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An International Comparison of the Incomes of the Vast Majority

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Introduction

Income levels and income inequality are two major dimensions of national and international well-being. The last two decades have witnessed a growing concern about both issues, from policy makers, social scientists, and the media. But the two dimensions 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. Sometimes these are implicitly combined, as in the case of poverty measures which count the number of people in each nation who live on less than one dollar a day (World Bank, 2000/2001, p. 3)

There are well-known problems with these traditional approaches. First of all, average income per capita also tells us nothing about income variations within a population. For instance, if four people with an average income of $50,000 are joined by one more with an income of $300,000, the per capita income of the group doubles[1]. Knowing that the Gini coefficient of the group is "high" alerts us to the fact that the average is unrepresentative, but does little to help us understand its real magnitude.

A simple alternative would be to measure the income per capita of the vast majority of this group, say the first 80 percent in the income ranking. Such a measure would combine the average level of income and its distribution into an intuitively useful statistic. Moreover, it would have obvious political resonance in any modern political system. There is evidence, for instance, that state-wide voting preferences in the US are correlated with changes in average local incomes (Altman, 2006) and it would be interesting to see if this relationship is stronger with vast majority incomes.

[1] With this income distribution, the ratio of the average per capita income of the first four people to the average is 0.50, which is representative of the income distributions in countries like Mexico, Nicaragua, and Guinea. The actual income levels in these particular countries are much lower, of course.

This paper is part of an ongoing project to analyze international inequality. International comparisons tend to focus on either GDP per capita or the incomes of the very poor (e.g. those living on less that $2 per day). The VMI adds a new dimension, because it combines information on income levels and their distribution into a single measure which is the average income of the vast majority of the population. We believe that this broadens the discussion of international inequality, and will ultimately shed new light on several important issues in the development literature such as the relationships between development and inequality, growth and inequality, trade liberalization and living standards, and political instability and inequality. In this paper we focus on the first issue by exploring the links between development and the incomes of the vast majority of the world's population.

In this paper we develop the preceding measure on an international scale. We begin by calculating the ratio of the disposable income per capita of the first 80 percent (the vast majority) of the population to the average income per capita, in any given nation. We call this the Vast Majority Income Ratio (VMIR), and show how it can be derived from a Lorenz curve. Multiplying this ratio by an appropriate average real per capita income measure (Net National Income per capita) then gives us the real income per capita of the vast majority of the population across nations, regions and/or time. It is shown that the VMIR varies considerably across countries. This implies that average per capita income measures such as GDP or Net National Income are not reliable proxies for the per capita incomes of international vast majorities. Indeed, we show that ranking countries by their vast majority incomes (VMIs) gives different results than ranking them by average per capita income. In next section of the paper we demonstrate that the VMIR, which is itself an equality measure, bears a constant ratio to (1- G) *across countries and across time*. This unexpected internal relation, which we call "The 1.1 Rule", also leads us to a new interpretation of the Gini Coefficient as the relative per capita income of the first seventy percent of the population in any given country. The theoretical foundations of these two empirical rules are addressed in a section on distribution theory and "econophysics". Policy implications are outlined next, as are connections to an earlier literature in which (1-G) was proposed as a discount factor for various measures of well-being. The paper ends with a summary and a discussion of potential areas of future research. The Data Appendix explains our sources and methods.

Measures of Income and Inequality on a World Scale

GDP per capita (GDPpc) is by far the most popular measure of international levels of development. It is fairly well understood and widely available across countries and time (Frumkin, 2000, pp. 144-154). But it is also recognized that GDPpc is an imperfect proxy for important factors such as health, education and well-being (Cowen, 2007). Therefore an alternative approach has been to work directly with the variables of concern, as in the UNDP Human Development Index (HDI) which combines GDPpc with life expectancy and schooling into a single composite index (UNDP, 1990, p. 12).

Both the GDPpc and the HDI suffer from that fact that "they are averages that conceal wide disparities in the overall population" (UNDP, 1990). As a result it becomes necessary to either supplement these measures with information on distributional inequality as in the Gini coefficient, or to directly adjust GDPpc and other variables for distributional variations. For instance, since a higher inequality implies a lower (1-G), the 1993 HDI multiplied its GDPpc component by (1-g) so as to penalize countries with higher inequalities. This use of (1-G) as a "inequality factor" was subsequently extended to the other two variables in the HDI using discount factors based on the degrees of inequality in their specific distributions, and later to gender-based inequalities by discounting a country's overall HDI according to the degree of gender-inequality in the three variables (Hicks, 2004, pp. 2-3). These earlier initiatives will be re-examined in light of our own finding that inequality-discounted GDP per capita can be interpreted as a measure of the relative per capita income of the first seventy percent of a nation's population..

In any case, while the HDI is presently the most important alternative to average income measures such as GDPpc, it is difficult to compile and is only available for recent years. Moreover, because it is an index, it can only provide rankings of nations at any moment of time and can only measure changes over time. As such, it cannot tell us about the absolute standard of living of the underlying population. This is precisely why GDPpc remain so popular (Hicks, 2004, pp. 2-3). In any case, it turns out that the rankings produced by the two measures are quite highly correlated (1991, pp. 322-323). We will therefore focus constructing an intuitive combination of average income and its underlying distributional inequality.

The Vast Majority Income as a Combination of Income and Inequality Information

The use of GDP per capita can seriously misrepresent international comparisons because the distribution of income and consumption can be highly skewed within countries. This is particularly true in the developing world, where a rise in GDP per capita can be attended by a worsening in the distribution of income, so that the standard of living of the vast majority of the population may actually decline at the same time. To this end, GDPpc is often supplemented with some distributional measure such as the Gini coefficient which is most often derived from the Lorenz curve of income or consumption inequality.

The Lorenz curve is based on an ordered ranking of individual or group incomes. Suppose we have 5 people with equal incomes of $20. Then the first person would represent 20 percent (a quintile) of the population and also 20 percent of total income; the first two people would represent 40 percent of the population and 40 percent of the income, and so on, until we reach 100 percent of population and income. Plotting the cumulative population proportion (x) on the horizontal axis and the cumulative income proportion (z) on the vertical axis would then give us the 45-degree line A (the line of equality) in Figure 1 below. But if instead incomes are

$5, $10, $15, $20, and $50 respectively[2], then when they are ranked from the lowest to the highest the first 20 of the population (the first person) will have five percent of total income; the first forty percent (the first two people) of the population will have 15 percent of total income, and so on. The resulting Lorenz curve will be therefore "bowed-inward" as in curve B below (Lampert, 2001, pp. 23-26).

Since the inequality of the underlying income distribution accounts for the inward-bow of the Lorenz curve, one way to summarize the underlying degree of inequality is to take the ratio of the area between the 45-degree line A and the curve B, to the area under the line A. This is the Gini coefficient G (Lampert, 2001, pp. 26-27). Under complete equality the Lorenz curve would be on the 45-degree line, so that G would equal zero. At the other extreme, under complete inequality the first four people would have zero incomes and the last would have $100, so that the Lorenz curve would run along the x-axis until it jumped to 100 percent of cumulative income at 100 percent of the population. In this case the area below the curve would be the same as that under line A, so that G would be one. In general the Gini Coefficient lies somewhere between 0 and 1, with higher Gini's representing higher degrees of inequality[3]. It should be obvious we could work instead with (1-G), which is the area under curve B divided by the area below line A. Then a higher (1-G) represents a higher degree of equality. This will become important subsequently.

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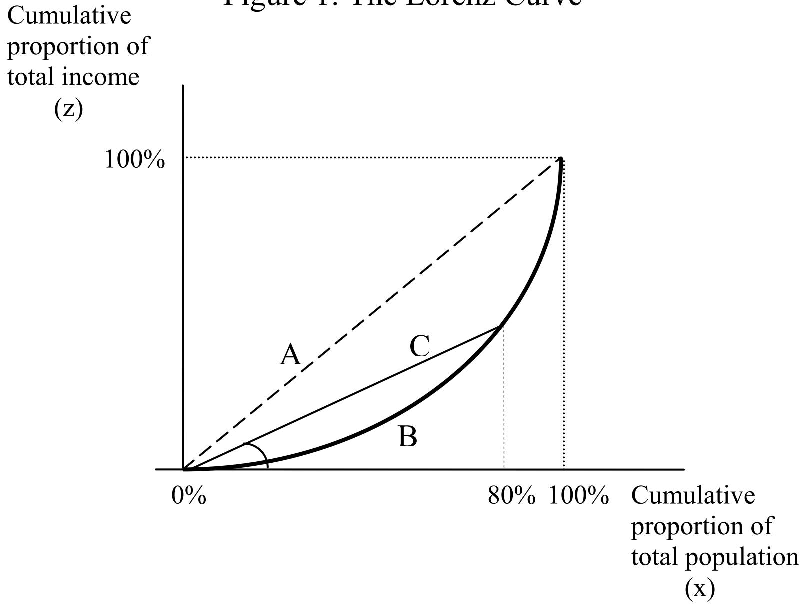
[2] These numbers are roughly the same as the actual income shares of each quintile of US households in 2000, which are 3.60, 8.90, 14.90, 23.00, and 49.60 taken from the World Income Inequality Database (UNU-WIDER, 2005 June, V 2.0a-a).

[3] Since Lorenz curves can cross, it is possible to have curves with different distributions yielding the same Gini. Thus the Gini is not an absolute indicator of inequality.

Figure 1: The Lorenz Curve



In addition to its interpretation as a ratio of two areas, the Gini coefficient can also be characterized in other ways, such as "the expected distance between two randomly drawn incomes over twice the mean" (Subramanian, 2004, p. 7). But none of these are particularly helpful when confronted with actual data.

To go beyond this, it is useful to note that calculating the ratio of the per capita income of any population subgroup to the average is a particularly simple and intuitive way of taking both dimensions into account. Consider our previous example in which there were five people with incomes of $5, $10, $15, $20, and $50, respectively. Then in order to compute the per capita income of the vast majority, i.e. the first 80 percent of the population, we average the first four incomes to get $12.5 per person, as compared to the overall average which is $20. The ratio of the vast majority income to the overall average (VMIR) is therefore 0.625 (= $12.5/$20). But we can also work backwards by first summing the cumulative income proportion of the first four quintiles (0.05 + 0.10 + 0.15 + 0.20 = 0.50) and dividing them by the corresponding cumulative population proportion (0.80) to get 0.625, which is the ratio of the vast majority per capita income to the average. This is useful because the cumulative income proportion is the y-axis of the Lorenz curve and the cumulative population proportion its x-axis. Therefore the vast majority income ratio (VMIR) is simply the slope of the ray through the origin to the point on the curve which represents 80 percent of the population -- i.e. the slope of the line C in Figure 1. Multiplying the VMIR by the average income per capita ($20) then gives us the actual level of the vast majority income per capita ($12.5). In this way we can use international income inequality data to calculate the VMIR and use the appropriate average per capita measure from national income accounts to calculate the level of the vast majority per capita incomes in any given year[4].

Evidently the same procedure would apply to the relative income ratio (IR) for any proportion of the population, such as the bottom quintile or decile[5]. But in this paper we have chosen to focus on the per capita income of the vast majority (the first 80 percent) of the population. This in part because average per capita income is often implicitly taken to be a proxy for the vast majority per capita income, and we wish to demonstrate that the two can differ markedly. But it is also because the notion of the income of the vast majority has obvious political resonance in any modern political system, and we wish in subsequent work to explore its links to voting preferences, political unrest, international convergence or divergence and a host of other issue. In the next section we will briefly discuss our sources and methods (with further details relegated to Appendix A) and then present our first set of empirical results.

