Choosing Among Rival Poverty Rates:

Some Tests for Latin America

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JEL Classification: I32; O15

Abstract: Poverty rates are now widely available, but are they reliable? Wide variations in estimated poverty rates for the same poverty line, year and country reflect an underlying reality: there is no widely accepted procedure for estimating national poverty rates. This paper proposes a simple, *ex post* procedure for selecting poverty rates that have certain desirable properties. Absolute poverty measures, estimated uniformly across countries, should be correlated with non-monetary indicators that reflect the consequences of physical deprivation (e.g. malnutrition, birth rates, school attendance). A series of non-nested hypotheses tests are used to choose among competing poverty and income measures. This method is applied to screen the 66 alternate poverty measures computed by Székeley, Lustig et. al. (2000) for 17 Latin countries. These tests identify 10-15 poverty measures that meet the standards set forth for useful poverty measures. This final group of poverty measures is then ranked using various performance criteria.

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National poverty rates, once a scarce statistic, are gradually displacing per capita income as the key social welfare indicator for developing countries. The United Nations' 2015 Millennium Development Goals target poverty rates, not per capita growth rates, while the World Bank hopes for a "world free of poverty." Poverty rates are now widely available, but are they reliable? Recently a number of analysts and organizations joined the World Bank in computing $1/ per day poverty rates for a number of countries. Unfortunately, as Table 1 illustrates, these competing estimates often do not agree. The World Bank estimates about 1.1 billion or just over 22% of those living in developing countries get by on less than $1 per day. However, comparable estimates by Javier Sala-i-Martin (2001), Surjit Bhalla (2002) and even venerable UNCTAD (2003) find much fewer $1/day poor, as low as a third of World Bank estimates.

Wide variations in poverty rates for the same poverty line, year and country are a source of unease and controversy. But they also reflect an underlying reality: there is no standard, widely accepted procedure for estimating national poverty rates. Over the years conventions for computing national account aggregates, price indices, unemployment rates, etc. have gradually converged. However there is no such consensus for computing poverty rates. One problem, emphasized by Deaton (2002) and Székeley, Lustig et. al. (2000) and others, is the "blowing up" problem. Survey data for a few thousand households must always be scaled up to create a national poverty rate. This scaling requires a series of adjustments and assumptions, from defining poverty lines and households to filling in missing survey entries. Different combinations of reasonable adjustments to the same survey can lead to widely different poverty estimates. This problem is illustrated quite dramatically by Székeley, Lustig et. al. (2000). In an extraordinary research effort (as anyone who has worked with even one income survey will attest) they compute over 60 different poverty measures using different adjustment methods applied to 17 Latin American income surveys. Their conclusion: the poverty rate for these 17 countries could be 13% or 65% depending on the adjustment method chosen; a range that makes the poverty rates in Table 1 look fairly precise!

A priori, Székeley, Lustig, et. al. (2000) cannot dismiss any of their 44 different poverty rate estimates as inaccurate. Similarly, the researchers who produced the estimates in Table 1 all stand by their methods. Given this standoff, how can everyday users of poverty data decide among these wide ranging estimates? Or should all poverty estimates be bracketed with large standard errors? Strong *a priori* arguments in favor of a particular methodology can be helpful, but rarely conclusive.[1]

This paper proposes a simple, *ex post* procedure for selecting poverty rates that have certain reasonable and, we would argue, desirable properties. We use a sequence of standard non-nested hypotheses tests to choose among competing regressors: in this case, rival poverty and income measures. Our working hypothesis is that absolute poverty measures, estimated uniformly across countries and over time, should be correlated with non-monetary indicators that reflect the consequences of physical deprivation (e.g. malnutrition, birth rates, school attendance).[2] The large data set of alternative poverty measures created by Székeley, Lustig et. al. (2000) (cited below as SLCM) offers a special challenge and opportunity to demonstrate this testing strategy for choosing among rival poverty rates. As it happens, fewer than 15 of 66 poverty measures pass our sequence of tests. These 10-15 measures contain most of the useful information about variations in living standards among these 17 countries. Some of these poverty rates are computed using similar methods, so less than ten different poverty measures "encompass" the entire set of 66 SLCM poverty indicators. The remaining 55 indices are statistically redundant in that they contain no additional information regarding variations in living standards and poverty related behavior. The concluding

[1] See the useful but inconclusive discussions of survey vs. national accounts-based poverty estimates in Deaton (2003), Ravallion (2001), Bhalla (2002) and Sala-i-Martin (2003).
[2] But similar procedures could be applied to relative or national poverty rates with some simple modifications (discussed below). Elsewhere we apply the same methodology to choosing among rival per capita income measures and to choosing the "power" of published CEPAL poverty rates for the 1990s. See McLeod (2003).

section explores the implications of these finding for choosing among poverty measures and computational methodologies.

1. Desirable Properties of Poverty Measures:

The testing strategy proposed here searches for poverty measures that display certain statistically verifiable characteristics. First, poverty measures should be estimated consistently across countries and over time. Second, they should measure absolute poverty, that is, capture some aspect of physical deprivation among poor populations, malnutrition for example. Not all poverty rates display these properties, or even aspire to. Relative poverty rates of the sort widely used in Europe, for example, do not have these properties.[3] Similarly, Brazil sets its poverty lines as multiples of its minimum wage. This approach is relevant to Brazil but is not comparable with other countries. There are, however, a significant number of poverty estimates that target the population below some constant level of subsistence consumption. All of the $1-per-day poverty measures reported in Table 1, for example, do attempt to measure absolute living standards consistently across countries and over time.

Given a consistent set of absolute poverty indicators, three criteria can be used to test the performance of rival poverty measures. Recall that our object is to take a potentially long list alternative poverty measure and narrow it down to a much shorter list of "useful" poverty measures. Our testing strategy involves three testable hypotheses:

(1) *Consistent absolute poverty measures should be correlated across countries or regions with other measures of physical deprivation and adaptive behavior.*

This follows from the definition of absolute poverty. Examples of physical deprivation indicators include anthropometric malnutrition indicators, and death or morbidity rates. Decision

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[3] A similar methodology could be applied to relative poverty rates, however, such as using a dependent variable of survey-based "happiness" scores (see Alesina et al. . While poverty measures that are consistent and measure absolute deprivation have some obvious advantages, researchers with different priorities may apply different criteria. What is important is that the performance criteria be testable in an objective fashion.

variables include birth rates, school enrollment and child labor force participation rates. We refer to these adverse outcome indicators and adaptive decisions as "correlates of poverty."

(2) *Absolute poverty measures should contain more information than per capita income for predicting variation in at least one correlate of poverty across countries*.

