 and the 2004 - during which the striking slump at the beginning of the 90's had conditioned and modified the poverty trends.

Following this section, the second section sketches the theoretical links between growth and inequality and their nexus with poverty. The third section specifies the data used and the methodology employed to derive the basic data on poverty and inequality from the surveys; the section follows illustrating the main trends in poverty, inequality and growth. Section four discusses the methodology used to compute the growth incidence curves and to develop the parametric estimations of the income and inequality elasticities. After the description of the results in section five, the last section concludes.

2 "Bringing poverty in from the cold": pro-poor growth and arithmetic identities

As Besley and Burgess [10] point out, the relationship between economic growth and poverty is ultimately a matter of quantification.

Several authors [19, 29] started looking at changes in poverty rates as decomposable in two separate and distinct effects: growth and inequality effects. Based on accounting techniques, the identity link between poverty, mean income and distribution is disentangled decomposing the rate of change of a poverty measure between two periods in growth and inequality components. The former component is obtained by measuring the poverty change due to observed growth, leaving the income distribution unchanged. The latter matches the poverty change due to the empirical inequality changes, while leaving mean income unchanged. Datt and Ravallion [19] analyze not only these direct and separate effects, but also whether their interaction may affect poverty reduction, allowing for a residual term. This latter term is due to the path-dependence of this decomposition; when applied with different reference years this methodology could furnish different results for the two effects. As the two authors suggest, the residual term, capturing this bias, can be interpreted as an interaction between the two components. In other cases, it has been eliminated, offering an exact decomposition [29]. This kind of approach suffers, however, from several drawbacks. The more relevant of them seems to be related to their likely path dependence. They ignore that the effects on poverty reduction are due to the interplay of growth and inequality, and not simply to their arithmetic sum; what matters is not only the extent of those effects, but also their shape and timing [12]. Further, this methodology is very sensitive to the inequality measure used. While the results may be useful for the evaluation of past dynamics, they may be quite useless for drawing conclusions on general causality effects. Finally, and related to this, this procedure may be quite uninformative on the relative extents of the growth and inequality effects on poverty reduction; if - let's say - the growth effect is larger than the inequality effect, it may be due either to a higher poverty sensitivity to growth or to small distributional changes with respect to the observed growth.

Recognizing these likely pitfalls, the literature is focusing on measuring this relation through parametric and semi-parametric estimation of poverty elasticities to growth and inequality. This empirical strategy basically stems from and is connected to the diffusion of the idea of "pro-poor" growth. Growth is defined as pro-poor if it results in higher growth rates for the poor than the non-poor; broadly, growth should be biased toward the poor regardless of its impact on the reduction of poverty levels. Even though the notion of pro-poor growth is still much debated [17, 31, 33, 41, 46], much effort has been put in trying to narrow it into broadly different definitions, such as absolute versus relative definitions or yet weak versus strong ones. Growth is defined as weakly pro-poor if it reduces poverty, regardless of its extent and its degree. A growth process is, hence, called pro-poor, even though the poor would receive a small fraction of the total benefits; a sufficient condition for applying this definition is that the growth rate in income among the poor is greater than zero. A deeper approach defines a process as pro-poor, depending on whether this had either a relative or an absolute impact. The relative notion characterizes growth as pro-poor if the growth rate of income of the poor exceeds the average income growth rate; growth needs to be relatively biased toward the poor, with the latter having an income growth exceeding the average. This relative view stems from the fact that growth, on top of reducing poverty, does imply a reduction in relative inequality. Growth is defined as absolute pro-poor if the absolute amount of the income gain of the poor exceeds, or is equal to, that of non poor. This view implies falling absolute inequality as consequence of economic growth episodes. Different approaches have been proposed to measure the degree of pro-poorness of growth and to assess whether poverty responds to growth and distributional changes and if so, to which extent; among them, the computation of the elasticity of poverty with respect to growth and inequality has gained high relevance in the literature, as it is a useful aggregate index that summarizes the growth-poverty relationship.

Estimates of this elasticity have been obtained in several ways. Ravallion [40, 41] have proposed to relate poverty changes to a distribution-corrected rate of growth, where the ordinary growth rate is corrected and weighed for an inequality factor, inferring it by a relation such as

$$POV = \alpha[1 - INEQ] * g \tag{1}$$

where the rate of poverty reduction (POV) is directly related to the ordinary growth rate, g, times a correction factor, which is a function of a measure of initial inequality ($INEQ$). Ravallion [42] extends this idea to take into account the likely presence of non-linearity[1] in the interplay between growth and inequality, by exploring a relation like

$$POV = \alpha[1 - INEQ]^{\theta} * g \tag{2}$$

This issue is parametrically developed by exploiting the properties of specific and well-known distributions. Given some measures of inequality and per capita income, growth and inequality elasticities of poverty can be properly estimated, once the empirical distribution of income can be described by some known distribution and if this latter may fit well the former. Much attention has been paid to the characteristics of the lognormal distribution to fit the income

[1] On the empirical correlation between growth and inequality many pieces of research have been furnished. An excellent survey of the issue is in Banerjee and Duflo [8]. Much of the effort of the literature has been focused in trying to assess whether or not this relationship can fit the Kuznets inverted-U hypothesis. It appears that omitted country or areas specific characteristics invalidate most of the studies confirming the inverted-U hypothesis [15, 23].

distribution [3, 12, 25, 32, 36, 39, 45] for its tractability and its satisfactory fit of the lower tails

> "The two functions most often used are the Pareto and the lognormal. The Pareto function fits the data fairly well towards the higher levels but the fit is poor towards the lower income levels. The lognormal fits the lower income levels better but its fit towards the upper end is far from satisfactory." [45]

Following this approach, poverty reduction at a given point of time is fully determined by the rate of growth of the mean income of the population and the change in the income distribution. Formally, the proportion of the population at time t with an income below the poverty line z (i.e. the headcount is used as poverty measure) is equal to the probability that income Y_t is lower than the poverty line:

$$H_t = \Pr(Y_t < z) \equiv F_t(z) \tag{3}$$

where $F_t(z)$ is the income distribution function.

In the spirit of previous studies [12, 25, 32, 36] and using the results obtained by Aitchison and Brown [3], if incomes follow a lognormal distribution the above poverty measure may be expressed by:

$$H_t = \Phi\left(\frac{\log\left(z/\mu_t\right)}{\sigma_t} + \frac{1}{2}\sigma_t\right) \tag{4}$$

where $\Phi\left(.\right)$ is the cumulative distribution function of the standard normal distribution and σ_t stands for the standard deviation of the logarithm of income. Under the lognormality assumption a one-to-one mapping between the Gini index and the Lorenz curve, and then the standard deviation, does exist. Hence, let be G_t the Gini coefficient at time t - our measure of inequality; it is easily verified that

$$G_t = 2\Phi\left(\frac{\sigma_t}{\sqrt{2}}\right) - 1 \tag{5}$$

For sufficiently small changes, the first-order approximation results in:

$$\frac{dH_t}{dt} = \frac{\partial H_t}{\partial \mu_t}\frac{d\mu_t}{dt} + \frac{\partial H_t}{\partial G_t}\frac{dG_t}{dt} \tag{6}$$

that in terms of elasticity can be expressed by:

$$\frac{dH_t}{dt} = \eta\frac{d\mu_t}{dt}\frac{H_t}{\mu_t} + \gamma\frac{dG_t}{dt}\frac{H_t}{G_t} \tag{7}$$

where η and γ are respectively the income and inequality elasticities of poverty and represent the direct effects of growth and inequality on poverty reduction.

Other indirect effects may influence poverty movements over time. The role of the initial inequality and the level of development, for which the ratio of poverty line over mean income is used as proxy [32], seem good candidates to indirectly explain why poverty does differently respond to income and inequality changes, across regions and over time. Formally, from (4) it is possible to derive the income elasticity of poverty as follow:

$$\eta = \frac{\partial H_t}{\partial \mu_t}\frac{\mu_t}{H_t} \equiv -\frac{1}{\sigma_t}\frac{\phi\left(\frac{\log(z/\mu_t)}{\sigma_t} + \frac{1}{2}\sigma_t\right)}{\Phi\left(\frac{\log(z/\mu_t)}{\sigma_t} + \frac{1}{2}\sigma_t\right)} \leq 0 \tag{8}$$

where ϕ and Φ are, respectively, the probability and cumulative distribution functions of the standard normal distribution.

The income elasticity is negative and decreasing, in absolute terms, in the ratio of poverty line over mean income (z/μ_t) and the standard deviation of log-income (σ_t).

Similarly, it is possible to derive the inequality effect; as shown above, the Gini is a positively correlated function of the standard deviation. If the standard deviation is used as inequality index, the inequality elasticity of poverty is given by:

$$\gamma^\sigma = \frac{\partial H_t}{\partial \sigma_t}\frac{\sigma_t}{H_t} \equiv \frac{\phi\left(\frac{\log(z/\mu_t)}{\sigma_t} + \frac{1}{2}\sigma_t\right)}{\Phi\left(\frac{\log(z/\mu_t)}{\sigma_t} + \frac{1}{2}\sigma_t\right)}\left(\frac{-\log\left(z/\mu_t\right)}{\sigma_t} + \frac{1}{2}\sigma_t\right) \geq 0 \tag{9}$$

Using the Gini coefficient as inequality measure, the poverty elasticity is derived from (9) and (5) as

$$\gamma^G = \gamma^\sigma \frac{\partial \sigma_t}{\partial G_t}\frac{G_t}{\sigma_t} \tag{10}$$

The inequality elasticity is positive unless average income is very low, negatively correlated to the ratio of poverty line over mean income (z/μ_t) and to the standard deviation of log-income.

