An International Comparison of the Incomes of the Vast Majority

Abstract

This paper expands the standard list of international economic measures to include the per capita income of the vast majority (VMI) of each nation's population. The VMI is an intuitive combination of information on national income and its distribution, and it gives rise to new international rankings. The measure is derived from the "two-class" approach to econophysics, not from the traditional social welfare functions or underlying utility functions. This gives rise to an empirically robust international relation we call the 1.1 Rule, as well as a new interpretation of the Gini coefficient (G) as being the percentage difference between national income per capita and the per capita income of the bottom seventy percent of the population. Ranking countries in terms of Sen's social welfare measure is shown to be equivalent to ranking them in terms of the per capita income of the bottom 70 percent.

Keywords

income distribution, inequality, econophysics, economic indicators, world, international

JEL Classification: D31, D63, N30, O50

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Introduction

National and international income and its distribution are generally treated separately, with GDP per capita (GDPpc) as the paramount measure of national income and the Gini coefficient (G) as the central measure of inequality. It is understood that that the greater the Gini coefficient, the less representative is the level of per capita national income. Our first concern is to provide a simple alternative to GDPpc which fulfilled two requirements: combining the level of income and distribution of income into a single intuitively meaningful statistic; and representing the economic situation of the vast majority of the population.

It can be shown from a Lorenz curve that the per capita income of any bottom fraction of the population satisfies the first requirement because it reflects both the level and the distribution of income. But this does tell us exactly how the two dimensions are linked, nor which particular measure of inequality is involved. Further consideration led us to the econophysics "two-class" (EPTC) the theory of income distribution. The EPTC approach argues on theoretical grounds that the distribution of wages and salaries is characterized by an exponential probability distribution function, while that of property income is characterized by a Pareto distribution. The overall Lorenz curve is then a combination of a large section corresponding to the exponential distribution and a small one corresponding to the Pareto. It is shown that such a curve can be approximated in a particularly simple manner.

From this foundation we derive several novel results which apply to the bottom 97 percentiles of the Lorenz curve, this being the population whose income is derived primarily from wages and salaries. Let x be some subgroup of this target population (e.g. the bottom 70 percent) , $\overline{y}(x)$ = the per capita income of this subgroup, G = the Gini coefficient of the whole income distribution, $\overline{y}$ = average net national income per capita of the whole population (NNIpc), and $\overline{y}' \equiv (1 - G)\,\overline{y}$ = the "inequality-discounted" average per capita income. Our first derived result is that the per capita income of any subgroup is proportional to inequality-discounted average income per capita through a constant of proportionality which is dependent solely on the population proportion x. In other words, $\overline{y}(x) = a(x)\overline{y}' = a(x)(1-G)\overline{y}$, where the constant of proportionality $a(x)$ depends only on the population proportion being considered.

We then test this theoretical proposition empirically and show that it is very powerful across a large sample of countries, at least for population subgroups between 50 and 90 percent (most of our data being in deciles). For instance, for x = 70, 80, 90, the corresponding coefficients $a(x)$ are 1, 1.1, 1.27, respectively, f*or all countries in our sample and to all time periods in each country*. The relations are so robust that they constitute general empirical rules. The fact that a(x) = 1.0 for x=70 allows us to define the 1.0 Rule; inequality-discounted net national income per capita is always equal to the per capita income of the bottom 70 percent of the population. This in turn implies that ranking countries by the Sen social welfare measure $W = \overline{y}(1-G)$ is equivalent to ranking them by the average per capita income of the bottom 70 percent. The corresponding finding that a(x) = 1.1 for x=80 implies the 1.1 Rule: 1.1 times the inequality-discounted net national income per capita is always equal to the per capita income of the bottom 80 percent of the population.

Our third contribution is to show that the Gini coefficient is the percentage difference between average per capita income and that of the bottom 70 percent: in other words, the Gini coefficient is a measure of the distance between average per capita income and that of the bottom 70 percent. Finally, we also show that the Gini coefficient is a linear function of the share of property income in net national income.

The first condition for a viable alternative to GDPpc was that it capture both the level and distribution of income. This is satisfied by the per capita income of any subgroup of the population. The second requirement was that any such measures also represent the economic situation of the great bulk of the population. This can be satisfied by choosing some portion (x) of the population large enough to qualify as the "vast" majority, i.e. somewhere between 70 and 90 percent in quintile data. We end up choosing 80 percent as the definition of the Vast Majority Income (VMI) for two reasons: it can be calculated even from quintile data; and it is the best on both theoretical and empirical grounds.

All of this pertains to the objective properties of per capita measures such $\overline{y}(0.70)$ or $\overline{y}(0.80)$, the latter being the VMI. We argue that these measures are superior to NNIpc for some uses because they combine the level and distribution of income into a direct measure of the historically achieved standard of living of the vast majority of the population. We can of course also interpret them as measures of social welfare in terms of traditional welfare theory, as in Sen's (1976) social welfare measure $W = \overline{y}(1 - G)$ discussed below. According to our findings, Sen's social welfare measure also represents $\overline{y}(0.70)$, the per capita income of the bottom the bottom 70 of the population in a given country. But we would argue that $\overline{y}(0.70)$ or $\overline{y}(0.80)$ are intuitively meaningful measures of national economic conditions in their own right, which need not to be tied solely to traditional social welfare theory and are indeed derived from an entirely different foundation.

Theory and measurement of income and inequality

GDP per capita (GDPpc) is by far the most popular measure of international levels of development (Frumkin, 2000, pp. 144-154), even though it is known to be an imperfect proxy for important factors such as health, education and well-being (Cowen, 2007). One important alternative has been to work directly with the variables of concern, as in the United Nations Development Programme (UNDP) Human Development Index (HDI) which combines GDPpc with life expectancy and schooling into a single composite index (UNDP, 1990, p. 12). But the HDI is difficult to compile and is only available for recent years. Because it is an index, it cannot tell us about the absolute standard of living of the underlying population, which is why GDPpc remains so popular (Hicks, 2004, pp. 2-3). Moreover, the rankings produced by the two measures are quite highly correlated (Kelley, 1991, pp. 322-323). In any case, both measures suffer from the fact that "they are averages that conceal wide disparities in the overall population" (UNDP, 1990). There is widespread agreement that international economic comparisons should not ignore inequality. But there is also considerable debate on how exactly to bring inequality into the picture (Gruen and Klasen, 2008, p. 213).

The traditional literature is posed in terms of particular social welfare functions based on special individual utility functions. Atkinson (1970) developed a measure of welfare loss which is the equally distributed equivalent income -- i.e. "the amount of income that, if distributed equally, would yield the same welfare as the actual mean income and its present (unequal) distribution". The theoretical foundations for the Atkinson measures can be found in social welfare functions which are "additively separable functions of individual incomes [Y_i] … based [in turn] on individualistic utility functions where people only care about their own incomes". In this case an increase in inequality reduces welfare according to the degree of "aversion to inequality factor" (ε) in the general measure of welfare loss $A = \left[\frac{1}{N} \sum_{i=1}^{N} Y_i^{1-\varepsilon} \right]^{\frac{1}{1-\varepsilon}}$. It has been argued that this measure can be directly treated as a measure of social welfare. An alternate approach is available in Sen's (1976) measure $W = \overline{y}(1-G)$, where $\overline{y}$ = national per capita income and G = the Gini coefficient. This can be derived from an assumed social welfare function in which "the weight of a person's income depends inversely on the rank in the income distribution", or as in Dagum (1990) "from a utility function where individuals consider not only their own income, but [also] their position in the income distribution". Social welfare functions with more severe penalties for inequalty have been proposed, as in Dagum (1990) in which the social welfare function $W = \overline{y}\frac{(1-G)}{1+G}$ is based on the assumption that individuals are negatively affected not only by the level of income inequality but also by their envy of people ahead on them in the queue. Measures of inequality other than the Gini coefficient can also be used, as in Lambert's general function W = W(x, I) or some convenient particular form such as $W = \overline{y}(1-I)$, where I = some general measure of inequality $0 \le I \le 1$ (Gruen and Klasen, 2008, pp. 214-217).

It is interesting to note that the Sen measure was included in the 1993 Human Development Report (HDR) of the UNDP as a basis for international comparisons, but then dropped because of concerns about its theoretical properties (Foster, Lopez-Calva and Szekely, 2005 ; Hicks, 1997 ; 2004 ; UNDP, 1993) With renewed interest in inequality after the Great Recession in 2008, the UNDP subsequently utilized a version of the Atkinson measure to calculate an inequality-adjusted HDI in the 2010 Human Development Report (Alkire and Foster, 2010 ; UNDP, 2010). The main difficulty in this case was that there was no justification for any particular inequality aversion factor (ε).While experimental behavioral economics may be viewed as having "discovered" that that people of different cultures and backgrounds care about equality and fairness (Engelmann and Strobel, 2004, pp.866-868; Fehr and Schmidt, 1999, pp. 855-856; Hoffman, McGabe and Smith, 1996, pp. 297-300; World Bank, 2006, Ch 4), none of this provides much support for any particular level of ε (Carlsson, Daruvala and Olof, 2005, p. 376).

