On the Turning Point in the Inequality-Development Relationship: Evidence from Six Inequality Measures

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This paper looks at the relationship between income inequality and economic development (per capita GNP) via six frequently used measures of income inequality. Applying multivariate instead of single-equation estimation to a widely used data set, we show that, contrary to previous results, the six turning points corresponding to each of the six inequality indices are not significantly different from each other. Constraining the six turning points to equal each other, we find a unique and significant turning point exists for the LDCs in this sample. These results are also confirmed for a sample that includes an expanded group of LDCs.

I. Introduction

The existence of a turning point in the relationship between aggregate income inequality and economic development has been the subject of much debate since first posited in a classic paper by Kuznets (1955). Kuznets concentrated on time-series data for England, Germany and the United States.[1] Subsequent studies have relied mostly on cross-sectional data from countries at different income levels as the basis of what has become known as the Kuznets inverted-U hypothesis: income inequality increases during the early phases of economic development but a turning point exists after which inequality declines. For example, Ahluwalia (1976), Ram (1995) and Sundrum (1990) have presented cross-sectional evidence favorable to the inverted-U hypothesis.[2] Anand and Kanbur (1993) have criticized this evidence arguing that the functional form used by Ahluwalia (1976) and other researchers to test the inverted-U hypothesis is arbitrary. They apply the Ahluwalia data set to several alternative functional forms that are capable of producing a turning point in the income inequality-per capita income space; the results are markedly different from those presented by Ahluwalia. Moreover, the data are unable to discriminate between the Ahluwalia functional form and some of the alternatives.

1. In a subsequent paper, however, Kuznets (1963, p.12) extended discussion to a cross section that included seven developed and eleven less-developed (LDCs) economies in order to address "...the leading question here: the differences among countries at different levels of development, or the changes over time in the course of development, in the distribution of income among the total population of the country."

2. Recent studies by Bruno *et al*. (1996), Deininger and Squire (1997), Jha (1996), Ram (1997), and Savvides and Stengos (1998) have employed panel data sets. Except for Jha who uses a different panel, the remainder disclaim the existence of an inverted-U relationship.

Anand and Kanbur (1993) demonstrate that the functional form of the relationship between income inequality and the level of income per capita (the inequality-development relationship) depends on the particular inequality index being considered. They derive specific functional forms corresponding to six commonly used inequality indices and the conditions under which each functional form yields a turning point in the inequality-development relationship.[3] Subsequently, they test the inverted-U hypothesis with the functional form appropriate for each index on a cross-country data set that contains the countries in the Ahluwalia sample. They (p.40) conclude that "an obvious feature of the estimates is the wide disparity among them in the fitted inequality-development relationship. They differ vastly in goodness-of-fit, in turning point, and in the predicted behavior of inequality in the long run."

The purpose of this study is to show that when an alternative and preferable estimation method is applied to the widely-cited Ahluwalia-Anand/Kanbur (henceforth AAK) data set, the differences in the six turning points are not significant and a unique and significant turning point in the inequality-development relationship can be established for the LDCs in this sample. Moreover, we are able to confirm these results by expanding the AAK sample cross sectionally. In deriving the six turning points, previous researchers applied single-equation (OLS) estimation to each of the six functional forms. As is well known, in situations where there exist cross-equation correlations, as is likely to be the case with six alternative measures of inequality, joint estimation in a multivariate setting improves the precision of parameter estimates by exploiting information contained in the covariance matrix across equations. The main conclusion of this paper is that the Anand-Kanbur claim that the different inequality measures yield turning points at widely different per capita income levels rests solely on the single estimation method adopted by these authors. When we subject the AAK data set to a multivariate estimation technique, we show that the turning points yielded by the various inequality measures are not significantly different. This finding calls into question the results of the previous cross-sectional literature on the Kuznets hypothesis. As a result, any claims put forward by these studies must be treated with considerable skepticism.