3 Data and Trends

3.1 Data

The data used are mainly from the "Survey on Household Income and Wealth" (SHIW) of the Bank of Italy. We employ the waves spanning the period between the 1977 and the 2004. The data are yearly until the 1984, after then they became every two years (with a period of three years between the 1995 and the 1998). The sample has been maintained as much representative as possible; starting in the 1977 with 2915 households and 9598 individuals interviewed, the sample size has been constantly increased during the time until the 2004, when

8012 households and 20581 individuals have been interviewed[2]. The data are recorded by regions[3] and areas (North, Centre and South/Islands), following the classification (table A.1, appendix) of the National Institute of Statistics (ISTAT). Regional GDP, GDP per capita and population share are drawn from the Data-base on Italian Regions (March 2006 version) of the CRENoS centre (Centre for North South Economic Research). The final data set used in the parametric analysis results in an unbalanced panel with 342 usable observations, across 19 regions spanning 18 periods of time.

Even though we acknowledge possible differences and drawbacks when choosing the relevant welfare measure [22], we employ the annually equivalent[4] net disposable income of the households as welfare indicator. In Italy there are two main data sources for poverty and distributional changes analyses: the Consumption Household Surveys ("Indagine sui Consumi delle famiglie") of the National Institute of Statistics (ISTAT) and the above mentioned surveys of the Bank of Italy. Since the former have been put under methodological revision in the 1997, the use of those data to carry out a longer period analysis is likely to create problems of consistency of the poverty measures between the periods before and after that year. This has ultimately induced our choice in favour of the income measure. The notion of income employed is ideally directed to measure the individual ability and possibility of earnings. Towards this end the definition of income used is as basic as possible, including job earnings (employed and autonomous jobs) as well as social and pensions transfers, but excluding financial incomes, as these latter can be independent from the individual capacities and skills.

The central issue for the identification of poor and non-poor is the definition of the poverty line, the main distinction being made between absolute and relative. We use a pseudo-absolute poverty line; once a relative poverty line in a given year is computed (in our case, the year base is the 1995), the poverty lines for the whole period of analysis are scaled using the consumer price index, given from the National Institute of Statistics. The benefit of this procedure is that the features of both the relative and the absolute poverty lines are taken into account [14]. Following the ISPL (International Standard of Poverty Line), we define the relative poverty line in the year-base 1995 as the per-capita mean income of a household of two components; the poor are those who have an equivalent income below or equal to this standard. This base poverty line is, then, scaled over time through the CPI (consumer price index), giving the annually

[2]The sample size has been increased only slightly until the 1984, maintaining it around the 1977 levels; after then, in the 1986, the Institute strongly scaled up the sample size, with 8022 households and 25068 individuals interviewed.

[3]The households are grouped across the 20 Italian regions, of which only 19 are taken into account in the final analysis, since data for the region Val d'Aosta are not available for large parts of the years of the surveys, and then dropped from the dataset. Given the small size of the region in terms of geographical size, income measure, and population density, the final analysis is not affected by this deficiency.

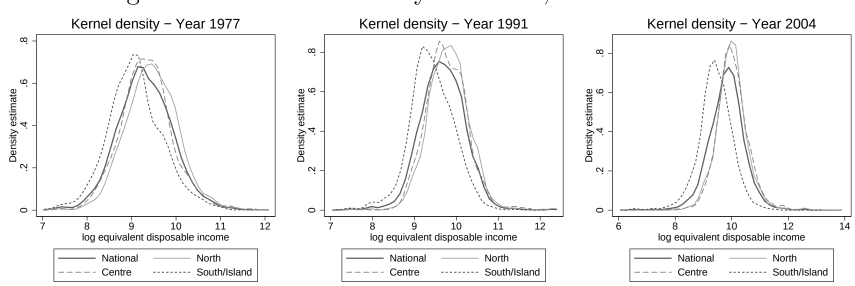
[4]As the reference unit is the household we employ an equivalence scale to allow the analysis to be implemented on homogeneous units. Following most of the studies on poverty in Italy, we apply the "Carbonaro's equivalence scale".

poverty lines for the period 1977-2004 (table A.1, appendix).

3.2 Trends: Poverty, inequality and growth across regions and areas

Italian performance in terms of poverty reduction, inequality and growth does reveal very contrasting features. Despite the impressive reduction in poverty over the whole period of analysis, huge differentials do persist across the three main areas of the country (i.e. North, Centre and South/Island). Southern regions are the poorer and the more unequal of the country, still showing significantly high poverty and inequality rates (figure A.1, appendix). Despite their noticeable development of the last decades the central regions have not yet caught up with the northern ones. The dualistic structure of the country is therefore apparent as northern regions still present lower poverty and inequality rates as well as higher rates of growth than the central and southern regions. The estimated density functions in Figure 1 provide an overview for the whole country and for its sub-areas for the years 1977, 1991 and 2004[5]. We approximate the income distributions using a non-parametric kernel density function, using the Gaussian kernel specification[6]. The key parameter driving the fit of the kernel function is the bandwidth. Following a large literature [18, 20, 38, 39, 44] we use the bandwidth $h = 0.9 * \min\{sd, 0.75IQR\}\, n^{-1/5}$, where sd is the standard deviation, IQR the interquartile range and n the number of observations.

Figure 1: Estimated density functions, across time and areas



Source: Author's calculation on SHIW. Incomes (log equivalent disposable income) are expressed in 1995 price.

Even though the initial tendency towards the bimodality of the national distribution becomes less apparent by the end of the period of analysis, important differences do persist across the main areas. The distributions of the southern regions are wider than the ones of the other regions and of the national ones as well as always behind these, confirming the higher poverty as well as inequality

[5] We use the 1991 as breaking year since at the beginning of the '90s Italy did face on with a strong economic crisis.

[6] We have tested the Epanechnikov kernel as well, but the results do not change from the ones reported.

rates of the South than both of the country as a whole and of the other parts of it.

These trends are confirmed by specific indices, where we use the headcount and the Gini as respectively poverty and inequality measures (Table 1). At national level, poverty in Italy has strikingly declined in the long period. Nonetheless, salient features are given by the different trends over the two distinct subperiods. While the headcount declined from 35.52% to 9.54% over the whole period, the trend clearly shows a reversion at the beginning of the '90s, when poverty incidence does slightly rise; the headcount ratio increases from 10.43% up to around 15% in the mid '90s, with an overall increase by around 2% by the end of the century. This general trend is followed at sub-area level, with a rapid decrease in poverty rates between the 1977 and the beginning of '90s and a slight increase in the successive period. Considerable differences do persist, however, among regions and areas. At the beginning of the period, the number of poor households in the North was 25.4% of the total, compared to the 32.4% in the Centre and to the 51.2% in the South/Island area; the subsequently sharp decrease in poverty has driven the headcount ratio - in the 1991 - to the 4.9% level in the northern regions, to the 5.8% level in the Centre and to the yet striking level of 21.4% in the southern regions. In the last years the headcount shows a slower rate of change, passing from 4.2% to 3.5% in the North, from 5.2% to 3% in the Centre and from 27.4% to 22.6% in the South, so that the initially enormous differentials between areas and regions do not disappear. While the gap between North and Centre does vanish by the 2004, the distance between these latter and the southern part of Italy remains marked. In the North, poverty rates reduced by around 85 percent over the whole period, with a huge reduction in the first part of the sample, when the reduction has proceeded at a rate around the 80%; in the second part of the sample - between the 1991 and the 2004 - poverty shows a much slower trend. The higher rate at which poverty fell - by around 48% - in the last decades in the centre part of the country has allowed the Centre to catch up the northern regions by the end of the period. In the South, instead, not only did the rate at which poverty decrease during the first part of the period fall much slower than the other two areas - by around 58%, but poverty rates also slightly increase between the 1991 and the 2004.

What about the driving forces behind poverty trends, namely, inequality and growth?

At national level, inequality clearly follows the poverty patterns showing a decreasing trend until the beginning of the '90s, with the Gini coefficient shifting from the 34.5% in 1977 to about 29%, and a remarkable increase in the last decade, shifting it up to the 34.4% in the 2004. After the huge decrease in the first years of the sample, inequality increased in all of the three areas along with the recession at the beginning of the 90's. Not only is the level of inequality strikingly higher in the South throughout all the period, but also its dynamic is characterized by different patterns; during the '90s the Gini shows a quite stable trend in the South, while it evolved with much more volatility in the Centre. Low levels of inequality and more stability have characterized the distribution of incomes in the northern regions; only in the last years, between the 2000 and

Table 1: Summary statistics. Growth, poverty and inequality.