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-a). 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. In addition, the temporal coverage is uneven for earlier years and for most non-OECD countries. In this paper we use the largest consistent data subset we were able to construct (643 observations), which is for the distribution of Personal Disposable (PD) income. To complement this, we use Net National Income per capita (NNIpc) rather than GDPpc as the appropriate measure of average national income per capita. NNI is more appropriate because it includes the factor income accruing from the rest of the world but excludes depreciation (which should not enter into personal income). Further details are in Appendix A.

Figure 2 and Table 1 display the VMIR ratio, which in this case is the ratio of the personal disposable income per capita of the vast majority to the average, by country, for the latest year

[4] We could do the same thing in terms of consumption rather than income, if we have distribution data on individual or household per capita consumption to which we can apply national accounts data on average per capita consumption.

[5] If we designate the population and income of the i^{th} group (e.g. second quintile, or fifth decile, etc.) by X_i and Y_i respectively, and the corresponding totals across all groups by X, Y, then the cumulative population and income proportions from zero to the i^{th} group are $\sum X_i/X$ and $\sum Y_i/Y$ respectively. But then the ratio $(\sum Y_i/Y)/(\sum X_i/X) = (\sum Y_i/\sum X_i)/(Y/X)$ = the per capita income of the i^{th} group over the per capita income of the whole.

available since 1990 for each of the countries in DB1[6]. The higher this ratio, the closer is the per capita income of the vast majority to that of the top 20 percent of their fellow citizens, hence the more equal the income distribution. It is immediately apparent that this ratio 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 sample (0.68)[7].

[Figure 2]

[Table 1]

Since the VMIR is a measure of equality, there are also transitional economies and developing countries sandwiched between the developed ones. For instance, Slovenia, the Slovak Republic and the Czech Republic are also at the very top end of the scale (0.80-0.81) next to Austria, Belarus is close to Canada, Poland close to Italy and Lithuania close to Belgium. India (0.70) stands alongside Israel above the US (0.68), while China (0.67) is not far below the US. Not surprisingly, the bottom end of this scale is dominated by developing countries, such as Nepal, the Philippines and Venezuela (0.62), with Chile and Guatemala bringing up the rear (0.45-0.46). In any case, it is evident that neither GDPpc nor NNIpc would be good proxies for the income levels of the vast majority because the VMIR varies so greatly across countries.

The discrepancy between vast majority incomes and the corresponding national average (NNIpc) is further compounded by the fact that their ratio 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 3]

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

[6] 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 range 1975-1989.

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

While the international patterns of the VMIR are important in their own right, our ultimate concern is with the absolute level of vast majority per capita incomes (VMI) in each country, which are derived by multiplying VMIR by NNIpc. Figure 4 displays both NNIpc and VMI by country, while Table 2 shows the same data 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 difference between these two. In this table, the countries themselves are listed in ascending order according to the degree to which their ranking changes when we use VMI rather than NNI. Thus Chile is first since it drops 10 ranks, while India is last because it gains 6 ranks.

Three interesting patterns emerge from this data. First of all, we find a great range in VMI's: in rounded figures, 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 Ethopia and 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 rich are more alike across nations than are the rest of their fellow citizens. 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 countries in the sample, along with their change in rankings when one considers VMI instead. This latter information is also displayed graphically in Figure 5, which shows the numerical difference in NNIpc and VMI rank for these same countries. We see Chile falls 10 places in the rankings, because of its highly unequal distribution of income, followed by Guatemala (-7) and then Guinea and Panama (-4). Luxemburg remains at the top by either measure, while the US drops from second to third while Norway rises from third to second. Small or zero rank changes occur for most developed countries. At the other end, countries like Bulgaria, Jordan, the Kyrgyz Republic and India gain in rankings, sometimes substantially so.

[Figure 4]

[Table 2]

[Figure 5]

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*. The question now is: how are these two different inequality measures related?

We know that the two measures have the same limits: both equal 1 under perfect equality, and both equal 0 under perfect inequality. We also noted previously in Figure 1 that both can be derived from a Lorenz curve, since the VMIR can be represented as a ray through the origin to the point on the Lorenz curve corresponding to an 80 percent population proportion, while (1-G) the area under the Lorenz curve and the perfect equality line, relative to the area of the triangle under the perfect inequality line 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 equality measures as we move across countries and time[8]. Nonetheless, this is precisely what we do find: across countries, and even across time, the ratio of VMIR to (1-G) is remarkably close to 1.1! We call this extraordinary empirical pattern the "1.1 Rule". Figure 6 and Table 3 displays cross section data on this ratio for the year 2000, with the overall sample mean ratio (which is 1.10) displayed on the figure and listed at the end of the table. Figure 7 and Table 4 display these same ratios across time for those countries with a sufficient temporal span in their data. Note that the ratios seldom go beyond ± 5 percent of the mean ratio.

[Figure 6]

[Table 3]

[Figure 7]

[Table 4]

The remarkable stability of VMIR/(1-G), and even its particular numerical value, pose interesting theoretical puzzles. Most of the probability distributions used to describe income distribution data would not predict anything like this. Nonetheless, although this has not been shown previously, it is possible to derive not only the regularity of this ratio but also its particular numerical value, from the mathematical formulations of a particular approach (Silva and Yakovenko, 2004) to the "econophysics" of income distribution A brief introduction to the related theory is presented in the next section. But first, we develop the implications of the "1.1 Rule" in a different direction, which is to construct a simple intuitive meaning for the Gini Coefficient.

[8] 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.

4. A New Interpretation of the Gini Coefficient

The "1.1 Rule" implies that VMIR ≈ 1.1·(1-G), where VMIR is the income ratio of the first 80 percent of the population. Since this rule holds across countries and over time, it is natural to ask if the income ratios corresponding to other cumulative proportions of the population also exhibit similar stability. For if they do, then for some population proportion x* there will be an income ratio IR(x*) ≈ (1-G). This in turn would mean that we could directly interpret (1-G) as the relative per capita income of the first x* percent of the population in *any* country.

For this procedure to be valid, we need to first establish that the income ratios for nearby other population proportions are stable across countries. Figure 8A plots the relative per capita income at cumulative population proportions from sixty to ninety percent, with the nations listed in ascending order of real NNIpc. Displayed on the right hand side of the graph are the population proportions, the means and the coefficients of variation (CVs) for each of the series shown. We see once again the remarkable constancy of the eighty percent ratio (VMIR) across nations as different as Cambodia and the United States. And now we see that the seventy percent ratio is also constant across nations, this time at a ratio essentially equal to one: its actual mean is 0.99, and almost all of its variations turn out to lie with a band of ± 5 percent of the mean. Figure 9, which plots the all-country *average* IR(x)/(1-G) ratio for each cumulative proportion of the population from ten percent to ninety percent (along with the corresponding ranges) yields the same result. Thus we can provide a new interpretation of the Gini Coefficient, 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.*

It is useful to note that the countries in Figures 8A and 8B are ranked in ascending order of real NNIpc. In Figure 8A, the IR(x)/(1-G) ratio of the ninety percent population fraction slopes *downward* as we go from the middle income countries to the rich ones, while in Figure 8B (which skips alternate deciles to avoid visual clutter) the lower population fractions slope *upward* over the same range. We will see in the next section that the theoretical derivation of the IR(x)/(1-G) ratios refers to *gross* incomes. But our present data is in terms of *disposable* income, and in this case relative tax rates also play a role. Then if the gross income ratios were constant for any population proportion, we would expect progressive tax rates to make the disposable income ratios trend downward at high ends of the income spectrum and trend upward at low ends[9] -- just as we find.

[Figure 8A]

[Figure 8B]

[9] Let y_G = gross per capita income, t = the effective tax rate, and y = disposable per capita income. Then $(y(x)/y) = (y_G(x)/y_G)\cdot(1 - t(x))/(1- t)$, which means that the disposable income ratio will be below the gross income ratio for groups with higher than average tax rates, and above in the opposite case. This would automatically be true if countries with higher inequality, i.e. lower (1-G) were also poorer countries in which the significant portions of the bottom end of the income distribution did not pay much in taxes.

[Figure 9]

It follows that knowledge of the Gini Coefficient and NNIpc is sufficient information to estimate the disposable per capita income of the first seventy percent of the population in any given country. Figure 10 shows that this rule is quite accurate, even though the actual data falls about 8 percent below the theoretical curve (the 45-degree line) at the lowest end of the equality scale and rise about 4 percent above it at the highest end. This too could be explained if the seventy percent population fraction was taxed at a relatively higher rate (relative to its own national average) in richer countries, and if richer countries generally have more equal income distributions. We could of course improve the predictions by running a simple regression. But that would miss the main point, which is to show that the rule in question follows from underlying distributions of gross income. This is the subject of the next section.

[Figure 10]

An Excursion into Distribution Theory and "Econophysics"

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 function (pdf), or functions, best characterize the available data. Pareto made the initial foray into the field at the beginning of the twentieth century, but as more data became available it became clear that the pdf named after him worked best for the upper tail of the income distribution (essentially the rich for whom the distribution of wealth becomes the telling factor). Gibrat's development of the lognormal pdf was more successful because it characterized a wider range. But it too often fails to capture distribution patterns at the bottom and top ends (Crow and Shimizu, 1988, p. 233-237;Dovring, 1991, pp. 30-31). More recently, attention has turned to a generalized exponential function whose parameter might make it possible to have a single function that fits the middle and also both "missing" ends (Clementi et al., 2007, Abstract;Dovring, 1991, pp. 34-35)[10].

An alternate approach within "econophysics" has been to fit the overall distribution using two distinct pdfs, with the exponential curve applicable to first 97-99 percent of the population of

[10] For instance, Clementi, et. al. (2007, Abstract) argue that the generalized exponential function is appropriate because its "bulk is very close to the stretched exponential one, whereas its tail decays following the power law... This makes it particularly suitable to describe simultaneously the income distribution among both the richest part and the vast majority of the population". They find that this function provides an excellent fit to the personal income distribution in Germany, Italy, and the United Kingdom.

individual-earners and the Pareto or some other power law applicable to the top 3 percent (Dragulescu and Yakovenko, 2002, pp. 1-2). This "two-class structure of income distribution" is derived "on the basis of a kinetic approach" to a diffusion model in which income from wages and salaries yields additive diffusion[11] while income from investments and capital gains yields multiplicative diffusion (Silva and Yakovenko, 2004, p. 6). These authors approximate the overall Lorenz curve through 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 fraction at the higher end is very small but its income fraction (f) is nonetheless significant. Thus the exponential curve is applicable in the population fraction range $0 \leq x < 1$, while the income fraction of the upper levels (the Pareto-like segment) kicks-in at $x = 1$. From our point of view, this particular formulation is quite apposite, because it can be used to derive both the patterns and even the numerical values obtained through our international data on IR(x)/(1-G).

Let z = the overall cumulative income share, z_{exp} = the cumulative income share stemming from the exponential section of the overall Lorenz curve, x = the population proportion in the exponential section of the Lorenz curve (which is approximately the whole population), G_{exp} = the Gini Coefficient of the exponential pdf, f = the proportion of total income in the Pareto tail, and $\theta(x-1)$ = the step function which is zero for $x < 1$ (i.e. along the exponential section) and one for $x \geq 1$ (along the Pareto section, which is a vertical line at $x = 1$). Then the two-function pdf , along with the general definition of the Gini Coefficient (Dragulescu and Yakovenko, 2001, p. 587) may be written as

(1.1) $$z = (1-f)\, z_{exp} + f\,\Theta(x-1)$$

(1.2) $$G = 2\int_0^1 (x-z)\,dx$$

Applying equation (1.2) to equation (1.1) gives

$$G = 2\int_0^1 \left[x-(1-f)\,z_{exp} - f\,\Theta(x'-1)\right]dx = (1-f)\left[2\int_0^1 \left(x - z_{exp}\right)dx\right] + f\left[2\int_0^1 \left(x-\Theta(x-1)\right)dx\right]$$

[11] 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 the econophysicists are merely returning the favor.