The following section explains the estimation procedure used by previous researchers and provides the rationale for multivariate estimation. Subsequently, Zellner's seemingly unrelated regressions (SUR) model is applied to the AAK data set. Section III expands the AAK sample and repeats the exercise. Income inequality indices for additional countries in the expanded sample are computed with decile shares of income from the World Bank. The final section concludes the paper.

II. Multivariate Estimates of the Inequality-Development Relationship: The AAK Sample

The inequality-development relationship has been extensively tested.[4] Frequently, the inequality index and functional form employed by researchers are arbitrary. In a recent contribution, Anand and Kanbur (1993) examine the theoretical basis underlying the Kuznets process, namely the shift of population from agricultural to nonagricultural sectors in the course

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3. Naturally, the existence of such a turning point is crucial if the inverted-U hypothesis were to be verified.
4. See Adelman and Robinson (1989) and Sundrum (1990) for recent surveys.

of development. They demonstrate that the Kuznets process yields a specific functional form of the inequality-development relationship that depends on the inequality index being considered. They focus on six widely used indices of inequality,[5] and provide the functional form of the inequality-development relationship implied by each index. Using cross-section data for the countries in the Ahluwalia (1976) data set, they estimate the inequality-development relationship for each of the six functional forms.[6] Their estimation method is OLS applied to each of the six equations separately. Along with Ahluwalia, they consider two samples: the full sample (60 countries) and a subsample that includes only LDCs (40 countries).

The application of single-equation estimation to a system of regression equations ignores any correlation that may exist between error terms across equations. In the regression model considered by Anand and Kanbur, each equation estimates the inequality-development relationship. The dependent variable in each equation is a measure of income inequality and the six inequality measures are directly related to each other. It would seem reasonable to expect the error term to exhibit some contemporaneous correlation across equations. The error term introduced into the six different functional forms reflects common unmeasurable or omitted factors that impact the inequality-development relationship. Consequently, an economic shock to this relationship (so as to lead, for example, to a positive deviation from the inverted-U hypothesis) will affect each of the six regression equations in a similar fashion. It is well known that, under such circumstances, considerable efficiency can be gained by estimating the system of regression equations jointly, rather than ignoring any information contained in the cross-equation covariance matrix. In what follows, we allow the error term to be correlated across equations and use the SUR method to incorporate such information into the estimation procedure.[7]

Tables 1 and 2 present SUR estimation results for the two samples considered by AAK and employ the functional form appropriate for each inequality index. The full sample contains six socialist countries. Following Ahluwalia (1976) and Anand and Kanbur (1993), we introduce a dummy variable ($D=1$ for the six socialist countries) as an explanatory variable to account for "consistently lower values of inequality" exhibited by these economies.

Before discussing the results, we examine the appropriateness of SUR estimation by testing whether the variance-covariance matrix across equations is a diagonal matrix. In that case, correlations between disturbances across equations are of no significance and multivariate estimation provides no gain in efficiency. An appropriate test of this hypothesis is the Lagrange multiplier statistic suggested by Breusch and Pagan (1980):

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5. The six indices are: (i) Theil's entropy index (T); (ii) an alternative measure due to Theil (L); (iii) the squared coefficient of variation (S^2); (iv) a decomposable transform of the Atkinson inequality index $A(\varepsilon)$, where is the inequality aversion parameter and the transform is $[1-A(\varepsilon)]^{1-\varepsilon}$; (v) the Gini coefficient (G); and (vi) the variance of log-income (σ^2).

6. For the 60 countries in the Ahluwalia sample, Anand and Kanbur calculated five of the six inequality indices with data on decile shares from Jain (1975). Estimates for the Gini coefficient were taken directly from Jain (1975). Estimates of per capita GNP in US dollars at 1970 prices were those of Ahluwalia (1976). For his study, Ahluwalia did not consider any one of the six inequality indices but looked at the income shares of five different percentile groups.

