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POVERTY ELASTICITY: A NOTE ON A NEW EMPIRICAL APPROACH

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

JEL Codes: D31, E62, H2, P16

Keywords: endogeneity, poverty elasticity

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, and 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 percent 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 percent a year from the 2000s), and the decrease in poverty level by approximately 60 percent (Chandy and 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.

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Based on this, Ravallion and 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, 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:

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

that is, 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:

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

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

Since then, equation (2) has been the basis for predicting the effect of economic growth on poverty. The preliminary results of Ravallion and Chen (1997), based on OLS estimations, indicated growth elasticity of poverty between −2 and −4, that is, a 1 percent growth in the average income would reduce poverty by 2 to 4 percent.[1] In summary, studies have focused on the development of new inference methods and on the construction of more representative databases. However, two important issues have been neglected: in (1)–(2), both $y_{i,t}$ and $\Delta y_{i,t}$ can be endogenous; and the functional form (1)–(2) may be incorrect.

This endogeneity can be generated by two main mechanisms. The first is the simultaneous determination of poverty and growth, generating a correlation with the component error $e_{i,t}$, and thus making the OLS estimations invalid. This type of endogeneity can be explained in two ways: (i) by the presence of non-observed factors that affect these two components simultaneously, such as the effects of trade openness on poverty and growth (Santos-Paulino, 2012), or else, as discussed in Beck *et al.* (2005), a process of financial development that simultaneously affects poverty, growth and inequality; and (ii) by the fact that the pattern of growth can directly impact (and in the same period) the measure of poverty, via effects of inequality and distribution, as discussed in White and Anderson (2001) and the famous Bourguignon's (2004) Poverty–Growth–Inequality Triangle.

The second problem that may bias this estimation lies in the assumed functional form for this relationship between poverty, growth, and inequality. In the specifications given by equations (1) and (2) the linear form assumes that the effects of growth on poverty and inequality are constant and independent of the levels of growth and inequality. However, this relationship is constantly challenged in the literature. White and Anderson (2001), for example, show that the pattern of inequality affects unevenly the pattern of poverty reduction, with different effects depending on the initial level of inequality. Non-linear mechanisms between poverty and growth also explain the so-called poverty traps (Ravallion, 2012), which prevent the convergence of levels of poverty. Thus the assumption of a

[1]For a summary, see Chambers and Dhongde (2011).

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constant linear relationship between growth, inequality, and poverty may bias the estimates of equations (1) and (2) due to a problem of incorrect specification, when in fact these relationships are non-linear.

Therefore, obtaining parameters from equations (1) or (2) can produce a severely biased estimation of the effect of economic growth on poverty, due to possible endogeneity problems and incorrect functional form. 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.

Another contribution of our article is to identify the direct and indirect effects of growth and inequality on poverty and inequality. Banerjee and Duflo (2003), for instance, assert that economic growth has a non-linear relationship with inequality. Several functional forms are tested, but the basic equation is:

$$\Delta y_{it} = y_{i0} + k(\Delta I_{i,t}) + g(I_{i,t}) + v_i + u_{it} \tag{3}$$

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

In other words, inequality has direct and indirect effects on poverty. In our estimation methodology indirect effects of inequality on poverty are modeled by specifying the set of instruments for growth, which capture the effects of past values of inequality on growth.

Therefore, this note proposes estimating poverty elasticities by controlling for possible endogeneity and capturing the non-linearities using a non-parametric estimation methodology system of equations denoted by (1) and (2) for a database similar to that of Chambers and Dhongde (2011). The empirical approach is based on a non-parametric estimation of models with instrumental variables using the methods of sieves (e.g., Ai and Chen, 2003; Horowitz, 2012). This estimator is based on the estimation of unknown function g in the equation:

$$Y = g(X) + U; \quad E(U|W = w) = 0, \tag{4}$$

or equivalent to

$$E(Y - g(x)|W = w) = 0, \tag{5}$$

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 non-parametric 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.

[2]The number of observations is smaller than that used in Chambers and 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.

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TABLE 1
ELASTICITY OF POVERTY; PARAMETRIC ESTIMATES

	With no Control		With Control	
	Coeff.	S.E.	Coeff.	S.E.
Growth elasticity	−3.0544*	0.1978	−2.1282#	1.1523
Inequality elasticity	4.8325*	0.4968	4.4279*	0.7938

Note: $^*p < 0.01$, $^{\#}p < 0.10$.

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 non-parametric model. In both cases, the difference between the estimates with control and without control for endogeneity lies in the previous estimation of (3), yielding a growth variable that is free of the effects of endogeneity. This new variable will substitute $\Delta y_{i,t}$ in the estimation of elasticities into (2).

Parametric estimations for equation (2), with control and with no 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, ΔI.[3] The comparison of results shows that if the endogeneity is neglected, the effect of growth elasticity of poverty tends to be overestimated.

