Poverty Elasticity: a New Empirical Approach

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Abstract

This note proposes a nonparametric estimation method controlled for endogeneity to calculate poverty elasticities for a panel of countries. Results show that usual estimates without control for endogeneity overestimate the growth elasticity of poverty.

Keywords: Poverty Elasticity, Endogeneity.
JEL: C53, E43, G17

1. Introduction

The past 20 years have been marked by substantial improvements in human development indices at a global level. World Bank and UN reports indicate reductions in infant and maternal mortality rates and in HIV infections, in addition to better access to education, potable water, sanitation, among others (WDR, 2012). Another striking aspect is the reduction of extreme poverty - it has been estimated that the percentage of individuals living on less than $1.25 a day decreased from 42% to 15.8% between 1990 and 2010.

The improvement in these indicators, especially the decline in the number of poor people, is largely due to the economic performance of developing countries. This association is supported by the relationship between the economic growth of this group of countries (around 6% a year from the 2000s), and the decrease in poverty level by approximately 60% (Chandy & Gertz, 2011). This same rationale leads international agencies to change their forecasts about poverty reduction from the perspective of a new world crisis. Recently, the millennium development goals partial report (MDG, 2010) has inferred that a world economic crisis could push about 64 million people into extreme poverty.

In brief, these data suggest a strong inverse relation between economic growth and poverty level, as suggested by Bruno et al. (1998). In this respect, the sign of the growth elasticity of poverty depends on how earnings distribution will respond to the economic growth process.

Based on that, Ravallion & Chen (1997) propose teasing apart the effects of growth and of inequality on poverty using a regression approach. This method has become quite popular due to its ease of application, as only aggregate information on poverty levels $p$, $n$, and $y$ is required.

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GDP $y$ and inequality $I$ is needed. Thus, one should take into account that: $p = f(y, I)$. By assuming a linear parametric structure for a panel of countries, one gets:

$$\ln(p_{i,t}) = \beta_1 \ln(y_{i,t}) + \beta_2 \ln(I_{i,t}) + v_i + u_{i,t}. \quad [1]$$

i.e., the logarithm of poverty of country $i$ at time $t$, $p_{i,t}$, is explained by the logarithm of output $y_{i,t}$, by the logarithm of inequality $I_{i,t}$, by a country-specific factor $v_i$ and by the idiosyncratic error term $u_{i,t}$. Alternatively, it is possible to eliminate the specific effects by using a first-difference equation:

$$\Delta \ln(p_{i,t}) = \beta_1 \Delta \ln(y_{i,t}) + \beta_2 \Delta \ln(I_{i,t}) + e_{i,t}, \quad [2]$$

where $e_{i,t} = u_{i,t} - u_{i,t-1}$.

Ever since, equation (2) has been the basis for predicting the effect of economic growth on poverty. The preliminary results of Ravallion & Chen (1997), based on OLS estimations, indicated growth elasticity of poverty between -2 and -4, i.e., a 1% growth in the average income would reduce poverty by 2% to 4%\(^1\). In summary, studies have focused on the development of new inference methods and on the construction of more representative databases. However, an important issue has been neglected: in (1)-(2), both $y_{i,t}$ and $\Delta y_{i,t}$ are endogenous. This could be explained by the recent developments in the economic growth literature. Banerjee & Duflo (2003), for instance, assert that economic growth has a nonlinear relationship with inequality. Several functional forms are tested, but the basic equation is:

$$\Delta y_{i,t} = y_{i0} + k(\Delta I_{i,t}) + g(I_{i,t}) + v_i + u_{i,t}. \quad [3]$$

Where $y_{i0}$ is the initial GDP and $k$ and $g$ are unknown functions.

Therefore, obtaining parameters from equations (1) or (2) may produce a biased estimation of the effect of economic growth on poverty, as parameter $\beta_1$ will be the sum of the effect of growth on poverty and of the effect of inequality on growth. In other words, inequality has direct and indirect effects on poverty. In practice, the predictions of the effect of growth on global poverty levels are not reliable, with relevant implications for the assessment of poverty-fighting policies.

Therefore, this note proposes estimating poverty elasticities by controlling for possible endogeneity using the system of equations denoted by (2) and (3). A database similar to that of Chambers & Dhongle (2011) will be used, in addition to an empirical approach based on a nonparametric estimation of models with instrumental variables using the methods of Sieves, e.g., Ai & Chen (2003) and Horowitz (2012). This estimator is based on the estimation of unknown function $g$ in the equation:

$$Y = g(X) + U; \ E(U|W = w) = 0, \quad [4]$$

or equivalent to

\(^1\)For a summary, see Chambers & Dhongle (2011).
\[ E(Y - g(x)|W = w) = 0, \]  

where \( X \) denotes the set of explanatory variables and \( W \) is a vector of continually distributed instruments. In this case, the estimation uses a set of instruments \( W \) to correct for possible endogeneity problems, now in a nonparametric context.

2. Results

The information was collected from World Bank’s PovcalNet analysis tool, totaling 139 observations for 83 developing countries.\(^2\) The data consist of: a) the head count poverty rate, which is defined as the proportion of households whose income (or consumption) is less than the per capita $1.25-a-day; b) the average per capita monthly income (or consumption) measured in 2005 PPP-adjusted dollars, and; c) the Gini index of income inequality.

This section conducts two types of estimations. In the first one, a parametric panel with and without control for endogeneity is used. In the second one, similar estimations are carried out using a nonparametric model. In both cases, the difference between the estimates with and without control for endogeneity lies in the previous estimation of (3), yielding a growth variable that is free of the effects of inequality. This new variable will substitute \( \Delta y_{i,t} \) in the estimation of elasticities into (2).