7. In addition to the intuitive appeal of multivariate estimation, we shall present shortly a Lagrange multiplier test for (the absence of) contemporaneous correlation between error terms across equations.

$$\lambda_{LM} = T \sum_{m=2}^{M} \sum_{n=1}^{m-1} r_{mn}^2, \tag{1}$$

where r_{mn} is the estimated correlation between the OLS residuals of equations m and n, T is the number of observations in each equation and M is the number of equations. Asymptotically, this statistic is distributed as chi-squared with $M(M-1)/2$ degrees of freedom. The value of the λ_{LM} statistic is 556.7 for the full sample and 385.5 for the LDC sample. Clearly, the hypothesis that the variance-covariance matrix is diagonal can be decisively rejected (at the 1 percent significance level).[8]

The SUR parameter estimates, especially those for the LDCs, compare well with the OLS estimates.[9] Of particular interest is the estimate of the turning point corresponding to each inequality index. Focusing on the full sample, two indices (L and G) yield nonpositive or nonreal turning points.[10] Of the remainder, two are significant (5 percent level).[11] As for the LDC sample, all turning points are positive and significant at the 5 percent level (except that for S^2 which is marginally insignificant at the 5 percent level).

Next, we test whether the difference between any pair of (positive) turning points is significant. Differences between turning points and corresponding significance tests are in Tables 3 and 4 for the full and LDC samples respectively. In addition to testing the difference between individual pairs of turning points, we also test the joint hypothesis that all differences between turning points are equal to zero, or alternatively turning points are jointly equal to each other. There are several ways of testing this nonlinear restriction. Although they are asymptotically equivalent, their finite sample distributions are not the same. As the literature does not provide clear-cut guidelines for choosing between them,[12] we compute two commonly used tests. The first is an F-ratio test for the significance of a set of nonlinear restrictions. Assuming that

8. As an additional diagnostic check, I tested for heteroscedasticity via the Breusch-Pagan Lagrange multiplier statistic. This is a test of the hypothesis $\sigma_i^2 = f(\alpha_0 + \alpha' z_i)$ where σ_i^2 is the estimated error variance for observation i and z is a vector of independent variables that includes the explanatory variables, the squares, and cross products of these variables. The null hypothesis holds if $\alpha = 0$. This statistic is asymptotically distributed as chi-squared with degrees of freedom equal to the number of variables in z. The values of this statistic are in Tables 1 and 2. The null hypothesis (homoscedasticity) cannot be rejected in any of the cases at any conventional significance level.

9. It should be emphasized, at this point, that the R^2 and SEE statistics in Tables 1 and 2 do not correspond to their counterparts in single-equation models. The reason is that these measures are based on the transformed residuals, where a consistent estimate of the covariance matrix of the error terms has been used as a weighting matrix to transform the residuals.

10. Anand and Kanbur (1993, Table 2) also find two of the turning points to be nonpositive (the turning point for σ^2 was inadvertently reported as positive in Table 2 by these authors).

11. The estimate of the turning point for each inequality index is a nonlinear function of the parameter estimates. In order to compute the standard error for each turning point the nonlinear function corresponding to each turning point is linearized around the estimated parameters. Then, the standard error is derived using results for the variance and covariance of linear functions of random variables. This method is also used to derive the standard error for differences between pairs of turning points (these will be presented and discussed in the next paragraph). Although Anand and Kanbur (1993) do not provide standard errors for their turning point estimates, our computation of t-statistic ratios for their four positive turning points shows these to be significant.

12. Engle (1984) provides a useful survey of the various tests.

the restrictions can be expressed in the form $c(\theta)=q$ the F-ratio statistic is:

$$\lambda_F=(c(\tilde{\theta})-q)'(Var[c(\tilde{\theta})-q]^{-1}(c(\tilde{\theta})-q)/J \tag{2}$$

where $Var[c(\tilde{\theta})-q]=[\partial c(\tilde{\theta})/\partial\tilde{\theta}']Var(\tilde{\theta})[\partial c(\tilde{\theta})/\partial\tilde{\theta}']'$, $\tilde{\theta}$ is the vector of parameter estimates, and J is the number of restrictions. This statistic follows an F-distribution with $(J, MT-K)$ degrees of freedom, where K is the total number of estimated parameters.[13] The second test is a likelihood ratio test given by:

