On world poverty: Its causes and effects

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Abstract

Recent advances in modeling directed acyclic graphs are used to sort-out causal patterns among a set of thirteen measures deemed relevant to the incidence of world poverty. Cross-section measures of the percent of population living on one and two dollars or less per day from eighty low income countries are exposed to a battery of tests of conditional independence with respect to measures of economic and political freedom, income inequality, income per person, agricultural income, child mortality, birth rate, life expectancy, relative size of rural population, illiteracy rate, foreign aid as a percentage of national income, international trade as a percentage of national income and percentage of population that is under-nourished. Motivation for the method of analysis precedes results. Results are presented as a graph that shows our measures of economic and political freedom, income inequality, illiteracy and agricultural income to be exogenous movers of poverty when measured as the percent of the population living on two dollars or less per day. Foreign aid and international trade are not connected to the other variables in the graph. Results on our measure of extreme poverty (people living on one dollar or less per day) show that such populations are immune from improvements in economic progress of the general economy. The "rising tide lifts all boats" argument apparently doesn't cover the extreme poor of our sample.

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On World Poverty: Its Causes and Effects

At one level of description it may be sufficient to say that living in poverty is a matter of chance, related to the circumstances of one's birth or the outcomes of nature or world events beyond an individual's influence. Apparently, none of us controls where, when, or if we are to be born. And, once born, few (knowingly) choose to live in poverty.[1] But people do live in states of near or below subsistence levels. People suffer and die from such "living." To affect change, one must get beyond an agnostic understanding of poverty as a chance event and focus on the causes of poverty. It is through the knowledge of such causes that we can (if possible) change outcomes to a preferable set of realizations.[2] Causal knowledge requires more than algebraic representation of relationships among variables and/or their correlations in data.[3]

This paper studies causes and effects of poverty. It focuses on an inductive, rather than an *a priori*, model of causation. A list of measured variables is specified without prejudice that each is a cause of, an effect of or unrelated to other included variables in our list. Specification of our list is based on recent writings on the economics of poverty and development (Sen [1981] and reading contained in Chenery and Srinivasan [1988]). The paper is organized as follows. First we review recent work on assessing causal relationships among a set of variables. This work comes from efforts in computer science (Pearl [1995], philosophy and statistics, Pearl [2000] and Spirtes, Glymour and Scheines [2000]) and mirrors recent applications in economics by the

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[1] Of course, there are those who do indeed choose to live in poverty. Particularly noteworthy are those religious communities whose members take vows of poverty. Such people may violate an axiom of rational choice, that more is preferred to less, if one does not include the perceived attributes of the religious life in the choice set. Other notable members of the set of people who appear to choose to live in poverty might arguably include artists (suffer for their art); but both groups, religious and artists, generally don't live at the minimum possible state of existence, where many of their similarly positioned colleagues actually die of starvation or exposure to elements of nature.

[2] See Russell (1948): "The power of science is its discovery of causal laws" (page 308).

[3] Linear algebra is symmetric with respect to the equal sign, for example, we can re-write $y = a + bx$ as $x = -a/b + (1/b)y$. Either form is legitimate for representing the information conveyed by the equation. A preferred representation of causation would be the sentence $x \rightarrow y$, or the words: "if you change x by one unit you will change y by b units, *ceteris paribus*." The algebraic statement suggests a symmetry that does not hold for causal laws; as

author and his former students (Bessler and Lee [2002], Bessler and Loper [2001], Bessler and Akleman [1998], Awokuse and Bessler [2002] and Bessler, Yang and Wongcharupan [2002]).[4] We follow our discussion of causality with a discussion of the variables considered in this study and their support for consideration in prior literature. Results follow. Limitations of the study and recommendations for future research on poverty and causal modeling conclude the paper.

Causal Modeling

One reason for studying causal models, represented here as X → Y, is to predict the consequences of changing the effect variable (Y) by changing the cause variable (X). The possibility of manipulating Y by way of manipulating X is at the heart of causation. Hausman (1998, page 7) writes: "Causation seems connected to intervention and manipulation: one can use causes to 'wiggle' their effects." Prediction of such 'wiggling' through intervention in development is what gives many of us hope for improving the lives of those of us living in poverty. A manipulation-based definition of causation is generally more in line with a philosophical definition of causality than other recently offered definitions that focus exclusively on predictability. For example, Bunge (1959) argues that causality requires a productive or genetic principle that models "how something comes into being." X causes Y if X is productive of Y. Definitions that focus on prediction alone, without distinguishing between intervention (first) and subsequent realization, may mistakenly label as cause variables that are associated only through an omitted variable. For example, Granger-type causality (Granger 1980) focuses solely on prediction, without considering intervention. The consequences of such focus is to

causal laws are asymmetric. Finally, knowledge of a correlation between x and y does not imply causation, as both may be "caused" by a third variable z.

