[Major Themes in Economics](https://scholarworks.uni.edu/mtie)

Volume 2 Article 5

Spring 2000

Income Inequality and Economic Growth: An Empirical Study About the Effects of Economic Growth on Income Distribution

Steve Schuler
University of Northern Iowa

Income Inequality and Economic Growth: An Empirical Study About the Effects of Economic Growth on Income Distribution

Steve Schuler

Abstract. The Kuznets inverted-U hypothesis has been a source of debate in development economics for years. Most of the recent studies on the subject have been panel studies. In this paper, the author re-considers the possibility of testing the Kuznets hypothesis in a cross-sectional study. The results suggest that the Kuznets hypothesis does hold. However, there are a number of qualifications about the research presented which must be considered.

I. Introduction

Imagine driving through a two-lane tunnel, both lanes going in the same direction. Traffic suddenly stops, and you are instantly in a stifling traffic jam. As far as you can see, neither lane is moving. Needless to say, you are not in the best of moods. After a while, traffic in the other lane begins to move. So you start to feel better about your situation because you think your lane will eventually begin to move. As time passes, and your lane has not moved an inch, you begin to grow anxious and much more frustrated than you were to begin with because you know the people in the other lane have it better than you do. They are getting out of the traffic jam before you.

The above example is a very simple way to describe a much more perplexing issue: the tolerance for income inequality during economic development. Known as the "Tunnel Effect," the example illustrates how low income citizens of developing countries may feel as their economy grows, especially if they are not reaping any of the rewards from economic development. We can then expect that as time passes the tolerance for this inequality will lessen, and may eventually lead to social unrest or upheaval. By studying the patterns of income distribution as they are related to economic growth, we may be able to see if the Tunnel Effect is inevitable.

Nobel laureate Simon Kuznets developed one early hypothesis on the subject, known as the Kuznets inverted-U hypothesis. The Kuznets hypothesis suggests that things will get worse before they get better, *i.e.* that there is a "long swing" or "inverted-U" in the distribution of income as per capita income grows. Figure 1 provides a graphical representation of the Kuznets inverted-U hypothesis.

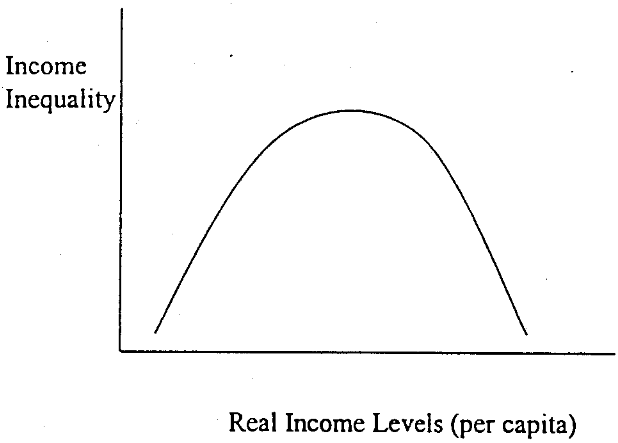


FIGURE 1. The Kuznets Inverted-U Hypothesis

In his initial work on the subject, Kuznets wrote the following description of his hypothesis.

> One might thus assume a long swing in the inequality characterizing the secular income structure: widening in the early phases of economic growth when the transition from the pre-industrial to the industrial civilization was most rapid; becoming stabilized for a while; and then narrowing in the later phases. This long secular swing would be most pronounced for older countries where the dislocation effects of the earlier phases of modern economic growth were most conspicuous; but it might be found also in the "younger" countries like the United States, if the period preceding marked industrialization could be compared with the early phases of industrialization, and if the latter could be compared with the subsequent phases of maturity [Kuznets, 1955, 18].

As one can imagine, this hypothesis has been widely discussed and highly controversial. The research presented here tests this hypothesis with data from 1982 to 1996.[1] The research was conducted as a cross-sectional study using 69 countries, excluding former communist nations. The results reveal that the Kuznets inverted-U does hold true in a cross-sectional analysis. However, there are a number of questions about this analysis that I must address.