$$\lambda_{LR}=-2\ln(L_R/L_U)=T\ln\left\{|\tilde{S}_R|/|\tilde{S}_U|\right\} \tag{3}$$

where L_R and L_U are the values of the likelihood functions for the restricted (equal turning points) and the unrestricted models, and $|\tilde{S}_R|$ and $|\tilde{S}_U|$ are the determinants of the restricted and unrestricted maximum likelihood estimators of the variance-covariance matrix (and are used to compute λ_{LR}). This statistic is distributed chi-squared with degrees of freedom equal to the number of restrictions.

Table 3 Differences between Turning Points: Full AAK Sample (60 Countries)

Inequality Index	S^2	$[1-I(2)]^{-1}$	σ^2
T	16.9 (0.251)	-2480.2 (0.816)	-714.4 (0.054)
S^2		-2497.2 (0.820)	-731.3 (0.055)
$[1-I(2)]^{-1}$			1765.8 (0.120)

Note: The numbers in parentheses are *t*-statistics. The symbols ** and * indicate that the difference is significant at the 5 percent and 10 percent level respectively. The various inequality indices are described in the text.

Table 3 shows that, for the full sample, none of the differences between (positive) pairs of turning points is significant. As for the LDCs in Table 4, only four of fifteen differences are significant at the 5 percent level and one at the 10 percent level (two-tail test). The value of the λ_F statistic in (2) is 0.27 and 3.70 for the full and LDC samples respectively. The hypothesis that differences between pairs of turning points are jointly equal to zero cannot be rejected for the full sample (at any conventional level) but can be rejected (5 percent level) for the LDC sample. The value of the likelihood-ratio statistic in (3) is 26.94 for the full sample and 10.80 for the LDC sample. The restriction that turning points are the same across

13. It should be pointed out that λ_F and the well-known Wald test are asymptotically equivalent; Judge *et al.* (1985, p.476), however, argue that λ_F has better finite sample properties and is preferable to the Wald test in the case of small or moderately-sized samples.

equations can be rejected (5 percent level) for the full sample but cannot be rejected (even at the 30 percent level) for the LDC sample. The two test statistics provide conflicting results. In summary, while the six inequality indices yield different turning points, all but a small minority of these differences is statistically insignificant.[14]

Table 4   Differences between Turning Points: LDCs in AAK Sample (40 Countries)

Inequality Index	L	S^2	$[1-\Pi(2)]^{-1}$	G	σ^2
T	-127.1 (1.538)	128.3** (2.381)	-226.8 (1.186)	-125.7 (1.126)	-257.1* (1.930)
L		255.4** (2.248)	-99.8 (0.780)	1.4 (0.009)	-130.0** (2.228)
S^2			-355.1 (1.639)	-254.0 (1.679)	-385.4** (2.492)
$[1-\Pi(2)]^{-1}$				101.2 (0.442)	-30.3 (0.300)
G					-131.4 (0.687)

Note: See note to Table 3.

Given that almost all differences between pairs of turning points are not significant and the inconclusive nature of the λ_F and λ_{LR} test statistics, I reestimated the system via SUR constraining the turning points yielded by the six inequality equations to equal each other. The unique turning point from restricted SUR estimation is 4684.1 and insignificant (*t*-ratio statistic equal to 1.33) for the full sample, and 594.0 and highly significant (*t*-ratio statistic equal to 6.19) for the LDC sample. In conclusion, when the turning point is constrained to be equal across inequality indices, a unique and highly significant turning point in the inequality-development relationship is evident for LDCs. The point beyond which inequality begins to decline is about 600 US dollars at 1970 prices. The same conclusion does not hold when developed and socialist economies are included along with LDCs in the sample.

