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Four Scenarios of Poverty Reduction and the Role of Economic Policy

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Abstract. The most favourable scenario for poverty reduction combines positive growth and redistribution. We study the conditions and policies that allow a country to achieve this scenario. Methodologically, we depart from the existing literature and estimate a single equation model where the dependent variable is defined from the combined evolution of growth and inequality. We then estimate a limited dependent variable regression using a rich specification of structural and policy factors. Our results point to a comforting picture: even countries that start from initially unfavourable conditions can achieve the favourable scenario of growth and redistribution by adopting appropriate policies.

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1. **Introduction**

Between 1993 and 2000, per-capita GDP in India grew at an average annual rate of 4.35%. Over the same period, the poverty headcount (defined as the share of population living on less than 1 dollar per day) decreased from 42.1% to 36%. Between 1992 and 1997, Lao had a very similar growth performance (4.3% on average per year), but its poverty headcount increased from 18.6% to 26.3%. In the course of the '90s, Mali and Senegal experienced a similar rate of poverty reduction: in both countries the poverty headcount decreased by an average annual 9.8%. However, it took Mali a growth rate of 3.3% per year to achieve this reduction in poverty, while in Senegal the growth rate was only 0.8%.

Why is the growth elasticity of poverty so different across countries and over time? The arithmetic discussed in Datt and Ravillon (1992) and Bourguignon (2004) indicates that the poverty reduction effect of growth depends on the underlying change in the degree of income inequality. In simple terms, growth is generally more effective in reducing poverty if it is accompanied by a decline in inequality. Explaining the growth elasticity of poverty therefore requires an understanding of the simultaneous evolution of income and inequality. While there is certainly no shortage of single equation estimates of the determinants of growth and inequality, only recently the applied literature has turned towards the estimation of a system of simultaneous equations. As discussed in Lundberg and Squire (2003), system estimation allows growth and inequality to be modelled as the joint outcome of other variables. This is particularly convenient from a theoretical standpoint as the evolution of growth and inequality must surely be the outcome of similar processes.

System estimation is however not immune from complications (see for instance Wooldridge, 2002, Chapter 9) and estimates turn out to be often quite sensitive to the choice of identifying restrictions and model specification. In this paper, we take a different methodological route and estimate a single equation, but with a dependent variable that combines both income and inequality dynamics. More specifically, we define four different scenarios, each corresponding to a specific combination of changes in growth and inequality. We then apply limited dependent variable regressions to study the effect that various structural factors and policy variables have on the probability of a country being in any of the four scenarios. With this approach we are able to accommodate a rich specification of right hand side regressors and are not confronted with the problem of system identification.

Our main results can be summarised as follows. The four scenarios we identify correspond to significantly different poverty dynamics. The probability of a country being in scenarios that are more favourable to poverty reduction increases the higher the growth rate of agricultural productivity, the more rapid the accumulation of human capital, the faster the transformation of the productive system, and the more widespread access to infrastructures is. We also detect some important structural effects linked to a country's legal origin and geographical position. Finally, we provide evidence of the importance of initial conditions: economies at earlier stages of economic development and initially characterised by wider inequalities are more likely to end up in a scenario favourable to poverty reduction. Taking together, these results highlight what we believe is an important story: countries are not destined by nature or colonial heritage to remain trapped into poverty. "Good" policies exist that can help countries to achieve scenarios of growth and redistribution that are most favourable to the reduction of the poverty headcount.

The rest of the paper is organised as follows. Section 2 surveys the relevant literature and sets our paper in the context of the existing research. Section 3 presents the dataset used for the empirical analysis and discusses the construction of the four scenarios. In this section we also present a few stylised facts that help characterise the four scenarios and set the stage for the subsequent econometric analysis. In Section 4 we introduce the econometric model. We then present the benchmark results. Section 5 provides some policy discussion and conclusions. In the Appendix, we report some additional results. We also provide a detailed description of variables.

2. **Our paper in the context of the literature**

Economic growth is generally good for the poor. A voluminous empirical literature estimates this effect by regressing the change in a poverty indicator (i.e. the poverty headcount ratio) on a measure of growth (i.e. the change in per-capita average income). The estimated coefficient of growth can be interpreted as the growth elasticity of (absolute) poverty. In an early contribution, Squire (1993) finds that a 1-percentage point increase in the growth rate of mean income raises the annual rate of decline in the poverty head-count index by 0.24 percentage points. Elasticities well in excess of two have been subsequently reported by Bruno et al. (1998) and Adams (2004). In a seminal paper, Dollar and Kraay (2002) regress the growth rate of average per-capita incomes on the growth rate of the income of the bottom quintile of the population. They find that the estimated coefficient is not statistically different from one, meaning that the income share of the bottom quintile of the population does not vary systematically with average incomes. Kraay (2006) provides additional evidence that most of the cross-country variation in poverty changes is due to the variation in the rate of average income growth.

An important feature of the growth elasticity of poverty is that it tends to differ significantly across countries (and over time). Datt and Ravaillon (1992) show that changes in an absolute poverty measure can in fact be decomposed into growth and distributional effects. This mathematical decomposition (subsequently refined by Bourguignon, 2003 and Kraay, 2006) implies that the net poverty reduction effect of growth is a function of the dynamics of income inequality. In other words, growth is more effective in reducing poverty if it is accompanied by a decrease in the inequality of income distribution in the population. Ravaillon (1997, 2001 and 2004), Bourguignon (2003), Epualard (2003), Kakwani et al. (2004), Mosley et al. (2004), Kalwij and Verschoor (2007) all provide evidence that the distributional effect is statistically significant and that changes in inequality effectively explain a considerable proportion of the cross-country variation in the growth elasticity of poverty.

A central implication of the above findings is that the search for pro-poor growth is very much a search for policies that promote economic growth and redistribution, or at least that promote one of the two processes without retarding the other. In this sense, one would like to search for variables that display a positive coefficient in a growth regression and a negative coefficient in an income inequality regression. However, Lundberg and Squire (2003) stress that single equation models of growth and inequality are not the appropriate econometric framework to undertake this search. They argue that single equation models cannot capture the potential trade-off that arises whenever a policy has positive (negative) effects on growth while simultaneously increasing (decreasing) inequalities. More generally, because growth and inequality are likely to be the outcomes of similar processes, a system of simultaneous equations appears to be the most appropriate tool to study how different factors and policies affect both outcomes at the same time. The validity of Lundberg and Squire's (2003) argument has been subsequently given by the theoretical findings in Garcia-Penalosa and Turnovsky (2006 and 2007) who show that growth and inequality are indeed both determined by similar causal factors, including productivity, intertemporal elasticity of substitutions, preference for leisure, and fiscal policies. In a recent contribution, Huang et al. (2009) further extend the simultaneous equations model to study the joint determinants of inequality and growth. Avom and Carmignani (2008) extend the approach to include a poverty equation in addition to the growth and inequality equations originally proposed by Lundberg and Squire (2003). They use this set-up to identify policy variables that are pro-poor in the sense that they promote growth without causing sharper inequalities. They find that, among others, agricultural productivity, infrastructures, and domestic financial development do qualify as pro-poor factors.