II. Literature Review

Since Kuznets's original work, many have sought the answer to the question of how economic growth affects income distribution. In 1962, Shortly after Kuznets's original description of the "long-swing," Oshima predicted the same type of relationship [1962]. Kuznets then supported his original work with a study in 1963 of eighteen countries, both developing and developed. Because the statistical techniques of Ordinary Least Squares regression were not yet known, Kuznets performed his analysis by eyeballing the inequality ratios as they compared to per capita income [Kuznets, 1963].

As time went on, many researchers decided to test the Kuznets hypothesis. They ran into a major roadblock, however, in that very few countries have data on per capita income and income distribution that dates past the middle 1980's. In order to study the entire "long-swing" it was necessary to have observations from before 1900 for many nations, and pre to post World War II for others [Kuznets, 1955, 18-19]. As an alternative, many researchers made the assumption that a cross-section of the world's countries would reveal all of the stages of development, from the poorest countries to the richest countries, in terms of per capita income and income distribution. This allowed them to take data from current points in time on many countries, and draw conclusions about the inverted-U [Ray, 1998, 201-202]. Paukert [1973] used the Gini[2] and per capita GDP in 1965 dollars and found that a Kuznets type relationship does exist, but he also found that the inverted-U was not inevitable in all countries. Other cross-sectional studies of the Kuznets hypothesis include those by Adelman and Morris [1973], Ahluwalia, Carter, and Chenery [1979], Papanek and Kyn [1986], Bourguignon and Morrisson [1989] and [1990], and Anand and Kanbur [1993].

Perhaps the most famous of these studies was done by Ahluwalia in

1976, which used linear regression techniques. His work covered 60 countries, of which 40 were developing countries, 14 were developed countries, and 6 were socialist. He used per capita GNP in 1970 dollars and income shares of the five quintiles of the population; that is, he divided the population into groups, each receiving 20% of the population based on their portion of GNP. Thus, Ahluwalia ended up with one group of the richest 20% of the population, a group of the poorest 20% of the population, and three groups in-between. He ran regressions on each income share using the following equation, which has since become one of the standard Kuznets-type equations.

Income Share of quintile = a + bY + cY^2 + Dummy Variable + error

The dummy variable simply took on the value of 1 if the country was socialist, and a value of 0 for all other countries. This accounted for the outlying value of the socialist countries, as they have traditionally had many government policies to control their distribution of income, despite having little or no economic growth. Ahluwalia included the square of per capita income (Y^2) to allow the regression equation to take the inverted-U form, for it is the quadratic term which allows the equation to take on a form different than that of a straight line. Ahluwalia found results that fit the inverted-U hypothesis, and thus he concluded that the Kuznets hypothesis did hold [Ahluwalia, 1976].

In more recent years, the discussion on the Kuznets hypothesis has shifted to panel data. Panel data allows researchers to use a few observations over time from many countries, thus resulting in a blend of cross-sectional and time-series data. The results of many of these studies have shown that the inverted-U does not exist, or that there are reasons other than that of economic growth that cause the inverted-U to occur in the cross-section. The most talked about problem is known as the "Latin Effect." Many believe that the reason the inverted-U occurs in a cross-sectional study is the fact that most of the middle income countries are Latin American. Most of these Latin American countries have high income inequalities, but these inequalities are caused by structural differences (mainly governmental)–not the stage of economic growth [Ray, 1998, 207-208]. I have tested for the Latin Effect, and the results can be found in Table 4 in the empirical analysis section.

III. Ram's work and counterhypothesis

In his attempts to recreate Kuznets' work, Rati Ram came up with some very different conclusions. In 1991, Ram indicated that in the United States, income distribution has gotten worse since the 1970's, in spite of continued economic growth [1991, 1113]. So Ram developed a counter hypothesis to Kuznets' inverted-U, namely that income distribution can take on an "uninverted-U shape" or an upright-U shape. Figure 2 is a graphical representation of Ram's counter hypothesis.

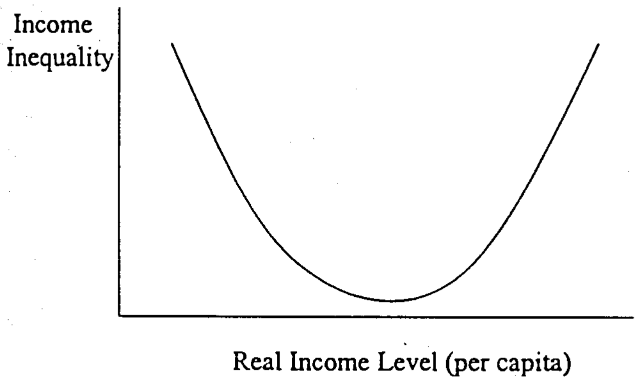


FIGURE 2. The Ram Uninverted-U Hypothesis

In his 1997 work, Ram studied 19 developed countries using a combination of cross-sectional and time-series data. His results again varied from the Kuznets hypothesis. Ram used the equation shown below, a typical equation for testing the Kuznets inverted-U hypothesis.