Some writers have used samples containing LDCs exclusively, expressing doubt about tests of the inverted-U hypothesis that combine data from developed and less-developed economies. Sundrum (1990, p.81) argues that income inequality is lower in developed economies compared to LDCs but this is not due to differences in income alone. Therefore, cross-section studies that include data from both developed (including socialist) economies and LDCs exhibit the tendency for 'double clustering' of the data: because variation in many variables between two groups (developed and less-developed economies) is greater compared to intra-group variation, a tendency exists for data to fall into two distinct clusters. Thus, tests of the Kuznets hypothesis with data from both groups may "... attribute to per capita income the effects of other variables." Bourguignon and Morrisson (1990, p.1120) and Ram (1995) include only

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14. I computed *t*-ratio statistics for the differences in turning points yielded by the OLS estimates (they are not provided by Anand and Kanbur). Four of six differences for the complete sample and eleven of fifteen for the LDC sample are indeed significant. Given the nature of single-equation estimation, no test of the joint hypothesis that all differences between turning points are equal to zero is feasible.

LDCs in their sample, the former arguing that the exclusion of developed economies "... avoids identifying significant income distribution determinants solely on the basis of the difference between developed and developing countries." Our results echo these sentiments.

III. Multivariate Estimates of the Inequality-Development Relationship: An Extension of the AAK Sample

As a way of checking the sensitivity of the results to the choice of sample, I extended the AAK data set with supplementary data on decile shares of income for seventeen LDCs and four developed economies.[15] Several researchers have raised concerns about the comparability of income distribution data across countries insofar as the income concept, population unit and coverage differ between income distribution surveys. Noting these concerns, an effort was made to include additional income distribution data that are comparable in terms of income concept (pre tax income) and population unit (household).[16] I computed the inequality indices (except the Gini coefficient) using the method described in Anand and Kanbur (1993, pp.50-51). The Gini coefficient is derived from a straight-line approximation of the Lorenz curve.

The income distribution surveys refer to different years. For purposes of extending the AAK sample, two issues of concern are the method for computing per capita GNP and the year for which it is computed. As for the year, since Ahluwalia does not specify his procedure for computing per capita GNP, Anand and Kanbur (who use the Ahluwalia figures) assume that the per capita GNP figures correspond to the years of the income distribution surveys. I shall maintain their assumption.[17] As for the method of computing per capita GNP in US dollars at 1970 prices, neither Ahluwalia nor Anand and Kanbur provide any information. Therefore, I adopted the following procedure (all the relevant data are from the *World Tables* of the World Bank): first, GNP deflators with 1970 as base year are obtained from real and nominal GNP figures in local currency. These deflators and nominal GNP figures yield an estimate of real GNP (in 1970 prices) for the year in question in local currency. Finally,

15. The additional LDCs (with the year of the income distribution survey in parentheses) are as follows: Barbados(70), Cyprus (66), Dominican Republic (76), Fiji (68), Greece (59), Hong Kong (71), Indonesia (71), Israel (70), Libya (n.d.), Nepal (76), Sudan (68), Sierra Leone (69), Suriname (62), Trinidad and Tobago (75), Venezuela (62), South Africa (68) and Zimbabwe (65). Additional economies included in the full sample are: Austria (70), Belgium (69), Ireland (73) and Italy (76). In keeping with the spirit of Ahluwalia and Anand and Kanbur who excluded Spain from the sample of LDCs, I excluded Ireland from the LDC sample even though its GNP per capita was lower than some of the LDCs. It should be emphasized, however, that the results reported below remain invariant to the inclusion of Ireland in the LDC sample.

16. Figures on decile shares of income for the additional countries are from the World Bank database and were kindly provided to me by George R.G. Clarke. A more detailed description of the data and the sources can be found in Clarke (1995).

17. For four of the LDCs (Cyprus, Greece, Suriname and Venezuela), the GNP per capita figure corresponding to the year of the income distribution survey was not available. Therefore, I used the figure for the nearest year. As an additional check on the results, I traced income per capita back to the year of the survey with the aid of average annual income-per-capita growth rates (from the *World Development Report* of the World Bank). The results are virtually identical to those reported below. This conclusion echoes the sentiments of Anand and Kanbur (1993, p.50) who claim that using GNP per capita figures that do not match exactly those of the survey year "... is unlikely to make a significant difference to the conclusions."