This second requirement reflects practical considerations: if per capita income provides all available information regarding variations in absolute deprivation across countries, why bother computing poverty rates? Of course, these tests can and should control for variations in public spending, health delivery systems, etc. Alternative models can be elaborate, and even include instrumental variables, as long as rival poverty measures are what distinguish each model.

(2A) *Useful absolute poverty measures should perform as well as or better than rival poverty measures in predicting at least one correlate of poverty.*

This is a slightly stronger version of #2 where the challenger is poverty rates rather than per capita income. If a particular poverty measure does not provide independent information regarding at least one NMP indicator, it can be dropped. Of course, adding new conditioning variables in the testing models or finding new correlates of poverty can render redundant poverty estimates "useful" once again. If needed, this stronger version of property 2 can help shorten the list of competing estimates and point to estimation methods that seem to produce more informative welfare indicators. A variation on this method is to use a points system and assign scores to each poverty measure. The top five or ten point getters would then make the short list of useful poverty measures.

(3) V*ariation in consistent absolute poverty rates over time should be correlated with changes in non-monetary indicators of deprivation and adaptive decisions, and add useful information to that provided by changes in per capita income or per capita consumption—conditioning on changes in health and education spending, etc.* .

This third criterion is a straightforward extension of (1) and (2) to the changes over time. Focusing on changes in poverty rates may expand the scope of our testing strategy to include poverty rates based on different "national" poverty lines. Rather than comparing poverty rates themselves, using changes in poverty may make poverty measures more comparable across countries. An analogous problem arises in comparing unemployment rates across countries. Definitions of unemployment vary widely across countries, yet changes in unemployment across countries may have similar consequences and antecedents.

These three, or three and a half, criteria form the basis of the series of non-nested hypothesis tests discussed in the next section. Of course these criteria can be refined and expanded upon. However, the question at hand is whether these applying these criteria can narrow the field of sixty-plus alternative poverty measures provided by SLCM. As it happens, we must proceed without the benefit of property (3) as SLCM only compute poverty rates for a single year in the mid 1990s. [4]

2. Non-monetary Correlates of poverty

Absolute poverty measures should be correlated with key physical indicators of poverty and/or the adaptive behavior of poor families. Our first task therefore is to select a set of non-monetary poverty (NMP) indicators. A number of potential correlates of poverty are listed in Table 2. Candidates for physical deprivation indicators include anthropometric evidence of malnutrition, such as wasting (low weight for height), stunting (low height for age) and low birth weight. Candidates for adaptive behavior indicators include higher birth rates (partly a response to high infant mortality), higher child labor force participation rates and higher illiteracy and lower school attendance rates.

Our hope is that these measures can provide independent corroboration of poverty and income measures. Whereas the consumption or income-based poverty measures are generally prepared under the auspices of the World Bank or local government agencies, most malnutrition indicators are tabulated by the World Health Organization and UNICEF while the U.N. Statistical Division estimates fertility rates. Unless these international agencies are in fact using income levels to estimate birth rates, or the incidence of stunting and wasting among children– and they claim they are

[4] McLeod (2003) and Gruben and McLeod (2003) are able to test changes in poverty over time using a series of World Bank and CEPAL poverty rates estimated for several years during the 1990s.

not—their data represent independent samplings of the same population polled by consumer and income surveys. Hence, correlations among poverty rates and physical deprivation measures or adaptive behavior can be used to test the predictive power of poverty measures across countries and over time.

Table 2 lists a number of non-monetary welfare indicators. The last column of Table 2 summarizes the outcome of a series of non-nested hypothesis (in this case the J-test of Davidson and McKinnon as discussed in the next session). There are always four possible outcomes of a non-nested hypothesis test of two alternative models. In some cases, per capita income does not add any additional information regarding variations in the NMP indicator to that provided by any of the 64 poverty measures. In Table 2 we see this is the case for all three of the malnutrition indicators we tested. For these indicators, once we have poverty indicators there is no reason to consult per capita income levels.

The second outcome is the reverse case: none of the poverty indicators adds any information not already provided by per capita income. This turns out to be the case for secondary enrollment rates in Table 2, for example. Yet a third outcome is that both models contain useful information for explaining variance in NMP indicators. This is the situation for a number of the indicators shown in Table 2. In this case, "both" may mean that some poverty rates dominate per capita income, but some do not or that for a given poverty indicator, both models can be statistically rejected by the other. This case is explored in more detail in the next section. The final outcome is that neither per capita income nor poverty rates predict variation in a given NMP indicator. This is the case for gross primary school enrollment, for example.

3. Tests for "Benchmark" Poverty Rates

The tests reported in Table 2 provide ten non-monetary poverty correlates that can be used to assess the performance of rival poverty rates. To begin, we use one of these NMP measures, the under five infant mortality rate, to test the three benchmark poverty measures identified by SLCM. Before proceeding there is a potential problem with using the standard Davidson and MacKinnon (1981) J-test applied in this context. The standard choice of regressors problem can be written in terms of two non-nested models:

$$M_1 : y = \mathbf{X}\_ \; + \_{1} \qquad (1)$$

$$M_2 : y = \mathbf{Z}\_ \; + \_{2}$$

where X and Z are n x k and n x l matrices of different regressors. Davidson and MacKinnon (1981) suggest testing the merged model,

$$y = (1 - \alpha)\, \mathbf{X}\_ \; + \; \alpha\, (\mathbf{Z}\_) + \; \_. \qquad (2)$$

estimating using an artificial regression that adds the fitted values $\mathbf{Z}'$ to a regression of y on X (Model 1). If M_1 encompasses M_2 (renders M_2 redundant) then a standard t-test is sufficient to reject the null that $\alpha = 0$. This test can be quite powerful. Davidson and MacKinnon show that if the M_1 is the "true model" plim $= 0$ as $n \to \infty$. Of course in our tests, n does not approach infinity; in fact it is only 17. This low n problem helps explain the high incidence "ties" of the "both" or "neither" variety among the tests reported in Tables 2 through 4. This problem can be mitigated somewhat, however, by turning to other encompassing tests including the Cox and Ericsson tests (see Appendix C for a discussion of how these additional tests can be used as tie breakers). In a broader context, the best remedy for this problem is simply to have more observations as is the case in Gruben and McLeod (2003) and McLeod (2003).