The system approach however does not come as a free-lunch. Wooldridge (2002) for instance discusses the pros and cons of system estimation in the context of simultaneous equations. One typical problem is that system estimation is generally less robust than single equation estimation and if one of the equations is misspecified, then 3SLS or GMM estimates of all model parameters will be inconsistent. With more specific reference to the estimation of growth and inequality equations, we identify two reasons that complicate the implementation of system estimation. First, just because growth and inequality are driven by very similar processes, theoretically sound identifying restrictions on the set of regressors in each equation are difficult to find and estimation results are likely to be sensitive to the specific choice of restrictions applied. Second, when the equations in the system are simultaneously endogenous, multicollinearity between any of the endogenous dependent variables and the other regressors can significantly reduce the precision of coefficient estimates. Avom and Carmignani (2008) try to deal with these problems by adopting parsimonious specifications of their equations, but this in turn increases the risk of misspecification.

Against this background, our paper departs from the existing literature and explores an alternative route: we estimate a single equation, but we define the dependent variable as a combination of growth and inequality dynamics. More specifically, we construct a limited dependent variable that takes value from 0 to 4 depending on the underlying values of growth and inequality. In this way, we can adopt a rich specification of the right hand side variables while accounting for the simultaneous evolvement of growth and inequality. Methodologically, our paper is therefore nested within the class of models with limited dependent variables that have been analysed in Maddala (1983).

3. Data and stylised facts

a. *The dataset*

Our dataset consists of observations taken over multiyear periods across a panel of developing and emerging economies. The starting point in the collection of the dataset is the PovcalNet database of the World Bank.[1] Here we find poverty measures for 99 countries over the period 1980-2005. These indicators are, however, available at different times for different

[1] Data can be downloaded from http://iresearch.worldbank.org/PovcalNet/povcalNet.html. See also World Bank (2007).

countries and in general no more than a few data points (say three or four) are collected for each country. Following Dollar and Kraay (2002), instead of simply taking five or ten year averages of the available data, we identify sub-periods of variable duration for each country as follows: starting from the first available observation, we count the years until we find the next observation, provided that between the two observations there are at least five years and no more than 10 years. We then compute the average annual percentage change in the poverty indicators over the sub-period and we proceed with the identification of the next sub-period in the same way. Thus, let p denote the poverty indicator and $t = 1, 2, ..., m\text{-}1, m, m\text{+}1, ..., n\text{-}1, n, n + 1, ...N$ denote years. Suppose that three observations on p are available at years 1, m, and n. Also let $10 \geq m - 1 \geq 5$ and $10 \geq n - m \geq 5$. We can then identify two sub-periods: the first one goes from 1 to m and the second goes from m to n. The average annual change in the poverty indicator is then simply computed as $\Delta_{p(i,j)} = [\ln(p_j) - \ln(p_i)]/(j\text{-}i)$, where $i = 1, m$ and $j = m,n$ and $i \neq j$.[2]

As a reference poverty indicator we use the poverty headcount on the 1 dollar per-day threshold. This is, in fact, the most common measure of poverty incidence used in both the academic and the professional practice. It might be interesting in the future to repeat the exercise by using different poverty lines and or different indicators (i.e. poverty gaps instead of poverty headcounts). Overall, we end up with 161 data points. Upon visual inspection, a few of these appear to imply unreasonably large changes in poverty. We therefore drop these outliers, remaining with a total of 145 observations, which constitute the core of our dataset. The appendix reports the complete list of countries and years after dropping the outliers.

The other variables in the dataset are constructed in a similar way. Taking the sub-periods identified from the PovcalNet database as the reference, we compute average annual percentage changes of a number of economic variables: agricultural productivity (*agr_prod*), the agriculture share of GDP (*agr_va*), the industry share of GDP (*ind_va*), the density of telecommunication infrastructures (*t_comm*), the share of irrigated land (*irrigated*), the credit to the private sector share of GDP (*credit*), the international trade share of GDP (*trade*), the number of years of formal education of the average individual in the population (*tyr*), the government consumption share of GDP (*govcons*), per-capita GDP (*y_pc*), and the Gini index of inequality of income distribution (*gini*).[3] For all of these variables we also include in the dataset their level at the beginning of each subperiod (we will refer to it as *initial value*) as well as their lagged value, defined as the average percentage change in the variable taken over the five years prior to the beginning of each sub-period. Finally, we include in the dataset a few variables that are meant to capture country fixed effects: British legal origin (*legor_uk*), socialist legal origin (*legor_so*), distance from equator (*lat_abst*), and ethnolinguistic fractionalization (*ethnix*). The legal origins are coded as dummy variables, while both *lat_abst* and *ethnix* are entered in levels, as they display no variation over sub-periods within each country.

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[2] Poverty indicators take the general form $p = (P/L)*100$ where, P is the total number of people falling below a given poverty line and L is the total population in a country. In our sample, all observations on poverty are greater than 1 and hence we can take logs. We could have also taken the simple difference between data in percentages, i.e. $\Delta_{p(i,j)} = [\ln(P_j/L_j) - \ln(P_i/L_i)]/(j\text{-}i)$. In fact, we re-estimated our results using this alternative definition and we found that, while actual figures differ, the qualitative flavour of our findings is unchanged.

[3] Gini data are also often available at very irregular frequencies across countries. Luckily enough, for most years and countries, the PovcalNet reports the Gini index together with the poverty measures.