Inequality[3] = a + b Log of Real GDP[4] + c Log of Real GDP squared + error term [Ram, 1997, 577].

Ram got his data from Deininger and Squire's high quality data set, which includes 289 observations (222 for income share variables) from 19 developed countries [1997, 578]. This data set includes three different types of dependent variables: Gini coefficients, income shares of the top

20% of the population, and income shares of the bottom 40% of the population. The income share of the top 20% of the population and the Gini coefficient are measures of inequality; thus he expected an inverted-U relationship. The income share of the bottom 40% is a measure of equality. For those regressions, Ram expected an upright-U relationship [1997, 578].

Ram also suggested that there are other variables (such as country-specific policies and historical factors), that may affect income inequality in a country. Ram attempted to fix this problem by using a dummy variable in a manner called the fixed effects approach. The dummy variable's presence in the model implies that the model permits income inequality to differ across countries that are at the same level of development. Ram then used the following equation after including the dummy variable:

Inequality = a + b (log of real income) + c (log of real income squared) + dummy + error [1997, 578]

Ram's findings are shown in Table 1.

The inclusion of the dummy variable greatly increases the model's explanatory power, as shown by the adjusted R^2. This statistic shows the amount of variation in inequality that is explained by the variation in the independent variables, namely real per capita income. A larger R^2 indicates that the model does a better job of explaining the variation in the dependent variable. In this case, an R^2 of .77 would indicate that the model explains 77% of the variation in income inequality. Thus one can conclude that the results of the equations using the Gini coefficient for the dependent variable had good explanatory power when the dummy variable was included in the model. Also of note are the statistics for the individual variables. Again, looking at the regressions using the Gini, one can see that both the independent variables (log of per capita GDP and log of per capita GDP squared) were significant. This is shown by the fact that the t-statistics for those variables exceed 2.00, which is the approximate value of t at the 95% confidence level.

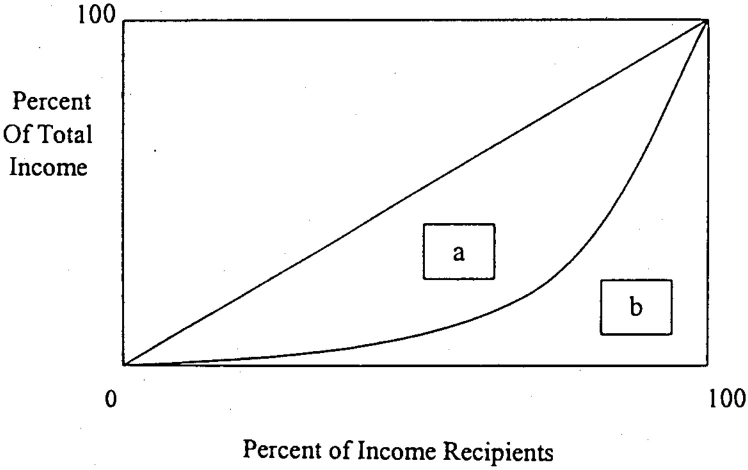
TABLE 1

Model	Coefficient of Constant	Log of per capita GDP	Log of per capita GDP Squared	Adj. R2
Gini				
Without Dummy	75.011 [7.00]*	-39.231 *	8.838 [4.14]*	0.06 [4.394]*
With Dummy		-18.369 [-3.49]*	3.994 [3.42]*	0.77 [2.165]*
Top 20%				
Without Dummy	0.720 [10.44]*	-0.291 [-4.73]*	0.064 [4.68]*	0.08 -0.03
With Dummy		-0.082 [-1.93]*	0.019 [2.06]*	0.66 [0.016]*
Bottom 40%				
Without Dummy	-0.038 [-0.64]*	0.228 [4.26]*	-0.054 [-4.57]*	0.11 [0.023]*
With Dummy		0.033 [1.08]	-0.010 [-1.45]	0.77 [0.012]