But the first term in square brackets is merely the Gini Coefficient (G_{exp}) of an exponential function (Dragulescu and Yakovenko, 2001, pp. 587-588). The second term, on the other hand, reduces to f[12]. Hence

(1.3) $G = (1 - f)G_{\exp} + f$

(1.4) $(1 - f) = (1 - G)/(1 - G_{\exp})$

In the third section of this paper we noted that any relative income ratio IR(x) can be represented as the slope of the ray from the origin to the point on the Lorenz curve corresponding to the population fraction x (see Figure 1). Thus IR(x) = z/x. Since our concern is with the vast majority of the population, we can confine ourselves to the range in which the exponential function characterizes the data in which x < 1, so that $\Theta(x-1) = 0$ and the second term drops out of equation (1.1).

(1.5) $z = \left[(1-G)/(1-G_{\exp})\right] z_{\exp}$

If the data represents single-earners (Dragulescu and Yakovenko, 2001, 586-587),

(1.6) $z_{\exp} = F_1(x)$, where $F_1(x) = x + (1-x)\ln(1-x)$

(1.7) $G_{1\exp} = \dfrac{1}{2}$

On the other hand, if the data represents two-earner family incomes (Dragulescu and Yakovenko, 2001, 587-588), then[13]

(1.8) $z_{\exp} = F_2(x)$, where $F_2(x)$ is implicitly defined through the relations
$x(\tilde{r}) = 1 - (1+\tilde{r})e^{-\hat{r}}$, $z(\hat{r}) = x(\hat{r}) - (\hat{r}^2 e^{-\hat{r}})/2$, and $\hat{r}$ varies from 0 to ∞.

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[12] This second term has two parts: $2\int_0^1 x\,dx = 2\left(x^2/2\Big]_0^1\right) = 2\left(\left(\frac{1}{2}\right) - 0\right) = 1$, and $-2\int_{x=0}^{1} \Theta(x-1)\,dx$.
In this latter part, if we define x' = x-1 and restate the integration limits accordingly, we get
$-2\int_{x'=-1}^{0} \Theta(x')\,dx' = -2\left(x'\Theta(x')\Big]_{x'=-1}^{0}\right) = -2(0-0) = 0$, since $\Theta(x') = 0$ when x' =-1 (i.e. x = 0), and $\Theta(x') = 1$ when x'=0 (i.e. x =1).

[13] In equation (1.8) the term $\hat{r}$ =r/R, where r = the per capita income of a given population fractile, and R = the average per capita income that *would* obtain if the whole income distribution could be characterized solely by an exponential pdf (which it is not, since the whole distribution is a mixture of two pdfs).

(1.9) $G_{2\exp} = \frac{3}{8}$

In either case, from equation (1.5),

$$IR(x)/(1-G) = a(x)$$

(1.10) where $a(x) = F_1(x)/x\left(1-G_{1\exp}\right)$ for single-earners

and $a(x) = F_2(x)/x\left(1-G_{2\exp}\right)$ for families

These are remarkable results. Although the Gini Coefficient of a pure exponential pdf is a constant (equations (1.7) and (1.9)), the overall Gini depends also on the fraction of total income (f) which accrues to the very rich (equation (1.3). Hence the overall Gini is an index of the relative income of the very rich, and its variations across countries and through time mark the changes in the relative fortunes of this particular segment of society. Secondly, *the ratio of the relative per capita income of any given population fraction IR(x) to (1-G) will be constant across space and time* (equation (1.10)).

Consider the vast majority income ratio relative to (1-G). We have already seen in Figure 6 and Table 3 that VMIR/(1-G) is indeed remarkably constant across nations. Moreover, we found that VMIR/(1-G) ≈ 1.1. Keep in mind that the econophysics argument applies to gross income whereas our data consists of disposable income in which relative taxes also play a role (see the discussion at the end of the previous section). Furthermore, our data is based on "personal-equivalent" units which are actually derived from household data (see the Data Appendix), so that the personal distribution will be the same as the distribution of household incomes[14]. While our existing data does not permit us to correct for the influence of relative taxes, we can account for the household distribution by using the formulation for two-earner families. To determine the vast majority income ratio, we set $x(\hat{r}) = 0.80$ in equation (1.8), use that to determine $\hat{r} = 2.995$, calculate $z(\hat{r}) = 0.576$ which corresponds to our chosen $x(\hat{r})$ (i.e. which represents $F_2(x)$), from which we get the predicted VMIR/(1-G) = $z/\left[x\left(1-G_{2\exp}\right)\right] = 0.576/\left[0.80\left(1-\frac{3}{8}\right)\right] = 1.15$. Given unknown influence of relative taxes and of actual household sizes in our international data, *the predicted value is remarkably close to our observed ratio of 1.1*. Figure 11 displays the actual average ratios for disposable income each decile, alongside the predicted values for gross income. Their differences are consistent with the influence of progressive taxation, which would be expected to raise lower incomes, and reduce higher ones, relative to the gross income of some portion of the population whose effective tax rate is equal to the average tax rate.

[14] We thank Victor Yakovenko for clarifying this and several other important points about the theoretical argument.

[Figure 11]

Inequality, Poverty and Policy

The preceding theoretical discussion indicates that the per capita *gross* income relative to the overall average per capita income ($IR_G(x) = y_G(x)/y_G$) of every population proportion *except the very rich*, is proportional to (1-G) through a constant a(x) which depends solely on the population fractile. The empirical evidence in terms of disposable income seems to supports this hypothesis, even though relative taxes play an unknown part. Since relative *disposable* income $IR(x) \equiv y(x)/y = (y_G(x)/y_G)\cdot\tau$ where a(x) is given for any population fraction along the exponential segment of the Lorenz curve, $\tau(x) \equiv (1 - t(x))/(1- t)$, t(x) = the effective tax rate of the given population proportion and t = the average tax rate, we can write the general rule as shown below.

(1.11) $y(x) = a(x)\tau(x)\left[(1-G)y\right]$

Three implications can be derived from the preceding relation. First of all, for given tax ratios, individual per capita disposable incomes will vary *solely* with the "inequality discounted real GDP per capita" $y' \equiv (1\text{-}G)y$. This is true even if changes in inequality affect the growth rate or vice versa. The evidence certainly does not point to any necessary linkages between the two (Aghion et al., 1999;Alderson and Nielsen, 2003). In any case, what matters in the end is their joint path. Our previous finding that the (1-G) represents the relative per capita income of the first 70 percent of the population now takes on an additional meaning: discounting real GDPpc by (1-G) as originally proposed by Douglas Hicks (2004, pp. 2-3) is equivalent to reducing all national per capita incomes to a common scale, which is the per capita income of the first 70 percent of the population in any given country.

A second implication is that incomes of the different population segments will be *all* affected in the same way by discounted GDPpc, so that their relative positions will not be changed unless tax ratios change. We have already seen that the Gini Coefficient is an index of the relative incomes of the very rich (equation (1.3)). Our present relation tells us that reducing this income fraction benefits all others proportionately, other things being equal. If follows that the only way to change the relative incomes of the vast bulk of the population is to change the corresponding tax ratios τ(x).

(1.12) $y(\chi_1)/y(\chi_1) = a(\chi_1)\tau(\chi_1)/a(\chi_1)\tau(\chi_1)$

Third, individual per capita incomes will be affected differently by equal percentage changes in G and y. This is because discounted GDPpc is itself affected differently. Whereas GDPpc growth will always lift individual per capita incomes by the same percentage, a given percentage reduction in inequality 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 individual per capita incomes with respect to growth will always equal one, whereas the absolute value of this elasticity with respect to inequality will be greater than one for G > 0.50, and less than one for G < 0.50. If we let $\tilde{y}(x), \tilde{y}$ represent percentage rates of change, and we leave aside changes in tax rates,

$$(1.13) \quad \tilde{y}(x) = -\left(\frac{G}{1-G}\right)\tilde{G} + \tilde{y}$$

Gini Coefficients range in our data from almost 0.60 (Guatemala) to 0.25 (Denmark), as shown in Table 2. Thus the partial elasticities of individual per capita incomes will range from –1.5 to – 0.33. 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. Figure 12 illustrates this effect for a given growth rate of three percent. Since all relative incomes below the very top ones will move in tandem at given tax rates, it is sufficient to consider vast majority incomes, which are shown for three different initial Gini's (0.60, 0.45, 0.25) which then all drop by twenty percent halfway through the exercise.

[Figure 12]

Three policy conclusions can be adduced from the foregoing results. First, one should conduct international comparisons in terms of discounted real GDP per capita y' = (1-G)·y or some equivalent such as the VMI = 1.1·y', because these usefully combine income levels and inequality to map national incomes onto a common scale: the income per capita of the first seventy or eighty percent of the population in each nation. Second, we should utilize taxation and subsidies to adjust the vast bulk of the distribution of disposable income toward socially desired norms. And third, given that growth and inequality are relatively independent social outcomes, in poorer countries we should focus equally (or even more) on reducing inequality rather than on stimulating growth.

Summary, Policy Implications and Future Research

Income levels and income inequality tend to be treated separately, the former through average per capita income measures such as GDP per capita and the latter through inequality measures such as the Gini coefficient (G). In this paper we demonstrate that the per capita income of any fraction of the population combines these two aspects in an intuitively useful manner. Of particular interest is the per capita income of the vast majority (the first eighty percent) of any nation. The progress of this measure, which we call the Vast Majority Income (VMI), has obvious significance in modern democracies.

The VMI is calculated in two steps: first, international income distribution data is used to calculate the Vast Majority Income Ratio (VMIR); and then international measures of average income are used to VMI itself. Since our present database is in terms of disposable income, we use Net National Income per capita (NNIpc) as the measure of average income.

Several interesting patterns come to the fore. For instance, the VMIR varies considerably across countries, which means that average income measures such as GDPpc or NNIpc are *not* a good proxies for vast majority incomes. Looking directly at the latter, it also becomes evident that the per capita incomes of the top quintiles are more alike than are those of the vast majorities: on an international scale, the rich are more alike than are the rest of us. A second finding is that the international rankings of nations can change substantially when assessed on this new scale. For instance, while Norway's real NNI per capita in 2000 is 10 percent lower than that of the US, the real per capita disposable income of Norway's vast majority is 4 per cent higher. An even greater contrast exists between Mexico and Venezuela: Venezuela's real GDP per capita is 6 percent lower, but its VMI is13 per cent higher.