The social welfare function approach to international comparisons has been criticized because it requires strong theoretical assumptions about individual behavior and psychology, about appropriate measures of individual "well-being" such as utility, about the aggregation of any such measures into indexes of social welfare, and about the effects of income, inequality, education, etc. on all of this (Fleurbaey and Mongin, 2005). Our own approach is therefore somewhat different. Our primary motivation is to combine information on the level and distribution of national income into a single statistic which has general intuitive appeal as a measure of the standard of living of the vast majority of the population[1]. The first step in this direction is to note that the per capita income $\overline{y}(x)$ of any proportion of the population reflects both the average per capita income and the degree of inequality.

If we designate the population and income of the ith fractile (quintile or decile) by X_i and Y_i respectively, then for the economy as a whole total population $X = \sum_{i=1}^{n} X_i$, total income $Y = \sum_{i=1}^{n} Y_i$ and per capita income $\overline{y} = Y/X$. Let x be some cumulative percentage of the population to which corresponds a total population $X(x) = \sum_{i=1}^{x} X_i$, total income $Y(x) = \sum_{i=1}^{x} Y_i$ and per capita income $\overline{y}(x) = Y(x)/X(x)$. But the cumulative population proportion is itself $x = \sum_{i=1}^{x} \frac{X_i}{X}$ and the corresponding cumulative income proportion is $y(x) = \sum_{i=1}^{x} \frac{Y_i}{Y}$. It follows that the per capita income of the bottom x percentage *relative* to the national average $IR(x)$ is equal to the ratio of the cumulative income proportion of the bottom x percentage of the population to this population percentage. This means that we can calculate the per capita income of (say) bottom 80 percent of the population simply by summing relative incomes up to 80 percent and dividing this by 0.80.

(1) $$IR(x) \equiv \bar{y}(x)/\bar{y} = \sum_{i=1}^{x} \frac{Y_i}{Y} \Bigg/ \sum_{i=1}^{x} \frac{X_i}{X} = \frac{\left(\sum_{i=1}^{x} Y_i \Big/ \sum_{i=1}^{x} X_i \right)}{(Y/X)} = y(x)/x$$

Since the y-axis of the Lorenz curve is the cumulative income proportion $y(x)$ and the x-axis is the cumulative population proportion x, the relative per capita income ratio $IR(x)$ of bottom x percentage of the population is simply the slope of the ray through the origin to the point on the Lorenz curve which represents the population proportion x. In the case of the vast majority, i.e. the eightieth population proportion VMIR is the slope of the line C in Figure 1. It is evident from this that $IR(x)$ is a measure of inequality since it depends crucially on the shape of the Lorenz curve. Indeed, it is similar to (1-G), which is the ratio of area beneath the Lorenz curve in Figure 1 to the area beneath the 45-degree line A[2], since both equal 1 under perfect equality, and both equal 0 under perfect inequality. But while (1-G) captures the whole shape of the Lorenz curve, $IR(x)$ only samples it at a single point. There is therefore no *a priori* reason to expect a stable relation between the two. Yet this is precisely what econophysics claims.

[Figure 1]

Econophysics and income inequality

It is widely acknowledged that "income and wealth distributions of various types can be obtained as steady-state solutions of stochastic processes" (Kleiber and Kotz, 2003, p. 14). But there is little agreement as to which probability distribution functions (pdfd) best characterize the available data. A recent approach within "econophysics" has been to characterize the overall income distribution as the union of two distinct pdfs, with the exponential curve applicable to first 97-99 percent of the population of individual-earners and the Pareto or some other power law applicable to the top 1-3 percent (Dragulescu and Yakovenko, 2002, pp. 1-2). The theoretical foundation for this "two-class structure of income distribution" is a kinetic approach in which income from wages and salaries yields additive diffusion[3] while income from investments and capital gains yields multiplicative diffusion (Silva and Yakovenko, 2004, p. 6). This leads to an approximation of the overall Lorenz curve as a weighted average of an exponential curve applicable to the vast bulk of the population, and a fixed term which kicks-in at the highest level in order to account for the Pareto tail (Silva and Yakovenko, 2004, Abstract). The approximation takes advantage of the fact that the population percentage at the higher end is very small but its income fraction (f) is nonetheless significant. This particular formulation gives rise to a strong relation between income and inequality which proves to be empirically very robust against a large sample of international data.

Let $y'(x)$ = the cumulative (pre-tax) income share stemming from the exponential section of the overall Lorenz curve, G' = the Gini Coefficient of the exponential portion of the overall curve, f = the proportion of total income in the Pareto section (i.e. total property income), and $\theta(x-1)$ = the step function such that $\theta = 0$ for $x < 1$ (i.e. along the exponential section) and $\theta = 1$ for $x = 1$ (along the Pareto section, which is approximated by a vertical line at $x = 1$). Then the overall Lorenz curve and the corresponding overall Gini coefficient[4] can be expressed as

(2) $y(x) = y'(x)(1-f) + \theta(x-1)$

(3) $\left(1-G\right)=\left(1-G'\right)\left(1-f\right)$

Since the step function $\theta\left(x-1\right)=0$ along the exponential section of the Lorenz curve, equation (2) reduces to $y\left(x\right)=y'\left(x\right)\left(1-f\right)$, which combined with equation (3) can be written as $\frac{y(x)/x}{(1-G)}=\left(\frac{y'(x)/x}{1-G'}\right)$. But we saw earlier in equation (1) that the left-hand side of this relation is simply $IR\left(x\right)\equiv\overline{y}\left(x\right)/\overline{y}$, the ratio of the relative per capita income of the bottom x percentage of the population to that of the whole population. Hence

(3) $\frac{\overline{y}(x)/\overline{y}}{(1-G)}=a(x)$, where $a(x)\equiv\left(\frac{y'(x)/x}{1-G'}\right)$

This is a very powerful result because for an exponential pdf the Gini coefficient is a constant and the cumulative income proportion $y'(x)$ is a parameter-free function of the cumulative population proportion x (Silva and Yakovenko, 2004, pp. 1-5), so that the term $a(x)\equiv\left(\frac{y'(x)/x}{1-G'}\right)$ in equation(3) is solely a function of x. The per capita ratio $IR\left(x\right)\equiv\overline{y}\left(x\right)/\overline{y}$ was previously shown reflect the degree of inequality inherent in a Lorenz curve, and to have the same limits as the equality index $\left(1-G\right)$. But now we see that the former is actually *proportional* to the latter through a constant of proportionality $a\left(x\right)=\left(\frac{y'(x)/x}{1-G'}\right)$ which depends only on x. It follows that *the per capita income of any cumulative population percentage x is proportional to the inequality-discounted average income per capita.*

(4) $\overline{y}\left(x\right)=a\left(x\right)\overline{y}\left(1-G\right)$, where $a\left(x\right)=\left(\frac{y'(x)/x}{1-G'}\right)$

The EPTC approach considers two types of populations for the lower part of the income distribution: individual earners and two-earner households. In the former case, the Gini coefficient is $G_1^{'} = 1/2$ and the Lorenz curve is $y = x + (1-x)\ln(1-x)$; in the latter case, which they argue is a good representation of overall family income, the Gini coefficient is $G_2^{'} = 3/5$ and the Lorenz curve is an implicit function $y(x) = f(x)$ since both y and x are functions of household income (Dragulescu and Yakovenko, 2001, pp. 585-588). The proportionality parameter $a(x) = \left(\frac{y'(x)/x}{1-G'}\right)$ can be directly calculated in either case, as shown in Table 1. Also displayed there are the actual empirical ratios calculated from our large international sample as discussed in the next section. Since the empirical evidence is in terms of "personal-equivalent" units derived from household data (see the Data Appendix), the relevant theoretical distribution is that of household incomes[5]. While the EPTC formula in equation (4) applies for the whole range of population proportions (x), we display only those above x = 0.70 because this is the region of our concern. We see that for x = 0.70, 0.80, 0.90, the theoretical 2-earner[6] ratios 1.00, 1.15, 1.32 are very close to the empirical ratios 0.99, 1.11, 1.27. Since the theory applies to pre-tax incomes while our data is for post-tax (disposable) incomes, such differences are consistent with the influence of progressive taxation which would lower the top post-tax incomes relative to their pre-tax levels.

Table 1 also brings up a second point of some interest: while the theoretical 1-earner and 2-earner household distributions generally yield somewhat different proportionality constants at any given population proportion, they yield the *same* constant at x = 0.75. Given that the actual data probably encompasses a mixture of 1-earner and 2-earner households, EPTC theory implies that observed ratios will have a minimum coefficient of variation (CV) at x = 0.75. Our decile data does not encompass this proportion, but we will see in the next section that the lowest empirical CV is at x = 0.80. Thus in addition to being calculable from quintile data, the 80 percent per capita income also has the best fit because it is "immune" to the earner-composition of households.