[4] While we do not mention that the work on causality emanates from economics, its foundations are actually found in early papers by Simon (1953) and Orcutt (1952). We do not list these authors above because their use by economists has generally been with respect to an *a priori* model and not an inductive model of cause from empirical data.

open oneself up to the frustration of unrealized expectations by attempting policy on the wrong set of variables.

Directed Graphs

Essentially, a directed graph is an illustration using arrows and vertices to represent the causal flow among a set of variables. A graph is an ordered triple <**V,M,E**> where **V** is a non-empty set of vertices (variables), **M** is a non-empty set of marks (symbols attached to the end of undirected edges) and **E** is a set of ordered pairs. Each member of **E** is called an edge. Vertices connected by an edge are said to be adjacent. If we have a set of vertices {A,B,C,D} the undirected graph contains only undirected edges (e.g. A — B). A directed graph contains only directed edges (e.g. C → D). A directed acyclic graph is a directed graph that contains no directed cyclic paths. An acyclic graph has no path that leads away from a variable only to return to that same variable. (The path A → B → C → A is labeled "cyclic" as here we move from A to B, but then return to A by way of C.) Only acyclic graphs are used in the paper.

Directed acyclic graphs are pictures (illustrations) for representing conditional independence as given by the recursive decomposition

$$\Pr(v_1,\ v_2,\ v_3,\ ...\ v_n) = \prod_{i=1}^{n} \Pr(v_i \mid pa_i)$$

where Pr is the probability of vertices (variables) v_1, v_2, v_3, ... v_n, pa_i the realization of some subset of the variables that precede (come before in a causal sense) v_i in order (v_1, v_2, v_3, ... v_n) and the symbol A represents the product operation, with index of operation denoted below (start) and above (finish) the symbol. Pearl (1995) proposes d-separation as a graphical characterization of conditional independence. That is, d-separation characterizes the conditional independence relations given by the above product (APr). If we formulate a directed acyclic graph in which the variables corresponding to pa_i are represented as the parents (direct causes) of v_i, then the independencies implied by the product given above can be read off the graph using the notion of d-separation as defined in Pearl (1995):

> Definition: *Let X, Y and Z be three disjoint subsets of vertices [variables] in a directed acylic graph G, and let p be any path between a vertex [variable] in X and a vertex [variable] in Y, where by 'path' we mean any succession of edges, regardless of their directions. Z is said to block p if there is a vertex w on p satisfying one of the following: (i) w has converging arrows along p, and neither w nor any of its descendants are on Z or (ii) w does not have converging arrows along p, and w is in Z. Furthermore, Z is said to d-separate X from Y on graph G, written* $(X \perp Y \mid Z)_G$*, if and only if Z blocks every path from a vertex [variable] in X to a vertex [variable] in Y.*

Geiger, Verma and Pearl (1990) show that there is a one-to-one correspondence between the set of conditional independencies, $X \perp Y \mid Z$, implied by the above factorization and the set of triples, X, Y, Z, that satisfy the d-separation criterion in graph G. If G is a directed acyclic graph with vertex set V, if A and B are in V and if H is also in V, then G linearly implies the correlation between A and B conditional on H is zero if and only if A and B are d-separated given H.

The notion of d-separation (directional separation) can be illustrated further. Consider three variables (vertices): A, B and C. A variable is a *collider* if arrows converge on it: A → B ← C. The vertex B is a collider, A and C are d-separated, given the null set. However, if we condition on B, we open-up the information flow from A to C. Conditioning on B makes A and C d-connected (directionally connected). Amend the above graph given above to include variable D, as a child of B, such that:

$$\begin{array}{ccccc} A & \rightarrow & B & \leftarrow & C \\ & & \downarrow & & \\ & & D & & \end{array}$$

If we condition on D rather than B, we, as well, open up the flow between A and C (Pearl, 2000 p.17). This illustrates the (i) component of the definition given above.