We will explain the economic rationale underlying the choice and interpretation of these variables later in Sections 3 and 4. However, it is immediately worth stressing that there is no direct measure of institutional quality in our dataset. In fact, in order to be able to compute average annual changes over the sub-periods identified from the PovcalNet database, we need variables that are available annually over the period 1980-2005. For most of institutional quality indicators, this is unfortunately not the case. Nevertheless, previous research (see La Porta et al., 1999) found that institutional quality is to a large extent explained by legal origins, geography, ethnic fragmentation, and per-capita income level. All of these determinants of institutional quality are included in our dataset, which is therefore capable of accounting, if not directly at least indirectly, for the role of institutions.

b. *Four scenarios*

Following Bourguignon (2004), let z be the 1 dollar per-day poverty line and let $F_t(z)$ be cumulative distribution function of per-capita income y; that is, $F_t(z)$ is the proportion of individuals in the population whose income y is below the poverty line z. $F_t(z)$ is therefore the poverty headcount p that we obtain from the PovcalNet dataset. The change in the poverty headcount between two points in time t and $t+n$ is then equal to:

$$(1) \quad \Delta p = F_{t+n}(z) - F_t(z)$$

Let now $G(\cdot)$ denote the distribution of relative income normalised by the population mean. If we denote the population mean at time t as $y_{m,t}$, then equation (1) can be rewritten as:

$$(2) \quad \Delta p = G_{t+n}(z/y_{m,t+n}) - G_t(z/y_{m,t})$$

Simply adding and subtracting the term $G_t(z/y_{m,t+n})$ on the r.h.s. of two we obtain:

$$(3) \quad \Delta p = \left[G_t\left(\frac{z}{y_{m,t+n}}\right) - G_t\left(\frac{z}{y_{m,t}}\right)\right] + \left[G_{t+1}\left(\frac{z}{y_{m,t+n}}\right) - G_t\left(\frac{z}{y_{m,t+n}}\right)\right]$$

Equation (3) decomposes the change in the poverty headcount in two effects. The first term in square brackets represents the change in the poverty headcount associated with a change in mean income, holding the relative income distribution constant. This can be readily associated with a growth effect: as per-capita average income grows, income distribution translates to the right and therefore the proportion of people falling below the poverty line decreases. The second term in square brackets represent a distributional effect: holding mean income constant, the relative income distribution changes. Thus, for instance, for any given level of mean income, a less dispersed distribution implies a smaller proportion of individuals below the poverty line. Vice-versa, a mean-preserving increase in dispersion will increase the proportion of poor.

The arithmetic of equation (3) implies that the growth elasticity of poverty depends on the evolution of inequalities: for any given rate of average per-capita income growth, the decrease in poverty is stronger the larger the decrease in inequality is. More generally, the decomposition identifies change in per-capita income and change in inequality as the two key dimensions underlying the change in poverty. We therefore use this two dimensions to partition our dataset in four scenarios as follows:

- Scenario 1: observations that combine a *positive* change in average per-capita income and a *negative* change in the gini index of inequality.
- Scenario 2: observations that combine a *positive* change in average per-capita income and a *positive* change in the gini index of inequality.
- Scenario 3: observations that combine a *negative* change in average per-capita income and a *negative* change in the gini index of inequality.
- Scenario 4: observations that combine a *negative* change in average per-capita income and a *positive* scenario in the gini index of inequality.

In simple words, scenario 1 combines growth and redistribution, scenario 2 corresponds to growth without redistribution, scenario 3 is negative growth with redistribution, and scenario 4 is negative growth without redistribution. Table 1 reports some simple statistics that help characterise the four scenarios. The statistics are computed for two samples. One is the full sample of 145 observations. The other is a restricted sample of 96 observations. This restricted sample excludes all the observations drawn from sub-periods for which it was not possible to collect data on the education variable *tyr*. We display both sets of statistics because some of the specifications used in the regression analysis of Section 4 do include *tyr* as a regressor and are therefore estimated on the restricted sample only.

INSERT TABLE 1 ABOUT HERE

The data in the table indicate that the majority of observations fall in either scenario 1 or scenario 2 and that most of the observations in this scenario effectively correspond to a decrease in the poverty headcount. However, in scenario 1 the average decrease in poverty is significantly larger than in scenario 2 (or any other scenario) and this in spite of the fact that average growth in the two scenarios is rather similar. This configuration is fully consistent with the argument that the growth elasticity of poverty increases if growth occurs together with redistribution.

Another interesting pattern that emerges from the table concerns the relationship between growth and redistribution. As it is clear from the large number of cases that fall in scenario 1, growth and redistribution are not necessarily incompatible. In fact, a country experiencing a decrease in inequality seems to be more likely to achieve positive rather than negative growth. Nevertheless, the average rate of decrease in inequality is somewhat larger when growth is negative rather than positive.

Finally, there are some noticeable differences between the two samples. The most intriguing of these differences concerns the extent of poverty reduction in scenarios 2 and 3. In the full sample, scenario 2 is characterised by a marginally stronger reduction in poverty. The situation is reversed in the restricted sample, where poverty reduction appears to be on average stronger in scenario 3. In fact, the two scenarios 2 and 3 have rather similar characterisation in terms of average chances in poverty, growth, and inequality. The econometric analysis in Section 4 will indeed account for the possibility that these two scenarios are merged into a unique one.

c. *Stylised facts*

A few stylised facts and empirical regularities help set the framework for the econometric analysis in the next section. First of all, we consider the variation of poverty across the four scenarios. Table 2 reports for each pair of scenarios, the bilateral difference in the average change in poverty and its statistical significance at usual confidence levels. It can be seen that with the exception of differences between scenario 2 and scenario 3, all other differences are statistically significant. In particular, scenario 1 clearly represents the most favourable situation in terms of poverty reduction, while scenario 4 is by far the least favourable one. We can therefore claim that poverty dynamics are significantly different across the four scenarios, with the combination of growth and redistribution clearly delivering a much faster rate of poverty reduction than any other scenario. This simple stylised fact therefore provides a strong justification for studying the policies and factors that affect the realisation of the various scenarios.

INSERT TABLE 2 HERE

Second, we look more closely at the relationship between growth and redistribution in our dataset. A few theoretical arguments have been proposed that imply a trade-off between growth and redistribution (see for instance, Alesina and Rodrik, 1994, Persson and Tabellini, 1994). If this trade-off effectively existed, then achieving the most favourable scenario for poverty reduction would be quite difficult. In fact, the empirical evidence on the trade-off is far from unanimous and recent work suggests that the relationship between growth and changes in inequality might be non-linear (see Banerjee and Duflo, 2003). As already noted, the simple statistics in Table suggest that growth and inequality do not necessarily move together: more than 1/3 of the observations in the full sample are indeed characterised by positive growth and falling inequalities. At the same time, another 1/3 of observations fall in the scenario where positive growth is accompanied by growing inequalities, so that overall a country going through a period of positive growth is equally likely to experience sharpening inequalities as it is to achieve redistribution.

To provide a bit more systematic evidence on the issue, we fit a scatter plot of growth and changes in inequality using two different methods. The first method (panel A of Figure 2) is a standard linear regression, which implicitly assumes a linear relationship between the two variables. The second method (panel B of Figure 2) is a non-parametric fit that is known as *lowess* (Cleveland, 1993). In a nutshell, let (Δy_i, Δg_i) be a generic observation on per-capita growth and changes in inequality. We then run a locally weighted polynomial regression of Δg_i on Δy_i using only a subset of observations that lie around Δy_i, with smaller weights being given to the observations that are more distant from Δy_i. The fitted value of this local regression evaluated at Δy_i is used as the smoothed value in constructing the curve that links Δg and Δy. The procedure is repeated for each observation (Δy_i, Δg_i) in the full sample until the curve can be traced out. With this procedure, we therefore impose as little structure on the functional form of the relationship as possible, which in turn allows us to better account for possible non-linearities.