	Poverty (Headcount)				Inequality (Gini)				Growth Rate GDP % (Real per-capita GDP)			
	National	North	Centre	South	National	North	Centre	South	National	North	Centre	South
1977	0.355	0.254	0.324	0.512	0.345	0.326	0.332	0.344	1.96	1.95	1.34	2.61
1978	0.306	0.209	0.215	0.493	0.332	0.313	0.274	0.344	3.31	3.26	3.60	3.30
1979	0.295	0.193	0.225	0.478	0.363	0.341	0.361	0.355	5.26	5.55	4.87	5.12
1980	0.256	0.163	0.172	0.436	0.339	0.333	0.337	0.280	3.26	3.75	1.98	3.36
1981	0.249	0.171	0.172	0.420	0.311	0.299	0.283	0.306	0.68	0.85	1.25	-0.07
1982	0.215	0.158	0.135	0.342	0.293	0.278	0.294	0.287	0.26	0.07	1.06	0.34
1983	0.215	0.146	0.188	0.333	0.296	0.271	0.311	0.294	0.90	0.54	1.49	1.57
1984	0.198	0.116	0.137	0.366	0.310	0.282	0.311	0.315	2.48	3.00	1.95	2.18
1986	0.217	0.134	0.151	0.379	0.302	0.272	0.284	0.328	2.36	2.69	3.12	1.34
1987	0.190	0.105	0.115	0.354	0.314	0.293	0.282	0.311	2.78	3.21	2.59	2.25
1989	0.108	0.048	0.060	0.224	0.293	0.271	0.277	0.286	2.75	3.37	2.13	2.06
1991	0.104	0.049	0.058	0.214	0.294	0.277	0.274	0.286	3.14	1.96	2.86	4.95
1993	0.151	0.073	0.099	0.302	0.320	0.288	0.310	0.327	-1.18	-1.04	-0.83	-1.64
1995	0.157	0.073	0.088	0.317	0.325	0.293	0.292	0.336	2.86	3.85	3.10	0.52
1998	0.142	0.066	0.084	0.287	0.337	0.301	0.332	0.326	1.66	1.27	2.08	2.05
2000	0.122	0.042	0.052	0.274	0.325	0.291	0.274	0.341	2.81	2.83	2.45	2.82
2002	0.106	0.033	0.048	0.242	0.323	0.286	0.289	0.318	-0.17	-0.78	-0.07	0.85
2004	0.095	0.035	0.030	0.226	0.344	0.321	0.303	0.318	0.22	-0.39	1.38	0.20

Source: Author's calculation based on SHIW and CRENoS database.

the 2004, it is possible to discover a spectacular increase in inequality, while during the '90s the income distribution has displayed only a slightly increasing trend.

Finally, two main indicators have been used to measure income growth; namely, the mean income from the surveys and the GDP per capita. The debate on which sources of data are more reliable, surveys or national accounts, is far from reaching a conclusion. A large prejudice against surveys and in favour of national accounts did seem to exist. However, with improvements in data collection and sampling procedures this prejudice is likely to be without basis [21]; even the risk of constant under-reporting of the surveys is not relevant, if the errors from the estimates are random. In our sample, the bias between national accounts - for measures of changes in GDP - and surveys does not affect the overall trends at both national and regional level (figure A.2, appendix); the gap between surveys and national accounts is not relevant and it narrows over time. The differentials in poverty and inequality are, as expected, coupled by the change in both mean income and GDP per capita, at national as well as at regional level. In the first part of the considered period both mean income from the surveys and real (per-capita) GDP show a rate of change much higher than those in the subsequent period. At national level the change in mean income from two consecutive surveys has been substantially high until mid '80s, at around 4,5%, then stable at about 3% until the beginning of the '90s, with a final decrease in the last decade, where it changed by around 2% by the end of the century, and by only around 1,5% between 2000 and 2004. This pattern is broadly respected by the trend in the GDP per capita (Table 1).

4 Methodology

4.1 Growth Incidence Curve

Preliminarily, the impact of growth on poverty can be graphically examined through the growth incidence curve (GIC), which illustrates the distribution of growth. The GIC plots the growth rate of income (or consumption) for each percentile of the distribution and allows looking beyond averages at what happens to the poor, the middle class and the non-poor, during the growth process. It allows to evaluate whether growth is pro-poor, according to both its relative and absolute definitions. Following Ravallion and Chen [17], the mean growth rate for the poor[7] is used as measure of the rate of pro-poor growth. Growth is called absolutely pro-poor if the mean growth rate for the poor is greater than zero ("weak" approach) or relatively pro-poor if the mean growth rate for the poor is at least as large as the growth rate in the overall mean. While the former only requires the poor to be better off on average in absolute

[7]This measure is different from the growth rate in the mean income of the poor, usually used in the poverty literature. For instance, the growth rate in the mean of the poor does not match with poverty measure satisfying the basic axioms, such as monotonicity or transfer axiom.

terms, the idea of "relative pro-poor growth" requires the distributional shifts to be pro-poor as well, namely that growth process should not widen the initial income differentials.

Formally, at each time t the growth incidence curve maps out the mean growth rate for the "poor", used as measure of pro-poor growth and defined by:

$$g_t(p) = \frac{L_t^{'}(p)}{L_{t-1}^{'}(p)}\,(\delta + 1) - 1 \tag{11}$$

where $L'(p)$ is the slope of the Lorenz curve at the pth-quantile, at time t and $t-1$, and $\delta = (\mu_t/\mu_{t-1}) - 1$ is the growth rate in mean income at time t. It is clear from (11) that if the Lorenz curve does not change, if - in other words - there are no distributional effects of the growth process, the rate of pro-poor growth corresponds to the growth rate in overall mean, in which case all incomes grow at the same rate ($g_t(p) = \delta_t$, for each quantile p). $g_t(p) > \delta_t$ if and only if $y_t(p)/\mu_t$ is increasing over time, where $y_t(p)$ is the income of the pth-quantile; further, if $g(p)$ is decreasing (increasing) for all p, inequality falls (rises) over time. The "absolute" rate of pro-poor growth can be, finally, computed as the area under the growth incidence curve up to the headcount index.

GIC curves have been constructed from the SHIW surveys for three intervals (i.e. 1977-2004, 1977-1991 and 1991-2004) to evaluate how growth have affected poverty rates in periods when they show different patterns and trends. The interpretation of the curve is based on the definition earlier furnished. If the GIC is above zero it indicates weak absolute pro-poor growth. If the GIC is negatively sloped it indicates relative pro-poor growth, meaning that the poor benefit more than the non-poor from growth, and inequality between the two groups fall.

4.2 The Size Income Distribution and Lognormality

Despite the controversy on the goodness of the lognormal distribution to fit well the whole income distribution, it is largely employed in distributional analysis due to its good tractability and its property of fitting quite well the lower tails. Singh and Maddala [45] find out that "...if one considers the entire range of income, perhaps the fit may be better for the lognormal but the fit towards the upper end is far from satisfactory".

In order to apply the parametric reference framework in (3)-(10), we test whether the chosen parametrization fits well the data. Lopez and Servén [36] offer a test of lognormality of the income distribution that exploits the one-to-one mapping between the Gini coefficient and the Lorenz curve, existing under the assumption of lognormality. Under this hypothesis, it follows from (5) that

$$\sigma = \sqrt{2} * \Phi^{-1}\left(\frac{1+G}{2}\right) \tag{12}$$

and it has been shown [3] that

$$L(p) = \Phi\left(\Phi^{-1}(p) - \sigma\right) \tag{13}$$

where $L(p)$ is the Lorenz curve with p percentiles.

The test compares the empirical quintiles, obtained by the observed distribution, with the theoretical ones; the theoretical quintiles, Q_{20j}, may be expressed as

$$Q_{20j} = L(.2j) - L(.2(j-1)) \tag{14}$$

where $j = 1, 2, 3, 4$ denotes the income quintile. Using (13) and (14), the theoretical quintiles are computed as

$$Q_{20j} = \Phi\left(\Phi^{-1}(.2j) - \sqrt{2}\Phi^{-1}\left(\frac{1+G^{it}}{2}\right)\right) - \Phi\left(\Phi^{-1}(.2(j-1)) - \sqrt{2}\Phi^{-1}\left(\frac{1+G^{it}}{2}\right)\right) \tag{15}$$

where $i = 1, ..., 20$ is the index of the Italian regions and $t = 1977, ..., 2004$ is the year of each income surveys from which the quintiles have been computed.

The test is based upon regressing the empirical quintiles shares, E^{it}_{20j}, on the theoretical ones, Q_{20j}

$$E^{it}_{20j} = \alpha + \beta Q^{it}_{20j} + v^{it}_j \tag{16}$$

where the disturbance has a two-part error component, such as $v^{it}_j = \mu_i + \varepsilon^{it}_j$, with μ_i being an unobservable region-specific effect and ε^{it}_j being the residual disturbance; both are assumed i.i.d. with zero mean and variance, respectively, σ^2_μ and σ^2_ε. Under the assumption of lognormality, the test is based on the joint null hypothesis that

$$\alpha = 0; \beta = 1 \tag{17}$$

We have performed this test by computing the empirical and theoretical quintiles shares from each survey, for each year and for each region, obtaining 1356 usable observations. Based on the results of the test (table 2), we should draw the conclusion that the lognormal does not fit the empirical distribution of income, as the null hypothesis in (17) is rejected for the main levels of confidence.