If converging arrows do not characterize our information flow, as illustrated above, but if instead information flow is characterized by diverging arrows, then the d-separation condition is different. This is given by the (ii) component of the definition above. Say we have three vertices K, L and M, described by the following graph: K ← L → M. Here L is a common cause of K and M. The unconditional association (correlation) between K and M will be non-zero, as they have a common cause L. If we condition on L (know the value of L), the association between K and M disappears (Pearl, 2000, p.17). Conditioning on common causes blocks the flow of information between common effects. In an unconditional sense, K and M are d-connected (as they have a common cause); while conditioning on L, variables K and M are d-separated.

Finally, if our causal path is one of a chain (causal chain), condition (ii) in the above definition again applies. If D causes E and E causes F, we have the representational flow: D→ E→ F. The unconditional association (correlation) between D and F will be non-zero, but the association (correlation) between D and F conditional on E will be zero. For causal chains, the end points (D and F) are not d-separated, while conditioning on the middle vertex (E) makes the end points d-separated (Pearl, 2000).

Policy and Directed Graphs

Consider the following simple graph on variables X, Y and U, where X represents GDP/Person, Y represents the percent of a country's population living on $2/Day or less and U represents an aggregate of omitted variables, say illiteracy rate, birth rate, percent of the population judged to be living in a state of under-nourishment, etc.:

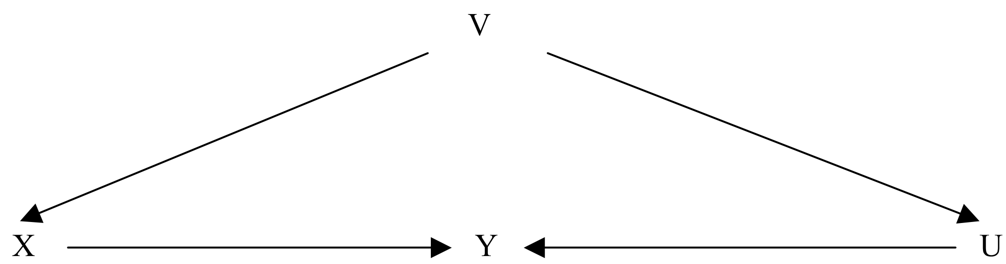
$$X \longrightarrow Y \longleftarrow U$$

Here we observe X and Y in an uncontrolled setting. We are interested in manipulating the percentage of a country's population living on two dollars or less per day by manipulating the level of GDP/capita. In this example, the policy analyst's task is to study a sample obtained from a distribution associated with passive observation and predict something about the distribution that would obtain if a particular policy is imposed (forced on one variable). What values will Y take on if we force X to take on a value of $X_{f=x0}$? (Here we use the notation that X is forced by way of policy to have a value of x_0 as $X_{f=x0}$.)

The distinction we want to stress here is that observing X and Y moving together in a passive sample may not necessarily give us reliable information on how Y will behave when we actively change X via some policy tool (laws, restrictions, etc.). Pearl (2000) is helpful here by introducing the "do" operator. The probability of Y, given we see X at x_0 (P(Y| see X = x_0)) does not necessarily equal the probability of Y given we set X = x_0 (P(Y| do X = x_0)). Here Pearl's verb "do" has the same interpretation as the verb "force" in the preceding paragraph. The two cases considered here illustrate Pearl's distinction between the verbs "seeing" and "doing".

Consider Table 1, which is a slightly revised version of Table 7.1 in Spirtes, Glymour and Scheines (2000, page 160). Here Y = 100 -.1 X + U and U is exogenous (has no arrows into it). The value of Y under passive observation when X = 200, has the same distribution as $Y_{Xf=200}$ (Y when a value of 200 is forced on variable X). In this simple case, inference on the effect of X on Y under a policy setting on X_f = 200 will be the same as that observed in the unmanipulated (pre-policy) data, X = 200. In this case Pearl's "seeing" is a good predictor of Pearl's "doing." That is because X is a parent of Y and there is no backdoor path from X to Y (say via U). So, a policy analyst may conclude that knowing how X and Y are related in uncontrolled (passive) setting is sufficient for predicting how they will behave under alternative policy settings.

