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A NON-PARAMETRIC MEASURE OF POVERTY ELASTICITY

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We estimate the growth elasticity of poverty (GEP) using recently developed non-parametric panel methods and the most up-to-date and extensive poverty data from the World Bank, which exceeds 500 observations in size and represents more than 96 percent of the developing world's population. Unlike previous studies which rely on parametric models, we employ a non-parametric approach which captures the non-linearity in the relationship between growth, inequality, and poverty. We find that the growth elasticity of poverty is higher for countries with fairly equal income distributions, and declines in nations with greater income disparities. Moreover, when controlling for differences in estimation technique, we find that the reported values of the GEP in the literature (based on the World Bank's now-defunct 1993-PPP based poverty data) are systematically larger in magnitude than estimates based on the latest 2005-PPP based data.

JEL Codes: C14, C23, I32, O15

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1. Introduction

The first of the United Nations Millennium Development Goals is to halve 1990 world poverty levels by 2015. One of many strategies advocated by policy makers to help achieve this goal is to foster economic growth. The rational is straightforward: rising mean incomes without any change in income distribution must lead to lower levels of absolute poverty as fewer households fall below the corresponding poverty line. As a practical consideration, however, there is no guarantee that policies that promote growth will not, at the same time, inflate income disparities. As Ravallion (2008) aptly notes, "Economic growth is hugely important to sustain poverty reduction . . . but we have also got to realize (that we need) policies and programs in place which would allow people to participate in and contribute to that growth. . . . So, it's a process of inclusive growth . . . and a big factor there is reducing inequalities of opportunity." Given the important role of a nation's income distribution in determining the efficacy of any growth-based

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poverty alleviation strategy, we estimate the growth elasticity of poverty (GEP)—i.e. the extent to which poverty declines if income increases by 1 percent, for a given level of inequality.

This paper is the first attempt (we are aware of) to adopt a non-parametric approach to estimate the growth elasticity of poverty. Additionally, we use the latest available data from the World Bank. Spanning the period between 1977 and 2007, our dataset is more extensive compared to previous studies and includes 116 developing countries that collectively represent more than 96 percent of the developing world's population. This extensive coverage is especially important because estimates of the GEP based on cross-country datasets are highly sensitive to the number of countries included and time spells covered (see Adams, 2004).

Conventionally, poverty is defined in terms of income and is measured as the proportion of people whose income falls short of a benchmark level called the poverty line. When measuring absolute poverty, the poverty line is fixed in terms of the cost of basic necessities or caloric intake, adjusting for inflation. For instance, the poverty line used by the World Bank for international comparisons is the familiar \$1 per day. The resulting absolute poverty rates depend on two factors, namely, average income and the relative distribution of income. However, the two factors are not independent of each other and growth in income is often accompanied by changes in the distribution of income.[1] Measuring the effect of each factor on poverty is a matter of considerable deliberation in the literature.

The total growth elasticity of poverty measures the responsiveness of poverty due to growth in average income without controlling for changes in the distribution of income. The sign of total GEP is ambiguous since the relationship between growth and poverty depends on how the distribution of income changes during the growth process. Partial growth elasticity of poverty, on the other hand, measures the change in poverty resulting from a change in mean income when the distribution of income is held constant. Kakwani (1993) analytically demonstrates that the partial GEP is negative because absolute poverty must decline if the income of an entire population is increased proportionally and there is no change in the relative distribution of income.[2]

In practice, it is difficult to observe the impact of distribution-neutral growth on poverty in order to obtain an estimate of the partial GEP. If detailed data are available, then the partial GEP can be estimated by holding the Lorenz curve of income distribution constant. This exercise is often referred to in the literature as the decomposition of changes in poverty into growth and inequality effects (Datt and Ravallion, 1992). Decomposition of poverty changes requires data on the distribution of income and hence has been limited to analyzing

[1]The relationship between growth and inequality is not straightforward. The Kuznets Hypothesis (Kuznets, 1955) postulates that there is an inverted U-shaped relationship between the level of economic development and income inequality. There is a large literature both supporting and opposing the hypothesis (see Frazer, 2006, for a review).

[2]Unlike the growth elasticity, it is not straightforward to analytically derive the inequality elasticity of poverty. Often, the inequality elasticity of poverty is derived by assuming a specific functional form for the distribution of income and/or by hypothesizing certain changes in the Lorenz curve. See Kraay (2006), Lopez and Serven (2006), Kakwani and Son (2008), and Bresson (2009, 2010) among others.

changes in poverty in specific nations where such data are available.[3] However, cross-country data typically consists of summary statistics such as the Gini index of income inequality.[4]

In the absence of detailed data on the distribution of income (i.e. the Lorenz curve), the partial GEP is estimated by regressing the change in poverty on changes in average incomes controlling for changes in the Gini index. This more widely used approach, based on cross-country data, estimates the statistical relationship between poverty, growth, and inequality. In the regression analysis, the coefficient on income is the growth elasticity of poverty and the coefficient on the Gini index is the inequality elasticity of poverty. A careful review of prior studies reveals potential problems with both the estimation and specification of the underlying poverty models. To start, these studies use linear parametric regression models despite the generally accepted belief that the relationship between poverty, growth, and income inequality is fairly complex. For instance, we find that although economic growth led to a decline in poverty in most of the countries in our dataset, there were about 10 countries in which poverty increased despite positive growth. In about 40 countries, growth was accompanied with an increase in inequality whereas in about 30 countries, there was a decrease in inequality with economic growth. In countries where inequality rose, contemporaneous poverty rates decreased and increased in roughly equal numbers of nations. The ambiguous nature of the relationship between these variables is echoed by Kraay (2006): "as is well understood, changes in absolute poverty measures are complicated non-linear functions of underlying changes in average income and measures of income inequality."

The fact that the growth elasticity of poverty appears to be a function of both the mean and distribution of income underscores our assertion that the relationship between poverty, average income, and the Gini index should not be assumed to be linear nor estimated using linear regression equations, as is common practice in the literature. By contrast, non-parametric methods are well-suited for estimating non-linear relationships, particularly when the functional form of that relationship is unknown. This is due to the fact that non-parametric estimators approximate the relationship between variables within small neighborhoods of a given point, using data-driven techniques that apply more weight to observations closer to the neighborhood in question, thus producing non-linear estimates of surfaces (or cross-sections) of unknown functional form. This more flexible estimation does come at a price: non-parametric estimators are biased when used over finite samples and this bias grows with the number of independent variables (also known as the curse of dimensionality). However, non-parametric estimators are asymptotically unbiased (i.e. consistent). Fortunately, our dataset is large and our model contains only two independent variables within the non-parametric function, implying very small bias.

[3]For instance, see Bigsten *et al.* (2003) for Ethiopia, Contreras (2003) for Chile, Kolenikov and Shorrocks (2005) for Russia, and Dhongde (2007) for India.