Table 3 reports "J-tests" for the three "benchmark" poverty measures reported by SLCM in Table 1 of their paper. Table 3 lists only the "significant" J-tests—Table A-1 reports J-tests for all 65 poverty and inequality measures. The dependent variable, y, for all the tests in Tables 3 and A-1 is the log of under-five mortality rate (U5MR). The benchmark poverty rate or headcount is H_1; the benchmark poverty gap is Pg_1; the benchmark Foster-Greer-Thorbeke or "gap-squared" measure is

Fgt_1. These three poverty measures plus a constant return constitute M_1. The first column of t-statistics are for all other income and poverty measures (each of these M_2s attempt to augment M_1, undermining its claim to be the only true model). The first entry, for example pits M_1 against an M_2 based on per capita income in 1987 PPP U.S. dollars (Y_{PC}). Evidently, none of the benchmark poverty measures meet our criteria, as in every case per capita income "encompasses" the benchmark poverty measures. Of course, these results are only for one indicator, the U5MR, and as we shall see later the benchmark poverty rates and gap measures do "tie" per capita income as models of some malnutrition indicators. However, in every case some other poverty measures turn out to be better, both compared to per capita income and to other poverty measures.

It is important to note that SLCM use "benchmark" to denote "common practice" rather than "best practice" techniques for computing national poverty rates.[5] In fact, one purpose of the SLCM study is to question the validity of common and often implicit assumptions widely used by agencies the compute national poverty rates and gaps. One example of a "benchmark" convention in Latin America is to use national rather than internationally defined poverty lines. It is not surprising, therefore, to find that none of the "benchmark" poverty measures passes a test that defines a useful poverty measure as one that is calibrated uniformly across nations and over time. As it happens, all three benchmark measures contain less information about variations in U5MRs than per capita income, as shown in the first row of Table 3).

One conclusion of this first round of "benchmark" tests is that one may be better off using per capita income to predict variations in welfare across countries rather than national poverty rates.

[5] Londono and Székely (2000) survey 111 papers on poverty and inequality and conclude the following are common practice (benchmark) methods: "The official poverty line of the country (i.e., that provided by the appropriate government agency) is used to determine the cutoff point from which individuals are considered to be poor; total household per capita income is used as a welfare indicator; missing or zero incomes are dropped from the sample; and no adjustment for misreporting or underreporting is performed. Relying on these choices implies assuming that: (a) Country-specific poverty lines reflect accurately what being poor means; (b) Current income is an adequate indicator of the standard of living of individuals; (c) Each individual in the household has the same needs; (d) There are no economies of scale in consumption, (e) Missing values and zero incomes are unreliable information that should be discarded, (f) Non-sampling errors in household surveys are small and the income or consumption" (quote from SLCM page 8).

Changes in these benchmark poverty measures might be a useful welfare indicator, but we cannot test this possibility here.

4. Ranking the Top Ten Poverty Indicators

The next step is to repeat J-tests similar to those in Table 3 for all eleven non-monetary poverty indicators. These results are reported in Table A-2. In some cases one or more poverty rates perform well in predicting the same indicator, pupils reaching grade 5, for example. In these cases we can use additional non-nested hypothesis tests including that proposed by Cox (1961) and Ericsson (1983) as discussed in Appendix C. Again it is not surprising to have “ties” as our small “n” reduces the power of the J-test. Unfortunately, Table A-2 is rather large so it is only available with the internet version of this paper.[6] Tables A-3 and A-4 include the complete data set for this paper, also available online.

Table 4 summarizes the results of these J-tests for all eleven poverty indicators. The first column of Table 4 identifies the “best” poverty rate associated with each indicator. Table C-1 reports the regression coefficients and R^2 statistics for these eleven poverty indicators. Sometimes there were several contenders for a given indicator (see the “contenders” column). In these cases the process of determining the “best” indicator could be quite involve (see Appendix C for a discussion of “tie-breakers”). Generally, contenders out-perform or perform at least as well as the “best” poverty measure but do not perform as well against income per capita. Hence the requirement that “useful” poverty measures outperform per capita income turns out to be a quite powerful screening device.

One caution in reaching a final ranking is that different poverty measures are likely to be sensitive to different strata of the poor population, and therefore to be correlated with different NMP indicators. A dollar per day poverty line, for example, should be a better predictor of severe poverty

[6] Tables A2, A3 and A4 are available in Spreadsheet and pdf format at www.forham.edu/economics/mcleod.

indicators than the \$2 a day line. Similarly poverty gaps and gap-squared indicators are designed to be more sensitive to the depth of poverty. It is gratifying, therefore, that three "gap" measures appear among the top 10-15 poverty measures and are sensitive to stunting and "pupils reaching grade 5" – indicators that one might expect to be associated with severe poverty. Similarly, child labor force participation is associated with severe poverty as measured by \$1/day consumption (H_{43}) and severe poverty measured by the poverty gap squared (Fgt_8) scaled up to fit the national account incomes. On the other hand, poverty rate $H_{38,}$ which is based on a higher \$2/day poverty rate for each country, turns out to be closely associated with under-five mortality rates and female illiteracy—two indicators we might also associate with severe poverty.

Narrowing SLCM's sixty-six poverty and inequality indicators to nine "best" and six "contenders" represents progress. Common denominators in these indices include uniform poverty lines-- usually \$1/day or \$2/day, use of total private consumption or national accounts for scaling up poverty methods, especially the ECLAC methodology described in Appendix B of this paper. Note that the ECLAC methodology was used to construct poverty rates H_{27} and H_{42}. More applications of this methodology to other data sets should help further narrow the list of "best practice" poverty rate computation techniques.

Nevertheless, consumers of poverty data may still prefer one or two poverty indicators over a group of nine or fifteen. This "best overall" poverty measures might be the poverty indicator most correlated with the whole range of "poverty correlates." There are a number of possible methods for arriving at this final ranking. Table 5, for example, ranks the fifteen poverty rates from Table 4 by average Pearson correlations for only the four poverty-dominated indicators identified in Table 2 (stunting, wasting, low birth weight babies and persistence to grade 5). Similar rankings are shown for the highest (absolute) correlation using all eleven poverty correlates identified in Table 2. The orderings vary somewhat depending on the type of correlation coefficient used and on whether the narrow or broad group of NMP indicators is the relevant universe. However, several poverty rates appear frequently among the top five indicators across most of the rankings shown, so we do not lose much by simply using the first set of ranking reported in Table 5.

One common theme evident among Table 5's top ranked poverty indicators is that scaling to national accounts and, not surprisingly, standards of international comparison are important. Of these scaling methods the "tried and true" ECLAC methodology seems to work well. Note that these are not ECLAC's poverty rates, which use poverty lines that vary from country to country. Rather it is an endorsement of the method long used by ECLAC to scale survey data to fit national accounting aggregates (see Appendix B and Altimir (1981)).

5. Concluding Comments:

This paper proposes and applies a series of plausible and testable criteria for choosing among rival poverty rates. These tests exploit the fact that absolute poverty rates estimated consistently across countries should be correlated with certain non-monetary poverty indicators. This method is used to screen more than 60 alternate poverty measures computed by Székeley, Lustig et. al. (2000). Many of the fifteen poverty measures that survive this screening highlight one adjustment issue (scaling to national accounts) and feature one adjustment method (ECLAC's method of scaling surveys to national accounts). These results demonstrate that even with a small sample of 17 countries the testing procedures proposed here can discriminate among rival poverty estimates. Similar tests applied to other datasets and poverty measures could, over time, help build a consensus on the best method for computing national poverty rates.