On the other hand, consider the graph below, where Y, X and U represent the same variables as they did in the previous example and V represents an Index of Freedom on each country:



Here we have a variable V that causes both X and U. V influences Y indirectly through both X and U. Accordingly, there exists two ‘paths’ from X to Y: the direct path X $\rightarrow$ Y and the ‘backdoor’ path X $\leftarrow$ V $\rightarrow$ U $\rightarrow$ Y.[5] This backdoor path is not blocked by converging arrows (we do not have, for example, X $\leftarrow$ V $\rightarrow$ U $\leftarrow$ Y).

We summarize this graph with three equations: Y = 100 -.1X + U; X=600-100V; and U = -5V. Will knowledge of how X and Y behave in passive settings be sufficient for predicting how they will behave in a policy setting? We might suspect that the answer here is “no”, because there is a backdoor path (not blocked by converging arrows) from X to Y via V and U.

Consider Table 2 (again a revision of Spirtes, Glymour and Scheines [2000 page 161]). When X = 200 in the unforced setting our distribution on Y is 60, 60 and 60. However, when we force X = 200 our distribution on Y is 55, 55, 55, 60, 60,and 60. The distribution of Y when X is observed to take the value of 200 in a passive setting is different from the distribution of Y when X is forced to equal 200. Here Pearl’s “seeing” is different from Pearl’s “doing”. Under the policy setting on X we cannot ignore V, as V influences both X and U. If we used our passive

[5] The word “path” refers to any sequence of variables and edges, without regard to direction. Following Pearl (2000, page 79), a set of variables Z satisfying the back-door criteria relative to an ordered pair of variables (X_i , X_j) in a

observations on X and Y from table 2, we might say that doubling GDP from $100 per capita to $200 per capita reduces the percent of people living on $2/day or less by 5 percent (65 - 60 percent). However, by taking account of V, we see that the average reduction in people living at poverty is 7.5 percent (65 - 57.5 percent).[6] We have understated the influence of GDP increases in reducing poverty because we failed to account for the backdoor path from GDP to poverty through Freedom (and the omitted variable birth rate). Here is the rule. If we want to predict the effects of manipulating one variable X on another variable Y, we need be sure that there does not exist an unblocked backdoor path from X to Y through another variable V. If such a path exists, we need to condition our prediction of the effects of X on Y on the values of V (For a more rigorous statement of the rule, see Spirtes, Glymour and Scheines, 2000, Theorem 7.1, page 164).[7]

Inference on Directed Graphs

Spirtes, Glymour and Scheines (2000) have incorporated the notion of d-separation into an algorithm (PC Algorithm) for building directed acyclic graphs, using the notion of sepset (defined below). PC algorithm is an ordered set of commands that begins with a general unrestricted set of relationships among variables and proceeds step-wise to remove edges between variables and to direct "causal flow." The algorithm is described in detail in Spirtes, Glymour and Scheines (2000). More advanced versions (refinements) are described as the Modified PC Algorithm, the Causal Inference Algorithm and the Fast Causal Inference

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DAG if: (i) no node in Z is a descendant of X_i and (ii) Z blocks every path between X_i and X_j that contains an arrow into X_i.

[6] In the passive observation of X and Y case, we conclude that the average GDP/Person change of $100 reduces the percent of people living off of $2/day on average by 5 percent (65 to 60 percent from table 2). In the policy setting we see that under the forced setting of GDP/Person our average poverty percentage is (55 percent+55 +55 percent +60 percent +60 percent +60 percent)/6 = 57.5 percent. So if we were at GDP of $100/Person and considered the effects of changing GDP/Person to $200, we would predict a change in percent living on $2/day to drop to 60 percent, when in fact it would drop to 57.5 percent.

Algorithm. Scheines, *et al.*, 1994 have incorporated these in software distributed under the name TETRAD II, which we use in this paper. We restrict our discussion to the PC algorithm, as it is the most basic and easily understood version (in our opinion) of their contribution.