A third and particularly striking result follows from empirical relation between the VMIR and the Gini Coefficient (G). Since the VMIR is the per capita income of the vast majority *relative* to the overall income per capita, it is a measure of equality: VMIR would equal one for a perfectly equal distribution and zero for a perfectly unequal one. The corresponding standard equality measure would be (1-G), which also has the same limits. Both measures vary substantially across countries and even vary over time in any given country, due to variations in the underlying social determinants. Both measures can be derived from a Lorenz curve, so that we would expect them to be related in some manner. But the VMIR assesses the Lorenz curve at only a single point (80 percent of the population) while the Gini coefficient takes in account the whole shape of the curve. Hence there is no particular theoretical reason for the ratio of the two measures to be the same across countries and across time. Indeed, most theoretical approaches to income distribution would expect this ratio to vary across time and space. Nonetheless, we find that there exists a remarkable relation which is stable in both dimensions, despite all the unevenness in the quality of international data: $VMIR/(1-G) \approx 1.1$. We call this the "1.1 Rule". It in turn leads us to a new and intuitive interpretation of the Gini coefficient itself. Namely, that (1-G) represents the relative per capita income of the first seventy percent of a nation's population. It follows that knowledge of the Gini Coefficient and average national income per capita is sufficient to estimate the disposable per capita income of the first seventy or even eighty percent of the population in any given country. These rules turn out to be remarkably accurate on an international scale.

The empirical strength of the two preceding rules raises the question of their possible theoretical foundations. Most theoretical approaches to income distribution predict something different. But there is one particular approach within the branch called "econophysics" which is shown to imply both the "1.1 Rule" and our new interpretation of the Gini Coefficient. We provide a brief introduction to this approach, and show how it can be used to derive the kinds of patterns we find at an empirical level. The Gini Coefficient is shown to depend solely on the fraction of gross income going to the very rich, i.e. to the top 1-3 percent of any nations population. Hence reducing gross income inequality is tantamount to reducing the income share of the very rich. Hence for any given level of inequality (i.e. for any given G) the per capita income of the remaining population, relative to the overall average, depends solely on G and on a constant with depends only on the population proportion being considered. It is this latter property that gives rise to a predicted theoretical value of VMIR = 1.15(G), which is very close to our empirical finding that VMIR = 1.10(G). This is a truly remarkable results given the variations in international data quality, and given the fact that the theoretical value applies to gross income while our empirical results are derived from disposable income (which also depends on the distribution of tax rates across income classes).

In the last section of the paper we draw three implications for the analysis of growth and distribution, and for socio-economic policy. First, that for given tax ratios individual per capita disposable incomes will vary *solely* with the "inequality-discounted real GDP per capita" $y' \equiv (1-G)y$. The latter takes both average income and inequality into account, and following our earlier results. In light of our new interpretation of the Gini, discounting real GDPpc by the degree of inequality amounts to translating all national per capita incomes to a common scale, which is the per capita income of the first 70 percent of the population in any given country. Furthermore, except for the very top, the incomes of the different population segments will be *all* affected in the same way by discounted GDPpc, so that their relative positions will not be changed unless tax ratios change. Finally, the partial elasticity of individual per capita incomes with respect to average income will always equal one, whereas this elasticity with respect to inequality will be $-G/(1-G)$. Hence the absolute value of this latter elasticity will be greater than one for mostly poor countries in which $G > 0.50$, and less than one for $G < 0.50$ for the rest. This means that in the poorest countries the partial effect of a reduction in inequality would be *greater* than that of an increase in the growth rate.

These results give rise to three broad policy conclusions. First, that it is important to conduct international comparisons in terms of discounted real GDP per capita y' or some equivalent measure such as the $VMI = 1.1 \cdot y'$, because this combination of income levels and inequality places us on a common international scale: the income per capita of the first seventy or eighty percent of the population in each nation. Second, that taxation and subsidies are the most effective way to adjust the distribution of disposable income of the vast bulk of the population. And third, given that growth and inequality are relatively independent social outcomes, in the case of poorer countries in particular it is equally (or even more) important to focus on reducing inequality rather than on stimulating growth.

This paper is part of an ongoing project to analyze international inequality. International comparisons tend to focus on either GDP per capita or the incomes of the very poor (e.g. those living on less that $2 per day). The VMI adds a new dimension, because it combines information on income levels and their distribution into a single measure of per capita income of the vast majority of the population. We believe that this broadens the discussion of international inequality, and will ultimately shed new light on several important issues in the development literature such as the relationships between inequality and development (Passé-Smith, 2003); trade liberalization (Taylor, 2007); gender (Seguino, 2007;Shaikh, 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-a). 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.

2. 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 income data "persons" is actually derived from household income data using an equivalence scale (UNU-WIDER, 2005 June, V 2.0a-b, pp. 17-18).

3. 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 four subsets discussed previously[15]. Earlier observations can be quite sparse, and many countries have information for only a few years. We hope to create a second database in the future comprised of those countries for which we are able to create a consistent time series. Of the four data combinations in our database, this paper focuses on Personal Disposable (PD) income covering 81 countries because this category had the greatest number of observations (643).

4. 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.

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[15] Since the number of persons per household varies by income class, the cutoff cumulative income corresponding to a particular percent of persons will differ from that corresponding to same percent of households. Thus income ratios at any given quintile will differ in the two sets. A similar difference will obtain between gross and disposable measures. Hence we cannot generally mix our four subsets.

5. To construct NNI, we began with real GDP per capita from the Penn World Tables in real international dollars (I$) which are themselves derived using Purchasing Power Parity estimates (Heston et al., 2006, September). For most countries, we then derived the ratio of NNI/GDP from United Nations data on "International transactions: gross and net national (disposable) income, saving, and lending aggregates (SNA 68) [code 30213]". For the remaining countries we obtained estimates for the depreciation ratio d = consumption of fixed capital (depreciation)/GDP from the Extended World Tables (Marquetti, 2004) and the ratio of g = GNI/GDP from the Penn World Tables (*op cit*) to construct n = (NNI/GDP) = (GNI-Depreciation)/GDP = (g – d). We then multiplied real GDPpc in international-$ 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.

Figure 2: VMIR (Vast Majority Income per capita, relative to average) by Country (2000 or closest year)

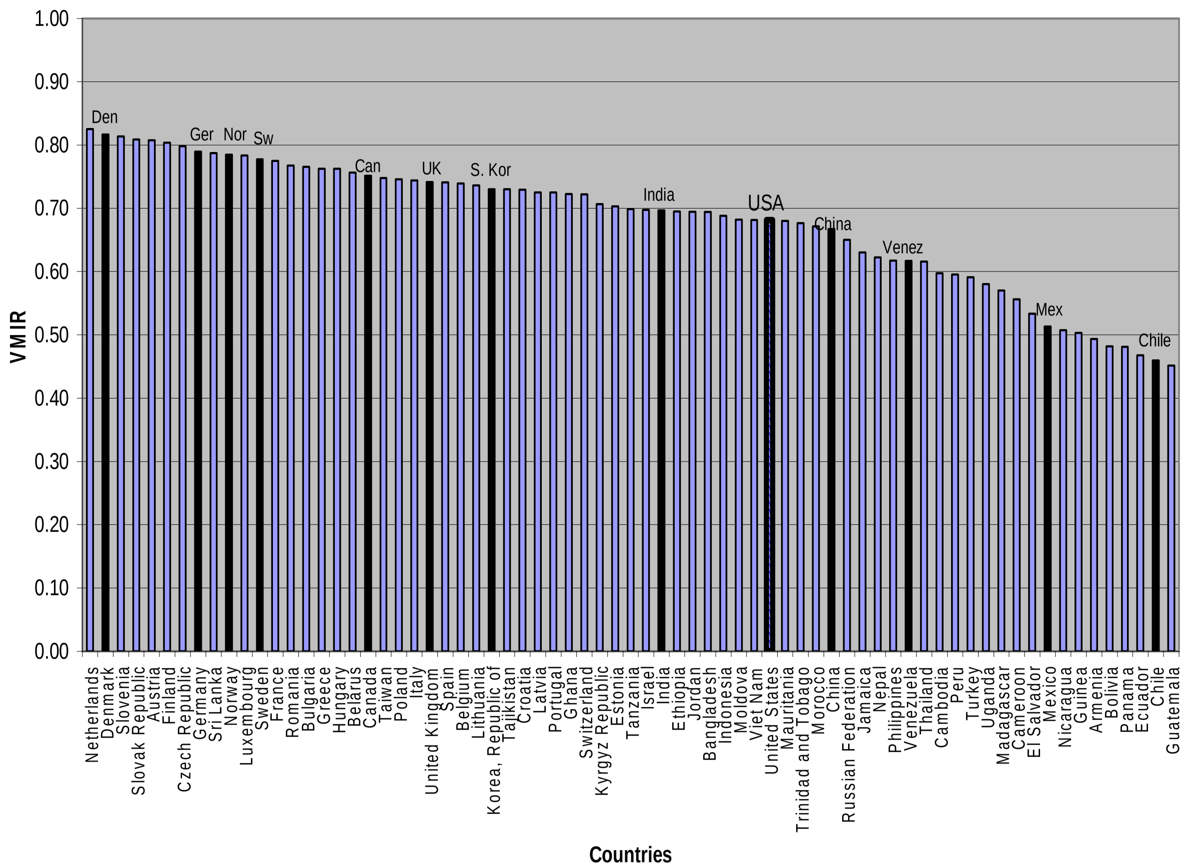


Table 1: VMIR by Country, 2000 or closest			
Country	VMIR	Country	VMIR
Netherlands	0.83	Israel	0.70
Denmark	0.82	India	0.70
Slovenia	0.81	Ethiopia	0.70
Slovak Republic	0.81	Jordan	0.69
Austria	0.81	Bangladesh	0.69
Finland	0.80	Indonesia	0.69
Czech Republic	0.80	Moldova	0.68
Germany	0.79	Viet Nam	0.68
Sri Lanka	0.79	United States	0.68
Norway	0.78	Mauritania	0.68
Luxembourg	0.78	Trinidad and Toba	0.68
Sweden	0.78	Morocco	0.67
France	0.78	China	0.67
Romania	0.77	Russian Federatio	0.65
Bulgaria	0.77	Jamaica	0.63
Greece	0.76	Nepal	0.62
Hungary	0.76	Philippines	0.62
Belarus	0.76	Venezuela	0.62
Canada	0.75	Thailand	0.62
Taiwan	0.75	Cambodia	0.60
Poland	0.75	Peru	0.60
Italy	0.74	Turkey	0.59
United Kingdom	0.74	Uganda	0.58
Spain	0.74	Madagascar	0.57
Belgium	0.74	Cameroon	0.56
Lithuania	0.74	El Salvador	0.53
Korea, Republic of	0.73	Mexico	0.51
Tajikistan	0.73	Nicaragua	0.51
Croatia	0.73	Guinea	0.50
Latvia	0.73	Armenia	0.49
Portugal	0.73	Bolivia	0.48
Ghana	0.72	Panama	0.48
Switzerland	0.72	Ecuador	0.47
Kyrgyz Republic	0.71	Chile	0.46
Estonia	0.70	Guatemala	0.45
Tanzania	0.70		