The scatter plot in panel A suggests that the correlation between growth and changes in the Gini coefficient is negative: as the growth rate increases, the increase in inequality decreases and eventually becomes negative. While nothing can be said about the direction of causality, the downward sloping regression line supports the view that there is no trade-off between growth and redistribution. The non-parametric fitted line in panel B indicates that the relationship might effectively be non-linear: sharply negative at negative values of the growth rate and then substantially flat. In fact, one might argue that the overall negative slope of the regression line in panel is largely driven by the observations at negative (or low positive) values of the growth rate. Once growth turns more significantly positive, the correlation is very close to zero, meaning that growth and redistribution move independently from each other. Even in this case, however, the data do not point to a systematic trade-off in the sense that countries do not necessarily have to accept a lower growth rate to promote more redistribution and vice-versa. The issue is then to understand which policies a country can implement to achieve a combination of growth and redistribution.

INSERT FIGURE 1 ABOUT HERE

Finally, we compute averages of explanatory variables (policies, country fixed effects, and initial conditions) in the four scenarios to see whether any systematic patterns can be identified. The statistics are reported in Table 3 for both the full and the restricted sample. There are indeed some regularities that are worth noting. Scenario 1, which combines growth and redistribution, is characterised by a somewhat lower initial per-capita income and a faster rate of agricultural productivity growth coupled with a more rapid decrease in the agriculture share of GDP than the other scenarios. Moreover, scenario 1 also appears to have the largest proportion of countries with UK legal origins, particularly in the restricted sample. On the other hand, and perhaps a bit surprisingly, average growth in education is lowest in scenario 1. Yet, differences in average *tyr* across scenarios are small. A faster rate of expansion of telecommunication infrastructures, international trade, and credit to the private sector also seem to characterise the scenarios with positive growth (scenarios 1 and 2) relative to the scenarios with negative growth (scenarios 3 and 4). Again, the comparison of averages of variables across scenarios does not say much about the direction of causality, and in fact it will turn out that for education, trade, and credit to the private sector a reverse causality cannot be excluded. Nevertheless, the existence of systematic differences suggests that there are some likely candidates to explain what affects the probability of a given country to end up in a given scenario.

4. **Econometric results**

a. *The model*

i. *Econometric setting*

Our purpose in this section is to understand what affects a country's probability to achieve one of the four scenarios identified in section 3. For each generic observation *i* in the dataset, the dependent variable is coded as follows: $s_i = 0$ if the observation falls in scenario 1, $s_i = 1$ if the observation falls in scenario 2, $s_i = 2$ if the observation falls in scenario 3, and $s_i = 3$ if the observation falls in scenario 4. The econometric model will therefore take the form of a multinomial model.

As well known[4], multinomial models vary according to whether the categories of the dependent variables are ordered or not. We argue that our dependent variable involves inherently ordered outcomes, going from the most favourable scenario to the least favourable

[4] See Greene (2008, chapter 23) for a textbook treatment of multinomial choice models.

scenario for poverty reduction. The probability of observation i falling in scenario j (j = 0, 1, 2, 3) is then defined as:

$$(4)\quad Prob(s_i = j|\mathbf{x}_i) = \Phi(\mu_j - \mathbf{x}_i'\boldsymbol{\beta}) - \Phi(\mu_{j-1} - \mathbf{x}_i'\boldsymbol{\beta})$$

where $\mathbf{x}$ is a vector of explanatory variables (i.e. the structural factors, initial conditions, and policy variables included in the dataset), Φ denotes the standard normal c.d.f., and the μs and the $\boldsymbol{\beta}$ are parameters to be estimated.

The intuition underlying the ordered probit model (4) is that "conduciveness to poverty reduction" is a latent process defined by some interaction between Δy (changes in per-capita income) and Δg (changes in income inequality), which are in turn explained by the vector of variables $\mathbf{x}$. While the latent process is not observed, the observed values of Δy and Δg allow identifying the four categories of the dependent variable s_i. In model (4), the stochastic component of the latent process is assumed to have a standard normal distribution. We also estimated a model using a logistic distribution and results were not qualitatively different.

Model (4) is estimated by maximum likelihood. The sign of the regression parameters $\boldsymbol{\beta}$ can be interpreted in terms of the effect that explanatory variables have on the probabilities: a positive estimated coefficient on the generic variable x_{ij} means that an increase in x_{ij} decreases the probability of being in the lowest category and increases the probability of being in the highest category.

The summary statistics discussed in Section 3 indicate that scenarios 2 and 3 are not very different from each other in terms of poverty, growth, and inequality dynamics. In particular, the poverty effect is not significantly different between these two scenarios. This similarity might put the ordering of the categories into question. In other words, it seems to be quite uncontroversial that on a hypothetical "conduciveness to poverty reduction" continuum spanning from left (most conducive or favourable) to right (least conducive or favourable), scenario 1 would be the first one, scenario 4 would be the last one and scenarios 2 and 3 would lay somewhere in between. However, can we actually assume that scenario 2 comes before scenario 3 on this continuum?

We tackle this issue in two ways. First, we will re-estimate the ordered probit model (4) by merging the two scenarios 2 and 3. In this way, the dependent variable s_i takes only three values: 0 for scenario 1, 1 for the merged scenario, and 2 for scenario 4. The ordering in this case seems to be pretty straightforward. Second, we also pursue a more drastic alternative and re-estimate a model with unordered outcomes. When outcomes are considered to be unordered, the multinomial logit (or probit) model becomes the relevant setting. The model specifies the probability of observation i to be in category J (where J = scenario 1,....., scenario 4) as:

$$(5)\quad \pi_{ij} = \frac{\exp(\mathbf{x}_i'\boldsymbol{\beta}_j)}{\sum_{l=1}^{m}\exp(\mathbf{x}_i'\boldsymbol{\beta}_l)}$$

The identification of model (5) requires $\boldsymbol{\beta}_j$ to be set to 0 for one of the category (the so called base outcome) and hence estimated coefficients are interpreted with respect to that category. Estimates from the multinomial logit (5) are reported and commented upon in the Appendix.

ii. Choice and interpretation of explanatory variables

The set of explanatory variables of model (4) includes country fixed effects, initial conditions, and policy variables introduced in the previous Section 3. British legal origin (*legor_uk*), distance from equator (*lat_abst*) and ethnic fragmentation (*ethnix*) are all significant determinants of the quality of governance and institutions. In turn good institutions strengthen growth and reduce inequalities.[5] We therefore expect negative coefficients on both *legor_uk* and *lat_abst* and a positive coefficient on *ethnix*. Among the country fixed effects we also include a dummy for socialist legal origins (*legor_so*). Socialist countries in our sample are peculiar in two respects: (i) they were characterised for most of the sample period by extremely low inequality, reflecting the socialist or communist ideology and (ii) most of them went through a prolonged period of negative growth and growing inequality in connection with the transition from plan to market. We thus expect *legor_so* to display a positive estimated coefficient in our model.