[4]Among several measures of income inequality, the Gini index is the most readily available and hence most widely used index across countries. It varies between 0, which reflects complete equality and 1, which indicates complete inequality (or between 0 and 100 if stated in percentage terms). It is proportional to the area between the diagonal and the Lorenz curve.

Typically, estimates of the GEP in the literature range between –2 and –4, i.e. a 1 percent increase in mean income reduces the poverty rate between 2 and 4 percent. We find that our non-parametric estimates are consistent with these findings and lie within this range. However, we show that the GEP varies significantly with the level of inequality. The GEP is low (–2.2) in nations with higher Gini values (52), but is much larger in magnitude (–3.8) in nations with lower Gini values (32). We also find that the GEP values do not differ significantly when alternate poverty measures such as the poverty gap and the squared poverty gap are used. Furthermore, when re-estimating the GEP using data based on the World Bank's obsolete 1993-PPP rates (instead of the revised 2005-PPP rates), we find that the GEP estimates are nearly one percentage point higher in low inequality nations. This is an important finding because most of the GEP estimates in the literature use data based on the now-defunct 1993-PPP rates.

The remainder of the paper is organized as follows. Section 2 provides a selective review of the literature. Section 3 introduces the non-parametric model we use to estimate the GEP, while data are described in Section 4. Estimation results and robustness exercises are reported in Section 5, and Section 6 concludes.

2. Review of Parametric Models of Poverty Elasticity

Equation (1) below is typical of the linear models used in the literature to measure the relationship between poverty, mean income, and the Gini index:

$$p_{it} = \alpha t + \beta y_{it} + \gamma g_{it} + \lambda_i + e_{it} \tag{1}$$

where p_{it} is the logarithm of headcount poverty measured as the proportion of the population earning income below the poverty line in nation i during time period t, y_{it} is the logarithm of the mean income level, g_{it} is the logarithm of the Gini index, the parameter λ_i captures nation-specific differences between countries, α is the trend rate of change, and e_{it} is a white-noise error term. Taking the first difference of equation (1) yields:

$$\Delta p_{it} = \alpha + \beta \Delta y_{it} + \gamma \Delta g_{it} + \Delta e_{it} \tag{2}$$

where $\Delta p_{it} \equiv p_{it} - p_{i(t-1)}$. Equation (2) represents the standard model in which the partial GEP equals β, and the Gini elasticity is equal to γ. Adams (2004) estimates equation (2) using a panel of 60 developing countries. He finds that when growth is measured by average income from surveys, the growth elasticity of poverty is –5, whereas when growth is measured by GDP per capita, the GEP is about –2. Using data on GDP per capita, Ram (2007) finds similar GEP estimates in a cross section of countries. It is important to emphasize that the standard model in equation (2) restricts the growth (Gini) elasticity of poverty to be constant. While the model includes both mean income and the Gini index as linear regressors, it does not interact these explanatory variables, which effectively prevents inequality from affecting the magnitude of the estimated GEP. Attempting to overcome this problem, Bourguignon (2003) estimates a more sophisticated version of equation (2):

$$(3)\quad \Delta p_{it} = \alpha + \beta \Delta y_{it} + \gamma \Delta g_{it} + \left(\delta_1 \frac{z}{y_{it}} \Delta y_{it} + \delta_2 g_{i0} \Delta y_{it} \right) + \left(\phi_1 \frac{z}{y_{it}} \Delta g_{it} + \phi_2 g_{i0} \Delta g_{it} \right) + e_{it}$$

where z/y_{it} is the ratio of the poverty line to mean income, and g_{i0} is the Gini index in the initial time period. By construction, equation (3) allows the growth and Gini elasticity of poverty to vary with both the initial degree of inequality and the level of development (as measured by the inverse of the ratio of the poverty line to mean income). Bourguignon (2003) uses a panel of approximately 50 countries, and finds that all of the coefficients in equation (3) are statistically significant. However, equation (3) does not specify the functional form in which the rate of economic growth, level of development, and initial degree of inequality interact and affect poverty. The joint effect of these three variables on poverty can be derived theoretically by assuming that incomes are distributed lognormally. Under the assumption of lognormality, the distribution of income is completely specified by the mean income and the Gini index. Bourguignon (2003) finds that imposing a lognormal income distribution leads to improved estimates of GEP. Kalwij and Verschoor (2007) also assume a lognormal distribution and estimate region-specific GEP. They find that the GEP exhibits considerable geographic variation, and that the variation in GEP across regions is largely accounted for by regional differences in the initial distribution of income (see also Besley and Burgess, 2003). However, Bresson (2009) shows that the assumption of lognormality leads to overestimation of the GEP and finds that more flexible functional forms better fit the distribution of income.[5]

The models specified in equations (1) through (3) are used to estimate the partial growth elasticity of poverty. The total GEP can be estimated by regressing changes in poverty on changes in mean income without controlling for changes in the distribution of income. Most of the estimated values of total GEP lie in the range between –2 and –4.[6] Ravallion (1997) tests the hypothesis that the total GEP is lower for countries with high initial inequality levels, by estimating the following model:

$$(4)\quad \Delta p_{it} = [\beta(1 - g_{i0})]\Delta y_{it} + e_{it}$$

where the term in the square brackets equals total GEP. To improve the fit of the model in equation (4), Ravallion (2004) replaces total GEP with $([\beta(1 - g_{i0})]^{\theta}\Delta y_{it})$, where $\theta \geq 1$, which better incorporates the non-linearity in the relationship between the GEP and initial inequality. For a value of $\theta = 3$, he finds that in countries with low initial inequality (a Gini index close to 20) the GEP equals –4, whereas in countries with high initial inequality (a Gini index close to 60), the GEP is very low, close to –0.6. Thus, higher initial inequality considerably limits the effectiveness of growth in lowering poverty.

[5]Klasen and Misselhorn (2008) also assume a lognormal income distribution, but propose an alternative measure termed the semi-elasticity of poverty which estimates absolute rather than proportionate changes in poverty.

[6]Squire (1993), Ravallion (1995), Bruno and Ravallion (1998), and the World Development Report (World Bank, 2001) estimate the GEP to be closer to –2, and Ravallion and Chen (1997) find that the GEP is about –3.

Although researchers are aware of the interdependence between growth and (current and initial) inequality levels, the models used to estimate the GEP either explicitly rule out or heavily restrict this non-linearity. While all of the parametric models discussed above have the advantage of computational simplicity and ease of interpretation, they fail to capture the inherent non-linear relationship between growth, inequality, and the poverty rate. Consequently, non-parametric methods, owing to their ability to estimate unspecified and highly non-linear empirical relationships, are well suited for this task. In the next section, we estimate the GEP conditional on the level of inequality by way of such a model.