Figure 3: VMIR Over Time, Countries with Sufficient Data

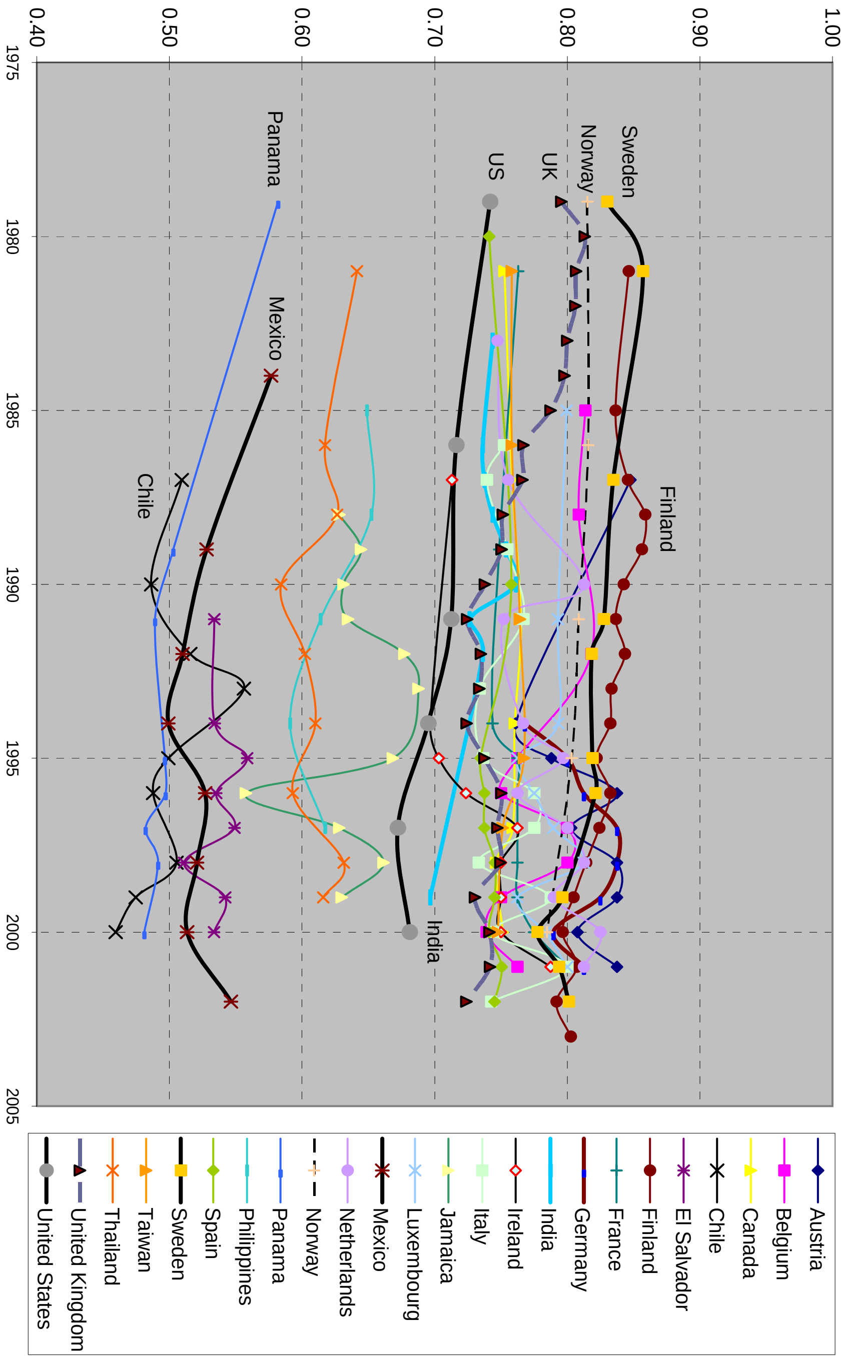


Figure 4: NNI vs VMI Per Capita, 2000
(International-$)

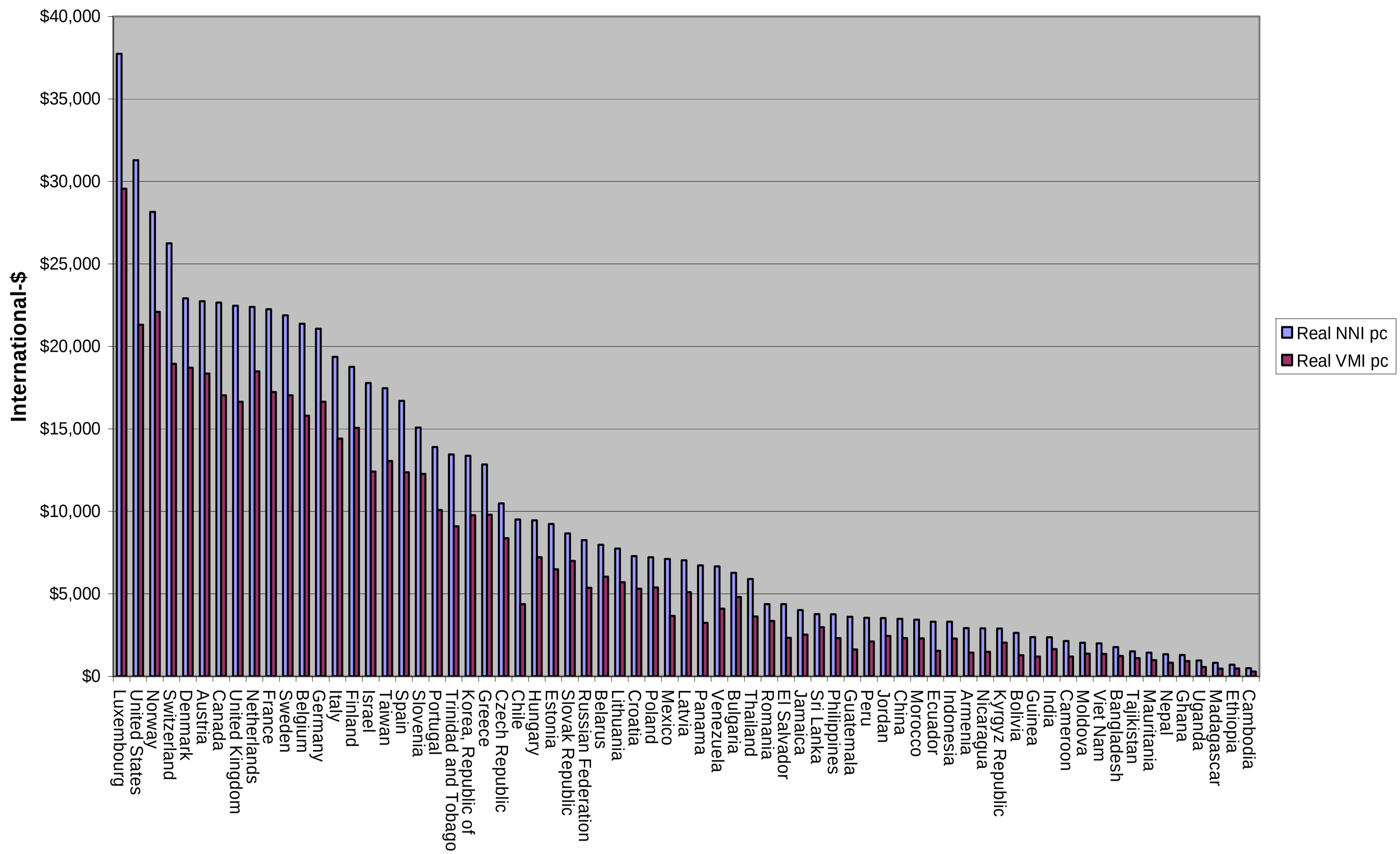


Table 2: Per Capita VMI and NNIpc, and Country Rankings by Each Measure							
		Real Per Capita (International-$)			Rank		
Country	Gini	NNI	VMI	AMI	NNI	VMI	Rank Difference
Chile	58.20	$9,512	$4,371	$30,077	25	35	-10
Guatemala	59.80	$3,614	$1,631	$11,547	45	52	-7
Guinea	55.10	$2,384	$1,200	$7,122	56	60	-4
Panama	57.80	$6,728	$3,236	$20,696	36	40	-4
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
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
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
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
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
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
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
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
India	36.00	$2,371	$1,651	$5,247	57	51	6
Coefficient of Variation		**89.40%**	**95.91%**	**82.21%**			