The initial conditions we consider are the initial levels of per-capita income (*i_y_pc*) and Gini coefficient (*i_gini*). The large body of theoretical and empirical work on conditional convergence suggests that negative growth should be more likely at higher initial levels of per-capita income. The coefficient on *i_y_pc* should therefore be positive, even though it is not entirely clear how a higher initial income could affect the likelihood of reductions in inequality. An initially higher level of inequality makes the reduction of inequality more likely, as it is probably easier to lower a Gini coefficient of, say, 60 than a Gini coefficient of, say, 30. As already discussed, a higher Gini does not seem to be an obstacle to growth, so that in the end *i_gini* should have a negative coefficient.

We then include in vector **x** three indicators that are meant to capture the structural transformation of the economy. These are the rate of agricultural productivity growth (*agr_prod*), the change in the agriculture share of GDP (*agr_va*), and the change in the industry share of GDP (*ind_va*). In the literature, industrialization is often seen as the key to growth accelerations.[6] A traditional Kuznets-type of argument then suggests that this transformation would be accompanied by an increase in inequality, at least at the early stages of development. However, it is unclear to what extent a shift from agriculture to industry effectively prevents redistribution. In this respect, our expectation is that the growth effect of sectoral shares is probably stronger than their distributional effect. The estimated coefficient on *agr_va* should hence be negative while the one on *ind_va* should be positive. At the same, the large weight that the agricultural sector maintains in many developing economies suggests that productivity growth in that sector is likely to impact significantly on the growth of the economy. To the extent that it reflects a transition from traditional to modern agriculture, a faster rate of productivity growth should also be associated with lowering inequalities. Consequently, *agr_prod* is expected to display a negative coefficient.

[5] The determinants of institutional quality are analysed by La Porta et al. (1999) and Acemoglu and Johnson (2005). Acemoglu (2008, chapter 22) provide a survey of the voluminous research on the relationship between institutions and growth. Finally, the effect of institutions on income inequality is investigated, inter alia, in Carmignani (2009).

[6] See, for instance, Aghion and Howitt (2009, chapter 10).

The increase in the density of telephone lines (*t_comm*) and the expansion of the proportion of irrigated land (*irrigated*) capture infrastructures development. Better infrastructures are expected to foster growth.[7] However, their contribution to the dynamics of inequality is ambiguous as it is likely to depend on their localisation on the territory. If governments decide to develop new infrastructures to satisfy the higher demand expressed by already economically more advanced areas, then the risk is that inequality in the country will increase. Avom and Carmignani (2008) provide evidence that this negative distributional effect might be statistically significant. Therefore, the coefficient on *t_comm* and *irrigated* is expected to be negative, but the prediction is somewhat ambiguous.

Finally, the policy environment is represented by the growth rates of credit to the private sector (*credit*), international trade (*trade*), the size of government (*gov_cons*), and education (*tyr*). All of these variables are quite commonly used in the applied analysis of growth and inequality. The survey of results presented by Durlauf et al. (2005) suggest that *credit, trade,* and *tyr* should all promote growth, while there is no consensus on the sign of the effect of *gov_cons* . A wider access to credit should also help reduce inequalities. Similarly, an increase in average education levels is usually regarded as an improvement in earning opportunities for the population at large, thus implying a potentially smoother distribution of income. A larger government should also contribute to reducing inequalities, to the extent that its size correlates with the extent of redistribution. On the contrary, results in Lundberg and Squire (2003) and Carmignani (2009) indicate that openness to trade can sharpen inequalities, even though the effect is not necessarily statistically strong. Overall, there is no ambiguity about the expected sign of *tyr* and *credit*, which should be positive. On the other hand, for both *gov_cons* and *trade* a clear-cut prediction cannot be made.

b. *Results*

The results of estimating model (4) are reported in Table 4. We initially tested for the potential endogeneity of the regressors by running separate regressions of Δy and Δg on the set of country-fixed effects and initial conditions plus each of the other variables.[8] We applied the endogeneity test of Hausman (Davidson and MacKinnon, 1993), using lagged values of the potentially endogenous variables as instruments. It turns out that *credit*, *tyr*, *gov_cons*, and *trade* are all endogenous to Δy and/or Δg. We therefore use their lagged values in the estimation of the ordered probit model.

INSERT TABLE 4 ABOUT HERE

To start with, model 1 provides our benchmark results. All of the statistically significant coefficients are in line with our *a priori* expectations. Among the country-fixed effects, those that matter the most are geographical location and socialist legal origin. Initial conditions are statistically very important: a richer country with a lower initial Gini coefficient is less likely to achieve the most favourable scenario for poverty reduction. The stage of structural transformation of the economy also matters: to generate growth and facilitate redistribution, the transition from agriculture to industry must be accompanied by the modernization of the

[7] Esfahani and Ramirez (2003), among others, discuss the positive contribution of infrastructures to growth.
[8] Country fixed effects and initial conditions are pre-determined and therefore treated as exogenous. In the end, we test for the endogeneity of *t_comm, irrigated, credit, trade, tyr,* and *gov_cons.*

agricultural system and hence by the acceleration of agricultural productivity growth. Finally, the development of telecommunication infrastructures and the increase in the education level of the population are also conducive to the achievement of a scenario of growth and redistribution.[9]

In model 2 we drop the variable *tyr* in order to maximise the number of observations available for estimation. The only noteworthy change concerns the variable *legor_so*, which now becomes statistically insignificant. In fact, education data for socialist countries are not widely available. The regression with *tyr* therefore includes few observations on socialist legal origins and these few observations are concentrated in the period that corresponds to the transitional recession. The recovery of several socialist countries, with positive growth and lowering inequalities, towards the end '90s and the early 2000s is therefore not captured by the estimates of model 2. However, it does affect the estimates of model 2, so that overall being of a socialist origin does not seem to be a disadvantage.

Model 3 makes use of a three-category definition of the dependent variable. As already discussed, scenarios 2 and scenario 3 are rather similar in terms of average changes in poverty, income, and inequality, so that their ordering might be questionable. We therefore collapse scenario 2 and scenario 3 together so that the dependent variable now only has three categories: 0 for scenario 1, 1 for scenarios 2 and 3, and 2 for scenario 4. The results do not dramatically differ from those reported for model 1. However, we do notice that the coefficient on *t_comm* is now less precisely estimated. When dropping the variable *tyr* (estimates available from the authors upon request) *t_comm* returns to be statistically significant, while *legor_so* becomes non-singificant. All in all, we believe that the core of our results holds true whether four or three categories are defined for the dependent variable.