3. Non-Parametric Estimation of Poverty Elasticity

Non-parametric regression models rely on data-driven estimation procedures that impose relatively few restrictions on the distribution of the underlying data or the functional form of the model in question. However, non-parametric estimation requires several assumptions to hold, chief among them being the smoothness/continuity of the conditional mean of the dependent variable, the appropriateness of the window width, and the orthogonality of the error term. Consider the general case, where Y is the dependent variable and X is a vector of regressors. The relationship between Y and X is expressed by way of the conditional mean of Y given X, i.e. $Y = m(X) + e$, where $m(X) \equiv E(Y|X)$. A linear parametric model specifies that the conditional mean of Y is a linear function of X, i.e. $E(Y|X) = \alpha + \beta X$. In practice, the relationship between Y and X is rarely so simple.

By contrast, non-parametric models do not specify a model's functional form, but approximate the conditional mean ($m(X)$) using data-driven techniques. A non-parametric panel model that measures the dependence of poverty on mean income and income inequality can be written as follows:

$$p_{it} = m(y_{it}, g_{it}) + \varepsilon_{it} \tag{5}$$

where $m(\cdot)$ is a smooth (but unspecified) function and ε_{it} is an i.i.d. shock. Following the local linear least squares (LLLS) estimation procedure (see Li and Racine, 2007), which we use to construct our initial poverty estimate ($\hat{m}_0(y, g)$), equation (5) is rewritten using a first-order Taylor series expansion around a given, fixed value (y_0, g_0):

$$p_{it} = m(y_0, g_0) + \{y_{it} - y_0, g_{it} - g_0\} \cdot \nabla m(y_0, g_0) + e_{it}. \tag{6}$$

Equation (6) can be further simplified as:

$$p_{it} = \alpha(y_0, g_0) + \{y_{it}, g_{it}\} \cdot \nabla m(y_0, g_0) + e_{it}. \tag{7}$$

Estimation of the fixed parameters $\alpha(y_0, g_0)$ (a scalar equal to $m(y_0, g_0) - (y_0, g_0) \cdot \nabla m(y_0, g_0)$) and $\nabla m(y_0, g_0)$ (a 2×1 vector equal to the gradient of $m(y, g)$ that captures the (local) marginal effect of a change in income or inequality on poverty) proceeds using what is essentially a weighted least squares estimator in which the weights are determined by the product of kernel functions:

$$(8) \qquad \begin{bmatrix} \hat{\alpha}(y_0, g_0) \\ \nabla\hat{m}(y_0, g_0) \end{bmatrix} = (X'K(y_0, g_0|X) \otimes X)^{-1} X'K(y_0, g_0|X) \otimes p$$

where X (in a balanced panel) is an NT × 3 matrix equal to (1, y, g) and the kernel is defined as:

$$(9)\ K(y_0, g_0|X) = \begin{pmatrix} k\left(\frac{y_{11}-y_0}{h_y}\right) \cdot k\left(\frac{g_{11}-g_0}{h_g}\right) & 0 & \cdots & 0 \\ 0 & \ddots & & \vdots \\ \vdots & & & 0 \\ 0 & \cdots & 0 & k\left(\frac{y_{NT}-y_0}{h_y}\right) \cdot k\left(\frac{g_{NT}-g_0}{h_g}\right) \end{pmatrix}.$$

In equation (9), $k(\cdot)$ is a standard-normal probability density function and h_y and h_g are the cross-validated window widths.[7] After the parameters in equation (8) are estimated, it is relatively straightforward to recover the estimated poverty rate ($\hat{m}(y_0, g_0)$), and the marginal effect of higher income or inequality on poverty ($\nabla\hat{m}(y_0, g_0)$) for a given level of income and inequality (y_0, g_0). If the data are first transformed by taking natural logarithms, the resulting marginal effects are interpreted as local estimates of the partial GEP, i.e. $\frac{\partial\hat{m}(y,g)}{\partial y}$, and the partial Gini elasticity of poverty, i.e. $\frac{\partial\hat{m}(y,g)}{\partial g}$.

Since we use panel data, the specification in equation (5) implicitly ignores any nation-specific effects in the data. A more appropriate model is given by:

$$(10) \qquad p_{it} = m(y_{it}, g_{it}) + v_i + \varepsilon_{it}$$

where v_i captures the nation-specific random effects.[8] We estimate equation (10) by following the two-step procedure of Wang (2003), which is specifically designed to efficiently estimate non-parametric random effects panel models.[9] Reminiscent of feasible generalized least squares, the first step of this procedure is to estimate the consistent but inefficient non-parametric model given in equation (5), which is accomplished vis-à-vis LLLS. The resulting residuals contain a predictable heteroscedastic structure, and as such can be used to construct the nation-specific variance covariance matrix (assuming the data are independent across cross-sectional units (i) and stationary across time periods (t)):

[7]Note that assuming a Gaussian probability density function as the kernel is a standard practice (see Pagan and Ullah, 1999) and the assumption does not imply that the joint distribution of the underlying data is Gaussian.

[8]It is worth noting that the poverty rate is completely explained by mean income and the Lorenz curve. However, the GEP is empirically estimated using data on summary statistics of the income distribution, i.e. the Gini index, rather than the entire Lorenz curve. As such, the mean income and the Gini index do not perfectly predict absolute poverty. Hence the existence of country-specific effects should not be ignored.

[9]An accessible description of the Wang (2003) estimation procedure can be found in Li and Racine (2007).

$$\hat{\Sigma} \equiv \hat{\text{cov}}\left(\hat{\varepsilon}_{it} | y_{i1}, \ldots, y_{iT}, g_{i1}, \ldots, g_{iT}\right).$$

Using the consistent estimates of poverty from the first step ($\hat{m}_0(y, g)$) and the above variance covariance matrix ($\hat{\Sigma}$), an efficient two-step estimate of both the poverty surface ($\hat{m}_1(y, g)$), and its corresponding gradient $\left(\nabla m(y, g) = \left[\frac{\partial p}{\partial y}, \frac{\partial p}{\partial g}\right]\right)$ is obtained:

$$\begin{bmatrix} \hat{m}_1(y, g) \\ \nabla \hat{m}_1(y, g) \end{bmatrix} = F_1(y, g)^{-1} F_2(y, g) \tag{11}$$

where,

$$F_1(y, g) = \frac{1}{h_y h_g} \sum_i \sum_t \sigma(t, t) \cdot K(X_{it}) \cdot (1 \quad X_{it})' (1 \quad X_{it})$$

$$F_1(y, g) = \frac{1}{h_y h_g} \sum_i \sum_t K(X_{it}) \cdot (1 \quad X_{it})'$$
$$\times \left[\sigma(t, t) \cdot p_{it} + \sum_{s \neq t} \sigma(t, s) \cdot (p_{is} - \hat{m}_0(y_{is}, g_{is})) \right]$$

$$X_{it} = \left(\frac{y_{it} - y}{h_y}, \frac{g_{it} - g}{h_g} \right)$$

and $\sigma(t, s)$ is the t–s element of $\hat{\Sigma}^{-1}$, h_y and h_g are the respective window widths of mean income and the Gini index, and $K(\cdot)$ is the Gaussian product kernel.