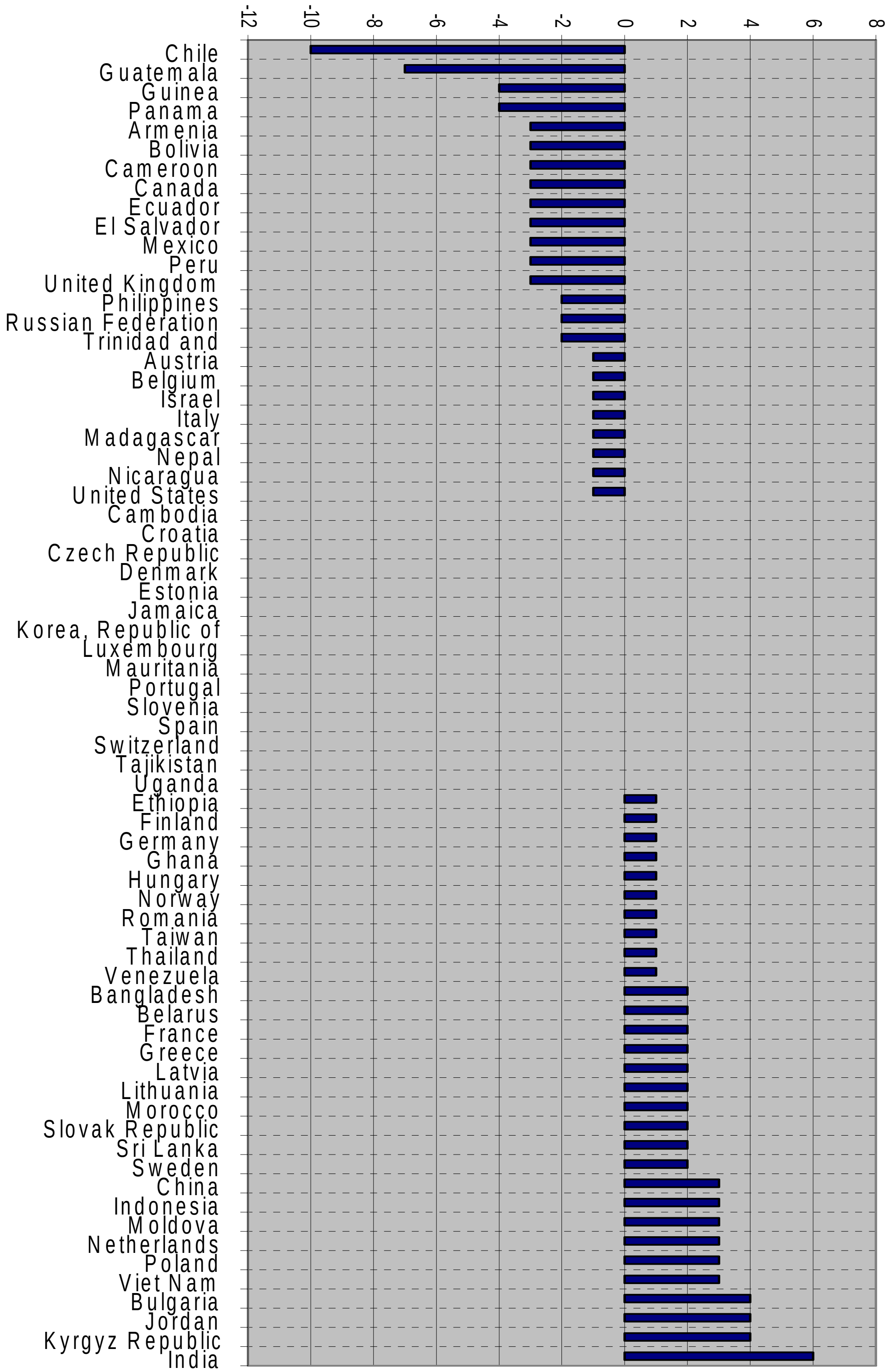


Figure 5: Rank Difference in going from NNI to VMI

Figure 6: The 1.1 Rule: VMIR/(1-G) by Country, 2000 or closest year

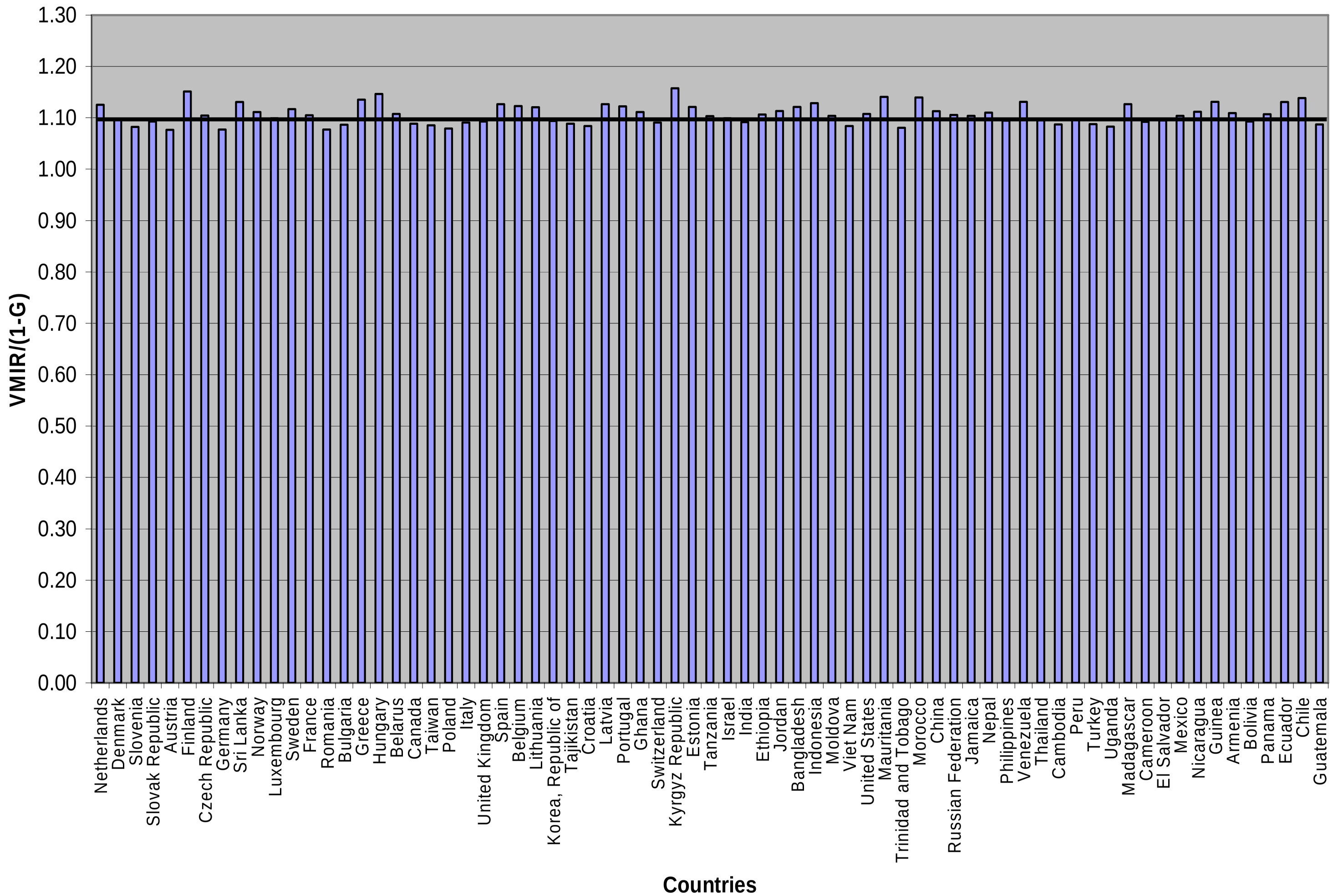


Table 3: VMIR/(1-G) by Country, 2000 or closest			
Country	VMIR/(1-G)	Country	VMIR/(1-G)
Armenia	1.13	Lithuania	1.10
Austria	1.10	Luxembourg	1.09
Bangladesh	1.08	Madagascar	1.11
Belarus	1.09	Mauritania	1.11
Belgium	1.08	Mexico	1.12
Bolivia	1.15	Moldova	1.13
Bulgaria	1.10	Morocco	1.10
Cambodia	1.08	Nepal	1.08
Cameroon	1.13	Netherlands	1.11
Canada	1.11	Nicaragua	1.14
Chile	1.10	Norway	1.08
China	1.12	Panama	1.14
Croatia	1.11	Peru	1.11
Czech Republi	1.08	Philippines	1.11
Denmark	1.09	Poland	1.10
Ecuador	1.14	Portugal	1.11
El Salvador	1.15	Romania	1.09
Estonia	1.11	Russian Federation	1.13
Ethiopia	1.09	Slovak Republic	1.10
Finland	1.09	Slovenia	1.09
France	1.08	Spain	1.10
Germany	1.09	Sri Lanka	1.09
Ghana	1.09	Sweden	1.08
Greece	1.13	Switzerland	1.13
Guatemala	1.12	Taiwan	1.09
Guinea	1.12	Tajikistan	1.09
Hungary	1.09	Tanzania	1.10
India	1.09	Thailand	1.11
Indonesia	1.08	Trinidad and Tobago	1.13
Israel	1.13	Turkey	1.11
Italy	1.12	Uganda	1.09
Jamaica	1.11	United Kingdom	1.11
Jordan	1.09	United States	1.13
Korea, Republ	1.16	Venezuela	1.14
Kyrgyz Republ	1.12	Viet Nam	1.09
Latvia	1.10	Overall Average	1.11

Figure 7: VMIR/(1-G) Over Time, Countries With Suficient Data
(Overall Average = 1.10)

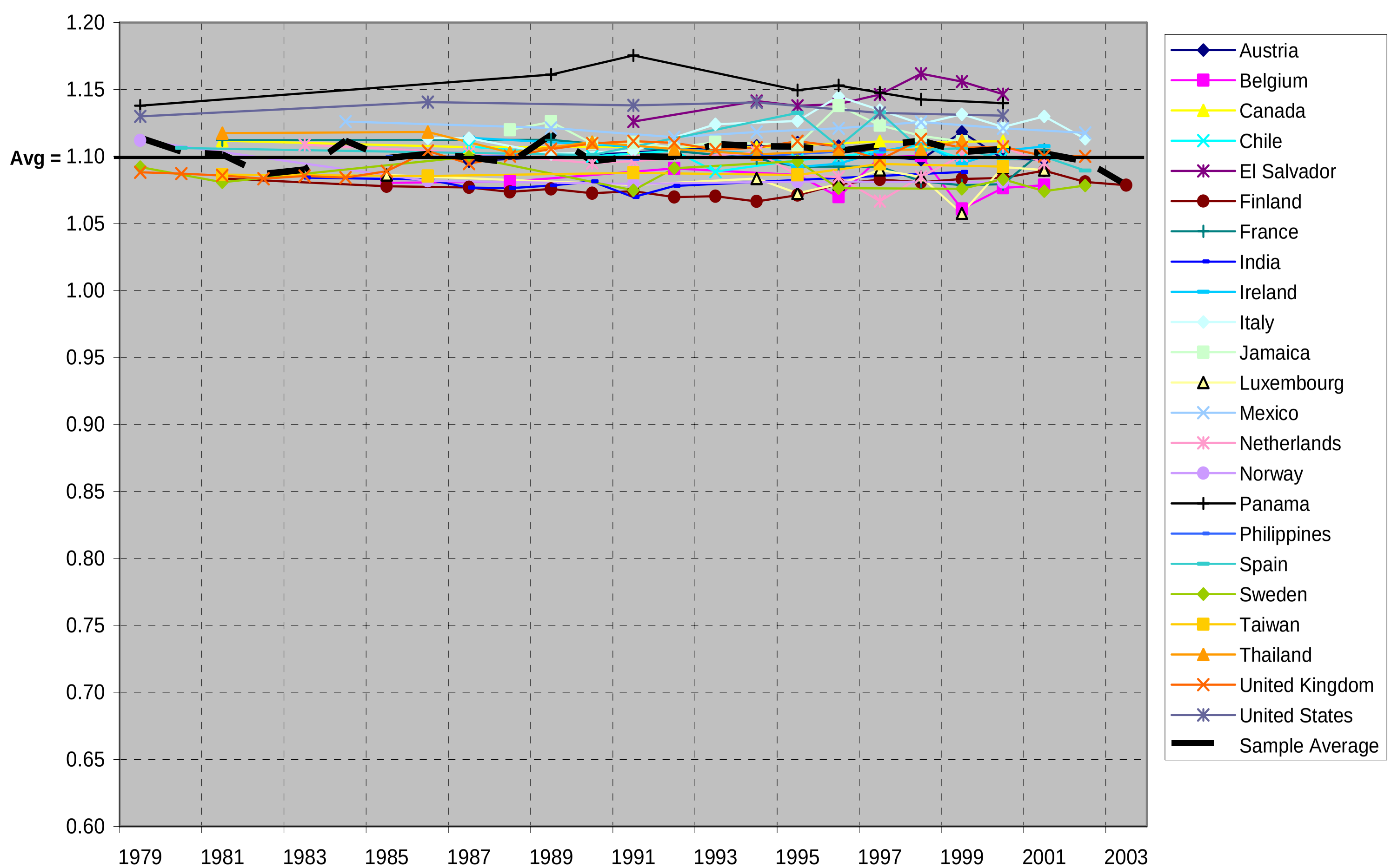
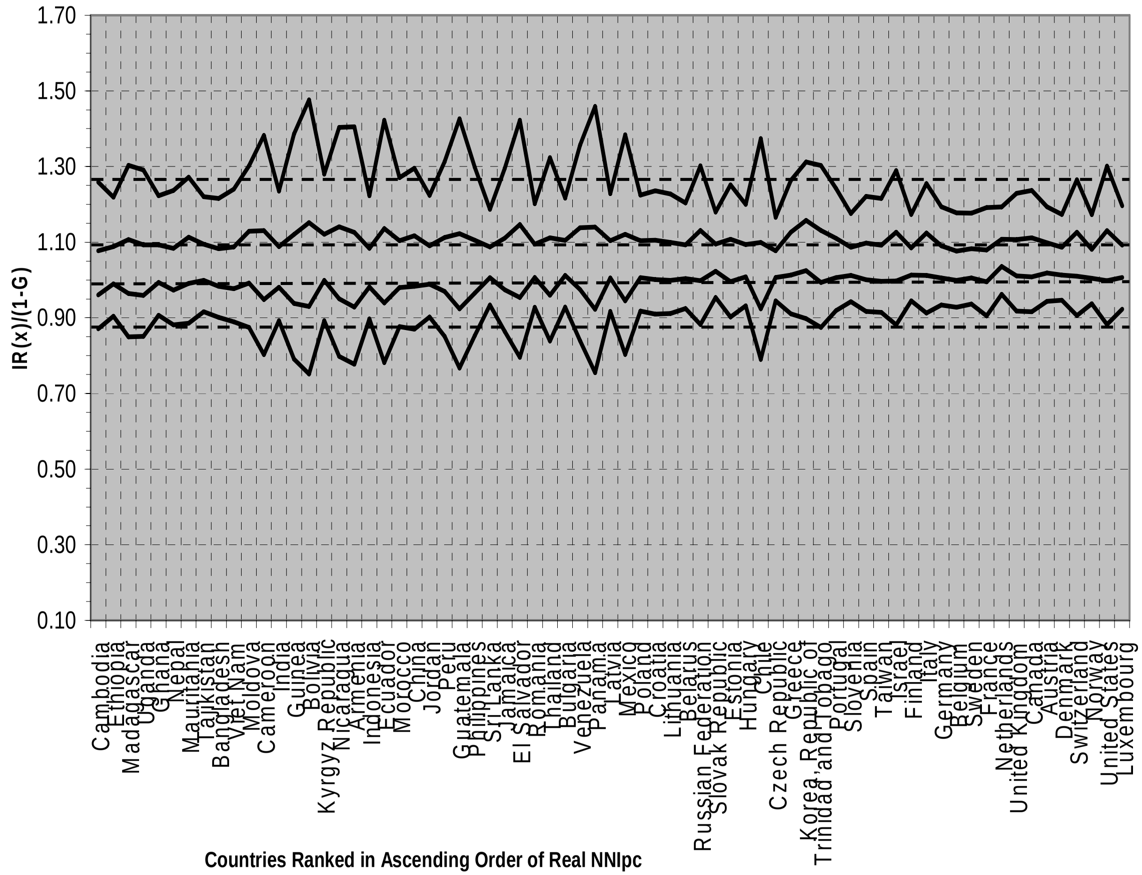