I used data on dollar exchange rates and population to convert real GNP (in 1970 prices) to per capita dollar terms.

The SUR results for the extended sample of LDCs are in Table 5. They are similar to those of the AAK sample in Table 2. Once more, five of the six estimates of the turning point are highly significant. Three of fifteen differences between pairs of turning points are significant at the 10 percent level (Table 6). The values of the λ_F and λ_{LR} statistics for the joint equality of turning points are 2.20 and 20.41 respectively. Comparison with the critical values shows the null hypothesis cannot be rejected at the 5 percent level for λ_F and the 2.5 percent level for λ_{LR}. Given the inability to reject joint equality of turning points, I constrained the turning point to be equal across equations. The constrained turning point is 540.4 and is highly significant (*t*-statistic equal to 3.33). It is noteworthy that this is not much different from the constrained turning point for the AAK LDC sample.[18] In conclusion, a turning point in the inequality-development relationship identified for the LDCs in the AAK sample is confirmed for an expanded LDC sample. Moreover, the turning points for the two samples are very similar.[19]

Before concluding this section, it is important to note a serious drawback of the data of the AAK studies and this paper: the data are in many cases more than two decades old and are purely cross sectional. Recently, panel data on income inequality have been compiled by the World Bank. Deininger and Squire (1996) describe a high-quality panel data set that contains estimates of the Gini coefficient that are designed to ensure intertemporal and international comparability of income inequality in terms of the recipient unit (household or personal), variable being measured (income or expenditure), and income concept (gross or net). Deininger and Squire (1977) use this data set to test the Kuznets hypothesis and are unable to find any relationship between income per capita and inequality. Ram (1997) uses the estimates for developed countries in this data set and finds that the inequality-development relationship is described by an uninverted-U pattern. Savvides and Stengos (1998) apply the threshold regression model to the Deininger/Squire data set to investigate the possibility that a threshold per capita income level characterizes the inequality-development relationship. They find a significant split in the sample with observations above the threshold displaying an uninverted-U pattern. No discernible pattern can be detected for observations below the threshold. Though it would be interesting to use the same panel data set to compare the turning points yielded

18. The difference in constrained turning point between the AAK LDC sample and the extended LDC sample is insignificant at any conventional level. It is also noteworthy that using GNP per capita figures that correspond to the year of the survey for the four LDCs of the previous footnote yields a turning point of 582.7 (*t*-statistic 3.39), virtually identical to that of the AAK LDC sample.

19. The results for the full sample (available on request) are very similar to those of Table 1. The same two turning points as Table 1 are nonpositive. Differences in turning points are not significant and the hypothesis of joint equality of turning points cannot be rejected (at any conventional level) based on λ_F. One difference with Table 1 is that the estimate of the constrained turning point (3589.1) is highly significant (*t*-statistic equal to 4.02). Given that two of the inequality indices yield nonpositive turning points, it would be inappropriate to claim that a turning point exists for the full sample. Indeed, if the two indices that yield nonpositive turning points are omitted from estimation, the resulting constrained turning point (3905.5) is insignificant (*t*-statistic equal to 0.73).

Table 6   Differences between Turning Points: Expanded LDC Sample (57 Countries)

Inequality Index	L	S^2	$[1-I(2)]^{-1}$	G	σ^2
T	-118.4 (1.172)	35.3 (0.911)	-323.5 (0.706)	-40.7 (1.228)	-399.6[*] (1.734)
L		153.7 (1.155)	-205.0 (0.530)	77.7 (0.949)	-281.2[*] (1.730)
S^2			-358.7 (0.754)	-76.0 (1.153)	-434.9[*] (1.749)
$[1-I(2)]^{-1}$				282.8 (0.632)	-76.1 (0.298)
G					-358.9 (1.645)

Note: See note to Table 3.

by the six inequality measures, this is beyond the scope of this paper and is left for future research. The aim of this paper is to see how the results of a widely cited study fare under an alternative (and preferable) estimation technique using exactly the same data to enable direct comparison. Our conclusion is that the results of previous studies are sensitive to the estimation method. Thus, serious doubts must be cast about the validity of claims by previous cross sectional studies of the Kuznets hypothesis.