4. Data

We use the most extensive dataset to date compared to previous GEP studies. The data are compiled from PovcalNet, the World Bank's global poverty monitoring database, and are drawn from nearly 675 household surveys, having passed many quality filters. Our data consist of more than 500 observations from 116 developing countries, collectively representing more than 96 percent of the developing world's population, and span the time period 1977 to 2007. Not surprisingly, data drawn from PovcalNet are widely used in international panel studies. Earlier studies, including Kalwij and Verschoor (2007), Ravallion (2005), and Adams (2004), use data from the same source but have smaller sets of countries, owing to the fact that the poverty database is continually updated and expanded. In 2008, the World Bank significantly revised its estimates of global poverty by making use of improved 2005-PPP data (see Chen and Ravallion, 2008). Prior to this revision, World Bank poverty estimates were based on less reliable 1993-PPP data. The revised poverty data are not only of better quality, but boast greater country coverage.

The data consist of: (1) the headcount poverty rate which is defined as the proportion of households whose income (or consumption depending on the underlying survey design) is less than the per capita \$1.25-a-day threshold which is equivalent to \$32.74 per month at 2005-PPP exchange rates;[10] (2) the average per capita monthly income (or consumption) measured in 2005 PPP-adjusted dollars; and (3) the Gini index of income inequality (measured from 0 to 100). A listing of the nations, time periods, and summary statistics is provided in Table 1.[11]

Table 2 summarizes directional changes in headcount poverty, average income levels, and the Gini index. A total of 94 countries with two or more time periods are included and changes are calculated over the longest possible interval between 1977 and 2007. Poverty declined in 65 of the 71 countries which experienced positive economic growth during this period. However, in nearly half of these countries, growth was accompanied by rising income inequality. Poverty increased in many countries in Eastern Europe, Central Asia, Latin America, and Sub-Saharan Africa. Overall, the negative relation between economic growth and poverty is less evident in countries where poverty increased than in countries where poverty declined. Consistent with our earlier assertions, there is empirical evidence that the relationship between these variables is non-linear (see Figure 1).

5. Results

As a benchmark exercise, we estimate the poverty surface ($\hat{m}_0(y, g)$) using LLLS estimation. The Gini index varies from 32 to 52, while monthly mean income varies from \$51 to \$256. Both the income and the Gini index ranges specified above correspond to each variable's respective lower 20th percentile values and highest 80th percentile values over the entire dataset. Given data boundary concerns inherent in non-parametric estimation, these income and Gini domain restrictions help to guarantee adequate data support. To put this into perspective, Figure 1 includes both the estimated surface and a scatter plot of the entire dataset. The general shape of the poverty surface conforms to our *a priori* expectations—i.e. poverty rapidly declines with higher mean income, but only gradually declines with lower values of the Gini index.

To estimate the partial GEP (i.e. $GEP(y, g) \equiv \dfrac{\partial \hat{m}(y, g)}{\partial y}$) for varying degrees of income inequality, we consider three levels of the Gini index: 32, 42, and 52 (labeled g_{low}, g_{middle}, and g_{high}, respectively). Next, holding inequality fixed (at either

[10]In addition to the headcount poverty rate, the World Bank's PovcalNet database also contains two alternate measures of poverty, the poverty gap and the squared poverty gap, which we use to conduct robustness exercises in Section 5.3.

[11]Such a large dataset obviously suffers from unavoidable problems such as measurement errors. Qualitative objections such as equating poverty merely to lack of income and ignoring other dimensions of welfare, combining income and consumption means, measuring income inequality using a Gini index, and drawbacks of the Purchasing Power Parity exchange rates, are acknowledged but are ignored due to a lack of better alternatives. For a detailed discussion on the limitations of the data, see Ferreira and Ravallion (2009).

TABLE 1

Nations, Periods, and Summary Statistics

		Averages		
Country	Years	Headcount Poverty Rate (%)	Monthly Income ($)	Gini Coefficient
Albania	1996, 2002, 05	0.54	150	30.1
Algeria	1988, 95	6.70	123	37.7
Angola	2000	54.31	63	58.6
Argentina (Urban)	1986, 1992, 96, 98, 2002, 05	2.98	369	48.5
Armenia	1996, 98, 2002–03	15.28	88	37.5
Azerbaijan	1995, 2001, 05	7.30	112	29.4
Bangladesh	1983, 85, 88, 1991, 95, 2000, 05	50.25	46	29.9
Belarus	1988, 1993, 1997–98, 2000, 02, 05	0.56	225	26.9
Benin	2003	47.33	53	38.6
Bhutan	2003	26.23	95	46.8
Bolivia	1990, 97, 99, 2002, 05	18.02	188	55.3
Bosnia & Herzegovina	2001, 2004	0.08	350	31.9
Botswana	1985, 1993	33.42	112	57.6
Brazil	1981–1990, 92–93, 95–99, 2001–03, 05, 07	13.49	251	58.7
Bulgaria	1989, 1994, 97, 2001, 03	0.59	277	27.5
Burkina Faso	1994, 98, 2003	65.91	43	45.7
Burundi	1992, 98, 2006	84.00	26	36.3
Cambodia	1994, 2004	44.37	59	40.1
Cameroon	1996, 2001	42.14	68	45.7
Cape Verde	2001	20.56	123	50.5
Central African Rep.	1993, 2003	72.61	33	52.5
Chad	2002	61.94	41	39.8
Chile	1987, 1990, 94, 96, 98, 2000, 03, 06	2.62	368	55.0
China (Rural)	1981, 84, 87, 1990, 93, 96, 99, 2002, 05	61.87	42	31.8
China (Urban)	1981, 84, 87, 1990, 93, 96, 99, 2002, 05	16.25	84	26.6
Colombia	1995, 96, 99, 2000, 03, 06	14.91	211	57.7
Colombia (Urban)	1980, 88–89, 1991	10.88	234	54.3
Comoros	2004	46.11	94	64.3
Congo, Dem. Rep.	2005	59.22	46	44.4
Congo, Rep.	2005	54.10	54	47.3
Costa Rica	1981, 86, 1990, 93, 96, 98, 2000, 01, 03, 05	7.58	239	46.3
Côte d'Ivoire	1985, 87–88, 1993, 95, 98, 2002	16.89	103	40.6
Croatia	1988, 1998–99, 2001, 05	0.00	513	27.5
Djibouti	1996, 2002	11.80	122	38.4
Dominican Republic	1986, 89, 1992, 96, 2000, 03, 05	7.79	222	50.3
Ecuador	1987, 1994, 98, 2003, 05, 07	11.32	222	54.3
Egypt	1990, 95, 99, 2004	2.68	106	31.8
El Salvador	1989, 1995–96, 98, 2000, 02–03, 05	13.66	190	50.8
Ethiopia	1981, 1995, 99, 2005	55.34	44	33.0
Gabon	2005	4.84	150	41.5
Gambia	1998, 2003	50.51	61	48.8
Georgia	1996, 99, 2002, 05	10.42	129	39.1
Ghana	1987, 88, 1991, 98, 2005	44.03	57	38.6
Guatemala	1987, 89, 1998, 2000, 02, 06	25.03	150	56.3
Guinea	1991, 94, 2003	66.48	39	43.6
Guinea-Bissau	1991, 93, 2002	47.42	62	46.5
Guyana	1992, 1998	6.72	195	48.1
Haiti	2001	54.90	64	59.5
Honduras	1990, 92, 94, 97, 99, 2003, 05–06	24.20	145	54.7
Honduras (Urban)	1986	12.98	207	55.1
Hungary	1987, 89, 1993, 98–99, 2002, 04	0.00	363	26.2
India (Rural)	1977, 1983, 87, 1993, 2004	55.74	43	30.7
India (Urban)	1977, 1983, 87, 1993, 2004	45.49	52	35.3