In model 4 we estimate the effect of each variable separately on (i) the probability of achieving positive growth and (ii) achieving redistribution. The underlying setting is a bivariate probit model. In practice, we estimate two probit equations: in the first one, the dependent variable takes value 1 if the gini indicator decreases (*gini_down*); in the second equation, the dependent variable takes value 1 if growth is positive (*y_pc_up*). However, we do allow for correlated disturbances across the two probit equations, much in the same spirit as the seemingly unrelated regression model for continuous variables (see Greene, 2008). A positive estimated coefficient now indicates that the regressor increases the probability of reducing inequality or achieving positive growth.

Model 4 is useful to understand whether a particular variable plays its role mainly through the distributional effect or the growth effect. Interestingly, a few variables appear to activate both effects. This is the case of agricultural productivity growth and telecommunication infrastructures. However, while *agro_prod* increases both the probability of reducing Gini and the probability of positive growth, *t_comm* generates effects of opposite sign. In particular, *t_comm* increases the probability of $\Delta y > 0$, but it also reduces the probability of $\Delta g < 0$. The aggregate estimates of models 1 and 2 suggest that in the end the growth effect dominates, so that *t_comm* positively contributes to the achievement of a scenario of growth and redistribution. Of the other variables that are significant in the aggregate models, most

[9] The estimated threshold parameters μ in model 1 are: μ_1 = -4.43 (-9.76, 0.89), μ_2 = -2.94 (-8.25, 2.36), μ_3 = -2.14 (-7.46, 3.16). Estimates for the other models are qualitatively similar and can be obtained from the authors upon request.

tend to affect the probability of positive growth more than the probability of redistribution. It is however important to stress that, with the exception of *t_comm*, none of the variables that promotes a positive growth also increases the likelihood of higher inequalities. Similarly, none of the variables that increase the probability of redistribution also decrease the probability of positive growth. Taken together, these findings mean that growth and redistribution are not mutually exclusive, as long as the appropriate set of policies and conditions is in place.[10]

Finally, we estimate a simplified specification of the benchmark model that only includes the statistically significant variables. We perform this exercise for both the restricted sample (model 5) and the full sample (model 6). All of the variables retain their sign and level of statistical significance, thus suggesting that the estimates are not determined by spurious correlations arising from the inclusion of irrelevant regressors. Note that the results on *legor_so* are consistent with the findings from the benchmark specifications. As an additional robustness test (not reported in the table, but available upon request), we take each of the non-significant variables from model 1 (or 2) and add it, one at the time, to the simplified specification of model 5 (or 6). None of these other variables turns out to be significant. At the same time, the estimated coefficients of the variables of the simplified specification remain very similar to those reported in the table.

5. **Conclusions**

In this paper we are concerned with the contribution of economic policies to poverty reduction. Our point of departure is the mathematical decomposition of poverty changes into growth effect and distributional effect. This decomposition indicates that searching for pro-poor policies boils down to identifying policies that promote growth and reduce inequalities, or at least that promote one of the two processes without retarding the other. The estimation of a system of two simultaneous equations, one for growth and another for inequality, provides a suitable econometric framework for this analysis and it has indeed been used in previous research. However, the system approach is not immune from complications. We therefore explore an alternative methodological route and estimate a single equation model where the dependent variable is defined from the combination of growth and income dynamics. More specifically, the dependent variable takes four values, corresponding to four different poverty reduction scenarios, from most favourable to least favourable. We then employ and ordered probit estimator to estimate the effect of policy variables and initial conditions on the probability to achieve the most favourable poverty reduction scenario.

The results point to a comforting picture as they suggest that policies do matter in affecting a country's ability to achieve a scenario of growth and redistribution, which in turn delivers the fastest rate of poverty reduction. The estimates indicate that growth and redistribution are not mutually exclusive, provided that the appropriate policies are in place. In particular, policies promoting the accumulation of human capital and the development of infrastructure are likely to be most conducive to the achievement of the growth with redistribution scenario. Supporting the structural transformation of the economy and the expansion of the industrial

[10] In the tables we only report the estimates of model 4 on the restricted sample. Estimates obtained from the full sample are available upon request from the authors. In general, the findings do not change significantly between the two samples.

sector is also going to play an important role. However, our findings indicate that while promoting structural transformation, governments should avoid treating agriculture as a "neglected sector". In fact, structural transformation should be accompanied by a process of modernization of the agricultural system to increase agricultural productivity.

6. **Appendix**

A. Variables description

Unless otherwise indicated, all of the variables are expressed in annualized percentage changes. WDI is the World Development Indicators Database of the World Bank, 2008 issue.

- ph$1, poverty headcount: Proportion of population living on less than 1 dollar per day. Source: PovcalNet, World Bank.
- l_yp_c, per-capita income: real per-capita GDP at constant US dollars (base year 2000). Source: WDI. This variable is expressed in levels
- l_gini, Gini coefficient of inequality of income distribution. Source: PovcalNet, World Bank. This variable is expressed in levels
- govcons, government size: total government consumption in percent of GDP. Source: WDI.
- credit, financial depth: domestic credit to the private sector in percent of GDP. Source: WDI.
- trade, international trade openness: exports plus imports in percent of GDP. Source: WDI.
- tyr, education: number of years of schooling of the average individual in the population. Source: Barro and Lee (2004) and UNESCO.
- Legor_uk, UK legal origin: dummy variable taking value 1 if country's legal system originates from the UK common low code. Source: La Porta et al. (1999). This variable is expressed in levels.
- Legor_so, Socialist legal origin: dummy variable taking value 1 if country’s legal system originates from the socialist law. Source: La Porta et al. (1999). This variable is expressed in levels.
- ethnic, ethnic fragmentation: probability that two randomly selected individuals are not from the same ethnic group. Source: La Porta et al. (1999). This variable is expressed in levels.
- Agr_prod. Agricultural productivity: agricultural output per worker employed in the agricultural sector. Source: WDI
- Agr-va. Value added of agricultural sector in percent of GDP. Source: WDI
- Ind-va. Value added of the industrial sector in percent of GDP. Source: WDI
- T_comm. Density of telecommunication infrastructures. Number of telephone mainlines per 1000 habitants. Source: WDI.
- Irrigated. Proportion of irrigated agricultural land in percent of total agricultural land. Source: WDI.