* The t-statistics for the corresponding variables are in the brackets and are not available for the one instance that they are not shown.
The t-statistics and coefficients are not shown for the dummy variable, because the dummy simply adjusts the model for having a different number of observations for each country.
Source: Ram, 1997, 580

III. Model and Variables

Some of the variables in my model may not be familiar to many readers; I feel it necessary to discuss them. For the most part, my model uses the same variables as Ram's, but I use a different measure of per capita income, as explained below. The inequality measures are largely the same as Ram's. The Gini coefficient measures income inequality by using a Lorenz curve. As illustrated in Figure 3, to calculate the Gini, a 45-degree angled line going through a square represents perfect equality. A Lorenz curve is then plotted against the 45-degree angle line. The Lorenz curve plots the percentage of total income received by each individual in society, beginning with the poorest on the left. The Gini index measures the ratio of the area between the 45-degree angle line and the Lorenz curve to the total area under the diagonal 45-degree line. A Gini coefficient of 0 equals perfect equality, while a Gini of 100 equals perfect inequality [World Bank, 1998, 236].



$$\text{Gini Coefficient} = \frac{\text{Area a}}{\text{Area a} + \text{Area b}}$$

FIGURE 3. The Lorenz Curve and Gini Coefficient

As mentioned previously, I used a different measure of per capita income. I actually used two different measures: per capita GNP based on exchange rates and GNP based upon purchasing power parity (PPP). Ram used per capita GDP, which obviously differs from GNP, but it should not be a significant difference. GNP measured with purchasing power parity is the amount of a foreign country's currency required to purchase an identical quantity of goods and services in that country as $1 would buy in the United States [Todaro, 2000, 43]. Thus, if prices were lower in a foreign country than in the United States, the GNP for the foreign country figured with purchasing power parity would be larger than the GNP figured with exchange rates. These figures are then put in terms of international dollars (I$) in order to facilitate comparisons between countries. For the United States, GNP figured using purchasing power parity is the same as GNP figured using exchange rates because purchasing power parity is based on the U.S. dollar.

To illustrate, consider the everyday lives of two people, one from India, the other from the U.S. The same goods and services will have very different prices in the different countries. If the Indian person gets a haircut, it will cost significantly less than a haircut in the U.S. In measuring GNP with exchange rates, we do not account for the price differences for the same good or service between countries. Using purchasing power parity takes care of this problem.

IV. Empirical Analysis

My results varied tremendously from Ram's. The differences between the two works are most likely due to the fact that I have only used cross-sectional data and have chosen to ignore the historical aspects of the problem. The different results may also be caused by my data set. As mentioned previously, 69 non-communist countries were studied, with one observation for each country. Cross-sectional data has advantages and disadvantages. The main advantages lie in simplicity, and as mentioned previously, not enough historical data is available for many countries to study the relationship between income inequality and per capita income in a time-series study. As Ram mentioned in his work, however, cross-sectional data fails to account for the historical nature of economic growth. Ram's panel data does account for this somewhat. But panel data has disadvantages in itself, mainly that it is difficult to use and understand. Table 2 shows my results using the following equation:

Inequality = a + b Log of Real GNP + c Log of Real GNP squared + error term

In interpreting the data, I first draw your attention to the adjusted R^2 column. The adjusted R^2 for the equation using the Gini as the dependent variable, and using exchange rates to measure GNP is .3288. This indicates that 32.88% of the variation in the Gini (inequality) was explained by the independent variables, namely GNP.

TABLE 2

Model	Coefficient of: Constant	Log of per capita GNP	Log of per capita GNP Squared	Adj. R2
Gini				
Exchange Rates	-57.92	28.8	-1.97	0.3288
	[-2.06]*	[3.94]*	[-4.32]*	
PPP	-150.85	50.08	-3.18	0.2368
	[-2.22]*	[3.06]*	[-3.28]*	
Top 20%				
Exchange Rates	-36.87	24.53	-1.68	0.3502
	[-1.63]*	[4.18]*	[-4.57]*	
PPP	-122.74	44.24	-2.8	0.2598
	[-2.24]*	[3.36]*	[-3.59]*	
Bottom 40%				
Exchange Rates	59.89	-12.78	0.88	0.297
	[4.31]*	[-3.54]*	[3.90]*	
PPP	93.27	-20.39	1.31	0.2046
	[2.78]*	[-2.53]*	[2.74]*	

* The t-statistics for the corresponding variables are listed inside the brackets.