To estimate the non-linear relations between the dependent variable poverty and inequality and growth explanatory variables, we follow the literature on non-parametric estimation with instrumental variables using the concept of sieves. This class of estimators is based on the approximation of an unknown function by a series expansion, projecting this relation in a linear combination of a set of orthogonal basis in the form $g(x) = \sum_{j=1}^{\infty} b_j \psi_j(x)$. Figure 1 shows an example basis $\psi_j(x)$ with order $j = 5$ built for approximating a variable x defined on the domain (0, 1). This projection allows approximation with the desired precision unknown functions via piecewise polynomials, with accuracy determined by the order of the expansion. This accuracy is related to the bias and variance of the sieves approximation to the unknown function $g(x)$. The determination of the optimal number of basis functions can be performed by several methods, the most common being generalized cross-validation, as discussed in Wood (2006). Sieves methods are numerically more stable than alternative methods such as kernel functions, are easier to implement, and also have properties of optimal convergence rates simultaneously for both non-parametric and parametric components, as discussed in Ai and Chen (2003) and Blundell *et al.* (2007).

In the second group of inferences, 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 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:

[3]Results omitted due to space constraints.

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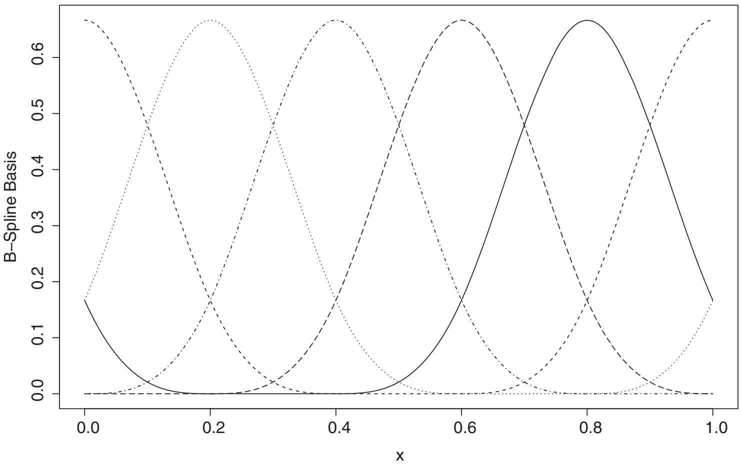

Figure 1. Spline Basis for a Sieve Expansion

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

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

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

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 $\hat{m}_k = n^{-1}\sum_{k=1}^{\infty} m_k\psi_k(W_i)$, $\hat{c}_{jk} = n^{-1}\sum_{k=1}^{\infty}\psi_j(X_i)\psi_k(W_i)$, $\hat{m}(w) = \sum_{k=1}^{J_n}\hat{m}_k\psi_k(w)$ and finally $\hat{f}_{XW} = \sum_{j=1}^{J_n}\sum_{k=1}^{J_n}\hat{c}_{jk}\psi_j(x)\psi_k(w)$, 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 2, which shows the marginal effects estimated by the non-parametric method and the respective 95 percent confidence intervals. Figure 2a 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 and Dhongde (2011). Conversely, inequality has a positive relationship with poverty, whose elasticity ranges between –2 and 1.

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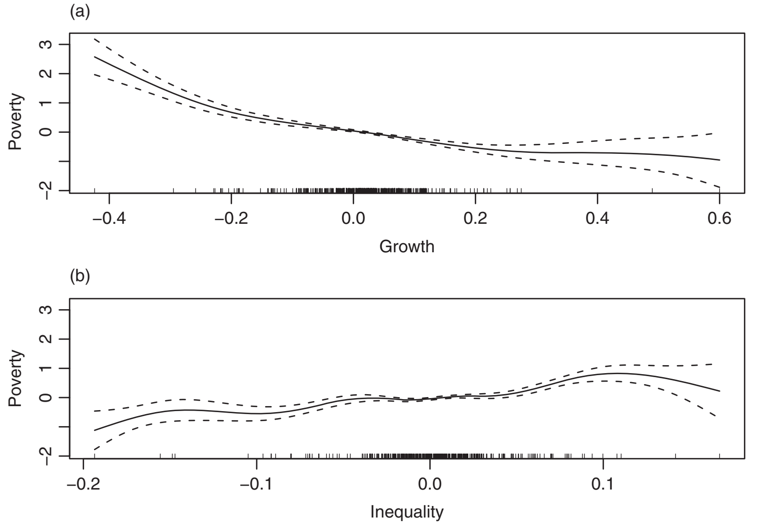

Figure 2. Growth Elasticity of Poverty (a) and Inequality Elasticity of Poverty (b). Estimation with no Endogeneity Control