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Table 1
Alternate $1/day Poverty Rate Estimates for Developing Countries

	1985-90		**1998-2000**	
	Millions of Persons	% of LDC Population	Millions of Persons	% of LDC Population
Javier Sala-i-Martin			350	7%
World Bank	1276	29%	1151	23%
UNCTAD	605	14%	508	10%
Surjit Bhalla	830	19%	559	11%

Sources: Sala-i-Martin (2002); World Bank (2003); UNCTAD (2002) and Bhalla (2002)

Table 2: Non-monetary Correlates of Poverty and Per Capita Income

Poverty related outcomes: malnutrition indicators	Average 1/ Reporting Frequency	Source Agency 2/	Non-Nested J-tests Summary 3/
Wasting: low weight for age, % of children under 5	3.6 yrs	WHO	poverty rates
Stunting: low height for age, % of children under 5	3.9 yrs.	WHO	poverty rates
Low-birth weight babies (% of births)	5 yrs	WHO/UNICEF	poverty rates
Death rate per 1,000 people (male and female)	4.6 yrs	World Bank	Per capita income
Infant Mortality Rates	2.1 yrs	UNICEF	Both
Under 5 Mortality Rate	4.2 yrs	UNICEF	Both
Life expectancy at birth, total (years)	2.8 yrs	World Bank	Both
Household adaptive decision variables			
Total Fertility rate (births per woman)	1.8 yrs	UN Stats. Div.	Per capita income
Birth rate, crude (per 1,000 people)	2.1 yrs	World Bank	Both
Labor force participation of children 10-14 (% of cohort)	2.8 yrs	ILO	Both
Education Indicators			
School enrollment, primary (% gross)	1.3 yrs	UNESCO	Neither
School enrollment, secondary (% net)	1.4yrs	UNESCO	Per Capita income
Illiteracy rates adults 15+ female	annual	UNESCO	Both
Pupils reaching grade 5 (% of cohort), total	4 yrs	OECD & WEI	Poverty Rates

1/ Average reporting interval 1990-2001.

2/ Data source: World Bank, World Development Indicators 2002 CD-Rom and WDI Online.

3/ As discussed in the text, this column summarizes the results of J-tests for of all poverty measures listed in Table A-1 against per capita income $PPP 1987 as reported in Table 1 of Székeley, Lustig et.al. (2000). Non-nested models can have four outcomes: joint significance (neither model dominates, but both have explanatory power as is the case with illiteracy rates for example), income or poverty indicators always dominates (per capita income dominates poverty as an explanation of child labor force participation, for example) or neither variable is significant (e.g., for school enrollment). As might be expected, poverty rates provide the most information about malnutrition indicators for example.

Table 3: J-Tests for Benchmark Poverty Rates

	Dependent Variable: Under 5 Mortality Rate (U5MR)	$M_1 = f(c,H_1)$			$M_1 = f(c,Pg_1)$		$M_1 = f(c,Fgt_1)$	
M_2:	Poverty Indicator:**	M_2 vs. M_1	M_1 vs. M_2	R^2	M_2 vs. M_1	M_1 vs. M_2	M_2 vs. M_1	M_1 vs. M_2
Y_{PC}	PPP GDP per capita $1987	0.66	3.80*	0.55	0.68	3.66*	0.71	3.59*
H_1	***Benchmark Poverty Rate***				1.38	-1.02	1.43	-0.86
H_2	All sources of income 1/	-0.14	2.16*	0.32	0.15	1.93	0.29	1.82
H_7	Sensitivity to missing data - max 3/	-1.55	1.94	0.28	0.03	0.31	0.66	-0.20
H_{10}	Different Poverty line definitions	-0.87	2.07*	0.30	-0.56	1.62	-0.36	1.40
H_{11}	Different Poverty line definitions	-0.09	2.17*	0.26	0.35	1.44	0.54	1.23
H_{12}	International comparisons - min	0.40	3.57*	0.48	0.41	3.48*	0.41	3.42*
H_{13}	International comparisons - max	-0.70	3.07*	0.40	-0.30	2.70*	-0.12	2.54*
H_{14}	All adjustments - min	-0.17	3.19*	0.42	-0.16	3.16*	-0.17	3.18*
H_{16}	Amsterdam Equivalence Scale	0.71	-0.45	0.17	2.48	-2.21	2.01	-1.55
H_{17}	Contreras Equivalence Scale	0.59	-0.27	0.17	2.61	-2.32	2.22	-1.76
H_{18}	Consumption Scale Economies e = .7	-0.44	0.83	0.20	1.82	-1.65	2.11	-1.81
H_{19}	Consumption Scale Economies e = .8	-0.30	0.56	0.18	2.50	-2.30	1.88	-1.53
H_{22}	Impute Missing, keep zeros	-1.75	3.22*	0.31	-0.69	2.32*	-0.04	1.08
H_{23}	Impute Missing, drop zeros	-1.74	2.83*	0.27	-0.07	1.01	0.40	0.48
H_{24}	Drop Missing, impute zeros	-1.24	2.32*	0.20	0.94	-0.67	1.12	-0.69
H_{25}	Drop Missing, keep zeros	-1.27	2.02*	0.22	0.67	-0.37	0.98	-0.53
H_{37}	Country studies 8/	2.29*	-2.87*	0.21	2.80*	-2.53*	3.20*	-2.73*
H_{38}	$2/day PPP poverty lines 8/	-0.10	3.45*	0.41	0.17	3.32*	0.29	3.25
H_{39}	ECLAC 8/	0.12	2.11*	0.27	0.37	1.69	0.50	1.49
H_{40}	Official Extreme Poverty 8/	-0.95	2.11*	0.30	-0.55	1.50	-0.30	1.22
H_{41}	World Development Indicators 9/	0.31	2.48*	0.32	0.51	2.31*	0.60	2.23*
H_{42}	ECLAC Type adjustment 9/	0.37	2.14*	0.30	0.57	1.77	0.69	1.58
H_{43}	$PPP 1987 Private Consumption 9/	0.51	3.42*	0.47	0.56	3.35*	0.59	3.30*
H_{44}	$PPP GDP per capita 1987 9/	0.42	3.44*	0.47	0.43	3.33*	0.44	3.27*
Pg_1	***Benchmark Poverty Gap index***	-1.02	1.38	0.25			1.14	-0.93
Pg_7	Different Poverty line definitions	-0.44	2.80*	0.30	0.02	2.09*	0.24	1.72*
Pg_8	International comparisons - min	0.34	3.22*	0.45	0.33	3.08*	0.32	3.00*
Pg_9	International comparisons - max	-0.72	3.39*	0.44	-0.41	3.04*	-0.26	2.89*
Pg_{10}	All adjustments - min	-0.03	2.72*	0.38	0.00	2.64*	0.01	2.60*
Pg_{11}	All adjustments -- max	-0.49	2.35*	0.31	-0.19	2.09*	-0.01	1.92*
Fgt_1	***Benchmark FGT(2) index***	-0.86	1.43*	0.25	-0.93	1.14		
Fgt_7	Different Poverty line definitions	-0.51	2.92*	0.32	-0.13	2.43*	0.08	2.05*
Fgt_8	International comparisons - min	0.33	3.11*	0.41	0.32	2.91*	0.31	2.79*
Fgt_9	International comparisons - max	-0.68	3.67*	0.46	-0.43	3.35*	-0.30	3.18*
Fgt_{10}	All adjustments – min	0.08	2.51*	0.34	0.13	2.30*	0.15	2.17*
Fgt_{11}	All adjustments – max	-0.56	2.59*	0.34	-0.34	2.33*	-0.20	2.16*