Nonetheless, this test cannot be conclusive on this issue as the authors also point out. The above test does reject the hypothesis that incomes follow a *two-parameters* (i.e. mean and variance) lognormal distribution. Rejecting hypothesis (17) does not strictly imply the rejection of lognormality more generally, as the empirical distribution may be described by a *three-parameter* lognormal density. This could occur if a shift parameter makes incomes following a lognormal distribution only over the range above some unknown minimum level τ.

Table 2: Lognormality test

	Pooled OLS	Fixed Effects	Random Effects
β	.9319***	.9307***	.9319***
(s.e.)	*.0062*	*.0061*	*.0062*
α	.0109***	.0111***	.0109***
(s.e.)	*.0008*	*.0008*	*.0008*
R^2	0.95	0.95	0.95
# obs.	1356	1356	1356
Test of joint hypothesis $H_o : \alpha = 0; \beta = 1$ (p-value)	0.000	0.000	0.000

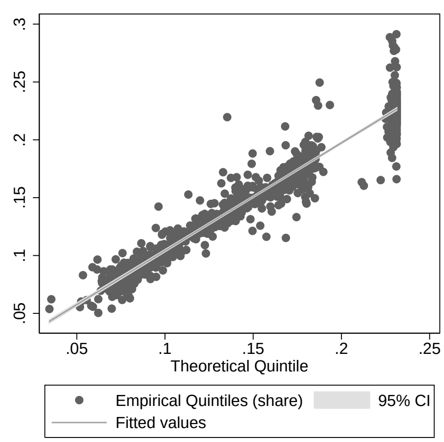
Note: *** Significant at 1% level of confidence.

In presence of a shift parameter, while the Gini coefficient does not change the Lorenz curve does, and (13) may be re-written as

$$L(p) = p\tau + (1-\tau)\,\Phi\left(\Phi^{-1}(p) - \sigma\right) \tag{18}$$

As sustained by Lopez and Servén, estimation of (16) without taking into account this factor does produce a positive intercept and a slope less than one. More specifically, the bigger the shift τ, the larger the constant, and the smaller the slope[8]. We maintain that this is in fact the case, by looking at the coefficients of (16) in table 2 and figure 2 below.

Figure 2: Lognormality fit



Source: Author's calculations based on SHIW

[8] A weakness of this statement may be that we cannot be more precise on the exact order of magnitude of this effect. Nevertheless, it is yet possible to maintain the goodness of this approach as what matters is the direction of this effect. We thank prof. Marselli for having highlighted this point.

The coefficients in table 2 do respect the expected pattern. Firstly, these are almost identical across the three methods of estimation. Secondly and more importantly, the intercept (α) is slightly positive and the slope (β) is slightly less than one. The satisfactory magnitude of the R-squared would imply the slope and the intercept should be very close to their expected values under the null of a slope slightly less than one and an intercept slightly higher than zero. Careful inspection of figure 2 reveals that the estimated points cluster along the 45-degree line, implying that the lognormal distribution fits quite well the empirical distribution. Finally, looking at the upper tails of the distribution, it is possible to see that there are a number of observations clustering around the upper quintile under observation; this would respect what previously stated about the properties of the lognormal distribution of fitting the lower tails better than the upper tails of the empirical distribution.

4.3 Econometric specification

Poverty, mean income and inequality are all aspects of one income distribution; this implies that the relationship among them depends on the characteristics of the initial distribution and this must be taken into account in analyzing how and the extent by which poverty responds to changes in mean income and in inequality. The econometric framework used in this study reflects some shortcomings. Firstly, "the econometric methodology one might follow has to fit the characteristics of the data and the model uncertainty arising from of a lack of theoretical guidance in choosing the set of regressors" [25]. There exists no evidence in developed or industrialized countries for growth and inequality elasticities of poverty, as this assessment has found application almost exclusively in the developing world.

In order to proceed in the construction of a suitable and reliable model, we follow two steps. Firstly, the estimation of a basic model is performed without initially considering the role of the level of development and initial inequality. An improved model is further tested to assess whether and the extent by which the elasticities are affected by these last factors. The possibility that area heterogeneity exists is finally tested to evaluate whether structural differences between North, Centre and South do affect poverty responses across regions and over time. The availability of panel data allows us to control for unobserved time-constant regional-specific characteristics that may affect both poverty and income. One of the simplest specifications used to estimate the basic relationship [1, 10, 16] is given by:

Model "A"

$$\log P_{it} = \alpha_i + \eta \log \mu_{it} + \gamma \log G_{it} + d_t D_t + \varepsilon_{it} \tag{19}$$

where P_{it} represents the poverty measure (i.e. the headcount) for the region i at time t, μ_{it} the mean income derived from the survey, G_{it} the inequality measure (i.e. the Gini coefficient in our work, even though some of the quoted works use different measures, such as the standard deviation of the mean incomes in logs),

α_i the regional fixed-effects, D_t time dummies, and ε_{it} are the (idiosyncratic) errors.

The estimated coefficients give the (partial) elasticity of poverty with respect to income (η) and inequality (γ). When income distribution changes during the process of economic growth, the pure growth effect - derived without considering inequality changes - does not take into account the role that distributional movements have on poverty rates, both directly and indirectly through the growth channel; to take into account these effects, the distributional-neutral income elasticity of poverty is derived by the above specification (Model "A").

Following the ideas developed in previous studies [12, 25, 32], we analyze the role of the level of development by using the ratio of poverty line over mean income and the initial level of inequality as proxies for the "crowdedness" near the poverty line; both measures are intended to capture whether and the extent by which the level of development and the initial characteristics of the income distribution affect both the income and the inequality elasticity of poverty. We depart from the analyses developed in those studies; while they prefer to model these effects in terms of growth and inequality changes on poverty changes, we implement a level model so that our final specification to test is given by:

Model "B"

$$\log P_{it} = \alpha_i + [\eta_1 + \eta_2 (z/\mu_{it}) + \eta_3 G_{it}] \log \mu_{it} + \\ + [\gamma_1 + \gamma_2 (z/\mu_{it}) + \gamma_3 G_{it}]\, logG_{it} + d_t D_t + \varepsilon_{it} \quad (20)$$

where the terms in squared brackets on the right hand side are intended to capture the interaction between income, inequality, and the factors above discussed. The density near the poverty line is captured by the term (z/μ_{it}) (POVRATIO); its interaction with both mean income and inequality (log) is intended to measure the impact that the "crowdedness" near the poverty line has on the degree of reaction of the poverty measure with respect to both income and inequality changes. The initial inequality impact is proxied by the interaction between the initial level of the Gini index (G_{it}) with the income and inequality measures.

The estimator used is the *efficient* GMM (Generalized Methods of Moment) that allows to have consistent and efficient estimates of the parameters as well as to deal with the necessity of capturing the fixed effect terms the panel data structure allows to analyze.

The main issue behind the estimation of such a model is the possible correlation between the explanatory variables - mainly mean income - and the errors. The presence of endogeneity would undermine the consistency of the OLS estimates or it would be cause of asymptotic least squares bias. This can arise for several reasons, the most important ones in our case being the measurement errors in income and the "joint" causation of poverty and income. Income and poverty measures are derived from the same surveys data and the error term is therefore possibly correlated with measurement errors of income. This shortcoming might be, for instance, due to lower participation rates in the surveys among richer groups than among poorer groups; were this phenomenon confirmed the consequence would be to overstate poverty and understate income

[22]. Measurement error might likely be only of minor concern for the relatively good reliability of the surveys we use and since as survey methods improve this bias would decrease over time. Unobserved time-varying characteristics that affect income may affect poverty as well. In fixed effects regressions the estimates are robust to any correlation between the explanatory variables and the time-invariant error component. However, the bias would remain due to any correlation between the explanatory variables and time-varying omitted variables. The panel structure can avoid this problem by introducing time-dummies[9]. At the same time, this inclusion might be the source of endogeneity in models like the one we present. The reference is to the "joint" causation, or simultaneity bias, of poverty and income [24]. Generalizing the Timmer's conclusions [47], it has been shown [24] that the introduction of time dummies in a level model does avoid to cancel out this source of bias if both the variables are subject to same shocks, even when the errors are serially independent. If income is trended and the errors serially independent, the estimation of a level model produces consistent OLS estimates and is superior to a model in differences, by avoiding or canceling out the joint causation effect; however, when introducing time-dummies, the global trend present in the data is canceled out and the consistency of the least squares estimations cannot be maintained. If our variable contained a trend, this would have been eliminated by adding time-dummies, suggesting the need for caution on this issue. This turns out to be the key argument in our choice of estimating models "A" and "B" in levels and it is strictly connected to the results obtained in the previous sub-section on the size income distribution and the lognormality fit. As shown there, incomes follow a lognormal distribution only conditioned on the presence of a shift parameter. While the estimation of the theoretical linkages in (3)-(10) is allowed since the lognormal specification does fit well our data, at the same time it requires to be strongly cautious on the use of a first-difference model as the distribution is lognormal only due to the presence of that shift parameter. This two interacting elements drive ultimately our preference for level models to exploit those theoretical relations.