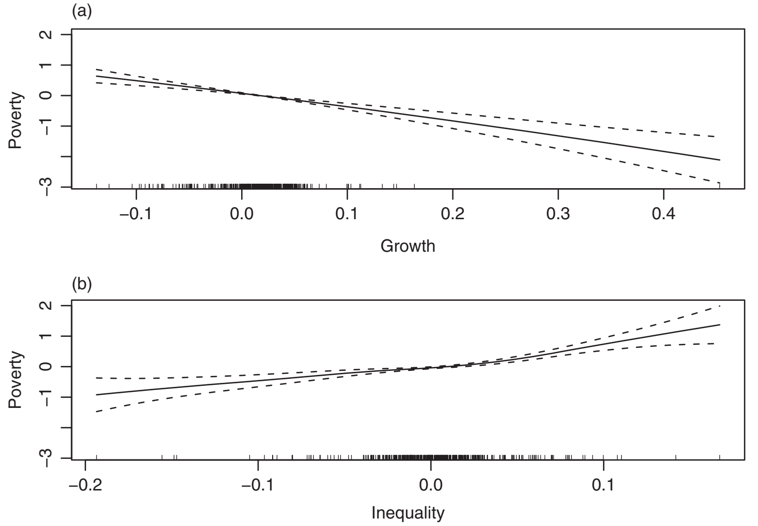

Figure 3. Growth Elasticity of Poverty (a) and Inequality Elasticity of Poverty (b). Estimation with Endogeneity Control

The effect of inequality on growth is controlled by the sieve specification system using I_t, I_{t-1} and ΔI as the set of instruments. Figure 3 displays the estimations for inequality elasticity of poverty and for growth elasticity of poverty, controlling for the effect of inequality on growth. In Figure 3a, note that the relationship between growth and poverty remains negative, but it ranges between

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1 and −2. Moreover, the non-linear association between growth and inequality suggested in (2) seems to be corroborated, since when the effect of inequality on growth is controlled, the growth elasticity of poverty becomes linear. That is, by comparing this result with that of (Figure 2a), 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.

To check the validity of the procedure for non-parametric estimation with instrumental variables, we need to check if indeed there is the problem of endogeneity, and especially if the form of the procedure performed, assuming that growth is an endogenous variable and inequality is exogenous, following Banerjee and Duflo (2003) for construction of the instruments set, is valid.

This analysis is based on two procedures, the first using the non-parametric endogeneity test proposed by Blundell and Horowitz (2007), which uses an estimate based on kernel functions and Fourier Series expansions for the sieves estimations, and a similar version using the thin-plate splines assumed in our article. The Blundell and Horowitz test can be interpreted as a non-parametric version of the Wu–Hausmann endogeneity test.

In the usual Wu–Hausmann procedure the test statistic is based on the standardized quadratic difference between the estimator obtained by ordinary least squares and instrumental variables estimator. In Blundell and Horowitz (2007), a test statistic is formulated in terms of the integrated quadratic differences between the usual non-parametric and the non-parametric estimator controlling for endogeneity (see Blundell and Horowitz, 2007, pp. 1038–40). The Blundell and Horowitz estimator is based on kernel regression, which involves additionally the determination of bandwidths for these estimations. To perform a procedure analogous to that proposed in Blundell and Horowitz (2007), we replace the estimation by kernel estimation by our method based on splines. In this case we use the asymptotic critical values of this test, since the analytical approach proposed in Blundell and Horowitz (2007) is specific to the kernel method assumed.

The results obtained with the Blundell and Horowitz (2007) test indicate rejection of the null hypothesis of exogeneity for the growth variable, using the same set of instruments used in the non-parametric estimation, obtaining a test statistic with a value of 6.6380, while the critical values of 95 percent and 90 percent significance levels are given by the values of 6.3104 and 4.4534, respectively, using the analytical approximation for the asymptotic critical values, indicating rejection of the null hypothesis of exogeneity. In the version of the test using splines, the obtained test statistic takes the value of 7.387, indicating a p-value of 0.005 for the null hypothesis of exogeneity using the standard asymptotic distribution, and again rejecting the null hypothesis of exogeneity. The non-parametric tests for endogeneity for the inequality variable obtain opposite results, not rejecting the null hypothesis of exogeneity, with a test statistic in the Blundell and Horowitz (2007) procedure with a value of 0.1930, which compared to the critical values of 0.6847 and 0.4905, respectively, for 95 percent and 90 percent significance levels obtained by the analytical approximation, indicate the maintainability of the null hypothesis of exogeneity for inequality. The test based on splines obtains a statistical test with a value of 2.253, corresponding to a p-value of 0.133 for the null

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hypothesis of endogeneity, also supporting the assumption of exogeneity assumed for inequality.

Comparison of parametric results with non-parametric ones, either with or without control, indicates that the former overestimate the elasticities of poverty, mainly the growth elasticity of poverty. In short, the use of a new empirical method allows us to conclude that the previous estimations of the growth elasticity of poverty are biased owing to the fact that the endogeneity problem is neglected. Furthermore, this overestimation is aggravated by the use of linear parametric models in the empirical approach.

3. Final Remarks

This note suggests a new empirical strategy for the calculation of poverty elasticities, controlling for endogeneity and robust to incorrect parametric specifications. This new rule suggests that previous empirical studies overestimated the effect of growth on poverty. Thus, the influence of economic crises and/or expansions on poverty is lower than that suggested by international reports (i.e., MDG, 2010).

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