TABLE 1 (*continued*)

Country	Years	Averages: Headcount Poverty Rate (%)	Averages: Monthly Income ($)	Averages: Gini Coefficient
Indonesia (Rural)	1984, 87, 1990, 93, 96, 99, 2002, 05	51.06	44	27.2
Indonesia (Urban)	1984, 87, 1990, 93, 96, 99, 2002, 05	41.57	58	35.4
Iran	1986, 1990, 94, 98, 2005	2.43	223	43.3
Jamaica	1988, 1990, 93, 96, 99, 2002, 04	1.65	224	42.8
Jordan	1986, 1992, 97, 2002, 06	1.16	187	38.5
Kazakhstan	1988, 1993, 96, 2001–03	3.00	168	32.3
Kenya	1992, 94, 97, 2005	26.57	95	47.4
Kyrgyz Republic	1988, 1993, 98–99, 2002, 04	20.30	108	39.4
Lao PDR	1992, 97, 2002	49.65	48	32.7
Latvia	1988, 1993, 96, 98, 2002, 04	0.07	317	31.1
Lesotho	1986, 1993, 95, 2002	47.95	77	57.4
Liberia	2007	83.65	27	52.6
Lithuania	1988, 1993, 96, 98, 2002, 04	0.77	247	31.1
Macedonia	1998, 2000, 02–03	0.99	231	35.1
Madagascar	1980, 1993, 99, 2001, 05	76.97	33	45.9
Malawi	1997, 2004	78.47	32	44.7
Malaysia	1984, 87, 89, 1992, 95, 97, 2004	1.76	250	46.4
Mali	1994, 2001, 06	66.23	38	43.2
Mauritania	1987, 1993, 95, 2000	32.17	75	42.6
Mexico	1984, 89, 1992, 94, 96, 98, 2000, 02, 04, 06	5.52	249	49.8
Moldova	1988, 1992, 97, 99, 2002, 04	19.46	83	34.1
Mongolia	1995, 98, 2002, 05	22.70	73	32.3
Morocco	1984, 1990, 98, 2000, 07	5.28	139	39.9
Mozambique	1996, 2002	78.02	33	45.8
Namibia	1993	49.14	147	74.3
Nepal	1995, 2003	61.78	47	42.5
Nepal (Rural)	1984	80.19	29	28.6
Nepal (Urban)	1984	51.06	49	35.9
Nicaragua	1993, 98, 2001, 05	22.37	130	53.2
Niger	1992, 94, 2005	72.28	35	40.5
Nigeria	1985, 1992, 96, 2003	59.01	45	43.3
Pakistan	1987, 1990, 92, 96, 98, 2001, 04	41.53	53	31.4
Panama	1979, 1991, 95–97, 2000, 02, 04, 06	10.66	274	54.5
Papua New Guinea	1996	35.82	86	50.9
Paraguay	1990, 95, 97, 99, 2002, 05, 07	12.21	231	53.9
Peru	1985, 1990, 94, 96, 2002, 05–06	6.48	227	48.1
Philippines	1985, 88, 1991, 94, 97, 2000, 03, 06	26.61	90	43.6
Poland	1985, 87, 89, 1992, 96, 99, 2002, 05	0.74	293	30.6
Romania	1989, 1992, 94, 98, 2000, 02, 05	2.00	179	28.5
Russian Federation	1988, 1993, 96, 99, 2002, 05	1.60	242	38.2
Rwanda	1984, 2000	69.95	36	37.8
Senegal	1991, 94, 2001, 05	49.40	55	44.0
Sierra Leone	1989, 2003	58.08	48	52.7
Slovak Republic	1988, 1992, 96	0.09	394	21.6
South Africa	1993, 95, 2000	23.98	161	57.9
Sri Lanka	1985, 1990, 95, 2002	16.31	83	35.4
St. Lucia	1995	20.93	99	42.6
Suriname	1999	15.54	186	52.9
Swaziland	1994, 2000	70.72	41	55.7
Tajikistan	1999, 2003–04	34.09	59	32.6
Tanzania	1991, 2000	80.56	28	34.2
Thailand	1981, 88, 1992, 96, 99, 2002, 04	7.01	151	43.8
Timor-Leste	2001	52.94	49	39.5
Togo	2006	38.68	56	34.4

TABLE 1 (*continued*)

Country	Years	Averages: Headcount Poverty Rate (%)	Monthly Income ($)	Gini Coefficient
Trinidad and Tobago	1988, 1992	2.79	226	41.4
Tunisia	1985, 1990, 95, 2000	5.89	157	41.5
Turkey	1987, 1994, 2002, 05	2.04	217	42.8
Turkmenistan	1988, 1993, 98	34.25	64	34.1
Uganda	1989, 1992, 96, 99, 2002, 05	62.07	44	42.6
Ukraine	1988, 1992, 96, 99, 2002, 05	1.06	176	28.3
Uruguay	1981, 89	0.00	406	43.0
Uruguay (Urban)	1992, 96, 98, 2000–01, 05–06	0.37	406	44.5
Uzbekistan	1988, 1998, 2002–03	30.18	88	35.4
Venezuela	1981, 87, 89, 1993, 96, 98, 2003, 05–06	8.76	215	48.1
Vietnam	1992, 98, 2002, 04, 06	39.81	63	37.1
Yemen	1992, 98, 2005	11.65	111	36.9
Zambia	1991, 93, 96, 98, 2002, 04	62.41	46	51.5
Total Observations	524			

TABLE 2

Cross Country Changes in Average Income, Gini Index, and Poverty

	Decreased (65)		Increased (29)	
	Inequality Increased	Inequality Decreased	Inequality Increased	Inequality Decreased
Income increased	32*	27	11	1
Income decreased	1	5	7	10

Note: *Number of countries in each category.

the low, middle, or high level), income is varied over the values $51, $73, $99, $141, $180, $212, and $256. These values correspond to seven income deciles over the entire dataset, beginning with the lowest 20th percentile and terminating at the highest 80th percentile (i.e. 20th, 30th, . . . , 80th percentiles), which helps to guarantee adequate data support. Plots of these estimates are provided in Figure 2, along with 95 percent confidence intervals (which are discussed in Section 5.4).