Table 4: VMIR/(1-G) Over Time, Countries With Sufficient Data

Country	1979	1980	1981	1982	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002	2003	Country Average
Austria									1.10							1.11	1.11	1.11	1.10	1.10	1.12	1.10	1.10			1.10
Belgium							1.08			1.08				1.09			1.09	1.07	1.10	1.10	1.06	1.08	1.08			1.08
Canada			1.11						1.11				1.11			1.11			1.11	1.11		1.11				1.11
Chile									1.11			1.10		1.10	1.09		1.10	1.10		1.11	1.10	1.10				1.10
El Salvador													1.13			1.14	1.14	1.14	1.15	1.16	1.16	1.15				1.14
Finland			1.08				1.08		1.08	1.07	1.08	1.07	1.07	1.07	1.07	1.07	1.07	1.08	1.08	1.08	1.08	1.08	1.09	1.08	1.08	1.08
France			1.11								1.11					1.10	1.09	1.09	1.09	1.08	1.08	1.08	1.10			1.09
India					1.08			1.08	1.08	1.08	1.08	1.08	1.07	1.08							1.09					1.08
Ireland									1.11							1.10	1.09	1.09	1.10	1.11	1.09	1.10	1.11			1.10
Italy								1.11	1.11		1.10		1.10		1.12		1.13	1.14	1.13	1.12	1.13	1.12	1.13	1.11		1.12
Jamaica										1.12	1.13	1.11	1.11	1.11	1.11		1.11	1.14	1.12	1.12	1.11					1.12
Luxembourg							1.09						1.08			1.08	1.07	1.08	1.09	1.08	1.06	1.09	1.09			1.08
Mexico						1.13					1.12			1.11		1.12		1.12		1.13		1.12		1.12		1.12
Netherlands					1.11				1.10			1.10	1.10			1.10	1.09	1.08	1.07	1.08	1.10	1.11	1.10			1.09
Norway	1.11							1.08					1.08				1.08					1.08				1.09
Panama	1.14										1.16		1.18				1.15	1.15	1.15	1.14		1.14				1.15
Philippines							1.10			1.10			1.10			1.10			1.11							1.10
Spain		1.11										1.10					1.13	1.11	1.13	1.10	1.11	1.10	1.10	1.09		1.10
Sweden	1.09		1.08						1.10				1.07	1.09			1.10	1.08			1.08	1.08	1.07	1.08		1.08
Taiwan			1.09					1.09					1.09				1.09		1.09			1.09				1.09
Thailand			1.12					1.12		1.10		1.11		1.11		1.10		1.10		1.11	1.11					1.11
United Kingdom	1.09	1.09	1.09	1.08	1.09	1.08	1.09	1.10	1.09	1.10	1.11	1.11	1.11	1.11	1.11	1.11	1.11	1.11	1.10	1.11	1.11	1.11	1.10	1.10		1.10
United States	1.13							1.14					1.14			1.14			1.13			1.13				1.14
Sample Average	**1.11**	**1.10**	**1.10**	**1.09**	**1.09**	**1.11**	**1.10**	**1.10**	**1.10**	**1.10**	**1.12**	**1.10**	**1.10**	**1.10**	**1.11**	**1.11**	**1.11**	**1.10**	**1.11**	**1.11**	**1.10**	**1.11**	**1.10**	**1.10**	**1.08**	**1.10**

Figure 8A: Relative Per Capita Incomes of Various Population Proportions over (1-G), 2000 or closest year (countries ranked in ascending order of real NNIpc)



Pop. Prop.	Mean	CV
0.90	1.27	0 .06
0.80	1.11	0.02
0.70	0.99	0.03
0.60	0.88	0.06

Figure 8B: Relative Per Capita Incomes of Various Population Proportions over (1-G), 2000 or closest year (countries ranked in ascending order of real NNIpc)

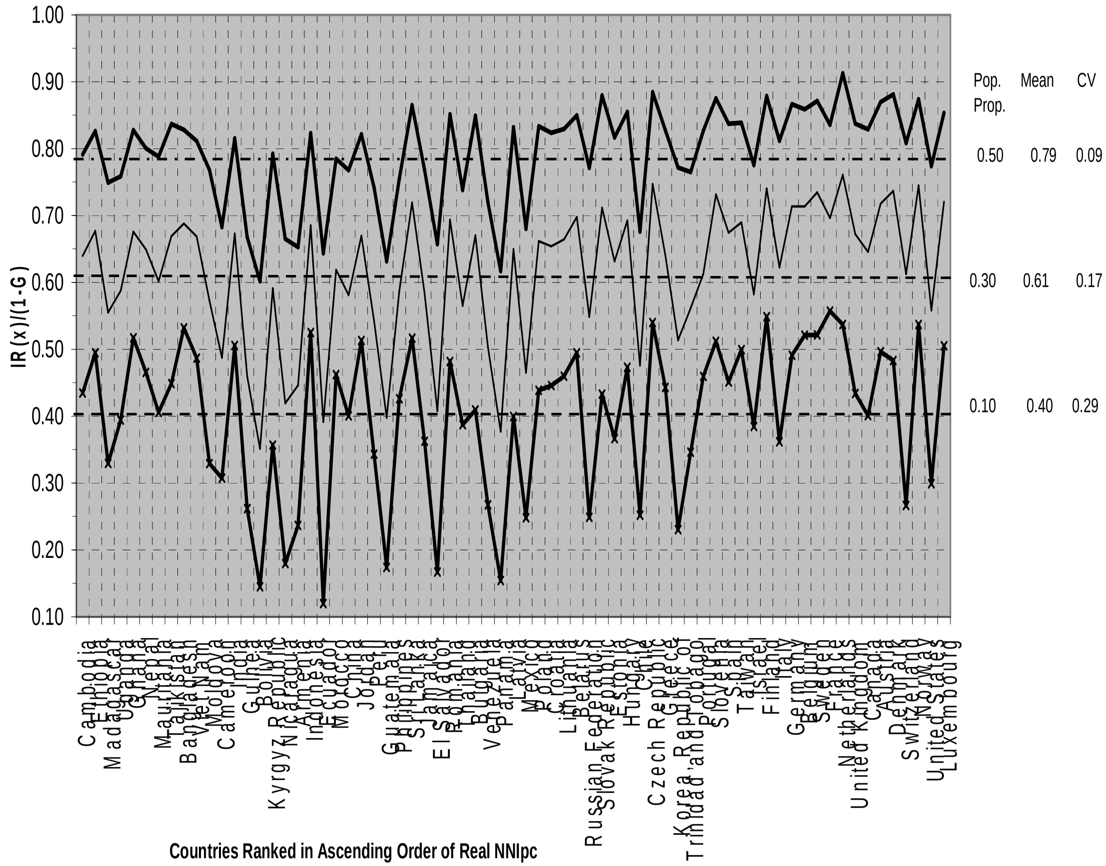


Figure 9: A Simple Interpretation of the Gini Coefficient
(average IR/(1-G) ratios for various cumulative income proportions)