* Significant at the 5% level. See Table A-1 for a full list of poverty measures and notes.

Table 4
Consistent Absolute Poverty Rates for Latin America in the 1990s

Poverty related adverse outcomes:	H*: Top Poverty Indicator	Other Contenders	J-tests against Y_{pc}: Y_{PC} vs. H*	J-tests against Y_{pc}: H* vs. Y_{PC}
Wasting: Low weight for height, % of children under 5	H_{27}	H_{23} H_1	2.98*	1.46
Stunting, low height for age, % of children under 5	Pg_9		2.81*	1.31
Low-birthweight babies (% of births)	H_{27}		2.50*	-1.00
Infant Mortality Rates	H_{41}	H_{43},H_{44}	0.39	1.89
Under 5 Mortality Rate	H_{38}	H_{43}, H_{12}	3.25*	3.06*
Life expectancy at birth, total (years)	H_{44}	H_{12}	0.87	1.64
Household Decision Variables				
Birth rate, crude (per 1,000 people)	H_{42}	H_5	5.16*	4.08*
Child Labor force participation, % of 10-14 age group	H_{43}	Fg_8,H_{44}	1.49	0.42
Population Growth Rate	Fg_8	H_{39},H_{42}	1.75	0.41
Adult Female Illiteracy Rate, ages 15 and above	H_{38}	H_{44}	4.62*	3.80*
Pupils reaching grade 5 (% of cohort), total	Fgt_4	H_{35}	2.87*	1.59

Table 5: Rankings of Poverty Rates using Average Correlation Coefficients

Top 10 Poverty Measures (plus four runner ups):		From Table[5/]	Four Main Poverty Correlates: Average 5/ Pearson Corr.	Rank	Four Main Poverty Correlates: Spearman5/ Rank Corr. Corr.	Rank	All Poverty Correlates from Table 4: Average5/ Pearson Corr.	Rank	All Poverty Correlates from Table 4: Spearman 5/ Rank Corr. Corr.	Rank
H_{27}	ECLAC-type adjustment[2/]	A4	0.61	1	0.67	1	0.53	8	0.56	6
H_{42}	ECLAC-type adjustment[1/]	A7	0.59	2	0.63	2	0.58	2	0.57	5
H_{23}	Impute Missing values, drop zeros	A3	0.58	3	0.63	3	0.48	12	0.50	11
H_{35}	GDP current prices	A4	0.57	4	0.59	5	0.51	11	0.51	9
Fgt_4	Scale to National Accounts-min[2/]	5	0.57	5	0.59	4	0.51	10	0.51	10
Pg_9	International comparisons - max	7	0.54	6	0.49	10	0.53	7	0.49	12
Y_{PC}	PPP GDP per capita $1987	1	0.50	7	0.48	12	0.59	1	0.59	1
H_{12}	International comparisons - min	7	0.48	8	0.50	8	0.57	3	0.58	2
H_{39}	ECLAC[3/]	A5	0.48	9	0.53	7	0.51	9	0.51	8
H_{44}	$PPP GDP per capita 1987 [1/]	A7	0.48	10	0.50	9	0.57	5	0.58	3
Fgt_8	International comparisons - min	7	0.48	11	0.54	6	0.57	4	0.58	4
H_{43}	$PPP 1987 Private Consumption [1/]	A7	0.46	12	0.48	11	0.55	6	0.55	7
H_{38}	$2/day PPP poverty lines [3/]	A5	0.37	13	0.43	14	0.45	13	0.47	13
H_5	Urban Areas [4/]	2	0.36	14	0.44	13	0.41	14	0.41	14
H_{41}	World Development Indicators [1/]	A7	0.32	15	0.38	15	0.39	15	0.39	15
Gini	Gini coefficient	1	0.25	16	0.29	16	0.30	16	0.29	16

1/ Headcount ratios computed based on a range of alternative International Comparisons.

2/ Headcount ratios computed for a range of alternative adjustments to National Accounts aggregates.

3/ Headcount ratios for a range of poverty lines

4/ Poverty rates that use the same poverty line for all countries, in this case in urban areas.

5/ These are averages of the absolute value of the correlation coefficients—clearly correlations with per capita income are generally negative.

6/ See Table 4-- the four poverty correlates clearly dominated by poverty measures, as opposed to per capita income, include wasting, stunting, low birth rate babies and persistence to grade five (% of age cohort).