B. Multinomial logit

In section 4 we argue that our dependent variable is inherently ordered and therefore we estimate a ordered probit model. While we believe that the characterisation of poverty reduction scenarios presented in Table 1 supports our argument, we acknowledge the possibility that theoretical our scenarios might not represent ordered categories. In this case, the appropriate econometric framework would be a multinomial logit (or probit) model. The multinomial logit model is written as follows:

$$(6) \qquad \text{Prob}\left((s_i = j|\mathbf{x}_i\right) = \frac{\exp\left(\mathbf{x}_i'\boldsymbol{\alpha}_j\right)}{\sum_{j=0}^{s} \exp\left(\mathbf{x}_i'\boldsymbol{\alpha}_j\right)}$$

where all the variables are as in model (4). Estimates of (6) are reported in Table 5 below.[11] A set of estimated coefficients is reported for each scenario, with the exception of scenario 1. This is because scenario 1 is chosen as the base scenario. Then, the estimated coefficients measure the marginal effect that each regressor has on the probability of a given scenario relative to the base scenario.

INSERT TABLE 5 ABOUT HERE

While the interpretation of coefficients is clearly different from the ordered probit model estimated in the paper, we believe that the multinomial logit results are qualitatively in line with those reported in table 4. In particular, a higher initial per-capita income and a lower intial degree of inequality reduce the probability to achieve the growth and redistribution scenario. At the same time, faster agricultural productivity growth and better infrastructure increase the likelihood of a country to achieve growth and redistribution.

[11] We exclude *tyr* to maximize the number of observations. In fact, when *tyr* is included, all coefficients retain the sign reported in table 5. However, the small number of observations imply large standard errors and only few of the coefficients turn out to be statistically significant at either 1% or 5% confidence level.

Table 1. Characterisation of poverty reduction scenarios

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Full sample	Rest. Sample	Full sample	Rest. Sample	Full sample	Rest. Sample	Full sample	Rest. Sample
Total N. of cases	55	34	54	42	15	11	21	9
Average change in poverty per year (%)	-7.57 (2.25)	-8.47 (2.07)	-2.25 (2.27)	-0.45 (1.86)	-1.05 (4.47)	-2.65 (3.63)	16.96 (3.65)	11.82 (4.02)
Average change in income p.c. per year (%)	2.63 (0.30)	2.26 (0.30)	2.78 (0.31)	2.76 (0.27)	-1.61 (0.58)	-1.39 (0.52)	-3.73 (0.49)	-1.47 (0.58)
Average change in Gini per year (%)	-1.66 (0.25)	-1.56 (0.28)	1.69 (0.25)	1.49 (0.25)	-2.27 (0.48)	-2.08 (0.50)	3.76 (0.40)	3.10 (0.55)

Notes: The averages reported for the change in poverty, the change in income, and the change in Gini in each scenario are equivalent to the estimated OLS α coefficients in the following regression: $\Delta z_i = \alpha_1 S_1 + \alpha_2 S_2 + \alpha_3 S_3 + \alpha_4 S_4 + \varepsilon_i$, where *z* is the (percentage change in) poverty headcount, per-capita income, and Gini, *i* is a generic observation in the dataset, S_t is a dummy variable taking value 1 if observation *t* falls in scenario *t* (where *t* = 1, 2, 3, 4), and ε is a disturbance. The figures in brackets are the standard errors of the estimated α in that regression.

Table 2: Statistical significance of differences across scenarios

	Baseline scenario							
	Scenario_1		Scenario_2		Scenario_3		Scenario 4	
	Full sample	Rest sample	Full sample	Rest sample	Full sample	Rest sample	Full sample	Rest sample
Scenario_1	..	..	-5.31**	-8.03***	-6.52***	-5.82*	-24.53***	-20.3***
Scenario_2	5.31**	8.03***	..	..	-1.21	2.20	-19.22***	-12.27*
Scenario_3	6.52**	5.82*	1.21	-2.20	..	..	-18.01***	-14.48*
Scenario_4	24.53***	20.3***	19.22***	12.27*	18.01***	14.48*	..	..

Notes: The table reports the estimated β coefficients in the following regression: $\Delta p_{it} = c + \beta_1 S_j + \beta_2 S_k + \beta_3 S_m + \mu_i$, where *p* is the percentage change in the poverty headcount, *c* is constant term, *i* is a generic observation in the dataset, μ is a disturbance, and *S* are dummy variables taking value 1 if observation *i* falls in scenario *j*, *k*, or *m* respectively (where *j* = 1, ..4; *k* = 1,..4; *m* = 1,..4; and *j*≠*k* ≠*m*≠*j*). Therefore, one scenario at the time is omitted from the regression. The omitted scenario is called “baseline scenario”. The estimated β coefficients are then equal to the difference between the average change in poverty in the baseline scenario and the average change in poverty in any other scenario. Regressions are estimated by OLS, with Newey-West corrected standard errors. Estimates of the constant term are not reported. *,**,*** denote statistical significance of the estimated coefficient at 10%, 5%, and 1% confidence level respectively

Table 3. Averages of structural and policy variables in the different scenarios

	Scenario 1		**Scenario 2**		**Scenario 3**		**Scenario 4**	
	Full sample	Rest. sample	Full sample	Rest. sample	Full sample	Rest. sample	Full sample	Rest. sample
Legor_uk (proportion of cases)	0.273	0.412	0.241	0.286	0.267	0.364	0.095	0.222
Legor_so (proportion of cases)	0.327	0.029	0.185	0.071	0.067	0.000	0.524	0.111
Lat_abst (average level)	0.295	0.213	0.246	0.210	0.194	0.175	0.350	0.205
Ethnic (average level)	0.489	0.510	0.429	0.406	0.574	0.486	0.452	0.473
I_yp_c (average level)	6.765	6.970	6.970	7.015	7.037	7.446	7.151	7.422
I_gini (average level)	3.770	3.842	3.681	3.727	3.911	3.935	3.443	3.663
Agr_prod (average growth)	2.418	2.323	1.906	1.269	0.991	0.835	-1.585	-0.362
Agr_va (average growth)	-3.045	-2.342	-2.969	-2.871	-0.567	-0.812	-2.819	-1.307
Ind_va (average growth)	-0.080	0.097	0.376	0.206	-0.864	-0.730	-2.920	-0.955
T_comm (average growth)	8.561	9.219	9.413	10.431	3.295	3.948	5.461	7.210
Irrigated (average growth)	1.134	1.814	0.477	0.880	2.465	3.041	-0.300	0.167
Credit (average growth)	2.567	0.082	3.368	3.694	-2.088	-1.323	-5.013	-4.322
Trade (average growth)	2.124	2.619	2.489	2.468	1.449	1.478	0.354	1.247
Govcons (average growth)	-0.112	-0.758	0.065	0.852	-1.281	-1.187	2.264	1.943
Tyr (average growth)	1.687	1.687	1.893	1.893	2.121	2.121	2.032	2.032

Notes: For the dummy variables legor_uk and legor_so, the average reported in the table corresponds to the proportion of observations coded as 1 on the total of observations in each scenario. For i_yp_c and i_gini the table reports the average level of observations in each scenario. For all other variables, the table report the average annual percentage change of observations in each scenario. See the Appendix for variables definition.