Finally, the resulting local estimates of the GEP (i.e. $GEP(y, g)$) are averaged to produce an inequality-specific mean GEP. For example, the mean GEP for low inequality nations equals $GEP_{low} = \sum_{y \in Y} GEP(y, g = g_{low})$, where Y denotes the various income percentiles listed above. The mean GEP for median and high inequality nations, denoted GEP_{middle} and GEP_{high}, are calculated in a similar fashion. These results are reported and discussed in Section 5.2.

5.1. *Non-Parametric Hausman Specification Test*

Because equation (10) assumes a random effects specification, it is important to first conduct a non-parametric Hausman specification test to verify that the

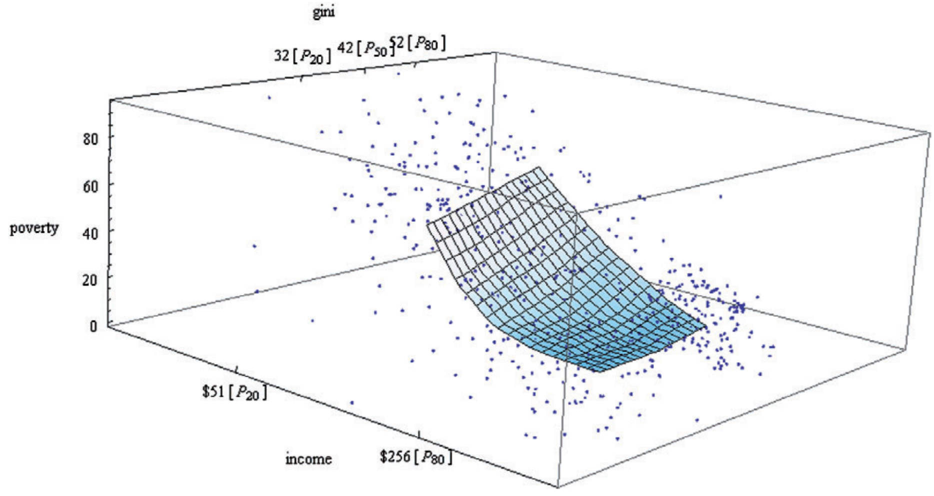

Figure 1. Estimated Poverty Surface [$\hat{m}(y, g)$] and Scatter Plot of Dataset

Notes: The *i*-th dataset percentiles (i.e. P_i) are reported in square brackets. Poverty is measured using the headcount ratio of poverty.

nation-specific differences in poverty rates (i.e. v_i) are not correlated with mean income or the Gini index. To that end, we employ the non-parametric bootstrap $\hat{J}$ specification test of Henderson *et al*. (2008). Like most Hausman-style tests, the random effects specification is appropriate under the null hypothesis, and the $\hat{J}$ test statistic is calculated as follows:

$$\hat{J} = \frac{1}{N \cdot \prod_i T_i} \sum_{i=1}^{N} \sum_{t=1}^{T_i} \hat{u}_{it} \hat{E}_{-it}(\hat{u}_{it} | y_{it}, g_{it}) \hat{f}_{-it}(y_{it}, g_{it}) \tag{12}$$

where $\hat{u}_{it}$ are the residuals from the random effects estimator, $\hat{E}_{-it}$ is the leave-one-out kernel estimator of the conditional mean of the residuals, and $\hat{f}_{-it}$ is the leave-one-out kernel estimator of the joint density of mean income and the Gini index. Henderson *et al*. (2008) describe a wild bootstrap procedure for obtaining the empirical distribution of $\hat{J}$, which we also employ in the present context.[12] Calculating equation (12), we obtain a $\hat{J}$ test statistic of 0.017, with a corresponding p-value of 0.545, thus confirming the validity of the random effects specification.

5.2. *Growth Elasticity of Poverty*

Although the foregoing non-parametric Hausman test affirms the appropriateness of the random effects specification, Table 3 nonetheless provides average estimates of the GEP for both the random effects (i.e. Wang, 2003) and the fixed effects (i.e. Henderson *et al*., 2008) estimators at various inequality levels. Not

[12]See Henderson *et al.* (2008, pp. 268–69) for a detailed description of the wild bootstrap procedure.

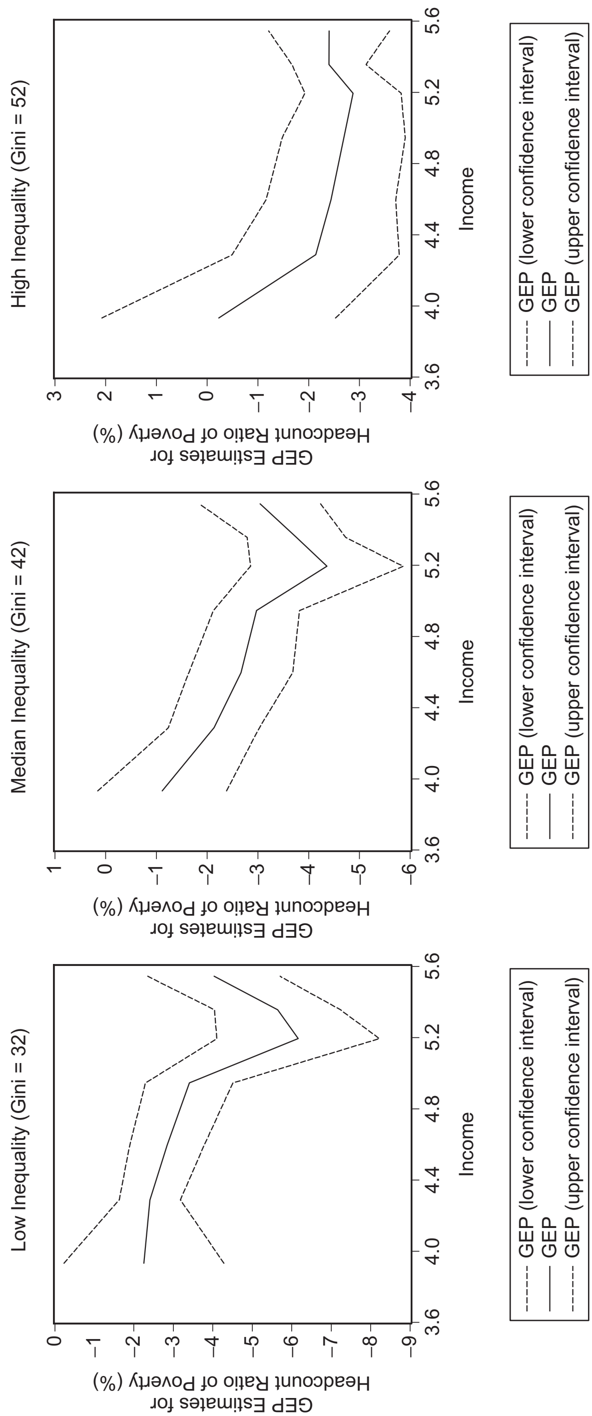

Figure 2. Growth Elasticity of Poverty (GEP) vs. Income for Varying Levels of Inequality

Notes: Income is equal to the natural log of mean per capita monthly income measured in 2005-PPP-adjusted dollars.