Table A-1: U5MR J-Tests for Benchmark Poverty Measures

	Dependent Variable: U5MR	IADB Paper			M_1 = f(c,H_1)			M_1=f(c,Pg_1)		M_1=f(c,Fgt_1)	
					M_2 vs.	M_1 vs.		M_2 vs.	M_1 vs.	M_2 vs.	M_1 vs.
M_2:	Poverty Indicator:	Source:	col.	page	M_1	M_2	R^2	M_1	M_2	M_1	M_2
Y_{PC}	PPP GDP per capita $1987	Table 1	8	36	0.66	3.80*	55%	0.68	3.66*	0.71	3.59*
H_1	Benchmark Poverty Rate	Table 1	3	36				1.38	-1.02	1.43	-0.86
H_2	All sources of income 1/	Table 2	5	36	-0.14	2.16*	32%	0.15	1.93	0.29	1.82
H_3	Money Incomes only 1/	Table 2	7	36	0.02	1.92	28%	0.40	1.76	0.59	1.69
H_4	Labor income only 1/	Table 2	9	36	0.42	1.47	24%	0.74	1.30	0.92	1.25
H_5	Urban Areas 1/	Table 2	11	36	0.09	1.51	31%	0.34	1.40	0.47	1.34
H_6	Alt. Equivalence Scales -- min 2/	Table 3	3	37	-0.44	0.83	20%	1.82	-1.65	2.11	-1.81
H_7	Sensitivity to missing data - max 3/	Table 4	4	37	-1.55	1.94	28%	0.03	0.31	0.66	-0.20
H_8	Scale to Nat. Accounts - min 4/	Table 5	4	37	0.48	1.42	23%	0.67	1.06	0.79	0.88
H_9	Scale to Nat. Accounts - max 4/	Table 5	4	38	0.39	0.06	17%	0.90	-0.49	1.20	-0.70
H_{10}	Different Poverty line definitions	Table 6	3	38	-0.87	2.07*	30%	-0.56	1.62	-0.36	1.40
H_{11}	Different Poverty line definitions	Table 6	4	38	-0.09	2.17*	26%	0.35	1.44	0.54	1.23
H_{12}	International comparisons - min	Table 7	3	39	0.40	3.57*	48%	0.41	3.48*	0.41	3.42*
H_{13}	International comparisons - max	Table 7	4	39	-0.70	3.07*	40%	-0.30	2.70*	-0.12	2.54*
H_{14}	All adjustments - min	Table 8	2	39	-0.17	3.19*	42%	-0.16	3.16*	-0.17	3.18*
H_{15}	All adjustments -- max	Table 8	3	39	-0.38	2.17*	28%	0.03	1.78	0.24	1.56
H_{16}	Amsterdam Equivalence Scale	Table A2	6	41	0.71	-0.45	17%	2.48*	-2.21*	2.01*	-1.55
H_{17}	Contreras Equivalence Scale	Table A2	5	41	0.59	-0.27	17%	2.61*	-2.32*	2.22*	-1.76
H_{18}	Consp. Scale Economies e = .7	Table A2	4	41	-0.44	0.83	20%	1.82*	-1.65*	2.11*	-1.81
H_{19}	Consp. Scale Economies e = .8	Table A2	3	41	-0.30	0.56	18%	2.50*	-2.30*	1.88	-1.53
H_{20}	Consp. Scale Economies e = .9	Table A2	2	41	-0.66	0.78	20%	1.62	-1.35	1.51	-1.04
H_{21}	Impute Missing and zeros	Table A3	6	42	-1.57	1.92	27%	0.22	0.06	0.78	-0.36
H_{22}	Impute Missing, keep zeros	Table A3	5	42	-1.75	3.22*	31%	-0.69	2.32	-0.04	1.08
H_{23}	Impute Missing, drop zeros	Table A3	4	42	-1.74	2.83*	27%	-0.07	1.01	0.40	0.48
H_{24}	Drop Missing, impute zeros	Table A3	3	42	-1.24	2.32*	20%	0.94	-0.67	1.12	-0.69
H_{25}	Drop Missing, keep zeros	Table A3	2	42	-1.27	2.02*	22%	0.67	-0.37	0.98	-0.53
H_{26}	World Development Indicators 5/	Table A4	11	42	0.68	-0.26	17%	1.25	-0.71	1.56	-0.85
H_{27}	ECLAC-type adjustment	Table A4	10	42	0.49	1.32	24%	0.70	1.03	0.82	0.93
H_{28}	Sector of Activity	Table A4	9	42	0.55	0.89	20%	0.76	0.51	0.89	0.37
H_{29}	UN Population Statistics 6/	Table A4	8	42	0.41	1.00	19%	0.76	0.35	0.94	0.14
H_{30}	Official Population	Table A4	7	42	0.45	0.93	19%	0.81	0.29	0.99	0.08
H_{31}	Survey Population	Table A4	6	42	0.83	0.32	17%	1.15	-0.06	1.29	-0.15
H_{32}	UN Population Statistics 7/	Table A4	5	42	0.45	1.69	24%	0.57	1.34	0.68	1.12
H_{33}	Official Population 7/	Table A4	4	42	0.48	1.60	24%	0.62	1.23	0.74	1.01
H_{34}	Survey Population 7/	Table A4	3	42	0.76	1.04	20%	0.97	0.65	1.10	0.49
H_{35}	GDP current prices	Table A4	2	42	0.57	1.41	24%	0.74	1.10	0.85	0.94
H_{36}	WB Poverty Assessment 8/	Table A5	6	43	0.72	0.38	18%	0.93	0.21	1.05	0.13
H_{37}	Country studies 8/	Table A5	5	43	2.29*	-2.87*	21%	2.80*	-2.53*	3.20*	-2.73*

Notes : see next page. *T-test significant at the 5% level. For example, the null that Model 2 (c, P_{cy}) contains no additional power to predict variations in U5MR among countries beyond that contained in Model 1 (c, H_1) can be rejected with a high degree of confidence.