Looking more closely at that same model, one can see that both independent variables are statistically significant. The significance of the variable is determined by the t-statistic shown in brackets. Again, at the 95% level of confidence, the value of t is 2.00. Thus, a t-statistic of 3.94 means that the log of GNP is statistically significant. One can find similar results with the log of GNP squared. Looking at the rest of the results, we can see that the adjusted R^2 is between .2046 and .3502 and all of the independent variables are independent.

Looking now at the coefficients, the coefficient for the log of GNP is 28.8. This means that every time the log of GNP increases by 1, the Gini coefficient increases by 28.8. The signs of the coefficient are as expected. For the regressions using the Gini and the income share of the Top 20% of the population (which are both inequality measures) we expect that for an inverted-U to occur, the coefficient of GNP will be positive, while the coefficient of GNP squared will be negative. As one can see, this did occur. In the regressions using the income share of the Bottom 40% of the population (a measure of equality), we expect the coefficient of GNP to be negative, and the coefficient of GNP squared to be positive. This also occurred. In this model, the constant does not bear much importance, because the coefficient of the constant simply shows us the level of inequality where the inverted-U begins. One of the problems with the cross-sectional analysis of the inverted-U hypothesis is this the assumption that all of the countries start at the same point or the same level of economic development. Thus, the coefficient of the constant will represent the starting point of the Kuznets process for *all* of the countries in the model. This seems to be an obvious departure from reality, and will be discussed later.

We must make several qualifications of the model, the first of which is Multicollinearity. Multicollinearity occurs when two or more of the independent variables of a model are highly correlated. This violates the assumption made by Ordinary Least Squares Regression that the independent variables are independent, unrelated, and uncorrelated with each other [Abraham, 1999]. In this case, the log of GNP (when measured with exchange rates and when measured using purchasing power parity) and the log of GNP squared are highly correlated. The correlation coefficients for the exchange rate and purchasing power parity variables are shown in Table 3.

Multicollinearity can cause t-statistics to be small and insignificant, and it can also cause coefficients to be perverse both in size and in sign [Abraham, 1999]. In this case the perverse coefficient is the coefficient of the log of GNP, but only the size is affected, not the sign. For the equations dealing with Gini or the income share of the top 20% of the population, the coefficient of the log of GNP is perverse in size.

TABLE 3

Variables	Coefficient of Correlation
Log of GNP and Log of GNP2 using exchange rates	0.9961
Log of GNP and Log of GNP2 using PPP	0.9982

We assume that the coefficient is not perverse in sign, because we assume that the countries studied represent the rise of the inverted-U, where inequality gets worse with per capita income growth. The multicollinearity is something that I shall do nothing about, because it appears to have had little effect on the model, and there are very few solutions for the problem.

Returning to a topic discussed earlier, the Latin Effect, we must determine if the inverted-U is the result of this so called Latin Effect. To do so, I inserted a dummy variable that took the value of 1 for all Latin American countries, and a value of 0 for all other countries in the model. One can then interpret the coefficient of the dummy variable as the importance of being Latin American [Ray, 1998, 208]. The results are shown in Table 4.

The coefficient of the dummy variable indicates that it is quite important, suggesting the Latin Effect does indeed exist. Perhaps more important are the effects of the inclusion of the dummy variable on the other statistics. As one can see, the adjusted R^2 increases, but the other independent variables (log of GNP and log of GNP squared) become statistically insignificant in all regressions except one. This leads me to conclude that the Latin Effect is the main reason the inverted-U shows up in the cross-section.