[Table 1]

Empirical Patterns of the Vast Majority Income on an International Scale

1. International Variations in *Relative* Vast Majority Incomes (VMIR)

Our distribution data is derived from the World Income Inequality Database (WIID2a) published by the United Nations University (UNU) and the World Institute for Development Economics Research (WIDER) (UNU-WIDER, 2005 June, V 2.0a-b). The distribution data is mixed, consisting of gross and disposable income (or consumption in some cases), by households or persons, and by quintile or decile, and the temporal coverage is uneven for earlier years and for most non-OECD countries. In this paper we stick to the distribution of Personal Disposable (PD) income, which is the largest consistent data subset we were able to construct (643 observations). In keeping with this, we use Net National Income per capita (NNIpc) rather than GDPpc as the appropriate measure of average national income per capita. NNI is better because it includes the factor income accruing from the rest of the world and excludes depreciation (which should not enter into personal income). Further details are in the Data Appendix.

Figure 2 display the ratio of the personal disposable income per capita of the vast majority to the average (VMIR) in rank order in the latest year available since 1990 in each country[7]. The higher this ratio, the more equal the income distribution. It is immediately apparent that the VMIR varies enormously across nations. As would be expected, at the top are developed countries such as the Netherlands (0.83) and Denmark (0.82), then Germany, Norway, Luxemburg and Sweden (0.78-0.79), followed by Canada, the UK and S. Korea (0.73-0.75), with the US at the bottom of the developed nations in our world-wide sample (0.68)[8]. The variations in VMIR make it evident that neither GDPpc nor NNIpc would be good proxies for the income levels of the vast majority. This lack of correspondence is compounded by the fact that the VMIR also varies over time. In Figure 3 we see that there has been a general downward drift in the VMIR with the advent of neoliberalism in the 1980s, which signals rising inequality over this period. This holds not only for the UK and US, but also for the Scandinavian countries beginning from their relatively more equal berths and for developing countries such as Mexico, Panama and Chile beginning from already high initial levels of inequality.

[Figure 2]

[Figure 3]

2. International Variations in *Absolute* Vast Majority Incomes (VMI)

Our ultimate concern is with the absolute level of vast majority per capita incomes (VMI) in each country. The latter can be derived directly from the data, as noted at the end of the section on the theory and measurement of income and inequality, or by multiplying each country's VMIR by its NNIpc. Table 2 displays both NNIpc and VMI by country, along with a measure of the relative per capita income of the top twenty percent of the population which we call the Affluent Minority Income (AMI). The table also displays national rankings by NNI and VMI per capita and the change in ranking in going from NNI to VMI, with countries ranked according to the gain or loss in ranking by this move.

Three interesting patterns emerge from this data. First of all, we find a great range in VMI's: in rounded numbers, at one end of the scale with we have Luxemburg ($30,000), Norway ($22,000) and the US ($21,000), and at the other end Ethiopia, Madagascar ($500) and Cambodia ($300). A second interesting finding is displayed in the last row of Table 2, which shows the per capita incomes of the rich (AMIs) have a considerably lower coefficient of variation (82 percent) than that of the vast majority incomes (96 percent). Apparently the international rich are more alike across nations than are the rest of the world's population. The third finding is that because the ratio of VMI to NNIpc (i.e. the VMIR) varies so substantially across countries, country rankings differ according to which measure is used. The last few columns in Table 2 display these ranking numerically for each country in the sample, along with its change in rankings when one uses VMI in place of NNIpc. We see that India gains 6 places, followed by the Kyrgyz Republic, Jordan and Bulgaria, each of whom gain 4 places. Luxemburg remains at the top by either measure so that its rank does not change, while the US drops from second to third while Norway rises from third to second. Small rank changes occur for most developed countries. At the other end, countries with highly unequal income distributions like Guinea and Panama lose 4 places, Guatemala loses 7 places and Chile loses a whopping 10 places. Income distribution clearly matters to the standard of living of the vast majority.

[Table 2]

3. The "1.1 Rule" Linking Relative Vast Majority Incomes to the Gini Coefficient

The VMIR, which is the vast majority income relative to the overall average, and (1-G), where G is the Gini Coefficient, are both measures of the degree of income equality. *Both vary substantially across countries and across time,* in accordance with varying social and historical determinants of inequality. We know that the two measures have the same limits: both equal 1 under perfect equality, and both equal 0 under perfect inequality. As noted previously, both can be derived from the Lorenz curve. But while (1-G) captures the whole shape of the Lorenz curve, the VMIR only samples it at a single point. There is therefore no *a priori* reason to expect a stable relation between the two. For instance, if two different countries had differently shaped Lorenz curves that just happened to intersect at the 80 percent population point, they would have equal VMIRs but unequal Ginis. Obviously the opposite could also hold, in principle.

But the EPTC approach specifically predicts that for any population proportion x, the ratio of the per capita income of x to the inequality-discounted *average* income per capita is a fixed number, e.g. $\frac{\left(\bar{y}(0.80)/\bar{y}\right)}{(1-G)} \equiv a(0.80)$ (equation (4)). Since $VMIR\left(\equiv \bar{y}(0.80)/\bar{y}\right)$, this is equivalent to predicting that the ratio of VMIR to (1-G) will be a particular *constant* on the order of 1.15 across countries and through time (Table 1, x = 0.80, Household income based distribution). Figure 4 shows that this ratio is indeed extraordinarily stable across countries with an average of about 1.1. Figure 5 shows that individual country ratios are also stable across time, with a mean of 1.10 and variations which seldom go beyond ± 5 percent of this mean. We therefore call this the "1.1 Rule": the per capita income of the vast majority can be derived by simply multiplying inequality-discounted NNIpc by 1.1. It should be said that because we are concerned with operating rules of thumb rather than best fit, we use the overall average of 1.1 as the benchmark. A regression of VMIR against (1-G) with no constant gives us the same result: $\beta = 1.104$ ($t = 479.17$) and an adjusted $R^2 = 0.986$.

(5) $$\frac{\left(\frac{\bar{y}(0.80)}{\bar{y}}\right)}{(1-G)} = a(0.80) \approx 1.1 \quad \leftrightarrow \bar{y}(0.80) \approx 1.1(1-G)\,\bar{y} \qquad \text{[The 1.1 Rule]}$$

[Figure 4]

[Figure 5]

4. A New Interpretation of the Gini Coefficient: The 1.0 Rule

Figure 6 plots the ratios of relative per capita incomes to (1-G), i.e. of $\frac{(\bar{y}(x)/\bar{y})}{(1-G)} \equiv a(x)$ at various population deciles. Displayed on the right hand side of the charts are the cumulative population proportions along with the corresponding means of these ratios along with their coefficients of variation (CV). We now see that ratios in the range x = 0.60-0.90 are very stable even across countries as structurally different as the United States and Cambodia. It was noted in the section on econophysics and in Table 1 that x = 0.75 gives rise to the same theoretical constant of proportionality for income distributions of both single- and dual-earner households. This particular population proportion is bracketed in our data by x = 0.70 and x= 0.80, and we see that these two population proportions do indeed have the lowest empirical CV's, with that of x = 0.80 being the lowest (0.02).

The seventy percent ratio is almost as stable. Its empirical average of 0.99 is virtually the same as the predicted value of 1.01 (see Table 1) and almost all of its values to lie within 5 percent of its mean: i.e. $a(0.70) \approx 1.0$. This allows us to provide a new interpretation of the Gini Coefficient, one which is both simple and intuitive: (1-G) represents the relative disposable per capita income of the first seventy percent of a nation's population; equivalently, G represents the percentage difference between NNIpc and the per capita income of the first 70 percent of the income distribution. We call this the 1.0 Rule.

(6) $$(1-G) \approx \left(\frac{\bar{y}(0.70)}{\bar{y}} \right) \quad \leftrightarrow \quad G \approx \left(\frac{\bar{y}-\bar{y}(0.70)}{\bar{y}} \right)$$ [The 1.0 Rule]

The sixty and ninety percent cumulative population proportions in Figure 6 also give rise to tolerably good empirical rules of thumb, with small but somewhat higher coefficients of variation. Figure 6 shows that the EPTC rules are somewhat less robust at lower population proportions, with the CV's rising as we move towards the lower deciles. This is to be expected on at least two grounds: underreporting of lower incomes (Dragulescu and Yakovenko, 2001, p. 588), and socially determined floors to household incomes. Even so, the highest CV, which is for the bottom decile, is only 0.29.

[Figure 6]

Universal Rules and Shape Restrictions on Lorenz Curves

We also performed some experiments which led us to conclude that our two rules are not statistical artifacts. First, we checked the statistical procedures used for fitting Lorenz curves to actual data. Second, we generated the proportionality coefficients associated with the probability distribution functions (pdfs) typically used to study income inequality. Third, we did the same for the functional forms typically used to represent Lorenz curves.