Briefly, when applying PC algorithm, one begins by forming a complete undirected graph G on the vertex set **V**. The complete undirected graph shows an undirected edge between every variable of the system (every variable in **V**). Edges between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation). Fisher's z-statistic is used to test whether conditional correlations are significantly different from zero, where $z(\rho(i,j|k)n) = 1/2(n-|k|-3)^{1/2} \times \ln\{(|1 + \rho(i,j|k)|) \times (|1 - \rho(i,j|k)|)^{-1}\}$, n is the number of observations used to estimate the correlations, $\rho(i,j|k)$ is the population correlation between series i and j conditional on series k (removing the influence of series k on each i and j) and |k| is the number of variables in k (that we condition on). If i, j and k are normally distributed and $r(i,j|k)$ is the sample conditional correlation of i and j given k, then the distribution of $z(\rho(i,j|k)n) - z(r(i,j|k)n)$ is standard normal.

The remaining edges are then directed by using the notion of sepset. *The conditioning variable(s) on removed edges between two variables is called the sepset of the variables whose edge has been removed (for vanishing zero order conditioning information the sepset is the empty set).* To illustrate, edges are directed by considering triples X — Y — Z, such that X and Y are adjacent as are Y and Z, but X and Z are not adjacent. Direct edges between triples: X — Y — Z as X → Y ← Z if Y is not in the sepset of X and Z. If X → Y, Y and Z are adjacent, X and Z are not adjacent and there is no arrowhead at Y, then orient Y — Z as Y → Z.

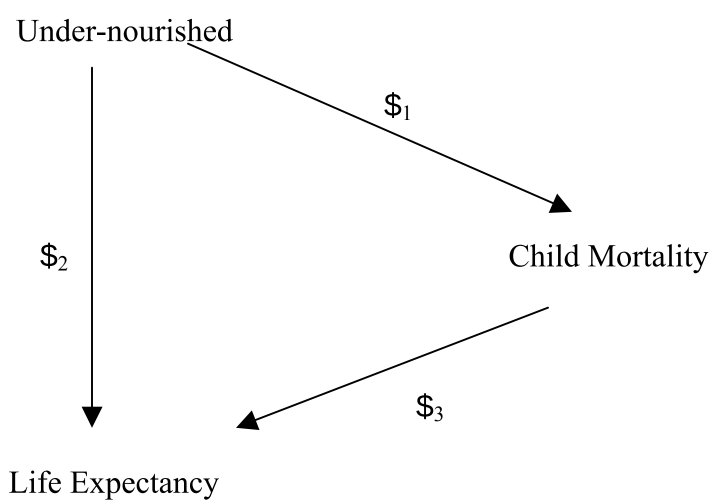
[7] Econometricians know this rule from their introductory textbooks as the condition that for an unbiased estimator the right-hand-side variables in a regression equation must not be correlated with the error term, where the error term is the theoretically defined error and not the observed residual from a particular fit model.

If there is a directed path from X to Y and an edge between X and Y, then direct (X — Y) as X → Y.

Spirtes *et al*. (1999) show the connection between directed graphs and the counterfactual random variable model (the random assignment experimental model) of Holland (1986). First one needs to have a *causally sufficient* set of variables. This means that *there is (are) no omitted variable(s) that in fact causes (cause) any two of the included variables under study.* If variable X causes both Y and Z and we leave X out of the analysis, then an apparent causal flow from Y to Z (or vice versa) may be due to the fact that X causes both Y and Z, so the causal flow identified as running from Y to Z would be spurious (Suppes, 1970). Second, one needs to constrain himself (herself) to causal flows that respect a *causal Markov condition*. That is to say, if X causes Y and Y causes Z, we can factor the underlying probability distribution on X, Y and Z as $Pr(X,Y,Z) = Pr(X).Pr(Y|X)Pr(Z|Y)$. In other words, we require causal flows respect a genealogy condition that one need only condition on parents in order to fully capture the probability distribution generating any variable. One need not condition on grandparents, uncles or aunts, or siblings. [Here A is a parent of B if A → B; A is a grandparent of C in the causal chain A → B → C; D is a sibling of C if B → C and B → D and no causal flow between C and D exists. The variable C is an uncle (aunt) of E if B → C and B → D and D → E.] Our third requirement for correspondence between PC algorithm and the randomized experiment is that the probabilities, Pr, we attempt to capture by graph G are *faithful* to G if X and Y are dependent if and only of there is an edge between X and Y.