IV. Conclusion

The inverted-U hypothesis has occupied the empirical attention of researchers since Kuznets' (1955) seminal contribution. Based on historical evidence, Kuznets (1955, p.4) observed a narrowing of income inequality for England, Germany and the United States "...particularly noticeable since the 1920's but beginning perhaps in the period before the first world war." As for the upward portion (widening income inequality) of the inverted-U curve, Kuznets was tentative relying on 'conjectural conclusions' and questioning the reliability of empirical information. Kuznets (1955, p.19) did, however, go on to speculate about this portion of the curve: "... to make it more specific, I would place the early phase in which income inequality might have been widening, from about 1780 to 1850 in England; from about 1840 to 1890, and particularly from 1870 on in the United States; and, from the 1840's to the 1890's in Germany." Thus, the Kuznets hypothesis was born.

While the Kuznets hypothesis described the historical evolution of income distribution, tests have been based almost exclusively on cross-section data. Notwithstanding this drawback, early empirical evidence in its favor (e.g., Ahluwalia (1976)) propelled the Kuznets hypothesis to gain widespread acceptability, acquiring "the force of economic law."[20] Recent criticisms of the Ahluwalia methodology by Anand and Kanbur (1993) have cast serious doubts over the validity of cross-section estimates of the inequality-development relationship. Moreover, recent panel tests (see, for example, Deininger and Squire (1997), Ram (1997)) have proved

20. See Bourguignon and Morrisson (1990, p.1114) and Bruno *et al.* (1996, p.3) on this.

disappointing insofar as confirmation of the Kuznets hypothesis is concerned.

In this paper we examine cross-section evidence on the inverted-U hypothesis via a widely used data set in order to provide comparability and contrast to previous results. Our objective is to investigate the existence of a turning point in the inequality-development relationship with various functional forms corresponding to different inequality indices. In common with Anand and Kanbur (and in contrast to Ahluwalia), we employ the functional form appropriate for each inequality index. Our point of departure is the use of a multivariate instead of single-equation estimation technique. We demonstrate that the turning points yielded by various inequality indices are not significantly different from one another. When we restrict the estimate of the turning point to be equal across equations, the constrained estimate is highly significant for the group of LDCs in the AAK sample. This conclusion is confirmed when the AAK sample of LDCs is expanded with income distribution data from the World Bank. Our evidence points to a turning point in the inequality-development relationship for LDCs that is approximately equal to 600 US dollars at 1970 prices.

Our results would appear to indicate the existence of a turning point in the inequality-development relationship for the LDCs in the sample. This, however, would not be an appropriate interpretation of our results. Our main conclusion is that claims by previous cross sectional studies of the Kuznets hypothesis are dependent on the estimation technique. Changes in the estimation method yield contrasting results. This finding, along with those from panel studies, calls into doubt previous research on the Kuznets hypothesis that purports to show an inverted-U relationship. Any claims that the inverted-U hypothesis describes the evolution of income inequality should be laid to rest.

Finally, a cautionary note on the methodology employed in this as well as other studies of the Kuznets hypothesis is in order. Doubtless, variables other than per capita income determine income inequality. Some studies (e.g., Bourguignon and Morrisson (1990), Sundrum (1990)) have attempted to account for these factors. These studies are concerned with the wider issue of what determines income inequality, rather than the specific issue which is the subject of this study, i.e., the evidence on the Kuznets hypothesis using a multivariate estimation method. While looking into the determinants of income inequality within a multivariate framework would constitute a significant extension of our study, it is outside the scope of this paper. Such an extension would clearly warrant a separate study to justify an adequate treatment of this issue.

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