TABLE 3

Average Growth Elasticity of Poverty* (GEP)

Inequality	Gini	Alternative GEP Estimates for Headcount Ratio of Poverty: Random Effects	Fixed Effects
Low	32	–3.8	–3.2
Medium	42	–2.9	–2.6
High	52	–2.2	–2.1

Note: *Averaged across income levels.

surprisingly, the results are fairly similar, further suggesting that GEP estimates are robust to differences in the non-parametric estimation procedures.

The mean GEP estimates in Table 3 lie in the range of –2 to –4, and are consistent with previous estimates in the literature that use linear models and 1993-PPP based poverty data. However, we find that the GEP varies with the extent of income inequality. The GEP is small in nations with very unequal distributions of income (i.e. $GEP_{high} = -2.2$), which noticeably contrasts with the much larger (in absolute magnitude) GEP of nations with more egalitarian income distributions (i.e. $GEP_{low} = -3.8$). To put this into perspective, our model predicts that an economy growing at an annual real rate of 4 percent will be able to reduce the headcount poverty ratio by nearly 16 percent if the Gini index is close to 30. But if the Gini index equals 50, the same growth performance will reduce poverty by only 8 percent.

To investigate this issue more closely, we re-estimate the growth elasticity of poverty at various levels of income inequality, while holding mean *income* constant. Specifically, we estimate equation (10), holding monthly mean income fixed at either $51, $141, or $256 (these correspond to the 20th, 50th, and 80th percentile values in the overall dataset), while inequality is varied over seven deciles, beginning with a Gini index of 32 (i.e. the lowest 20th percentile) and terminating at a Gini index of 52 (the highest 80th percentile). Plots of these GEP estimates are provided in Figure 3.[13] As expected, all of the estimated GEPs are negative and decline in *magnitude* with greater inequality. Moreover, nations with lower mean incomes, all else equal, generally have lower magnitude GEP values. This latter distinction is very clear when comparing desperately poor nations (i.e. mean monthly income of $51) with developing nations (i.e. mean monthly income $141–256). The difference in GEP values between very poor and developing nations is nearly two percentage points (for a given level of inequality). In particular, poor nations with high inequality (i.e. Gini index of 52) have corresponding GEP values of nearly zero. This suggests that poverty alleviation strategies based on economic growth alone are not likely to be very effective in these cases. Coordinated reductions in income equality and substantially higher

[13]Note that the results in Figure 3 should not be confused with the Gini elasticity of poverty. The partial growth elasticity of poverty (GEP) is a function of two variables, income and the Gini index. As such, $GEP(y, g)$ is itself a surface, and can be estimated along either income or Gini cross-sections.

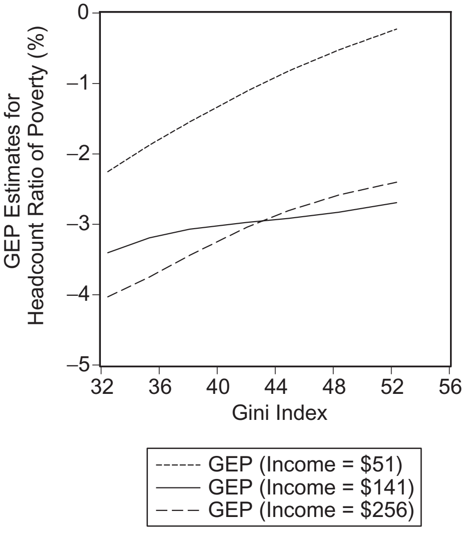

Figure 3. Growth Elasticity of Poverty (GEP) vs. Inequality for Varying Income Levels

economic growth rates are required to meaningfully affect poverty rates in underdeveloped nations with high inequality.

5.3. *Alternative Poverty Measures*

Up to this point, our analysis is based on the most common poverty measure, the headcount ratio (HCR). To ensure that our results are not the product of our preferred poverty metric, we also consider the poverty gap (PG) and the squared poverty gap (SPG). Unlike the HCR, which is not sensitive to the income shortfall of the poor, the poverty gap (PG) captures the *depth* of poverty by measuring the average income shortfall of the poor as a proportion of the poverty line. Similarly, the squared poverty gap (SPG) is equal to the sum of the squared shortfall of the poor's income as a proportion of the poverty line, and is used to measure the *severity* of poverty. The partial GEP will increase in magnitude as we move from the HCR to the PG and the SPG measures because the PG and the SPG measures take into account the average incomes of the poor. If the distribution of income is held constant and overall average incomes increase, then the average incomes of the poor will also increase proportionally. However, as evidenced in Table 4, we find no systematic change in GEP estimates when poverty is measured in these alternate ways. Because empirical studies are forced to rely on the Gini index as a proxy for the distribution of income, they often fail to show a systematic increase in the partial GEP values. We find that for a given level of inequality, GEP estimates for the three poverty measures are not statistically significantly different. In low inequality countries, a 1 percent rise in average income leads to approximately a 3.8 percent decline in all three measures of poverty, while a similar rise in income in high inequality countries reduces HCR and SPG measures by 2.2 percent and PG by 2.5 percent.

TABLE 4
Growth Elasticity of Poverty for Alternative Poverty Measures

	Inequality		
Poverty Measures	Low	Medium	High
Headcount ratio	–3.8	–2.9	–2.2
Lower 95% confidence interval	–5.3	–4.0	–3.5
Upper 95% confidence interval	–2.4	–1.8	–0.8
Poverty gap	–3.7	–3.3	–2.5
Lower 95% confidence interval	–5.2	–4.4	–4.1
Upper 95% confidence interval	–2.3	–2.1	–1.0
Squared poverty gap	–3.9	–2.5	–2.2
Lower 95% confidence interval	–9.7	–9.3	–9.5
Upper 95% confidence interval	1.9	4.3	5.2

5.4. *Confidence Intervals*

In order to determine the robustness of our GEP point-estimates, we calculate 95 percent confidence intervals for our random effects GEP estimates in Figure 2 using a seven-step data-driven bootstrap technique.[14]