Table A-1 (cont.) : U5MR J-Tests for Benchmark Poverty Measures

	Dependent Variable: U5MR	IADB Paper			$M_1 = f(c,H_1)$			$M_1=f(c,Pg_1)$		$M_1=f(c,Fgt_1)$	
M_2:	Poverty Indicator:	Source:	col.	pp.	M_2 vs. M_1	M_1 vs. M_2	R^2	M_2 vs. M_1	M_1 vs. M_2	M_2 vs. M_1	M_1 vs. M_2
H_{37}	Country studies 8/	Table A5	5	43	2.29*	-2.87*	21%	2.80*	-2.53*	3.20*	-2.73*
H_{38}	$2/day PPP poverty lines 8/	Table A5	4	43	-0.10	3.45*	41%	0.17	3.32*	0.29	3.25*
H_{39}	ECLAC 8/	Table A5	3	43	0.12	2.11*	27%	0.37	1.69	0.50	1.49
H_{40}	Official Extreme Poverty 8/	Table A5	2	43	-0.95	2.11*	30%	-0.55	1.50	-0.30	1.22
H_{41}	World Development Indicators 9/	Table A7	5	44	0.31	2.48*	32%	0.51	2.31*	0.60	2.23*
H_{42}	ECLAC Type adjustment 9/	Table A7	4	44	0.37	2.14*	30%	0.57	1.77	0.69	1.58
H_{43}	$PPP 1987 Private Consumption 9/	Table A7	3	44	0.51	3.42*	47%	0.56	3.35*	0.59	3.30*
H_{44}	$PPP GDP per capita 1987 9/	Table A7	2	44	0.42	3.44*	47%	0.43	3.33*	0.44	3.27*
Pg_1	Benchmark Poverty Gap index	Table 1	4	36	-1.02	1.38	25%			1.14	-0.93
Pg_2	Alt. Equivalence Scales -- min 10/	Table 3	7	37	-0.49	1.18	23%	-0.30	0.67	0.17	0.02
Pg_3	Sensitivity to missing data - max 11/	Table 4	6	37	-1.12	1.88	29%	-1.20	1.70	-0.74	1.15
Pg_4	Scale to Nat. Accounts - min 12/	Table 5	5	38	0.45	1.71	25%	0.60	1.34	0.71	1.12
Pg_5	Scale to Nat. Accounts - max 12/	Table 5	6	38	0.21	0.56	18%	0.67	-0.29	1.11	-0.79
Pg_6	Different Poverty line definitions	Table 6	5	38	-0.32	1.52	25%	-0.03	1.09	0.15	0.88
Pg_7	Different Poverty line definitions	Table 6	6	38	-0.44	2.80*	30%	0.02	2.09*	0.24	1.72
Pg_8	International comparisons - min	Table 7	5	39	0.34	3.22*	45%	0.33	3.08*	0.32	3.00*
Pg_9	International comparisons - max	Table 7	6	39	-0.72	3.39*	44%	-0.41	3.04*	-0.26	2.89*
Pg_{10}	All adjustments - min	Table 8	5	39	-0.03	2.72*	38%	0.00	2.64*	0.01	2.60*
Pg_{11}	All adjustments -- max	Table 8	6	39	-0.49	2.35*	31%	-0.19	2.09*	-0.01	1.92
Fgt_1	Benchmark FGT(2) index	Table 1	5	36	-0.86	1.43	25%	-0.93	1.14		
Fgt_2	Alt. Equivalence Scales -- max /13	Table 3	8	37	-0.27	1.13	22%	-0.06	0.59	0.26	0.07
Fgt_3	Sensitivity to missing data-max /14	Table 4	8	37	-0.87	1.86	29%	-1.05	1.74	-0.99	1.53
Fgt_4	Scale to National Accounts-min /15	Table 5	7	38	0.52	1.62	23%	0.67	1.20	0.79	0.96
Fgt_5	Scale to National Accounts-max	Table 5	8	38	-0.01	1.07	20%	0.28	0.32	0.56	-0.13
Fgt_6	Different Poverty line definitions	Table 6	7	38	-0.16	1.42	24%	0.10	0.97	0.25	0.74
Fgt_7	Different Poverty line definitions	Table 6	8	38	-0.51	2.92*	32%	-0.13	2.43*	0.08	2.05*
Fgt_8	International comparisons - min	Table 7	7	39	0.33	3.11*	41%	0.32	2.91*	0.31	2.79*
Fgt_9	International comparisons - max	Table 7	8	39	-0.68	3.67*	46%	-0.43	3.35*	-0.30	3.18*
Fgt_{10}	All adjustments - min	Table 8	7	39	0.08	2.51*	34%	0.13	2.30*	0.15	2.17*
Fgt_{11}	All adjustments -- max	Table 8	8	39	-0.56	2.59*	34%	-0.34	2.33*	-0.20	2.16*
Gini	Gini coefficient	Table 1			1.24	-0.38	18%	1.56	-0.71	1.80	-0.90

Notes for Tables A-1 and Table 3:

1/ same poverty line for all countries
2/ economies of scale in consumption
3/ missing and zero incomes
4/ alternative adjustment methods
5/ National Account Adjustments
6/ Wage GDP - Non Wage GDP
7/ Private Consumption
8/ Head Count for a range of poverty lines
9/ Alternative International Comparisons
10/ economies of scale in consumption
11/ missing and zero incomes
12/ alternative adjustment methods
13/ economies of scale in consumption
14/ missing and zero incomes
15/ alternative adjustment methods

Appendix B: ECLAC (CEPAL) Adjustment Method

Note that 3 of the top ten and 2 of the top five ranked poverty rates reported in Table 5 above were based on the ECLAC method of scaling surveys to fit national accounting aggregates. IADB Working Paper #437, Székeley, Lustig et. al. (2000) describe CEPAL's (ECLAC's) method of adjusting survey data in some detail. For additional information, see their paper or Altimir (1987) or ECLAC (1995). Székeley, Lustig et. al. (2000) are not able to reproduce the ECLAC methodology exactly, as some intermediate control totals have never made public by ECLAC. Also note that the poverty rates reported in Tables A4 and A7 use ECLAC adjustment methods, but not the actual national poverty lines preferred by ECLAC. The following description of the ECLAC adjustment method is taken directly from Székeley, Lustig et. al. (2000) page 21.

"Perhaps the source with the longest tradition of adjusting household survey data is ECLAC, which also performs the most elaborate method. As explained by Altimir (1987) and ECLAC (1995), their adjustment consists of four main steps. The first is to create a household account in the National Accounts. The second is to impute values for zero and missing incomes in the original survey (the specific method for imputing is not specified). The third is to aggregate incomes from the National Accounts and the household survey (including those that were imputed in the second step) into: (i) household labor incomes net of (estimated) taxes and social security contributions, (ii) profits, (iii) social security benefits, (iv) property rents, (v) imputed rents from owner-occupied housing, and (vi) transfers and donations. The aggregates are divided over the total population in the country in both cases to obtain a per capita figure for each income source. The fourth step is to compare the per capita figure in the National Accounts (NA) for each of the six items with the one from the survey, to obtain an adjustment factor. By multiplying all survey incomes by their respective adjustment factors and adding over all households, the NA aggregate by source is obtained. An exception to this rule is property incomes. For this source, the original household incomes are ordered by quintile and the adjustment factor is obtained by comparing the NA aggregate only with the property rents from the richest quintile in the survey. Then, the incomes in the richest quintile are multiplied by the adjustment factor, which assumes that all under-reporting of property rents takes place at the top of the unadjusted income distribution. The next to last column in Appendix Table A4 presents the poverty estimates that result from applying the ECLAC adjustment to the extent possible, while relying on the rest of the choices and assumptions as for the computation of the benchmark measure as in Table 1 According to the Appendix Table, the head count ratio for LAC is reduced to 34.6 percent when performing this adjustment. This is much smaller than the 50.7 percent estimate obtained by using the benchmark poverty measure."

Appendix C: Tie Breakers and Tie-Makers: Some further Tests

Table C-1 reports the regression coefficients and R^2 statistics for the eleven "best" poverty indicators. Not surprisingly, the rankings in Table 5 do not vary much from what would be obtained using average R squares rather than correlation coefficients. The main purpose of this appendix, however, is to reduce the number of "ties" in which "both" or "neither" poverty measure dominates in predicted a given NMP indicator. These ties result in the contenders listed in the second colum of Table 4.