Parametric estimations for equation (2), with and without control for endogeneity, are displayed in Table 1. The “With Control” inference took into consideration that output growth is a function of current, \( I_t \), and lagged, \( I_{t-1} \), inequalities and of their growth, \( \Delta I \).\(^3\) The comparison of results shows that if the effect of inequality on growth is neglected, the effect of growth elasticity of poverty tends to be overestimated.

<table>
<thead>
<tr>
<th></th>
<th>Without Control</th>
<th>With Control</th>
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<tbody>
<tr>
<td></td>
<td>Coeff.</td>
<td>SE</td>
</tr>
<tr>
<td>Growth Elasticity</td>
<td>-3.0544*</td>
<td>0.1978</td>
</tr>
<tr>
<td>Inequality Elasticity</td>
<td>4.8325*</td>
<td>0.4968</td>
</tr>
</tbody>
</table>

Notes: *p-value < 0.01 and #p-value < 0.10.

In the second group of estimations, estimators of instrumental variables based on sieve methods were used to approximate the unknown function \( g \) through an expansion of series \( g(x) = \sum_{j=1}^{\infty} b_j \psi_j(x) \), with \( \{ \psi_j : j = 1, 2, \ldots \} \) a complete orthonormal basis of \( L_2[0, 1] \), the

\(^2\) The number of information is smaller than that used in Chambers & Dhongde (2011), as it was necessary to construct information on lagged inequality. Because of that, the following data were lost: i) one piece of information for each country and ii) countries with only one observation.

\(^3\) Results omitted due to space constraints.
control for endogeneity was obtained by expansions \( m(w) = \sum_{k=1}^{\infty} m_k \psi_k(w) \) and density \( f_{XW} = \sum_{j=1}^{\infty} \sum_{k=1}^{\infty} c_{jk} \psi_j(x) \psi_k(w), \) where:

\[
    b_j = \int_{[0,1]} g(x) \psi_j(x) dx,
\]

\[
    m_k = \int_{[0,1]} m(w) \psi_k(w) dw,
\]

\[
    c_{jk} = \int_{[0,1]} f_{XW}(x, w) \psi_j(x) \psi_k(w) dx dw.
\]

To obtain estimators for the unknown function \( g, \) and denoting the sample as \( \{ Y_i, X_i, W_j : i = 1, \ldots, n \}, \) the estimators for unknown terms \( b_j, m, m_k \) and \( f_{XW}, \) are determined by using \( \hat{m}_k = n^{-1} \sum_{i=1}^{n} m_k \psi_k(W_i), \) \( \hat{c}_{jk} = n^{-1} \sum_{i=1}^{n} \psi_j(X_i) \psi_k(W_i), \) \( \hat{m}(w) = \sum_{k=1}^{J_n} \hat{m}_k \psi_k(w) \) and finally \( f_{XW} = \sum_{j=1}^{J_n} \sum_{k=1}^{J_n} \hat{c}_{jk} \psi_j(x) \psi_k(w), \) where \( J_n \) denotes a truncation point for the expansions. The inference is based on a thin-plate spline expansion and on the regularization procedure (Horowitz, 2012), using automatic smoothness selection for penalized spline regression, as defined in Wood (2006).

The estimation of equation (2), without controlling for the effect of inequality on growth, is demonstrated in Figure 1, which shows the marginal effects estimated by the nonparametric method and the respective 5% confidence intervals. Panel ‘a’ depicts the effect of growth on poverty. The curve indicates a negative relationship with elasticity, ranging between 3 and -2. The results are in line with those obtained in the previous literature, especially with those of Chambers & Dhongde (2011). Conversely, inequality has a positive relationship with poverty, whose elasticity ranges between -2 and 1.

The effect of inequality on growth is controlled by the sieve specification system using \( I_t, I_{t-1}, \) and \( \Delta I \) as the set of instruments. Figure 2 displays the estimations for inequality elasticity of poverty and for growth elasticity of poverty, controlling for the effect of inequality on growth. In panel ‘c’, note that the relationship between growth and poverty remains negative, but it ranges between 1 and -2. Moreover, the nonlinear association between growth and inequality suggested in (2) seems to be corroborated, since when the effect of inequality on growth is eliminated, the growth elasticity of poverty becomes linear. That is, by comparing this result with that of panel ‘a’ (Figure 1), the fact that the effect of inequality on growth is overlooked leads to the overestimation of growth elasticity of poverty. On the other hand, inequality elasticity of poverty changed very slightly.
Figure 1: Growth Elasticity of Poverty (Panel a) and Inequality Elasticity of Poverty (Panel b). Estimation without Endogeneity Control

Figure 2: Growth Elasticity of Poverty (Panel c) and Inequality Elasticity of Poverty (Panel d). Estimation with Endogeneity Control

The comparisons of parametric results with nonparametric ones, either with or without control, indicate that the former overestimate the elasticities of poverty, mainly the growth elasticity of poverty. In short, the use of a new empirical method allows concluding that the previous estimations of the growth elasticity of poverty are biased owing to the fact that
the endogenous relationship between income inequality and economic growth is neglected. Furthermore, this overestimation is aggravated by the use of parametric models in the empirical approach.

3. Final Remarks

This note suggests a new empirical strategy for the calculation of poverty elasticities. The existence of endogeneity between growth and income inequality was taken into account. This new rule suggests that previous empirical studies overestimated the effect of growth on poverty. So, the influences of economic crises and/or expansions on poverty are lower than those suggested by international reports, i.e., MDG (2010). To estimate the real growth elasticity of poverty, it is necessary to assess the nonlinear relationships between income distribution and output dynamics.

4. References