Our first experiment indicates that our two rules are probably not statistical artifacts of the procedures used to fit Lorenz curves. We generated data from a lognormal pdf with Gini coefficients ranging from 0.10 to 0.50 and found that the widely used World Bank package POVCAL accurately estimated the Lorenz curves and Gini coefficients. We next investigated the properties of probability distributions themselves, using the three most widely used probability distributions in the study of income inequality: the Pareto, the Exponential and the Lognormal (Crow and Shimizu, 1988, p. 233-237; Dovring, 1991, pp. 30-31; Kleiber and Kotz, 2003, p. 14; Silva and Yakovenko, 2004). We picked combinations of parameter values for each pdf that gave us Gini coefficients within the 0.30-0.70 range observed in the actual international data, checking to make sure that the corresponding Lorenz curves are viable. As detailed in the Distribution Theory Appendix, we then calculated the proportionality coefficients $a(x)$ for population proportions between x = 0.70 and x = 0.90. For all three pdfs at x = 0.80 the coefficient value is not far from our empirically observed number of 1.1: for the Pareto pdf it is about 1.03 over the whole range of Gini's; for the exponential pdf it is constant at essentially 1.2; and for the lognormal pdf it is between 1.10-1.14. Secondly, the population proportion which comes closest to following our 1.0 Rule is roughly x = 0.75 in all three theoretical pdfs, which is not far from x = 0.70 predicted in the EPTC approach and found in the data. Finally, it is striking that the *minimum* coefficient of variation (CV) for these theoretical ratios occurs at x = 0.80, just as it does in the observed data in Figure 6

Our third line of investigation focused on the functions commonly used to fit Lorenz curves to actual data. The three general functional forms considered were the exponential, the General Pareto (which subsumes the Ortega, the RGKO, and the classical Pareto), and the Beta (Chotikapanich and Griffiths, 2003 pp. 7-8). As detailed in the Distribution Theory Appendix, the exponential functional form gives a coefficient $a(0.80)$ between 1.07-1.19 which is close to observed empirical ratio of 1.11. But for x = 0.70 the spread at $a(0.70)$

is between 0.61-0.99, so that the average is well below our empirical 1.0. The General Pareto is more complex, and the generalized Beta functional form the most complicated of all, but here too for plausible ranges of their parameters they give similar results.

It is our belief that the generally used pdfs and functional forms are "standard" precisely because they provide good fits to an overall income distribution which is itself derived from *two* different types of underlying distributions whose union imposes particular shape restrictions on the overall Lorenz curve. We believe that this is one of the great contributions of the econophysics "two-class" (EPTC) approach.

Policy Implications

Three main policy implications can be adduced from our empirical results and theoretical investigations. First, one can usefully supplement traditional rankings in terms of GDPpc with those in terms of the VMI, because the latter combines income levels and inequality into a simple measure: the income per capita of the vast majority of the population in each nation. This measure has an intuitive content in its own right which need not be restricted to that of traditional welfare theory. For our second policy implication, it is useful to note that our empirical rules $\overline{y}\left(x\right) \approx a\left(x\right)(1-G)\,\overline{y}$, in which $a\left(x\right) = 1.0, 1.1$ correspond to $x = 0.70, 0.80$ respectively, implies that the per capita income of the great bulk of the population will vary *solely* with the "inequality discounted real GDP per capita" $\overline{y}' \equiv (1-G)\,\overline{y}$. This is true regardless of any interaction between distribution and growth. But since the evidence does not indicate any robust linkages between the two (Aghion, Caroli and Garcia-Penalosa, 1999 ; Alderson and Nielsen, 2003), we can say something even stronger: per capita income growth (increases in $\overline{y}$) and greater equality (increases in (1-G)) have different effects on the per capita income of the vast majority of the population in a given country depending on the initial level of G. Let $\tilde{\overline{y}}(x), \tilde{\overline{y}}, \tilde{G}$ denote percentage rates of change of majority per capita income, GDPpc (which we take here as a proxy for NNIpc) and G, respectively, and note that the rate of change of (1-G) is $-\left(\frac{G}{1-G}\right)\tilde{G}$. Then the general proportionality rule implies that

$$(7)\quad \tilde{\tilde{y}}(x) = -\left(\frac{G}{1-G}\right)\tilde{G} + \tilde{\tilde{y}}$$

Thus while growth in GDPpc will always raise majority per capita incomes by the same percentage, a given percentage reduction in *in*equality as measured by the Gini coefficient will have more than a proportional effect in countries with Gini Coefficient above 0.50, and less than a proportional effect in the rest. To put it differently, the partial elasticity of majority capita incomes with respect to GDPpc will always equal one, whereas the absolute value of the elasticity with respect to G will be greater than one for G > 0.50, and less than one for G < 0.50. As shown in Table 2, Gini coefficients range in our data from 0.25 (Denmark) to almost 0.60 (Guatemala). Thus the absolute values of the partial elasticities of per capita incomes with respect to G range from 0.33 to 1.5. Eleven out of sixty-eight countries in Table 2 (i.e. 16 percent) have Gini's above 0.50, which means that for this group the partial effect of a reduction in inequality would be greater than that of an increase in the growth rate.

A third policy implication follows from EPTC equation (3): $(1-G) = (1-G')(1-f)$, where f = the share of property income in total household income, and $(1-G')$ is a fixed number. This immediately implies that *the index of equality* $(1-G)$ *is proportional to the wage and salary share in household income* $(1-f)$. Alternately, the index of inequality G is positive linear function of the share of property income.

$$(8)\quad G = G' + (1-G')f$$

Equation (8) is a theoretical relation. But given its robust empirical performance, we may conclude that the Gini coefficient will be sensitive to changes in the distribution between wage and property incomes, but not to the distribution of income *within* either income class. This proposition has found empirical support both inside and outside the EPTC literature (Checchi and García-Peñalosa, 2008, pp. 4-5; Silva and Yakovenko, 2004, p. 3) . The implications for political economy are striking.

Summary and Conclusions

One goal of this paper is to supplement the traditional use of GDP or NNI per capita as an indicator of national progress with some intuitively meaningful statistic which combines both the level and distribution of income. We propose using the income per capita of the bottom 80 percent of the population as a supplement, and for some uses as a preferred alternative, to GDP. We call this alternative measure the Vast Majority Income (VMI), and we show that it is has some remarkable theoretical and empirical properties.

On the theoretical side, we begin by using the econophysics "two class" (EPTC) approach to income distribution, which posits and tests the hypothesis the overall distribution of income is composed of two probability distribution functions (pdfs): the exponential pdf characterizing the distribution of wages and salaries, and the Pareto pdf characterizing the distribution of property income. The EPTC approach derives a simple approximation for the corresponding overall Lorenz curve, which we then use to demonstrate that the per capita income of *any* bottom fraction (x) of the population will be proportional to "inequality-discounted" national income per capita, the constant of proportionality being solely a function of x. Here, inequality-discounted national income per capita refers to the product of net national income per capita NNIpc and (1-G), where G = the Gini coefficient.

We test this theoretical result against a large sample of countries in the WIDER-UNU-World Bank database, and show that is extremely powerful across countries and through time. Even the worst fit, which is for bottom 10 percent of the population, has a coefficient of variation (CV) of only 0.29, while population proportions greater than 50 percent have CVs between 0.02-0.06. Of these, the 80 percent proportion is best both theoretical and empirical grounds.

These findings give rise to two simple rules. The 1.1 Rule says that the VMI, the income per capita of the bottom 80 percent of a country's population, can be calculated by multiplying GDP or NNI per capita by 1.1 (1-G). This allows us to simply and accurately estimate the VMI of any country from two easily available national statistics. For the bottom 70 percent of the population, the corresponding coefficient is 1. Hence the 1.0 Rule says that inequality-discounted NNIpc is equal to the per capita income of the bottom 70 percent. This latter result is of some interest, because Sen (1976) used traditional welfare theory to derive a measure of social welfare which equals inequality-adjusted NNIpc. From our point of view, using Sen's measure this is equivalent to assessing national progress in terms of the per capita income of the bottom 70 percent. But the obverse need not be true, since we would argue that the per capita income of the great bulk of the population has an intuitive content which need not be tied to traditional welfare theory. Indeed, we arrive at this measure and its properties from an entirely different foundation. Using the VMI changes the rankings of countries. In the developed world, Norway's VMI in 2000 is 4 percent higher than that of the US, even though its NNIpc is 10 percent lower. An even greater contrast exists between Venezuela and Mexico: Venezuela's VMI is13 per cent higher even though its NNIpc is 6 percent lower.

We investigate whether our two rules might be statistical artifacts of data-fitting procedures, and conclude that they are not. We do find that roughly similar results obtain from the probability distribution functions and curves which are commonly used to fit empirical income distributions and Lorenz curves. But we argue that these functions and curves are popular precisely because they are able to accommodate the shape restrictions inherent in the two distinct underlying pdfs identified by the EPTC approach.

We draw three main policy implications from our findings. First, we argue that for international comparisons a measure such as the VMI is preferable to GDP because the former combines income levels and inequality into a simple and intuitively monetary statistic: the per capita of the bottom 80 percent of the population. Such a measure is socially and politically relevant in the same way as the income of the poor. Second, we show that while growth in average per capita incomes and reductions in inequality both raise the VMI, the latter has a larger effect in countries with Gini coefficient greater than 0.50 (eleven out of sixty-eight countries in our sample). Finally, we show that the EPTC approach implies that the Gini coefficient is a simple function of the share of property income in total national income. At practical level, this means that the Gini will be sensitive to changes in distribution between labor and property income, but insensitive to changes in distribution within either class. Since incomes in the bottom 97 percent of the population are dominated by labor income, this result is consistent with the well-known insensitivity of the Gini to distributional changes in the middle range.