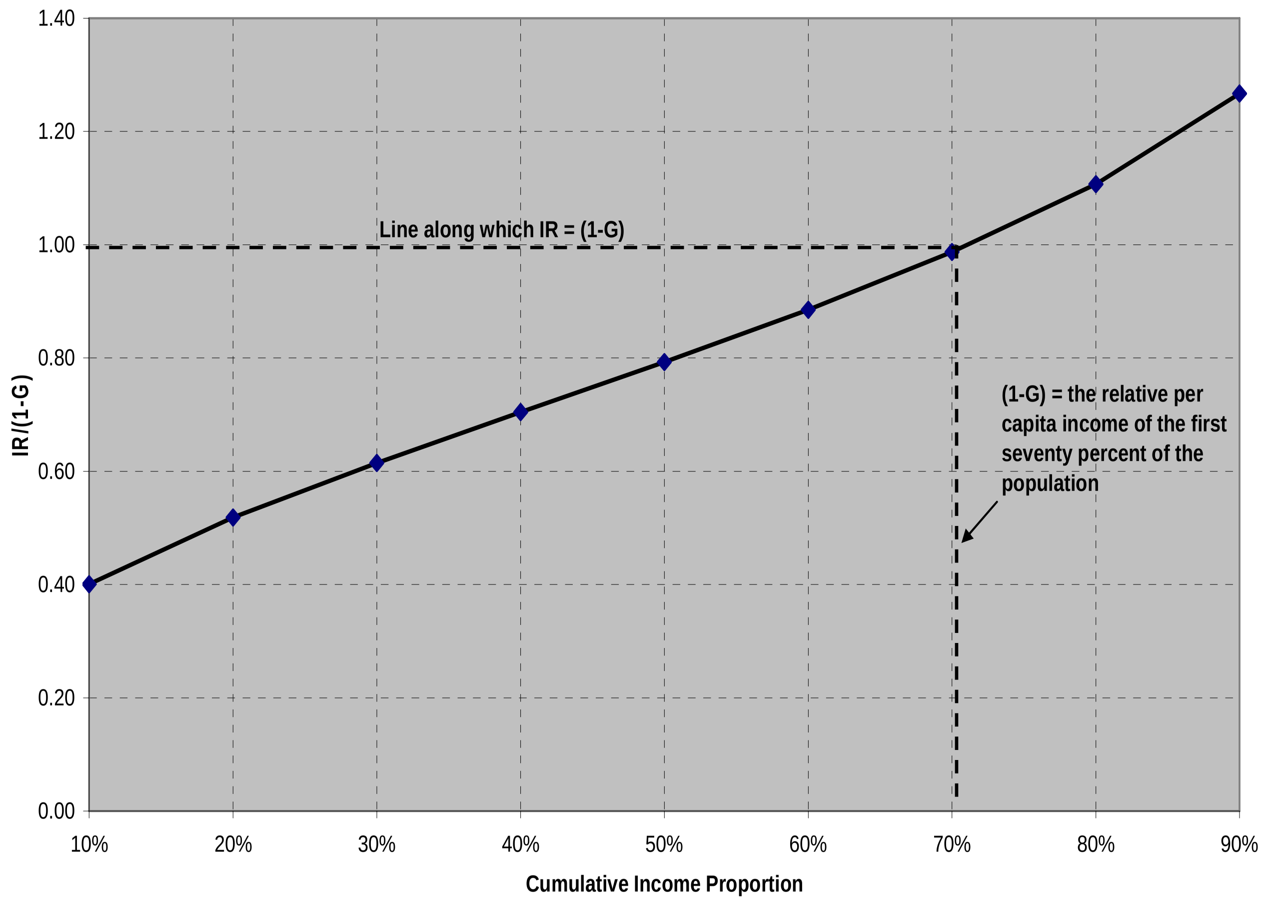


Figure 10: An Empirical Test of the Meaning of the Gini Coefficient

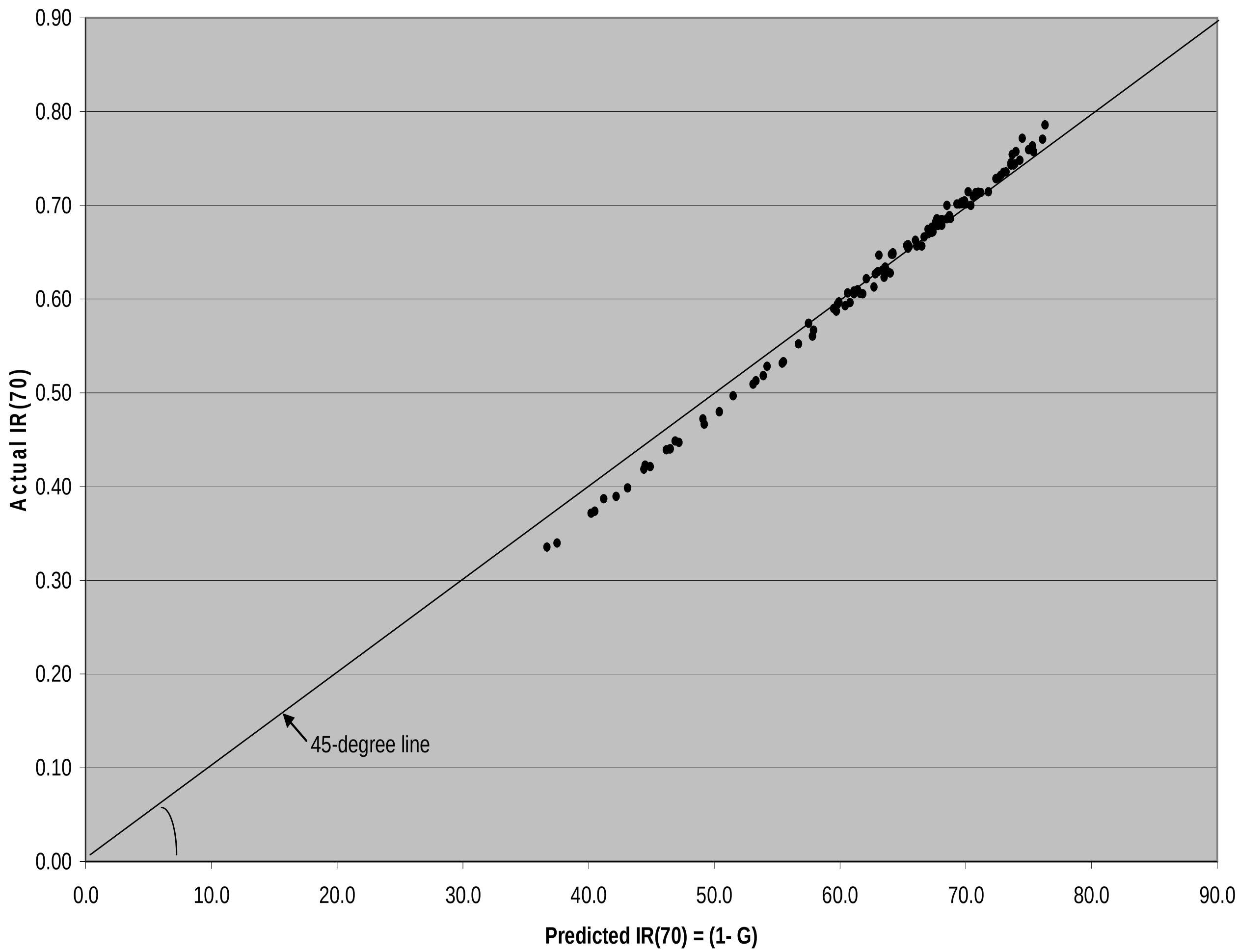


Figure 11: Actual Disposable Income IR(x)/(1-G) vs Econophysics Gross Income Ratios

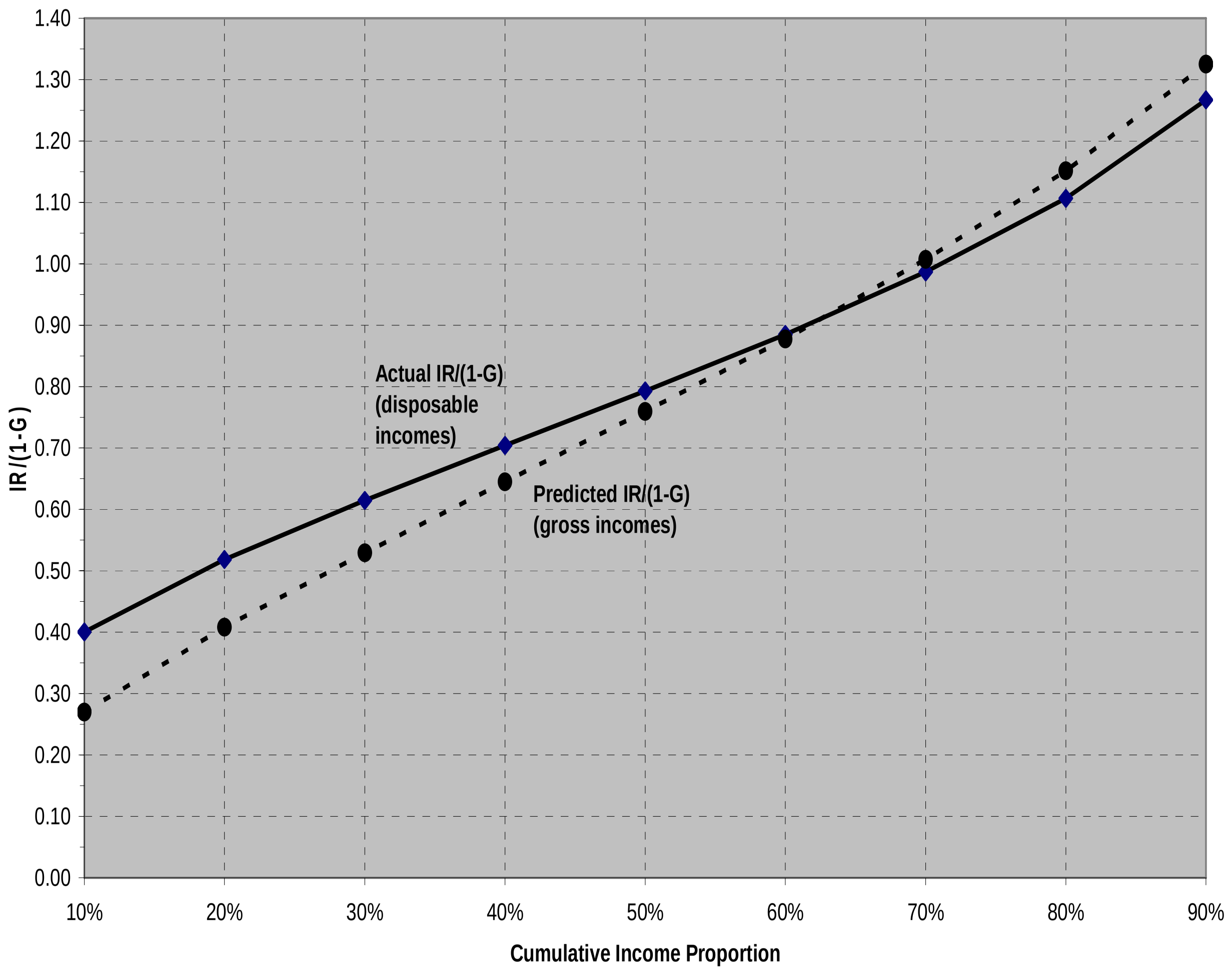
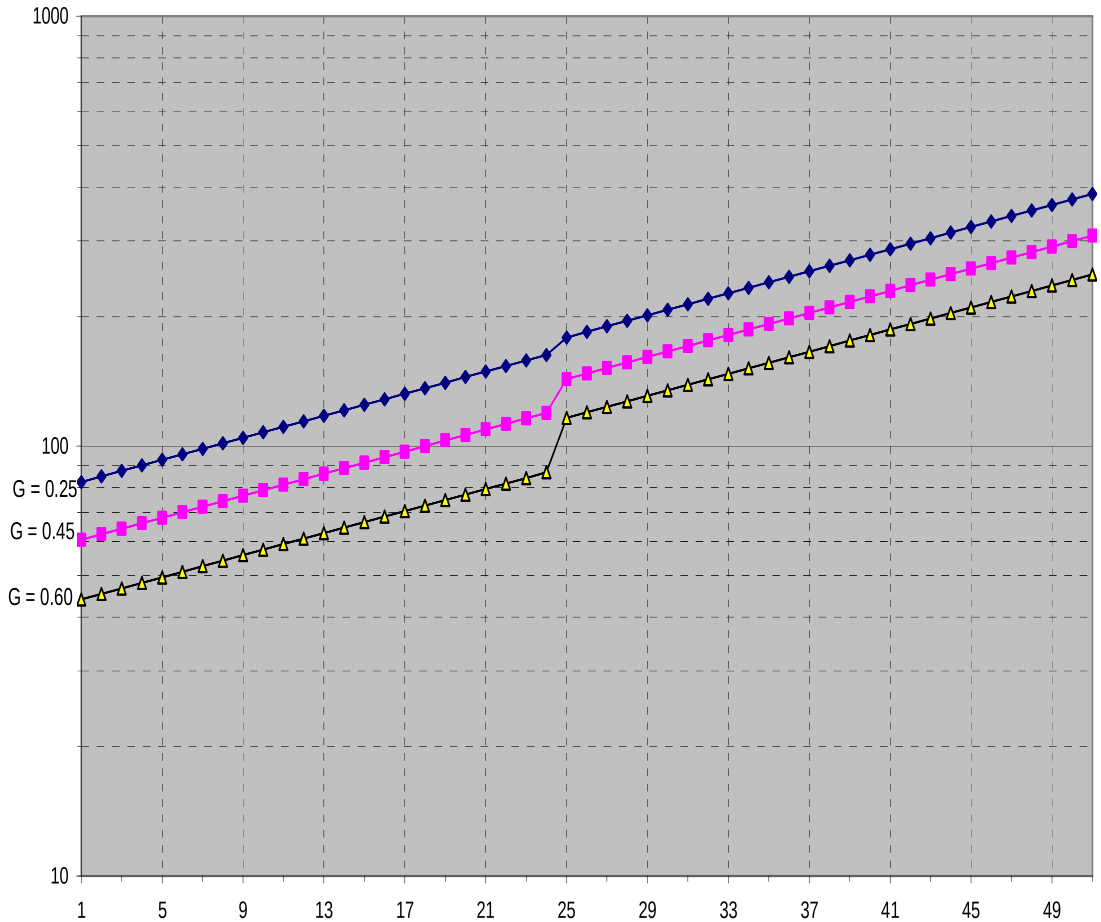


Figure 12: Effects on Vast Majority Incomes of a 20% Fall in Inequality, at Three Different Initial Gini Coefficients (for a given growth rate of real GDPpc)



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