Step 1, the random effects estimator, is used to generate in-sample point estimates of the poverty rate $(\hat{m}_h(y_{it}, g_{it}) = E\{p_{it}|y_{it}, g_{it}, h\})$. These estimates are then subtracted from the actual values of poverty to derive the model's residuals $(\hat{\varepsilon} \equiv p - \hat{m}_h)$. In Step 2, in-sample point estimates of the poverty rate are recalculated $(\hat{m}_d(y_{it}, g_{it}) = E\{p_{it}|y_{it}, g_{it}, d\})$ using an over-smoothed window width d, where $d >> h$. In Step 3, for each observation, a counter-factual value of the error term is randomly sampled from the normal distribution, i.e. $\varepsilon^*_{it} \sim \mathcal{N}(0, \hat{\varepsilon}^2_{it})$. In Step 4, a counter-factual dependent variable series is constructed by adding the counter-factual residuals from Step 3 with the over-smoothed conditional expectations of the poverty rate from Step 2, i.e. $p^* \equiv \hat{m}_d + \varepsilon^*$. In Step 5, the random effects estimator is used to generate point estimates of the counter-factual poverty rate at any desired point (y, g), i.e. $(m^*_h(y, g) = E\{p^*_{it}|y, g, h\})$. The original dependent variable and the over-smoothed window widths are used to calculate the conditional mean at the same arbitrary point (y, g), i.e. $\hat{m}_d(y, g) = E\{p_{it}|y, g, d\}$. Next, the difference between the two estimators is calculated, i.e. $\Delta = m^*_h(y, g) - \hat{m}_d(y, g)$. Step 6 simply repeats Step 5 at each point of interest (y, g) 250 times, and the upper (α) and lower (β) confidence intervals at that point are estimated—i.e. $Pr[\beta \leq \Delta \leq \alpha] = 0.95$. Finally, in Step 7, as is common practice, the confidence intervals from Step 6 are re-centered and the reported confidence intervals are thus $\left[\hat{m}_h - \frac{\alpha - \beta}{2}, \hat{m}_h + \frac{\alpha - \beta}{2}\right]$.

These confidence intervals were averaged to determine the 95 percent confidence intervals for the mean GEP values reported in Table 4. Examining the

[14]The data-driven confidence intervals were non-parametrically calculated using the "wild bootstrap" procedure described in Shao and Tu (1995). We prefer the confidence interval approach to the stronger confidence band approach because we are chiefly concerned with the distribution of the non-parametric point estimates of the GEP, conditional on *specific* values of income and inequality, which is what the confidence intervals reflect.

results in Table 4, our basic conclusions are unaltered: the GEP is probably no larger than 4.0–5.3 percent (in absolute magnitude) in nations with more equal income distributions, and the efficacy of growth-driven poverty strategies declines with higher inequality. In high inequality nations, the GEP is 0.8–3.5 percent (in absolute magnitude), marking about a 1.7 percentage-point decline in value as compared to nations with low inequality.

These confidence intervals also provide an opportunity to test whether the mean GEP estimates (for headcount poverty) are statistically different across inequality groups. Starting with low inequality countries, GEP_{low} (–3.8) lies outside the confidence intervals of the growth elasticity of poverty for high inequality countries. Moreover, GEP_{high} (i.e. –2.2) lies outside the confidence intervals of the low inequality mean GEP. Thus, GEP_{low} is statistically different from the high inequality mean GEP estimate. Although the confidence intervals of high and low inequality GEPs slightly overlap, their respective mean point estimates are statistically distinct at the 5 percent level of significance. However, GEP_{middle} *does* lie in the 95 percent confidence intervals of both GEP_{low} and GEP_{high}, implying that the middle inequality GEP is not statistically different from high and low inequality GEP at the 5 percent level of significance.

Finally, the confidence intervals for the poverty gap-based GEP estimates are remarkably similar to those for headcount poverty. However, the confidence intervals for GEP estimates based on the squared poverty gap are very wide, with lower confidence values averaging –9.5 percent, and upper confidence intervals averaging +3.8 percent. Given the width of these confidence intervals, little can be inferred except that the average GEP estimates of low, median, and high inequality nations are not statistically different when poverty is measured using the squared poverty gap.

5.5. *The Effect of New Purchasing Power Parity Measures*

As discussed in Section 4, the World Bank recently revised its estimates of global poverty. The previous global poverty line of \$1.08 was based on 1993-PPP rates and was revised to \$1.25 at 2005-PPP rates. Updating the poverty line and the subsequent recalculation of poverty levels revealed that the number of poor people in the world was nearly 500 million greater than previously thought.[15] Most of the prior estimates of the growth elasticity of poverty in the literature were based on the now-obsolete 1993-PPP rates (e.g. Kalwij and Verschoor (2007), Ravallion (2005), and Adams (2004) use this older dataset).

In order to better compare our results with the existing literature and disentangle the competing effects of improved data and empirical methods on our estimates, we repeat the random effects estimates of equation (10) using the "legacy" 1993-PPP based data. The estimates, shown in Table 5, provide some interesting results. The magnitude of the GEP estimates are larger using the legacy data, with the (absolute value) of the difference between the estimates declining

[15]Chen and Ravallion (2008) note that although the updated poverty line led to a rise in the global poverty count, the rate of reduction in headcount poverty was fairly similar between estimates based on the old and new data (i.e. the level of poverty is affected, but the secular downward trend in poverty rates still remains).

TABLE 5
Growth Elasticity of Poverty (GEP) Based on Different Purchasing Power Parity Measures

		Alternative GEP Estimators for Headcount Ratio of Poverty*	
Inequality	Gini	1993-PPP	2005-PPP
Low	32	–4.7	–3.8
Medium	42	–3.6	–2.9
High	52	–2.5	–2.2

Note: *Based on the confidence intervals, the alternative GEP estimates are not statistically significant.

with higher inequality. For low-inequality nations the average GEP is –4.7 (1993-PPP) compared to –3.8 (2005-PPP), while in medium inequality nations, the average GEP is –3.6 (1993-PPP) versus –2.9 (2005-PPP), and in high inequality nations, the difference between the estimates shrinks to only 0.3 percentage points (–2.5 versus –2.2). In all three cases, the point estimates based on the 1993-PPP data lie within the corresponding 95 percent confidence intervals for the 2005-PPP based estimates (see Table 4) and are thus not statistically different at the 5 percent level. Nonetheless, the ultimate point of this exercise is not to conduct hypothesis tests regarding the equality of parameter estimates derived from separate samples, but rather to observe if there are systematic differences in said estimates holding the estimation methodology fixed. With regard to this latter question, we can unambiguously conclude that the magnitudes of GEP estimates from the 1993-PPP data are universally larger.

6. Conclusions

To date, all the poverty models in the literature use linear parametric regression analysis despite cross-country evidence that the relationship between growth, inequality, and poverty is highly non-linear. This paper is the first to use non-parametric techniques to estimate the growth elasticity of poverty, which is well suited for estimating smooth non-linear surfaces of unknown functional form. Additionally, we use the most extensive dataset from the World Bank's poverty monitoring database, which reflect the World Bank's updated PPP measures.

Our estimates are shown to be robust to changes in estimation technique and choice of poverty measure, and fall broadly within the range of "traditional" estimates in the literature (i.e. between –2 and –4). We also find that the GEP is largely dependent on a nation's level of income inequality, which has important public policy implications. Finally, we discover that the World Bank's switch from 1993- to 2005-PPP based poverty measures affects the resulting GEP estimates in a systematic way. Specifically, GEP estimates based on the 1993-PPP measures are, in every instance, higher than estimates derived from the 2005-PPP data.

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