This paper is part of an ongoing project to analyze international inequality. International comparisons tend to focus on either average income per capita or the incomes of the very poor (e.g. those living on less that $2 per day). While both of these are important in their own right, we would argue that the VMI adds a third dimension which broadens the discussion of international inequality. It is our hope that this will ultimately shed new light on important issues such as the relationships between inequality and development (Passé-Smith, 2003), trade liberalization (Taylor, 2007), gender (Seguino, 2007), and political instability (Muller and Seligson, 2003).

Data Appendix

1. Our distribution data is derived from the World Income Inequality Database (WIID2a) published by the United Nations University (UNU) and the World Institute for Development Economics Research (WIDER) (UNU-WIDER, 2005 June, V 2.0a-b). This is an updated and modified compilation of the original WIID V 1.0 (September 2000) and an unpublished update by Deininger and Squire (D&S, 2004) from the World Bank. Most of the distribution data is for income but in some cases it is for consumption. The original income unit

is generally the households or family, but in about 70 percent of the cases the available data is in terms of equivalent personal income, gross or disposable, by quintile or decile. In effect this gives us four subsets of the data: personal-gross, household-gross, personal-disposable, and household-disposable. In creating our present database, we removed the following observations: those which did not report at least quintile data, those which did not cover the entire area or population of a country, those with quality rankings below 2 (1 being the highest), and those with no corresponding GDPpc data in the Penn World Tables. It should be noted that all the "personal" income data is actually derived from household income data using an equivalence scale (UNU-WIDER, 2005 June, V 2.0a-a, pp. 17-18).

The resulting general dataset spans 93 countries with 1054 observations ranging from 1950 (mainly for OECD countries) up to 2003. It is partitioned into the previously discussed four subsets. Earlier observations are often quite sparse, and many countries have information for only a few years. This paper focuses on Personal Disposable (PD) income covering 81 countries because this category had the greatest number of observations (643). In order to extract per capita income levels from the relative disposable income measures derived from the distribution data, we need a corresponding measure of average disposable income per capita. GDP seemed inappropriate since it excludes net income transferred from abroad, while it includes depreciation (which does not accrue to personal income). Hence we used Net National Income (NNI) = (GDP + net income transferred from abroad) – Consumption of Fixed Capital = Gross National Income (GNI) - Consumption of Fixed Capital. In order to estimate actual standards of living, it would be preferable to subtract personal taxes from NNI and then add back the social expenditures arising from the state (Shaikh, 2003). But such information is unavailable on a world scale. To construct NNI, we began with real GDP per capita from the Penn World Tables in real international dollars (I$) which are themselves derived using Purchasing Power Parity estimates (Heston, Summers and Aten, 2006, September). For most countries, we then derived the ratio of NNI/GDP from United Nations data on "International transactions: gross and net national (disposable) income, saving, and lending aggregates (SNA 68) [code 30213]". For the remaining countries we obtained estimates for the depreciation ratio d = consumption of fixed capital (depreciation)/GDP from the Extended World Tables (Marquetti, 2004) and the ratio of g = GNI/GDP from the Penn World Tables (*op cit*) to construct n = (NNI/GDP) = (GNI-Depreciation)/GDP = (g – d). We then multiplied real GDPpc in international-$ from the Penn World Table by n to get real NNIpc in international-$. Lastly, real NNIpc was applied to the various relative per capita income measures created from the income distribution data to derive corresponding levels of disposable per capita income. There were ten countries for we did not have data on consumption of fixed capital. Hence for these countries we used the average depreciation ratio of the two countries directly above and below them in a ranking based on real GDPpc.

Distribution Theory Appendix

We examined the properties of the three most widely used probability distributions in the study of income inequality: the Pareto, the Exponential and the Lognormal. We picked combinations of parameter values for each pdf that gave us Gini coefficients within our empirically observed 0.30-0.70, checking to make sure that the corresponding Lorenz curves are viable. For each pdf, the cumulative population proportion (x) is given by its cumulative distribution function (cdf) for incomes below the given value, while the corresponding cumulative income proportion is calculated either from the appropriate formula or by summing calculated income densities. These are used to calculate the IRGS for x between 0.70-0.90. For the Pareto distribution x = cdf = 1 – $(Ymin/Y)^k$, y = 1 – $(1-x)^{1-(1/k)}$, and G = 1/(2k -1), where Ymin = the minimum income > 0, and k = the shape parameter > 0. For this simulation, Ymin was fixed and k was varied to generate Gini's within the chosen range. For the 1-earner Exponential distribution (Dragulescu and Yakovenko, 2001, 586-587), the Lorenz curve y = x + (1-x)·ln(1-x) is parameter free and the Gini is fixed at G = 1/2 while for the 2-earner G = 3/8 and the Lorenz curve can be derived from the fact that both y and x are functions of a common third variable (Dragulescu and Yakovenko, 2001, 586-588). Finally, for the Lognormal distribution the population proportion $p(Y) = \frac{1}{Y\sigma\sqrt{2\pi}} e^{-\frac{(\ln Y-\mu)^2}{2\sigma^2}}$ was calculated for income levels (Y) between 1 and 500, and then cumulated to get the cumulative population proportion (x(Y)). For each income level, Y·p(Y) represents the income proportion, and these were cumulated to generate the corresponding cumulative income proportion (y(Y)). The Gini coefficient was then calculated from Brown's Formula (Brown, 1994):

$G = 1 - \sum_{j=1}^{n} (x_j - x_{j-1})(y_j + y_{j-1})$. Table 3 displays the ratios a(x) for $0.70 \leq x \leq 0.90$, with parameter values chosen to give $0.30 \leq G \leq 0.70$. The coefficient of variation of the ratios is also displayed in the last column. a(0.80) is about 1.03 over the whole range for the Pareto pdf, is constant at 1.2 for the exponential pdf, and ranges 1.10-0\1.14 for the lognormal pdf. All three of these ranges are close to our empirically observed ratio of 1.11. Conversely, the population proportion which gives us our 1.0 Rule is roughly 75 percent in all three theoretical pdfs, as opposed to seventy percent in the actual data. Remarkably, the *minimum* coefficient of variation (CV) for these theoretical ratios occurs at x = 0.80, just as it does in the observed data in Figure 6.

[Table 3]

Our next investigation focused on the functions used to fit Lorenz curves to actual data. The three general functional forms considered were the exponential, the General Pareto (which subsumes the Ortega, the RGKO, and the classical Pareto), and the Beta (Chotikapanich and Griffiths, 2003 pp. 7-8). In the case of the exponential functional form the Gini coefficients corresponding to different parameter values can be directly calculated, but in the other two cases they are calculated via Brown's Formula cited previously. Only parameter values corresponding to viable Lorenz curves are retained. The exponential function form of the Lorenz curve is the single parameter function $y = \left(\frac{e^{ax} - 1}{e^{a} - 1} \right)$ with $(1 - G) = \left(\frac{1}{a} - \frac{1}{e^{a} - 1} \right)$, and for x = .80 this gives a(0.80) between 1.07-1.19 which is close to observed empirical ratio of 1.11, but for x = 0.70 the a(0.70) spread is between 0.61-0.99 so that the average is well below our empirical 1.0. The General Pareto is a considerably more complex three parameter function of the form

$y = x^{\alpha}\left[1-(1-x)^{\delta}\right]^{\gamma}$, where $\alpha \geq 0, \gamma \geq 1, 0 < \delta < 1$. For x = 0.80 the a(x) ranges from 1.02-1.28 with an average of 1.18, while for x = 0.70 the corresponding ratio ranges from 0.79-1.04 with an average of 0.90. Finally, the generalized Beta functional form is $y = x - a x^{d}(1-x)^{b}$, where a > 0, $0 < d \leq 1, 0 < b$

≤ 1. This gives rise to the most complicated set of calculations because viable Lorenz curves turned out to require $0 < a < 1$ and $d > 0.6$, and high values of the parameter a required corresponding high values of d. As a result, with the Beta function we were only able to generate Gini coefficients at the low end of our chosen scale, between 0.30-0.40. Table 5 summarizes the results of these experiments.