Given our specification, the likely correlation between mean income and errors cannot be discharged and, how endogeneity tests also show, such a problem if not controlled for would have given inconsistent estimates. Although finding proper instruments is not an easy task, following the literature [41], we use the log per capita GDP ($\log GDPpc_{it}$) and lagged values of the log mean income ($\log \mu_{it-1}$) as instruments for the mean income (log). These instruments do accomplish the two specification conditions required; they are both relevant and orthogonal to the error structure. The latter condition is tested through the overidentifying restrictions test, or Hansen-J test, which is the key test to assess both the validity of the model and the exogeneity of the instruments. The second requirement is that the instruments are relevant, that is correlated with the endogenous regressor and with good explicatory power; apart from being

[9] Testing for their individual and joint significance in all the models analyzed, they results all significant.

correlated with the regressor the consequence of instruments with little explanatory power (weak instruments) is increased bias in the estimated coefficients, reducing the efficiency of the estimator. This peril is evaluated looking at the outcome of the first stage of the regression; as Baum et al. [9] suggest, low partial R-squared and, when there is one endogenous regressor, F-test of the joint significance of the instruments below 10 are good indicators for both low correlation of the instruments with the endogenous regressors and their weak explanatory power. The main hypothesis made throughout is that endogeneity is actually present in the model; several formal tests exist to evaluate this possibility. We prefer the general C-test[10] to the classical Hausman test, as in some case this latter statistics can return negative values that cannot allow making any judgment.

The motivation for using the GMM estimator derives, ultimately, from the consideration that "if heteroskedasticity is present, the GMM estimator is more efficient than the simple IV estimator..." [9]; in presence of heteroskedasticity, the IV estimator, although consistent, is not efficient [9, 37]. While the GMM is more efficient than the IV under heteroskedasticity of unknown form [9], two tests have been used. The first one is a modified White test for panel data, which tests for constant error variance across groups in the OLS case; by assuming constant variance within each cross-section units, this test infers for the presence of different variances between the panels. The second test, the Breusch-Pagan/Godfrey/Cook-Weisberg, specific for the IV model uses the fitted values of the dependent variable and its square.

Diagnostic tests have been implemented; the general result is that the model exhibits no serial correlation, but heteroskedasticity. Serial correlation has been tested taking into account the unbalanced, or better the unequally spaced nature, of our panel data set. At this aim, we used two tests: the Wooldridge test ([48], p. 274) and the locally best invariant (LBI) test for zero first-order serial correlation. The latter one, provided by Baltagi and Wu to deal with unequally spaced panels [6, 7], tests for the hypothesis of AR(1) process present in the data.

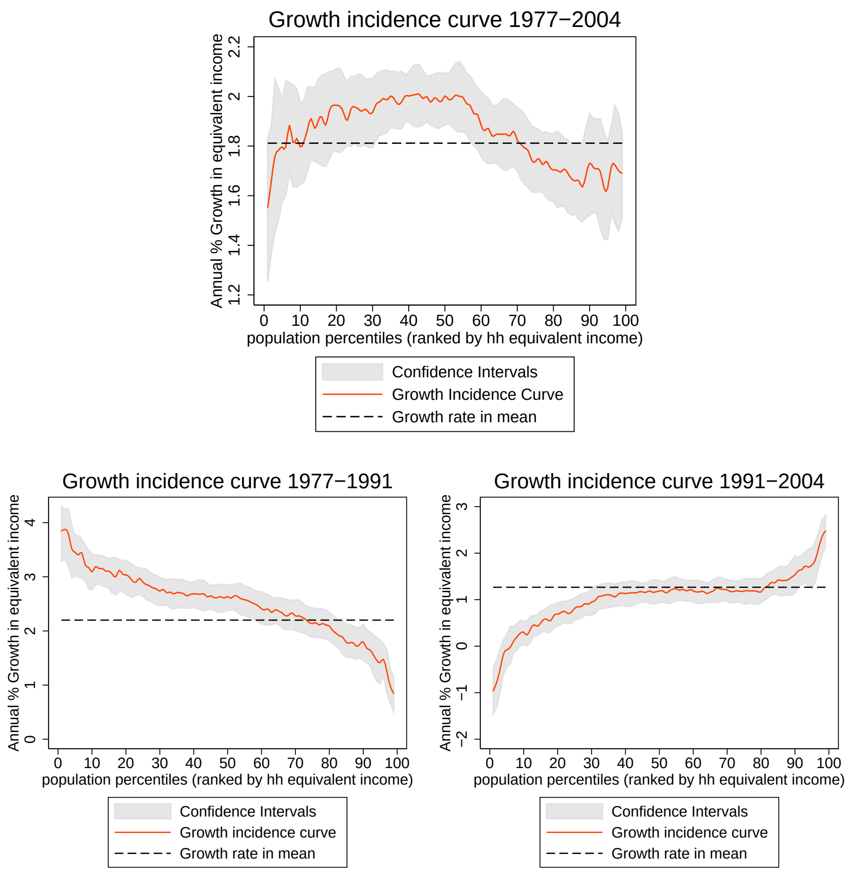
5 Results

5.1 Pro-poor growth and the Growth Incidence Curve

The results (Figure 3) confirm that growth had different effects in the different analyzed periods and across the main areas of the country. In the long run (1977-2004) growth has been weakly pro-poor as the GIC is always above zero, so that even the poorest have benefited from growth episodes. It is not possible to definitely claim that growth has been pro-poor in relative terms as well, since the growth incidence curve is not monotonically decreasing; it shows a reversion around the 55th percentile, but not a decreasing trend in the the lowest part of the distribution.

[10] The C-statistics is also known as "difference-in-Sargan or "distance difference".

Figure 3: Growth incidence curves, national analysis



An important caveat refers to the biases produced by the surveys; it is generally accepted that these are strongest at the extreme bounds of the distribution. We have dealt with these issues by trimming the distributions at the 1st and 99th percentile, and by generating confidence intervals using the bootstrap technique with 100 replications.

Although the poor have generally benefited proportionally more than the non-poor, the distribution of gains from growth seems to have been biased in favour of the upper-middle class, rather than the poorest parts of the distribution. As growth rates have been almost constant between the 20th and the 50th percentile the poor and the middle class have benefited in equal extents from growth episodes; growth has not been pro-poor in relative terms since it has not been positively biased towards the poorest part of the distribution. The decreasing trend in the final part of the distribution clearly shows that growth has favoured the upper-middle class with respect to the richest part of the population. Overall, growth has positively favoured poverty reduction with two distinct distributional effects. The gap between the lowest part of the population and the middle class does increase over time, whereas the distance between the upper-middle class and the richest part does narrow.

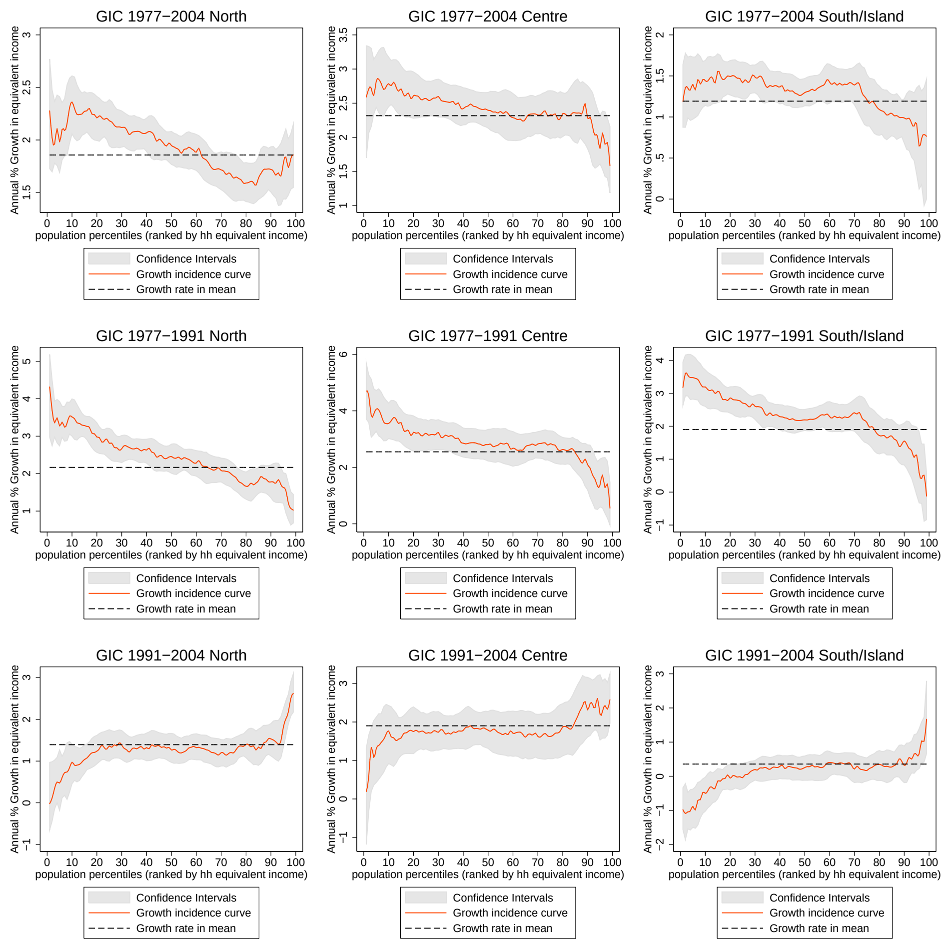
This general picture is characterized by different trends in the two analyzed sub-periods. In the first part of the sample, between the 1977 and the 1991, growth drove the very strong rate of poverty reduction as both the growth incidence curve was monotonically decreasing and most of the mean growth rates for the poor were higher than the growth rate in mean. This trend suggests that growth was pro-poor in absolute as well as in relative terms over this period, implying a reduction of inequality between the lowest and the highest part of the distribution as well. In contrast, between the 1991 and the 2004, growth was strongly against the poor; the annual growth rate for the poor was lower than the growth rate in mean for almost all of the percentiles and the upward slope of the curve suggests that the distribution of gains from the growth process has been unequal, favouring the upper classes of income.