TABLE 4

	Coefficient of				
Model	Constant	Log of Y	Log of Y2	Dummy	Adj. R2
Gini					
Exchange Rates	14.30 [0.468]*	12.11 [1.58]*	-0.92 [-1.92]*	-11.45 [-4.17]*	0.4625
PPP	-11.68 [-0.18]*	18.81 [1.21]*	-1.32 [-1.43]*	-12.75 [-4.81]*	0.4284
Top 20%					
Exchange Rates	21.05 [0.86]*	11.15 [1.81]*	-0.84 [-2.16]*	-9.18 [-4.16]*	0.4790
PPP	-11.25 [-0.22]*	19.18 [1.53]*	-1.31 [-1.76]*	-10.22 [-4.78]*	0.4440
Bottom 40%					
Exchange Rates	26.24 [1.71]*	[-1.30]*	[1.63]*	[3.88]*	0.4203
PPP	27.22 [0.83]*	-5.54 [-0.78]*	0.43 [0.93]*	6.05 [4.57]*	0.3888

* The t-statistics for the corresponding variables are listed inside the brackets.

V. Conclusions

The results displayed in Table 2 indicate that an inverted-U relationship does exist between income inequality and per capita income levels. When testing for the Latin Effect, however, it becomes apparent that the Latin Effect causes the inverted-U in the cross section. There are other qualifications that must be made clear. Multicollinearity, to some extent, distorts the relationship that can be seen in the model.

Other concerns lie with the variables and functional form used in the regression line. Economic development literature commonly states that per capita income is a poor measure of economic growth. First of all, per capita income should be measured using purchasing power parity estimates, rather than exchange rates, in order to most accurately reflect actual per capita income [Temple, 1999, 114]. The second suggestion about the economic growth measurement has to do with the overall aim of economic development. The United Nations Development Program (UNDP) has developed an overall measure of development called the Human Development Index (HDI). HDI incorporates educational attainment, literacy rates, average life expectancy, and GNP measured with purchasing power parity estimates, in order to capture the totality of economic development. In this researcher's opinion, HDI would be a much more representative measure of economic development than per capita income for the analysis of the Kuznets hypothesis.

Another problem has to do with the variables used to measure income distribution. While the Gini coefficient is a commonly used measure of income distribution, it is far from perfect, and it may not be the best measure. According to Gillis, Perkins, Roemer, and Snodgrass [1996], Lorenz curves from different countries can intersect or have different slopes and still generate the same Gini coefficient. "This happens when one distribution is very unequal in one part of its range–say, the bottom to around the middle–while another is unequal in a different part–say, in terms of the income shares of the very richest families" [1996, 73]. The authors also mention how the Gini is particularly insensitive in changes in income distribution for the low-income groups [1996, 73-74]. And according to Deininger and Squire, the income shares data should prove to be more accurate because income share measures recognize the fact that income distribution and economic growth evolve simultaneously [1998, 260]. So this researcher concludes the regressions using income share measures should be given more consideration as representing the true relationship between income distribution and economic development.

Other questions have been raised about the functional form of the regression equation that yields the inverted-U. To this end, Anand and Kanbur have set forth a specific functional form that researchers should use with specific measures of inequality. They have identified six types of equations for the following six inequality measures: Theil T, Theil L, Squared Coefficient of Variation (S^2), Decomposable transform of the Atkinson Index, Gini coefficient, and the variance of the Log of income [1993, 37]. I recommend reading their article if one would like more in-depth understanding of each of the functional forms.

Perhaps the biggest problem with the cross-sectional analysis lies in the fact that it assumes each country has the *same* inequality relationship, both qualitatively and quantitatively. As mentioned previously, the estimated coefficient of the constant shown in with each regression equation represents the estimated intercept of the Y-axis, or the starting point of the inverted-U. Obviously, not every country begins its path of economic growth at the same point, nor do they have the same curve quantitatively as they pass through the stages of economic growth. Unfortunately, the only solution to this problem is to study each country separately in a time-series analysis. This, of course, is the ultimate problem of studying a time-series question with cross-sectional data. But, we have no choice. If we are to study this relationship at all, we must do it in a cross-sectional study until we have enough data measurements from *all* of the countries of the world to study their growth individually. Perhaps then we can compare the results between countries.

From this analysis, we must clearly conclude that per capita income does not describe the majority of the variation in inequality. Again, I draw your attention to the adjusted R^2 of the models. None of them explain more than 35.02% of the variation in income inequality. We need to add other variables to the model in order to find the other determinants of income inequality. One could include variables for government expenditures and for the size of the agricultural sector. But regardless of what is done, if we are to fully understand inequality and its causes, we must perform further study.