Table 4: Regression results

	Model 1	Model 2	Model 3	Model 4		Model 5	Model 6
				Gini_down	Y_pc_up		
Legor_uk	0.092	-0.158	-0.120	0.719*	-0.637	..	..
Legor_so	2.719***	0.008	2.319**	-0.130	-5.284***	2.172***	0.413
Lat_abst	-3.311**	-2.868**	-3.578**	2.58	4.272**	-2.944**	-2.636***
Ethnic	-0.548	-0.409	-0.718	1.024	0.0138	..	..
l_yp_c	0.729***	0.397***	0.691***	-0.188	-1.659***	0.623***	0.402***
l_gini	-1.195*	-2.428***	-1.701**	2.080**	0.244	-1.624**	-2.204***
Agr_prod	-0.212***	-.177***	-0.215***	0.134**	0.255***	-0.198***	-0.171***
Agr_va	0.121***	0.108***	0.109**	-0.018	-0.196***	0.122***	0.117***
Ind_va	-0.051	-0.019	-0.052	-0.013	0.142	..	..
T_comm	-0.061**	-0.051**	-0.035	-0.050**	0.234***	-0.0561**	-0.053***
Irrigated	-0.035	-0.048	-0.056	0.107**	-0.007	..	..
Credit	-0.216	0.008	-0.324	0.415*	0.081	..	..
Trade	0.202	0.022	0.182	-0.071	-0.879	..	..
Govcons	-0.529	-0.261	-0.537	0.656	0.943	..	..
Tyr	-1.005***	..	-0.921**	0.071	2.681***	-0.607**	..
Obs.	89	122	89	90		93	134

Notes: Models 1, 2, 3, 5, and 6 are estimated using an ordered probit. Model 4 is estimated by bi-variate probit. To account for possible reverse causality, credit, govcons, trade, and tyr are all lagged. See Appendix for variables definition. *, **, *** indicate that estimated coefficients are

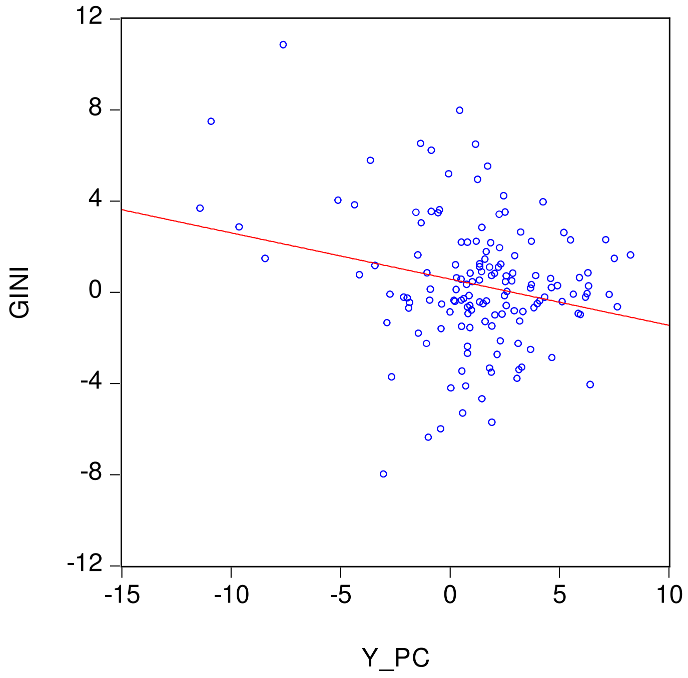
Table 5: Multinomial logit

	Scenario 2	**Scenario 3**	**Scenario 4**
Legor_uk	-0.962	-0.357	-1.157
Legor_so	-1.255	-4.592***	0.932
Lat_abst	-3.636	-1.857	-14.554**
Ethnic	-1.486	-0.254	-2.519
l_yp_c	0.549	0.412	2.649***
l_gini	-5.346***	-0.102	-16.222***
Agr_prod	-0.160*	-0.369**	-0.786***
Agr_va	0.095	0.348**	0.360**
Ind_va	0.094	-0.016	-0.245
T_comm	-0.042	-0.593***	-0.182
Irrigated	-0.229**	-0.029	-0.781***
Credit	0.120	0.929	-0.667
Trade	0.246	0.500	-1.437
Govcons	-1.318	-2.381	-0.208
Obs.		122	

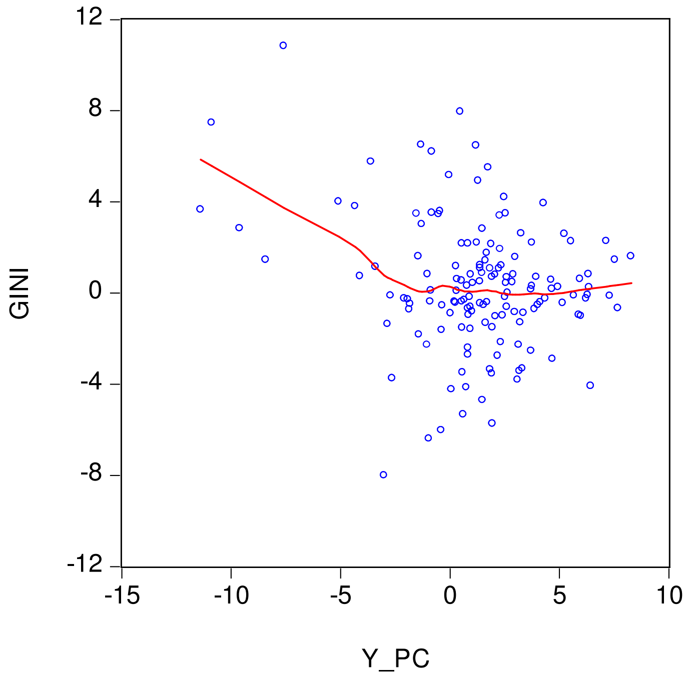
Notes: Scenario 1 is the base outcome in the multinomial logit regression. Estimated coefficients therefore measure the effect that regressors have on the probability of the other scenarios relative to the base scenario. To account for possible reverse causality, credit, trade, and govcons are lagged. See Appendix for variables definition. *, **, *** indicate statistical significance of the estimated coefficient at the 10%, 5%, and 1% confidence level respectively.

Figure 1: The relationship between growth and changes in inequality

Panel A: Regression line



Panel B: Non-parametric fit



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