The analysis is largely confirmed also at regional level (figure 4). All of the three main areas do follow the national pattern over the two reference sub-periods, with scale differences between regions; regions of the central area show, on average, higher rates of pro-poor growth than northern and southern regions. The overall effect - between 1977 and 2004 - of growth on cumulative poverty illustrates that while in the northern and central regions growth has largely favoured the poor, in the South it has been more biased in favour of the richest part of the distribution.

Coupling this analysis with the summary statistics and the trends offered in the previous section, it may be alleged that these results depend only in part on the differentials of growth rates between the three areas and among the regions within these areas; an important part for explaining why growth had these different effects on the poor in the several parts of the country should be attached also to the different trends in the distribution of incomes. In this regard, the well-known Italian dualism is confirmed not only in terms of macro and aggregate aspects (i.e. growth) but also with regard at the individual distribution of incomes.

Briefly, while the big reduction in poverty achieved in the first years of the sample has been driven by pattern of growth not biased against the poor, the renewed increase in poverty of the last decade may be explained not only by slight rates of changes in mean income, but also, or at least in part, by pattern of growth biased against the poor part of the distribution and in favour of the richest one. Although the pattern of Italian growth has positively affected poverty rates, it has entailed striking effects on inequality as well; to better quantify the role of inequality on poverty rates and the overall importance of these two distinct forces for poverty reduction, a more carefully empirical analysis is developed in the next sections, where a specific look at the single elasticities of poverty with respect to income and inequality is provided.

Figure 4: Growth incidence curves, across regions and periods



5.2 Income and Inequality Elasticities of Poverty: econometric results

We estimate income and inequality elasticities of poverty with the efficient GMM estimator, endowed with more time periods data than usually available in similar applications for developing countries. The results (table 3 and 4) predict that even if poverty strongly reacts to growth, it is also unmistakably influenced by inequality.

We firstly estimate the gross and distributionally-neutral income elasticities. Both the models are consistent with choice of the *efficient* GMM estimator. The key test, the overidentifying restrictions or Hansen-J test, passes in both the models. The main assumption behind the consistency of the parameter estimates is that the instruments are orthogonal to the errors terms; this statistic tests the joint hypothesis of the correct model specification and the orthogonality conditions and its low significance (high p-values) implies that actually the instruments are not correlated with the errors. Two tests confirm that the errors are independent, or more specifically do not follow an AR(1) process. Even if in the fixed effect structure the correlation in the composite errors $(\alpha_i + \varepsilon_{it})$ is generally dominated by the presence of the non-observed individual heterogeneity (α_i), the Wooldridge statistic tests for the presence of serial correlation in the idiosyncratic part of the error structure, because "sometimes, $\{\varepsilon_{it}\}$ can have very strong serial dependence, in which case the usual FE standard errors...can be very misleading. This possibility tend to be a bigger problem with large T" ([48], p. 274). This is the first test we perform and the high p-values imply that we cannot reject the null hypothesis of no first-order autocorrelation. Along with this and in order to take into account the unbalanced structure of the data set, the no correlation has been confirmed with the Baltagi/Wu locally best invariant (LBI) statistic[11].

Measurement errors and joint causation of poverty and income can cause inconsistency of the OLS estimates. The high values of the endogeneity test statistics (low p-values), which call for rejecting the exogeneity of the tested regressor, do require a more careful account of the OLS inconsistency. We deal with this issue by instrumenting mean income with its lagged value and with GDP per capita, and all the interaction terms related to the mean income with corresponding instruments. The relevance of these instruments is confirmed from the first stage fixed effect OLS regression (LSDV), where the endogenous variables are regressed on the full set of instruments. When the partial R-squared are not much relevant, the value of the F-test of excluded instruments above 10 suggests that the risk that weak instruments might affect the efficiency of the estimates can be removed [9]. This latter criterion is reliable only in the case one endogenous regressor is present in the model; as a matter of fact, in the first two specifications (table 3, columns 1 and 2) only one regressor (i.e. mean income) is considered endogenous. When, in the other models (i.e. table 3 - columns 3 and 4, and table 4), more regressors are tested as endogenous both the partial R-squared and the F-tests confirm the goodness of those instruments (see table A.2 and A.3 in appendix). Finally, the gain in efficiency of the GMM with respect to the IV estimator is confirmed from the heteroskedastic nature of these models; both the tests reject indeed the null hypothesis of homoskedasticity.

[11]Although exact critical values are not available for this statistic, values of the statistics above 1.5 or far below 2 are generally accepted as reliable indicators of no first-order correlation.

Table 3: Income and inequality elasticities (GMM estimation) - model “A”

	Dependent Variable: log(headcount)			
Variable *(s.d.)*	(1)	(2)	(3)	(4)
log(mean income)	-2.533***	-2.508***	-	-
	(0.570)	*(0.349)*		
log(Gini)	-	1.644***	-	1.527***
		(0.189)		*(0.175)*
log mean income*Area Dummy				
North	-	-	-2.142***	-2.148***
			(0.604)	*(0.376)*
Centre	-	-	-2.174***	-2.107***
			(0.633)	*(0.391)*
South-Island	-	-	-1.865***	-1.887***
			(0.677)	*(0.412)*
Time-Dummies	Yes	Yes	Yes	Yes
N-observation	323	323	323	323
R^2	0.738	0.834	0.761	0.843
Hansen-J	0.509	1.884	0.749	0.965
(p-value)	*(0.475)*	*(0.169)*	*(0.386)*	*(0.325)*
F-test for equality of income	-	-	45.12	13.625
elasticities across areas *(p-value)*			(0.000)	(0.000)
Diagnostic Tests				
Serial Correlation				
Wooldridge	0.002	1.086	0.057	3.065
(p-value)	*(0.966)*	*(0.311)*	*(0.813)*	*(0.097)*
Baltagi-Wu LBI	1.645	1.835	1.761	1.835
Heteroskedasticity				
OLS	178.24	425.43	315.95	458.90
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
IV	72.003	144.771	74.101	154.070
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*
Endogeneity	17.383	22.857	18.481	24.207
(p-value)	*(0.000)*	*(0.000)*	*(0.000)*	*(0.000)*

Note: The reported is the within R^2 from fixed effect estimation; for the Baltagi/Wu statistic, values above 1.5 (or far below 2) are accepted as indicator of no AR(1) process; time-dummies significant. Significance levels: ***1%, ** at 5%, and * at 10%.

The coefficients are highly significant and with the expected signs; poverty rates are correlated negatively to income changes and positively to inequality. Are both remarkable the size of the coefficients and the high stability of the income elasticity to the inclusion of the inequality term; a 1% increase in survey mean income reduces poverty measure by 2.5%, while a 1% increase in inequality will increase it by 1.6%. Controlling for inequality, income elasticity does not substantially change. The gross, or “empirical” [16], income elasticity is substantially equal to the distributional-neutral one. The gross income elasticity, computed in (1), picks up changes in inequality coinciding with growth; controlling for these changes in (2), the coefficient returns the distributionally-neutral income elasticity, giving a proper estimation of η of section 2. The goodness of fit improves in the second specification ((2)); the within R-squared substantially improves when inequality is controlled for, increasing the variation in the data explained by the included regressors by around 10 percentage points. The size of the coefficients suggests that both income and inequality affect poverty rates substantially, even if the effect of the former appears greater than the latter. Poverty rates do respond relatively more elastically to income than to inequality changes, even if also the latter effect is striking. We explore the possibility that inter-area differences exist in the elasticities of poverty, by including a complete set of area dummies in (3) and (4). The F-test on the equality of these elasticities across the areas confirms that the three parameters are different, and there exists substantial variation across North, Centre and South. The goodness of the econometric specification is - as above - confirmed. The first stage regressions for the relevance of the instruments confirm the relevance and the power of the chosen instruments (table A.2, appendix). Both the F-test of the excluded instruments and the high partial-R^2, ranging between 0.95 and 0.97, are good indicators of relevant and powerful instruments. The gross (3) and the distributionally-neutral income elasticity (4) are again similar. The interesting feature is the difference between the three areas, characterized for different income elasticities of poverty. Poverty in the North and in the Centre is more reactive to growth than in the South, where the gains from growth are lower than in the other two areas; while a 1% increase in survey mean income produces in the North and Centre a reduction in headcount by 2.14%, in the South the decrease is by 1.8 percent. In all the areas, finally, poverty is again very responsive to inequality, where a 1% increase in inequality implies an increase in poverty by 1.5%.