Yet another concern with the inverted-U hypothesis lies in the real world. While nations such as Mexico and Panama are examples of the Kuznets inverted-U actually holding true, other nations such as Taiwan, Iran, and South Korea have experienced improved income inequalities with economic growth. This points one to the conclusion that while the inverted-U may hold true for many countries as they pass through the many stages of economic growth, it will not hold true for all countries.

Clearly, the results of this research are not comprehensive on the subject, and it leaves many unanswered questions. On the other hand, this research indicates that, to some extent, the Kuznets hypothesis does hold up, and little evidence can be found in support of the Ram hypothesis (at least in cross-sectional analysis which includes developing countries). At the same time, it is apparent that the Latin Effect does exist and causes significant changes in the power of the Kuznets hypothesis in cross-section. In the end, however, this research serves to show that we know very little about the relationship between income distribution and its determinants, primarily economic growth.

Endnotes

1. Although the data represent a wide range of time, each country studied had one observation in the model. The wide range in dates is most likely due to inconsistent measurement of aggregate economic variables from country to country. More can be found in the *World Development Report* referenced at the end of this paper.
2. Gini coefficients are discussed later in this paper.
3. Ram used three types of inequality measurements: Income share of the bottom 40% of the population, Income share of the top 20% of the population, and Gini coefficients which will be discussed later in this paper.
4. The log referred to here is the natural logarithm form of the variables. The log form is what allows the curve to double over as in an inverted-U.

References

ABRAHAM, F. (1999): "Multicollinearity, Autocorrelation, and Heteroscedasticity," Lecture from Introduction to Econometrics at the University of Northern Iowa, Tuesday, April 13, 1999.

ADELMAN, I. AND MORRIS, C.T. (1973): *Economic Growth and Social Equity in Developing Countries*. California: Stanford University Press.

AHLUWALIA, M. (1976): "Inequality, Poverty and Development," *Journal of Development Economics*, 6: 307-342.

AHLUWALIA, M., CARTER, N., AND CHENERY, H. (1979): "Growth and Poverty in Developing Countries," *Journal of Development Economics*, 6: 299-341.

ANAND, S. AND KANBUR, S.M.R. (1993): "The Kuznets Process and the Inequality – Development Relationship," *Journal of Development Economics*, 40: 25-52.

BOURGNIGNON, F. AND MORRISSON, C. (1989): *External Trade and Income Distribution*. Paris: Development Centre Students, OECD.

BOURGNIGNON, F. AND MORRISSON, C. (1990): "Income Distribution, Development and Foreign Trade: A Cross-Sectional Analysis," *European Economic Review*, 34: 1113-1132.

DEININGER, K., SQUIRE, L. (1998): "New Ways of Looking at Old Issues: Inequality and Growth," *Journal of Development Economics*, 57:259-287.

GILLIS, M., PERKINS, D., ROEMER, M., AND SNODGRASS, D. (1996): *Economics of Development*, fourth edition. New York: W.W. Norton & Co.

KUZNETS, S. (1955): "Economic Growth and Income Inequality," *American Economic Review*, 45: 1-28.

KUZNETS, S. (1963): "Quantitative Aspects of the Economic Growth of Nations: VIII Distribution of Income by Size," *Economic Development and Cultural Change*, 11: 1-80.

OSHIMA, H.T. (1962): "The International Comparison of Size Distribution of Family Incomes with Special Reference to Asia," *Review of Economics and Statistics*, 54: 439-445.

PAPANEK, G.F. AND KYN, O. (1986): "The Effect on Income Distribution of Development, the Growth Rate and Economic Strategy," *Journal of Development Economics*, 23: 55-65.

PAUKERT, F. (1973): "Income Distribution at Different Levels of Development: A Survey of Evidence," *International Labor Review*, 108: 97-125.

RAM, R. (1997): "Levels of Economic Development and Income Inequality: Evidence From the Postwar Developed World," *Southern Economic Journal*, 64:576-584.

RAY, D. (1998): *Development Economics*, Princeton: Princeton University Press.

TEMPLE, J. (1999): "The New Growth Evidence," *Journal of Economic Literature*, 37: 112-156.

TODARO, M. (2000): *Economic Development*, Seventh edition. Reading, MA: Addison Wesley.

WORLD BANK (1998): *World Development Report: Knowledge for Development*, Oxford: Oxford University Press.