[Table 4]

Tables and Figures

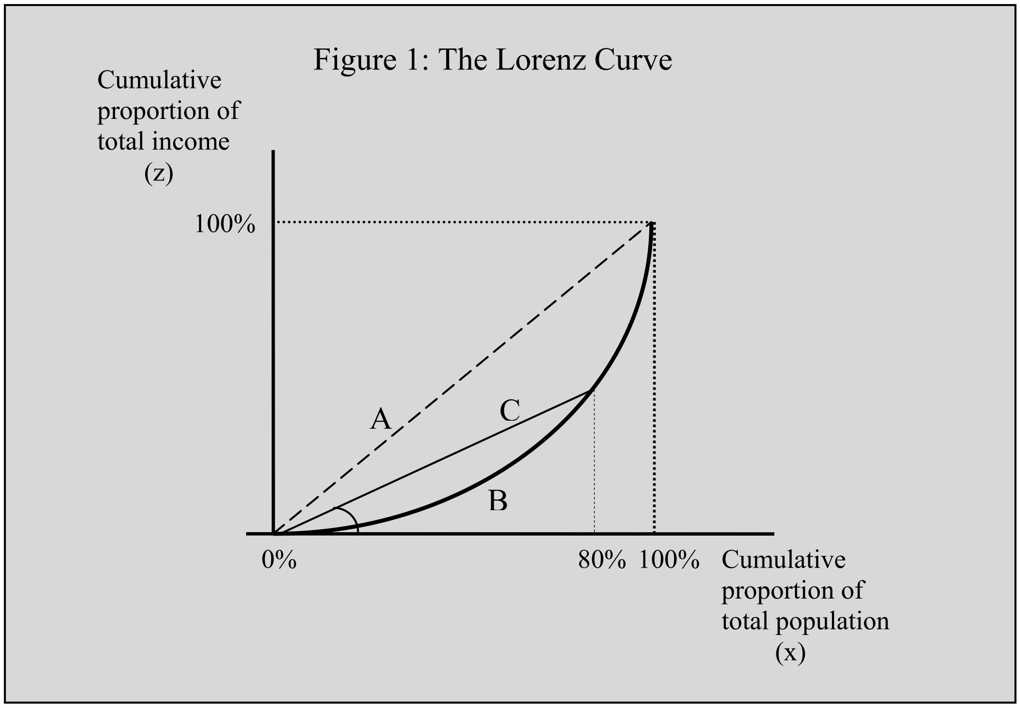

Table 1: Theoretical and Actual Constants of Proportionality a(x)			
Cumulative Population Proportion (x)	Econophysics 1-Earner Households	Econophysics 2-Earner Households	Actual International Data
0.1	0.1	0.27	0.4
0.2	0.22	0.41	0.52
0.3	0.33	0.53	0.61
0.4	0.47	0.64	0.7
0.5	0.62	0.76	0.79
0.6	0.78	0.88	0.88
0.70	0.97	1.01	0.99
0.75	1.08	1.08	NA
0.80	1.20	1.15	1.11
0.85	1.33	1.23	NA
0.90	1.49	1.33	1.27

Figure 2: VMIR (Per Capita Vast Majority Income relative to GDP) by Country
(2000 or closest)