5.2.1 Level of Development and Initial Inequality

The different degrees of sensitivity of poverty across North, Centre and South suggest the need to analyze whether the level of development and the initial inequality may be the source of the different elasticities (table 4, columns (1) and (2)). All the diagnostic tests pass, along with the hypotheses we have done about the structure of the model. The Hansen-J statistics confirm both the suitability of the models and the orthogonality conditions. The power of the instruments is highly notable. All the instruments are strongly relevant; in all the first stage regressions the partial R-squared range between 0.84 and 0.99 and, along with the relevant values of the F-tests, it does exclude the peril of inefficient estimates due to weak instruments.

Table 4: The role of initial conditions (GMM estimation) - model "B"

	Dependent variable: log(headcount)	
Variable *(s.d.)*	(1)	(2)
log(mean income)	-10.098***	-13.110***
	(1.019)	*(2.136)*
log(Gini)	1.863***	3.118***
	(0.207)	*(1.185)*
log(mean income)*POVRATIO	-1.687***	-2.949***
	(0.239)	*(0.682)*
log(mean income)*Gini	.0430	.548**
	(0.045)	*(0.213)*
log(Gini)*Gini	-	3.596**
		(1.543)
log(Gini)*POVRATIO	-	-4.141***
		(1.590)
Time-Dummies	Yes	Yes
N-observation	323	323
R^2	0.845	0.841
Hansen-J	3.780	2.851
(p-value)	*(0.286)*	*(0.415)*
Diagnostic Tests		
Serial Correlation		
Wooldridge	0.310	0.420
(p-value)	*(0.584)*	*(0.525)*
Baltagi-Wu LBI	1.837	1.891
Heteroskedasticity		
OLS	372.65	402.91
(p-value)	*(0.000)*	*(0.000)*
IV	261.129	402.222
(p-value)	*(0.000)*	*(0.000)*
Endogeneity	10.775	16.053
(p-value)	*(0.013)*	*(0.001)*

Note: The reported is the within R2 from fixed effect estimation; for the Baltagi/Wu statistic, value above 1.5 (or far below 2) are accepted as indicator of no AR(1) process; time-dummies significant. Significance levels: ***1%, ** at 5%, and * at 10%.

The high within R-squared of these two models suggests that about 84% of the variance is explained by the data. All the coefficients but one are highly significant. The most important evidence suggested by these two final specifications is the size of the coefficients; given the introduction of the interaction terms, the coefficients of the log(income) and log(Gini) do not longer reflect the income and inequality elasticities. These latter must now take into account the effect of the two added terms, which, as hypothesized, do affect their magnitude. They are strongly sensitive to the position of the poverty line in the income distribution and to the level of growth rates. The low levels of Italian growth rates over the whole period may, at least in part, explains the high magnitude of the coefficients, as lower growth rates would clearly imply much higher elasticities.

Estimating the impact of these factors on the income elasticity of poverty only (1), the interaction term between the initial level of inequality and log(mean income) results not significant. This implies that the income elasticity of poverty is not affected by the initial level of inequality, while it is affected by the density near the poverty line. However, when the most complete version is implemented (2), all the coefficients are significant, including the effect of the initial inequality on the income elasticity. The coefficients of income and inequality (log) are no longer directly interpretable as "net" elasticities; the presence of the interaction terms implies that these elasticities must now reflect also the influence of the initial level of inequality and the crowdedness near the poverty line. The negative sign on the coefficient log(income)*POVRATIO (-2.94) implies that the higher, in absolute terms, the ratio of the poverty line over mean income, the greater the sensitivity of the poverty measure to income changes; in other words, the higher the density around the poverty line, the higher the income elasticity of poverty. The relationship between these two terms may be driven by a couple of factors, such as the high impact that growth has on the upper-middle class along with the fact that we use a poverty line partly relative; what matters is not only the movement of the mean income with respect to the poverty line, but also the extent of the proportional changes between the mean income and the poverty line. Initial level of inequality does affect this elasticity as well; the positive coefficient (0.54) implies that the higher the initial level of inequality, the lower is the income elasticity. The difference in the magnitude of the two interaction terms suggests that this latter factor is less relevant than the ratio of poverty line over mean income in shaping the degree of sensitiveness of poverty to income. The same factors strongly determine the impact of inequality changes on poverty. Both its interaction terms are significant and relevant in size. The positive sign (3.59) of the former, capturing the effect of the initial level of inequality, implies that the higher the initial level of inequality the stronger the inequality elasticity of poverty. This means that the higher the level of initial inequality, the greater the effect of the change of the income distribution on the poverty measure. We take this as an indicator that in southern regions, where higher is the initial Gini, changes in the distribution that would reduce inequality may produce stronger poverty reductions. Finally, the ratio of poverty line over mean income also strikingly affects the extent by which poverty rates respond to changes in distribution; the negative sign on the interaction between them (-4.19) confirms that higher is the density near the poverty line, lower is the inequality elasticity of poverty.

In all the specifications, poverty is shown to be very responsive to growth as well as to inequality in the reverse direction. The notion of pro-poor growth refers to poverty-reducing policies as the ones that maximize the impact of growth on poverty reduction. Yet no definitive consensus exists on the effect of inequality; this has been sustained to have positive, negative or no role in determining poverty reduction both directly and indirectly through the growth channel. The magnitude of the inequality elasticity, instead, confirms the determinant role of policies aimed at reducing inequality to achieve the maximum benefits in terms of poverty reduction. Different factors can influence these links; the level of development is strongly relevant for determining the extent by which poverty respond to survey mean income and distributional changes. The difference in the estimated elasticities across the three main areas may be well explained by these last factors. Areas with different level of development and initial inequality do present different rates of responsiveness to survey mean income changes, with the southern part of the country reacting less elastically than the northern and the central.

6 Conclusion

This paper deals with the evaluation of poverty sensitivity to growth and distributional changes in Italy, across its regions and over a three-decade period, between the 1977 and the 2004. Poverty is still of high concern in Italy due to the huge differentials between northern, central and southern regions, to the strong differences between the poorest, middle and richest parts of the income distribution, and because of the recent trends of the 90's, figuring out an increase in poverty and inequality indices.

The growth incidence curves used to plot the distribution of benefits across the percentiles of the population highlights interesting features of the Italian growth process. In the long-run, between 1977 and 2004, growth has been pro-poor in the weak absolute connotation, positively favouring poverty reduction, as the GICs are always above zero. Nonetheless, the distribution of gains from growth seems to have been biased in favour of the upper-middle class, suggesting that growth has not been pro-poor in relative terms. While the gap between the lowest part of the population and the middle class has increased over time, the distance between the upper-middle class and the richest part narrows. In the two analyzed sub-periods, the behaviour of poverty reactions to growth is very dissimilar. Between the 1977 and the 1991, growth has driven the strongest rate of poverty reduction, given that both the growth incidence curve is monotonically decreasing and most of the mean growth rates for the poor have been higher than the growth rate in mean. The striking recession at the beginning of the 90's has reversed these trends not only causing lower growth rate in GDP and surveys mean income, but also distorting the distribution of gains of the growth process. During this period not only the annual growth rate for the poor is lower than the growth rate in mean for almost all of the percentiles, but also the upward slope of the curve suggests that the distribution of gains has been unequal, favouring the upper classes of income; the renewed increase in poverty may be explained not only by slight rates of changes in mean income, but also, or at least in part, by pattern of growth biased against the poor part of the distribution and in favour of the richest one. The comparison between North, Centre and South highlights the different degrees of poverty sensitivity to growth in those areas; while in the northern and central regions growth has largely favoured the poorest part of the distribution, in the South growth has been more biased in favour of the richest and the upper-middle parts of the distribution.

Income and inequality elasticities of poverty have been estimated to analyze the rate at which poverty responds to growth episodes and distributional changes. Overall, poverty across Italian regions is highly sensitive to both growth and distributional changes. The distributional-neutral income elasticity coefficient at about -2.5 suggests that a 1% increase in surveys mean income reduces the poverty index by about 2.5 percent. The inequality elasticity coefficient of 1.6 implies an high sensitivity of poverty to inequality changes as well, where a 1% reduction in inequality turns out in a reduction of poverty by about 1.6 percent. The differentials between areas can be due to their different degrees of sensitivity; the northern and central regions respond more elastically to change in surveys mean income (respectively -2.14 and -2.17) than the southern part of the country (-1.8). Across the country the inequality elasticity is remarkably high, with a coefficient of about 1.5. While poverty sensitivity to inequality is quite stable even when areas differentials are taken into account, the disparity in the rate at which the three different areas respond to change in income is consistent with the picture of poverty across them; the benefits from growth are higher in northern and central part of the country than in the southern. The level of development and initial level of inequality are good candidates to explain those differentials. Higher initial levels of inequality are associated with greater inequality elasticity and lower income elasticity of poverty, reccomending that had stronger redistribution policies been undertaken southern regions would have benefited more than the northern and central parts of country. Finally, the higher, in absolute terms, the ratio of the poverty line over mean income, used as proxy for the density around the poverty line, the greater the sensitivity of the poverty measure to income changes. On the inequality side, the negative sign on the interaction term (-4.19) implies that higher is the density near the poverty line, lower is the inequality elasticity of poverty.