In principle, Davidson and MacKinnon's J-test should be a powerful tool for choosing among regressors. As discussed in section 3 of the paper, Davidson and MacKinnon (1981) show that if the M_1 is the "true model" plim = 0 as $n \rightarrow \infty$. However, with n = 17 the J-test turns out to be much less powerful in discriminating among models or regressors—hence the large number of "both" or "neither" model outcomes. Davidson and MacKinnon (1981) also show that the the J-test is asymptotically equivalent to the negative of the Cox statistic (see Cox(1961). However, for low n the power of the two tests may differ. This appears to be the case for several of models tested here. Table C-1 provides Cox tests for a number of the variables and poverty measures presented Table 4. Specifically, these tests break ties, and in some cases create ties and more importantly help to explain the selection process for distinguishing "best" poverty indicators (H*) for "contenders.

A typical example of this final selection process is the choice between H_{44} and Fgt_8 as the "best" model of child labor forces participation rates. Given y, (the log of child labor force participation among the age 11-15 cohort) where M_1 is $y = f(c, H_{44})$ and M_2 is $y = f(c, Fgt_8)$, the J-test statistic is 2.81 for M_1 vs. M_2 and -2.25 for M_2 vs. M_1 implying that "both" models contain independent information regarding variations in y. The Cox tests shown in Table C-1 show a similar result, though M_2 (Fgt_8) is rejected by M_1 (H_{44}) with a much higher degree of confidence (at greater than 1% confidence level, Cox statistic -3.1) whereas M_1 (H_{44}) is barely rejected by M_2 (Fgt_8) at the

5% confidence level (Cox statistic -1.99).   Moreover, the J-tests for per capita income are inconclusive, neither model can be rejected for both H_{44} and Fgt_8. Fortunately the Cox statistic is for Y_{PC} is significant as show in the third line of Table C-1. The model based on H_{44} encompasses a model based only on Ypc at the 5% confidence level, but Fgt_8 does not (Cox statistic -.88). Hence the Cox test serves as a tie-breaker. Applying our criteria that any poverty measure should outperform per capita income, leads to a choice of H_{44} over Fgt_8 as the "best" predictor of child labor force participation.

Similar reasoning applies to the U5MR contenders. H_{38} and H_{43} both contain independent information regarding variations in under five mortality, but only H_{38} outperforms Ypc. Hence, H_{38} is chosen over H_{43} as the best predictor of U5MR among countries.   The story for "stunting" (low height for age) is a variation on this theme. Both the Cox statistic and the J-tests show both Pg_9 and Pg_3 contain independent information regarding variations in log incidence of stunting among children under 5. However, Pg_3 is "encompassed" by Y_{PC} where Pg_9 is not.

Table C-1: Additional Non-Nested Hypothesis Tests: Ties Makers and Tie-Breakers

Dependent	Model 1:				M₁ vs M₂			M₁ vs M₃		
Variable: 1/	X_1	Beta	t-stat	R^2	X_2	Cox-Stat.	J-test	X_3	Cox-Stat.	J-test
Child Labor	**H_{44}**	0.61	4.55	0.45	**Fgt_8**	2.0*	-2.3*	**Y_{PC}**	-0.41	.42
Child Labor	**Fgt_8**	0.42	4.05	0.34	**H_{44}**	-3.1**	2.8**	**Y_{PC}**	-1.37	1.52
Child Labor	**Y_{PC}**	-1.12	-4.24	0.37	**H_{44}**	-2.0*	1.5	**Fgt_8**	-0.88	.98
Infant Mortality	**Y_{PC}**	-0.57	-3.67	0.53	**H_{41}**	-2.2*	2.6*	**H_{12}**	-0.51	.61
Infant Mortality	**H_{41}**	0.35	2.60	0.24	**Y_{PC}**	-9.5**	3.3**	**H_{12}**	-4.3**	2.6*
Infant Mortality	**H_{12}**	0.26	3.48	0.44	**Y_{PC}**	-2.3*	2.1*	**H_{41}**	-0.70	1.0
U5MR	**H_{38}**	0.40	3.32	0.41	**Y_{PC}**	-5.0**	3.1**	**H_{43}**	-3.0**	2.3*
U5MR	**Y_{PC}**	-0.62	-3.95	0.53	**H_{38}**	-2.8**	3.3**	**H_{43}**	-0.61	.60
U5MR	**H_{43}**	0.58	3.42	0.46	**H_{38}**	-2.1*	2.6*	**Y_{PC}**	2.0*	1.7
Pop Growth	**Y_{PC}**	-0.46	-5.76	0.51	**Fgt_8**	-3.9**	1.8	**H_{39}**	-9.7**	4.5**
Pop Growth	**Fgt_8**	0.20	4.43	0.67	**Y_{PC}**	-0.52	.41	**H_{39}**	-5.3**	3.5**
Pop Growth	**H_{39}**	0.55	9.93	0.68	**Y_{PC}**	-5.4**	3.3	**Fgt_8**	-4.9**	2.9**
Stunting	**Pg_9**	0.87	4.02	0.57	**Y_{PC}**	-1.55	1.3	**Pg_3**	-1.4	2.2*
Stunting	**Y_{PC}**	-0.79	-2.78	0.37	**Pg_9**	-5.4**	2.8**	**Pg_3**	-4.8**	2.9**
Stunting	**Pg_3**	0.75	3.76	0.48	**Pg_9**	-3.1**	2.5*	**Y_{PC}**	-2.7**	1.7
Wasting	**H_{23}**	1.24	4.43	0.49	**Y_{PC}**	-2.7**	1.5	**H_{27}**	-2.0*	1.8
Wasting	**Y_{PC}**	-0.84	-2.45	0.33	**H_{23}**	-6.2**	3.0*	**H_{27}**	-8.6**	2.7**
Wasting	**H_{27}**	0.68	3.58	0.46	**Y_{PC}**	-0.65	1.0	**H_{23}**	-2.6*	2.1
Low-birth weight	**H_{27}**	0.25	3.20	0.20	**Y_{PC}**	0.65	-1.0			
Low-birth weight	**Y_{PC}**	-0.09	-0.52	0.01	**H_{27}**	-8.6**	2.2*			
To Grade 5	**Fgt_4**	-0.13	-6.01	0.66	**Y_{PC}**	2.1*	1.62	**Y_{PC}**	1.7	1/
To Grade 5	**Y_{PC}**	0.24	7.59	0.53	**Fgt_4**	4.7**	2.8**	**Fgt_4**	2.1**	1/

1/ This is second set of tests is the Ericsson IV test. The Cox test indicates a "tie" in this case, as both Y_{pc} and Fgt_4 have independent information regarding variations in "pupils reaching grade 5" However, four other tests including Ericsson's IV and the Sargan test hold that Y_{PC} cannot reject the Fgt_4 based model at the 5% confidence level. Thus four of five encompassing tests suggest that Fgt_4 "encompasses" Y_{PC} as a model of "persistence to grade 5".