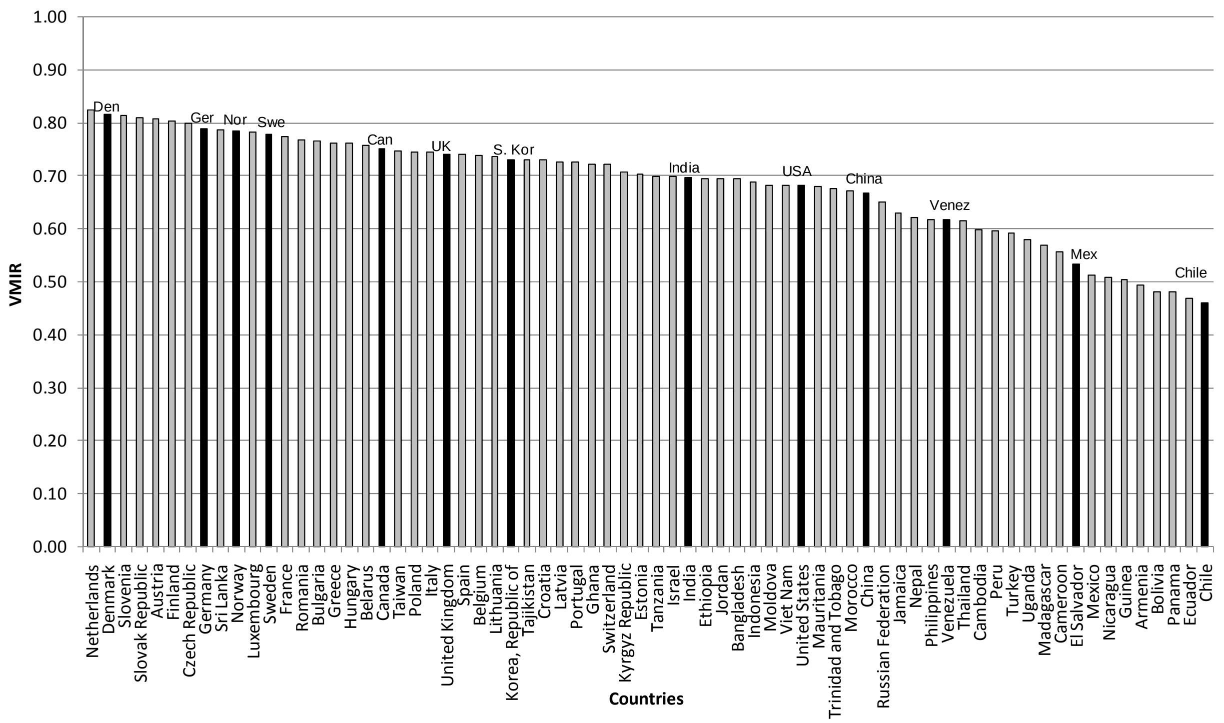

Figure 3: VMIR Over Time, Countries with Sufficient Data

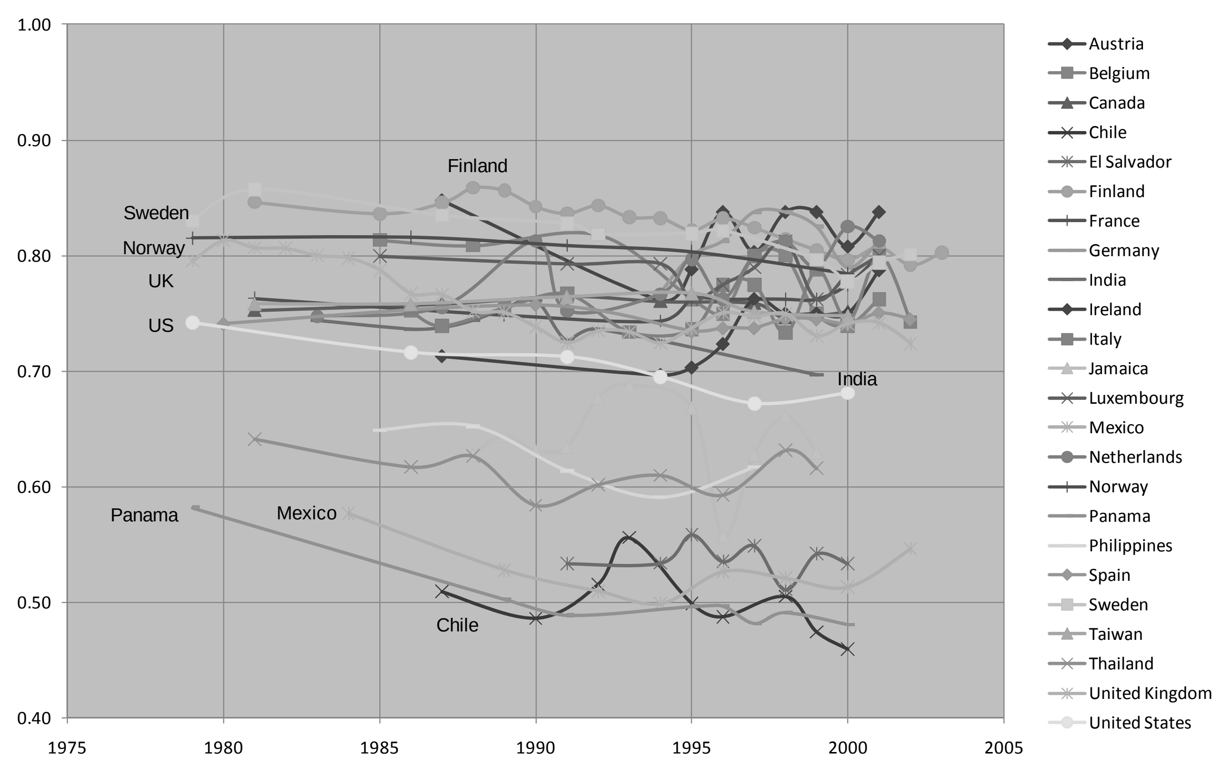

Table 2: Per Capita VMI and NNIpc, and Country Rankings by Each Measure

		Real Per Capita (International-$)			Rank		
Country	**Gini**	**NNI**	**VMI**	**AMI**	**NNI**	**VMI**	**Rank Difference**
India	**36.00**	$2,371	$1,651	$5,247	57	51	6
Kyrgyz Republic	**37.00**	$2,886	$2,039	$6,275	54	50	4
Jordan	**36.30**	$3,526	$2,449	$7,833	47	43	4
Bulgaria	**30.70**	$6,282	$4,809	$12,175	38	34	4
Viet Nam	**37.30**	$1,993	$1,359	$4,531	60	57	3
Moldova	**39.55**	$2,021	$1,379	$4,590	59	56	3
Indonesia	**36.50**	$3,308	$2,277	$7,434	51	48	3
China	**40.30**	$3,478	$2,320	$8,111	48	45	3
Poland	**32.45**	$7,228	$5,390	$14,579	33	30	3
Netherlands	**25.50**	$22,404	$18,483	$38,087	9	6	3
Bangladesh	**35.85**	$1,768	$1,227	$3,930	61	59	2
Morocco	**39.20**	$3,436	$2,306	$7,954	49	47	2
Sri Lanka	**27.60**	$3,767	$2,965	$6,971	43	41	2
Latvia	**34.30**	$7,034	$5,100	$14,772	35	33	2
Lithuania	**33.00**	$7,742	$5,702	$15,904	31	29	2
Belarus	**30.75**	$7,979	$6,035	$15,755	30	28	2
Slovak Republic	**26.15**	$8,651	$6,999	$15,262	28	26	2
Greece	**32.30**	$12,847	$9,796	$25,052	23	21	2
Sweden	**28.20**	$21,892	$17,023	$41,369	11	9	2
France	**28.20**	$22,248	$17,242	$42,271	10	8	2
Ethiopia	**36.15**	$697	$484	$1,546	68	67	1
Ghana	**33.90**	$1,290	$932	$2,723	65	64	1
Romania	**29.85**	$4,374	$3,358	$8,437	40	39	1
Thailand	**44.60**	$5,893	$3,630	$14,944	39	38	1
Venezuela	**45.80**	$6,666	$4,113	$16,878	37	36	1
Hungary	**30.30**	$9,464	$7,216	$18,455	26	25	1
Taiwan	**31.55**	$17,463	$13,059	$35,083	17	16	1
Finland	**25.98**	$18,754	$15,069	$33,490	15	14	1
Germany	**27.60**	$21,078	$16,641	$38,825	13	12	1
Norway	**27.40**	$28,153	$22,092	$52,394	3	2	1
Cambodia	**44.50**	$494	$295	$1,288	69	69	0
Uganda	**46.90**	$963	$559	$2,580	66	66	0
Mauritania	**38.90**	$1,432	$974	$3,263	63	63	0
Tajikistan	**33.30**	$1,511	$1,104	$3,142	62	62	0
Jamaica	**43.30**	$4,013	$2,528	$9,953	42	42	0
Croatia	**33.95**	$7,278	$5,310	$15,154	32	32	0
Estonia	**36.50**	$9,227	$6,489	$20,178	27	27	0
Czech Republic	**25.90**	$10,487	$8,370	$18,956	24	24	0
Korea, Republic of	**36.90**	$13,371	$9,765	$27,792	22	22	0
Portugal	**34.70**	$13,894	$10,073	$29,178	20	20	0
Slovenia	**25.15**	$15,079	$12,267	$26,329	19	19	0
Spain	**32.48**	$16,694	$12,370	$33,989	18	18	0
Denmark	**24.85**	$22,900	$18,702	$39,693	5	5	0
Switzerland	**35.90**	$26,246	$18,949	$55,431	4	4	0
Luxembourg	**28.25**	$37,736	$29,560	$70,438	1	1	0
Madagascar	**48.50**	$814	$464	$2,214	67	68	-1
Nepal	**42.55**	$1,337	$832	$3,357	64	65	-1
Nicaragua	**55.50**	$2,913	$1,478	$8,651	53	54	-1
Israel	**38.05**	$17,779	$12,405	$39,277	16	17	-1
Italy	**33.80**	$19,366	$14,407	$39,203	14	15	-1
Belgium	**31.33**	$21,381	$15,804	$43,689	12	13	-1
Austria	**26.45**	$22,733	$18,362	$40,217	6	7	-1
United States	**39.75**	$31,283	$21,309	$71,178	2	3	-1
Philippines	**44.15**	$3,752	$2,316	$9,496	44	46	-2
Russian Federation	**42.50**	$8,265	$5,374	$19,825	29	31	-2
Trinidad and Tobago	**40.20**	$13,445	$9,094	$30,850	21	23	-2
Cameroon	**50.80**	$2,145	$1,193	$5,952	58	61	-3
Bolivia	**58.05**	$2,642	$1,273	$8,118	55	58	-3
Armenia	**56.05**	$2,923	$1,443	$8,844	52	55	-3
Ecuador	**58.80**	$3,310	$1,548	$10,354	50	53	-3
Peru	**46.50**	$3,553	$2,115	$9,307	46	49	-3
El Salvador	**53.45**	$4,372	$2,333	$12,526	41	44	-3
Mexico	**54.20**	$7,115	$3,653	$20,962	34	37	-3
United Kingdom	**33.05**	$22,454	$16,645	$45,689	8	11	-3
Canada	**32.40**	$22,655	$17,021	$45,192	7	10	-3
Guinea	**55.10**	$2,384	$1,200	$7,122	56	60	-4
Panama	**57.80**	$6,728	$3,236	$20,696	36	40	-4
Guatemala	**59.80**	$3,614	$1,631	$11,547	45	52	-7
Chile	**58.20**	$9,512	$4,371	$30,077	25	35	-10
Coefficient of Variation		**89.40%**	**95.91%**	**82.21%**			

Figure 4: The 1.1 Rule: VMIR/(1-G) by country (alphabetical order), for 2000 or closest Year (overall average = 1.11)

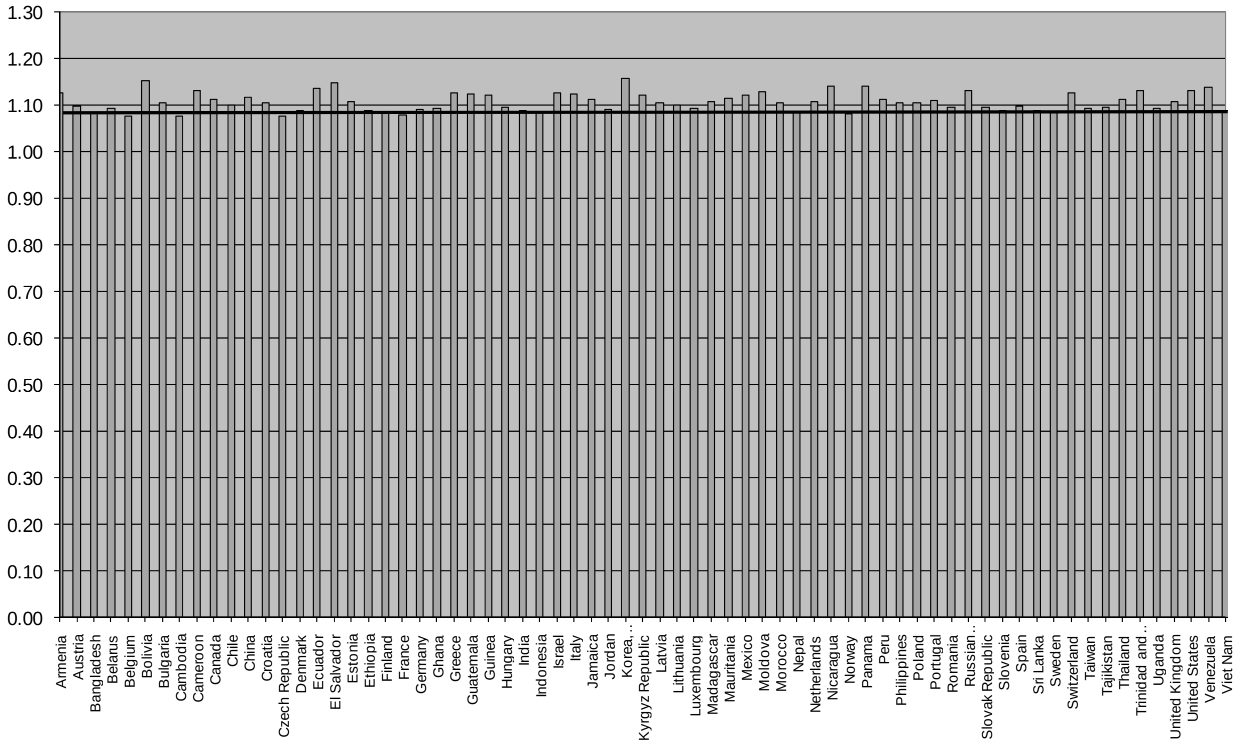

Figure 5: a(80) Over Time, Countries With Suficient Data (Overall Average = 1.10)

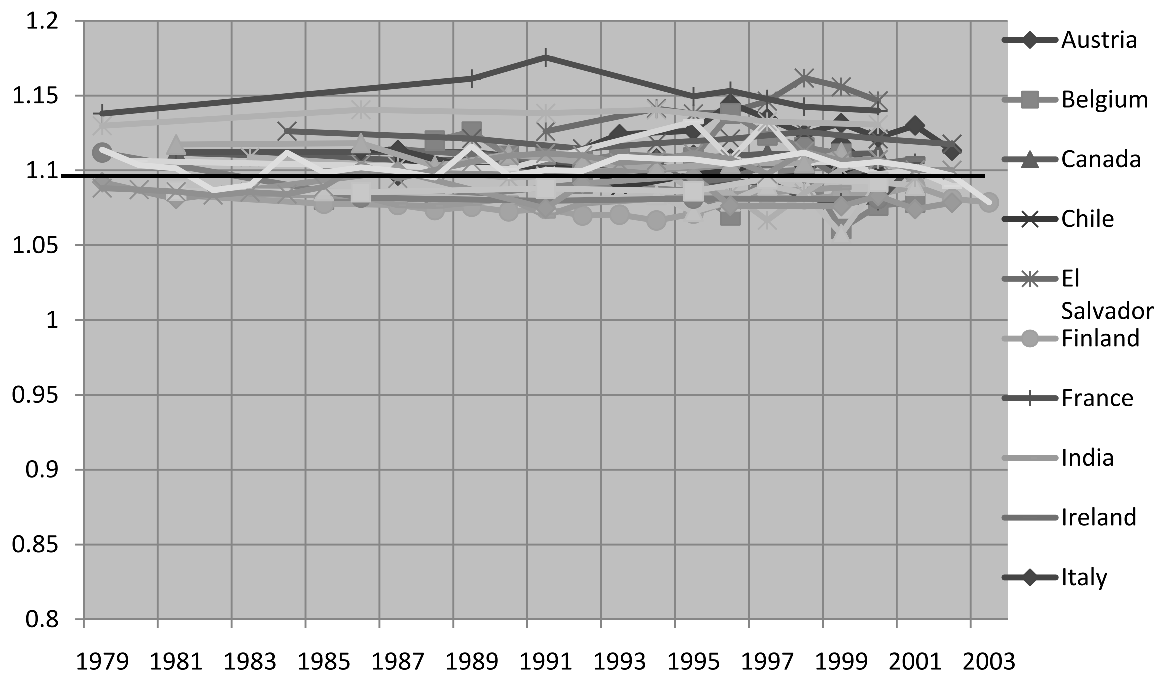

Figure 6: Relative Per Capita Incomes of Various Population Proportions over (1-G), 2000 or closest year (countries ranked in ascending order of real NNIpc)