It is possible to claim that growth-oriented policies have surely favoured the strong reduction in poverty across Italian regions. However, the fact that the extremely relevant role of inequality within and between the regions in shaping those poverty trends has not been taken fully into account could be seen as one of the major concerns of the differentials between and within the three areas as well as for the still considerable retard of large parts of the country.

Appendix

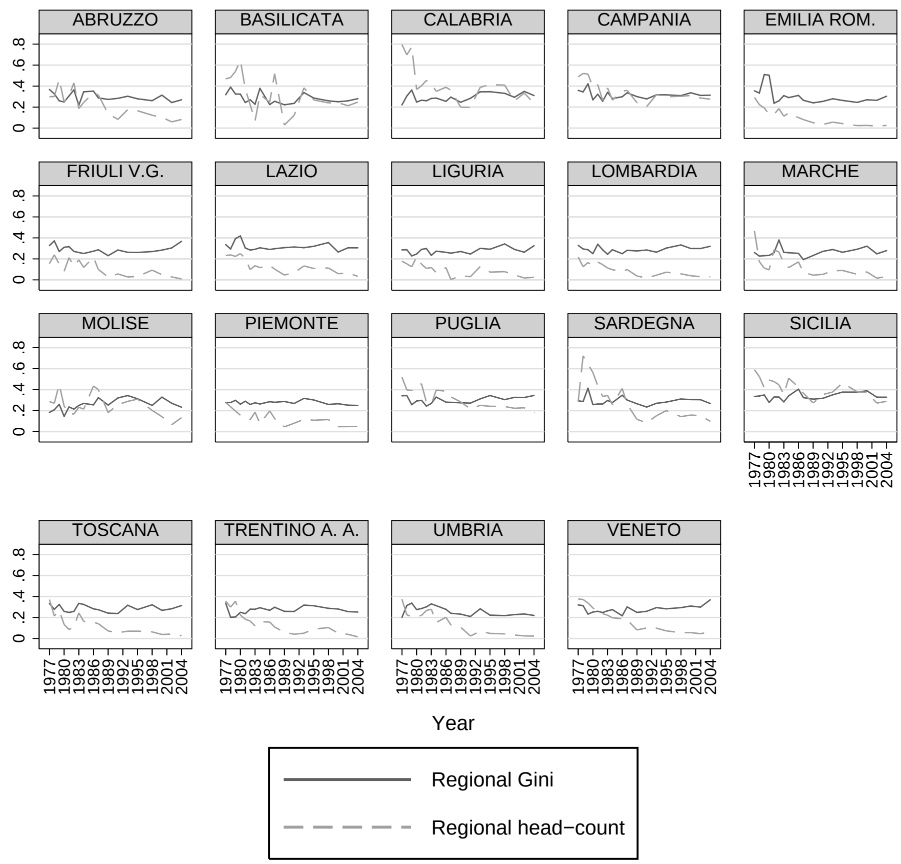
Table A.1: Classification, CPI, Poverty line

Region name	Area	Year	CPI	Poverty line
Piemonte	North	1977	19.99	1665.735
Lombardia	North	1978	22.42	1874.999
Trentino - Alto Adige	North	1979	25.74	2151.226
Veneto	North	1980	31.19	2611.605
Friuli - Venezia Giulia	North	1981	36.74	3071.985
Liguria	North	1982	42.79	3582.587
Emilia Romagna	North	1983	49.06	4109.93
Toscana	Centre	1984	54.36	4545.198
Umbria	Centre	1986	62.86	5265.063
Marche	Centre	1987	65.83	5507.809
Lazio	Centre	1989	73.48	6143.969
Abruzzi	South/Island	1991	83.24	6964.281
Molise	South/Island	1993	91.38	7642.294
Campania	South/Island	**1995**	**100**	**8370.753**
Puglia	South/Island	1998	108.1	9048.543
Basilicata	South/Island	2000	112.7	9433.587
Calabria	South/Island	2002	118.8	9944.189
Sicilia	South/Island	2004	124.5	10505.02
Sardegna	South/Island			

Source: Classification and CPI (year base 1995) are from National Institute of Statistics (ISTAT).

Note: Yearly poverty line from author's calculation on SHIW, in euros (€).

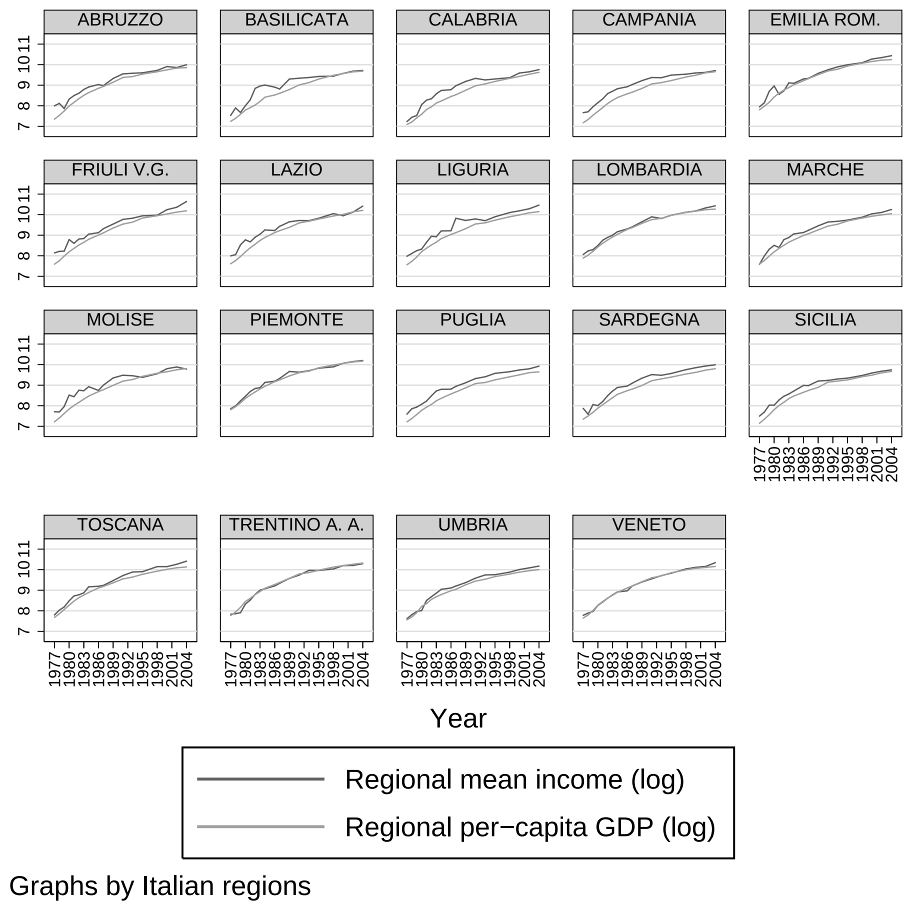
Figure A.1: Head-count and Gini, by regions



Graphs by Italian regions

Source: Author's calculations based on SHIW.

Figure A.2: Survey vs National Account



Source: Author's calculations based on SHIW and CREnOS Database

Table A.2: First Stage (Summary) Results for model "A" (Reference to Table 3)

Model	(1')	(2')	(3')	(4')
Endogenous variable: log(mean income)				
F-test of excluded	14.12	17.31	-	-
instruments	*(0.0000)*	*(0.0000)*		
Partial-R^2	0.1448	0.1514	-	-
Instruments	log(mean income) $_{t-1}$; log(GDPpc)			
Endogenous variable: log(mean income)*North				
F-test of excluded	-	-	1236.34	1804.17
instruments			*(0.0000)*	*(0.0000)*
Partial-R^2	-	-	0.9685	0.9735
Instruments	log(mean income) $_{t-1}$; log(GDPpc)*North			
Endogenous variable: log(mean income)*Centre				
F-test of excluded	-	-	585.27	618.48
instruments			*(0.0000)*	*(0.0000)*
Partial-R^2	-	-	0.9727	0.9726
Instruments	log(mean income) $_{t-1}$; log(GDPpc)*Centre			
Endogenous variable: log(mean income)*South/Island				
F-test of excluded	-	-	843.10	843.90
instruments			*(0.0000)*	*(0.0000)*
Partial-R^2	-	-	0.9503	0.9501
Instruments	log(mean income) $_{t-1}$; log(GDPpc)*South/Island			

Table A.3: First Stage (Summary) Results for model "B" (Reference to Table 4)

Model	(1')	(2')
Endogenous variable: log(mean income)		
F-test of excluded	676.32	155.06
instruments	*(0.0000)*	*(0.0000)*
Partial-R^2	0.9662	0.8439
Instruments	log(mean income) $_{t-1}$; log(GDPpc)	
Endogenous variable: log(mean income*POVRATIO)		
F-test of excluded	29165.82	2390.25
instruments	*(0.0000)*	*(0.0000)*
Partial-R^2	0.9988	0.9873
Instruments	Log(mean income)$_{t-1}$*POVRATIO; log(GDPpc)*POVRATIO	
Endogenous variable: log(mean income)*Gini$_{t-1}$		
F-test of excluded	11737.81	2493.20
instruments	*(0.0000)*	*(0.0000)*
Partial-R^2	0.9991	0.9868
Instruments	log(GDPpc)*(Gini)$_{t-1}$; log(mean income)$_{t-1}$*(Gini)$_{t-1}$	

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