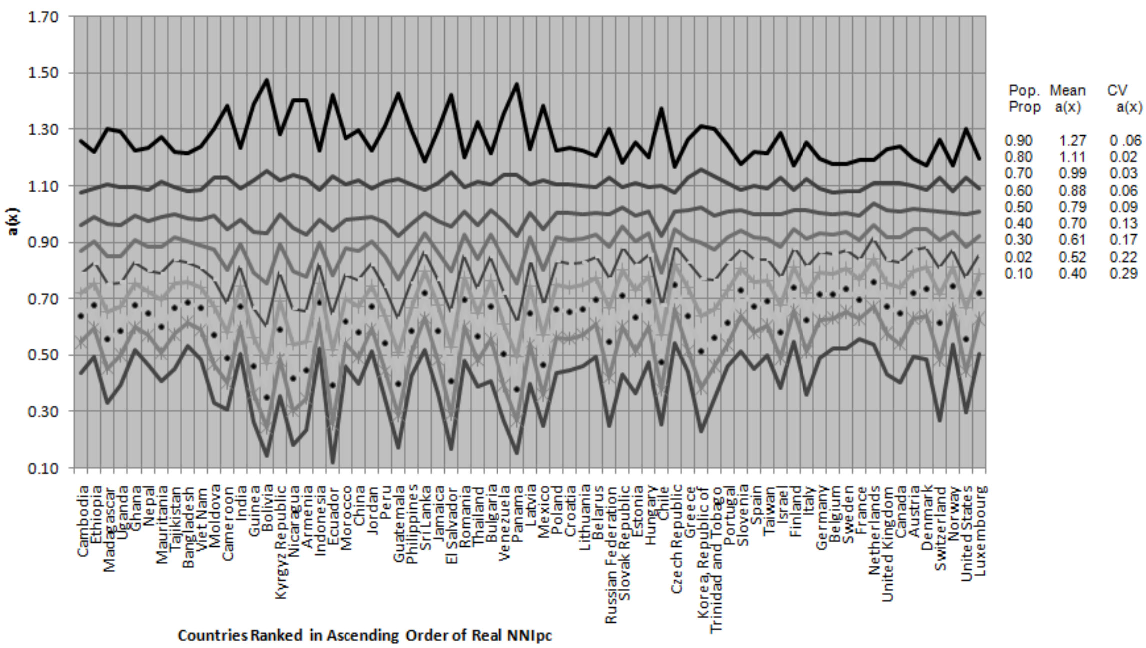

Table 3: Probability Distributions and a(x) coefficients						
						CV
G	**0.30**	**0.40**	**0.50**	**0.60**	**0.70**	
Pareto Distribution (Ymin = 2.50)						
k	*2.17*	*1.75*	*1.50*	*1.33*	*1.21*	
a(0.70)	0.973	0.959	0.944	0.928	0.911	0.026
a(0.75)	1.001	0.995	0.986	0.976	0.964	0.015
a(0.80)	**1.035**	**1.038**	**1.038**	**1.035**	**1.030**	**0.003**
a(0.85)	1.076	1.091	1.103	1.111	1.115	0.015
a(0.90)	1.128	1.161	1.191	1.216	1.237	0.036

Exponential Distribution (parameter free)						
a(0.70)			0.968			-
a(0.75)			1.076			-
a(0.80)			**1.195**			-
a(0.85)			1.330			-
a(0.90)			1.488			-
Lognormal Distribution (μ = 1.5)						
σ	*0.55*	*0.75*	*0.96*	*1.20*	*1.47*	
a(0.70)	1.003	0.982	0.950	0.896	0.825	0.072
a(0.75)	1.047	1.048	1.036	1.007	0.951	0.037
a(0.80)	**1.097**	**1.121**	**1.136**	**1.133**	**1.106**	**0.025**
a(0.85)	1.155	1.206	1.250	1.288	1.305	0.079
a(0.90)	1.217	1.306	1.393	1.487	1.577	0.164

Table 4: Beta Functional Form and a(x) for 0.30 ≤ G ≤ 0.40

		x =	**0.70**	**0.75**	**0.80**	**0.85**	**0.90**
a	**b**	**d**					
0.1	**0.9**	**0.80**	1.007	1.013	1.019	1.025	1.031
0.2	**0.3**	**0.75**	1.006	1.018	1.032	1.047	1.064
		0.80	1.003	1.014	1.027	1.041	1.058
	0.6	**0.75**	1.011	1.026	1.040	1.056	1.073
		0.80	1.008	1.022	1.036	1.051	1.068
0.3	**0.3**	**0.75**	1.009	1.030	1.052	1.077	1.106
		0.80	1.004	1.023	1.044	1.068	1.096
		0.95	0.992	1.007	1.024	1.045	1.070
	0.6	**0.75**	1.018	1.041	1.065	1.090	1.117
		0.80	1.013	1.035	1.058	1.082	1.109
		0.95	1.001	1.020	1.040	1.062	1.087
	0.9	**0.75**	1.027	1.049	1.070	1.090	1.111
		0.80	1.023	1.043	1.063	1.083	1.104
		0.95	1.011	1.029	1.048	1.066	1.085

0.4	0.3	0.75	1.014	1.045	1.078	1.114	1.158
		0.80	1.006	1.035	1.065	1.100	1.142
	0.6	0.75	1.026	1.059	1.093	1.129	1.168
		0.80	1.019	1.050	1.082	1.117	1.155
	0.9	0.75	1.039	1.068	1.098	1.127	1.156
		0.80	1.032	1.061	1.089	1.117	1.145
0.5	0.3	0.95	0.984	1.015	1.049	1.090	1.141
	0.6	0.95	1.003	1.038	1.075	1.117	1.164
	0.9	0.95	1.021	1.053	1.087	1.120	1.155
0.75	0.3	0.95	0.968	1.030	1.100	1.183	1.286
	0.6	0.95	1.005	1.068	1.136	1.210	1.294
	0.9	0.95	1.035	1.091	1.147	1.204	1.263
0.8	0.3	0.95	0.660	0.708	0.764	0.829	0.910
	0.6	0.95	0.805	0.861	0.922	0.988	1.063
	0.9	0.95	0.893	0.946	0.999	1.053	1.108
a(x) Mean			0.988	1.017	**1.048**	1.082	1.120
a(x) Std. Dev.			0.0779	0.0722	0.0691	0.0698	0.0762
a(x) CV			0.0789	0.0710	0.0659	**0.0645**	0.0680

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[1] Gruen and Klasen (2008, p. 6 footnote 6) mention that utility functions are also judged in terms of their "intuitive appeal".
[2] The Gini coefficient itself can be characterized in a variety of ways, but none of them is particularly intuitive (Subramanian, 2004, p. 7)

[3] The key finding is that "the majority of the population … has a very stable in time exponential ("thermal") distribution of income" which is analogous to the equilibrium distribution of energy in statistical physics following the Boltzmann-Gibbs law of the conservation of energy (Dragulescu and Yakovenko, 2002, pp. 1-2). Yakovenko has pointed out that Gibbs developed his notion of the distribution of particles from his study of social patterns. In this regard econophysics is merely returning the favor.

[4] The Gini coefficient of the whole Lorenz curve is G = (1+f)/2 (Silva and Yakovenko, 2004, p. 5), which yields equation (2) in the text.

[5] We thank Victor Yakovenko for pointing out that the "personal-equivalent" units upon which our data is based are actually derived from household data (see the Data Appendix), so that the relevant income distribution is the distribution of household incomes.

[6] It can be shown that an equally weighted average of 1-earner and 2-earner households will have a IR/(1-G) ratio close to that of the 2-earner households.

[7] Sixteen observations comprising eleven countries (Fiji, Mauritius, Costa Rica, Japan, Malawi, Nigeria, New Zealand, Lesotho, Cote d'Ivoire, Dominican Republic, Mali) were excluded from Figures 2-3 because the only data on them was in the years 1975-1989.

[8] Countries like Japan are not in this sample because their data is in terms of gross income rather than disposable income.