The Causal Sufficiency, Markov and Faithfulness conditions can be violated. Thus any result based on observational data must be viewed with caution. The causal sufficiency condition suggests that one find a sufficiently rich set of theoretically relevant variables upon which to two conduct an analysis. Failure to include a relevant variable may lead one to put an edge between variables when in fact both are effects of an omitted third variable. Failure of the Markov condition has been noted in quantium mechanical experiments (see Spirtes, Glymour and Scheines, 2000). Failure to require the condition would require us to ignore statistical dependency even in experimental designs. Finally, the faithfulness condition can be violated if parameters between causes happen to be of the correct magnitude to cancel one another.

Scheines *et al.* (1999, p. 181) illustrate a violation of the faithfulness condition in the following graph (amended for our use on poverty related variables). Here we write the parameter values connecting three apparently relevant development variables, life expectancy, under-nourished and child mortality, as subscripted greek symbols $\$_1$, $\$_2$ and $\$_3$ close to their respective causal arrows. That is, the betas represent the linear coefficient associated with the causal relation indicated by the directed edge (→).



If $\$_2 = -(\$_3\$_1)$ then the under-nourished and life expectancy are uncorrelated. Thus, we will fail to place an edge between under-nourished and life expectancy even though the true model requires one. (This last illustration is a hypothetical causal graph and not meant to represent our prior beliefs or our empirical findings. In fact, the expected signs, $\$_1 > 0$, $\$_2 < 0$ and $\$_3 < 0$, make the violation of faithfulness in this example implausible.)

The faithfullness assumption says that if zero correlations are observed, it is because the edge is not present and not because of cancelling of deep parameters from the underlying structural model. Theorists, of course, tell us that such cancellations can arise, as we have just demonstrated through a constructed example; whether or not such an example can be found in real world data is another matter. It seems to us that demonstration of such requires either a random assignment experiment or *a priori* knowledge of the true model.

This concludes our review of directed graphs and topics related to policy analysis and causal inference. Below we apply these ideas to thirteen variables associated with poverty.

Data Studied

Poverty measures are discussed in Sen (1981). Economic and physical measures representing deprivation are considered. The *World Bank* offers economic measures across a large number of countries. *FAO* offers physical measures over a similar set of countries. We use both. The countries studied are listed in Table 3. The immediate concern this list brings to mind is that we are not studying all countries. Many "developed" countries are not on our list. This omission includes countries from Western Europe, North America and the Pacific-rim. Our reason for exclusion is that both the World Bank economic measures of poverty and the FAO physical measures of poverty are not available for the entire world. For example, the FAO measure of undernourishment, given in Table 1 of FAO 2000 page 27, is not given for the United States, Canada or several European countries; similarly, the World Bank measures on the percent of population living on \$2/day or less are not given for these countries (World Bank, World Development Report 2000/2001 Box 1.2 page 17 and Table 4 page 280 and 281). Yet, we suspect (with probability near one) that some members of these more affluent populations live in states of economic or physical poverty.

Consequently, there is a selection bias present in our study if we attempt to make statements with respect to the entire world population. On the other hand, if we constrain ourselves to making statements on what is generally called the "developing" world (or with respect to economies in transition), these eighty countries would be *prima facie* a useful sample. We include twenty-four countries from sub-Saharan Africa, nineteen of the former Soviet Union or Eastern European nations, sixteen countries from the Americas, seven countries from North Africa and the Middle East and five countries from South Asia.

One might question whether South Korea, several eastern European countries and Portugal should be in our sample as all have poverty rates near zero. Rather than edit the original World Bank data set, we keep these countries in the sample.

The variables we study are as follows:

$1/Day measure of Poverty. The World Bank's measure of the percent of each country's population living on $1.08 or less per day is our economic measure of extreme poverty where prices are measured in terms of 1993 purchasing power parity terms. (See World Development Report 2000/2001 Box 1.2 page 17 and Table 4 page 280 and 281.) The average value of this measure over our sample is 19.62 percent. The minimum value of less than two percent is observed for several countries: Algeria, Azerbaijan, Belarus, Bulgaria, Chile, Czech Republic, Estonia, Georgia, Hungry, Jordan, South Korea, Latvia, Lithuania, Morocco, Poland, Portugal, Slovak Republic, Slovenia, Thailand, Tunisia and Uruguay. The high value is observed as 72.8 percent in Mali. Other countries for which relatively large values of extreme poverty measure are observed are: Nigeria (70.2 percent), Central Africa Republic (66.6 percent), Zambia (63.7 percent), Madagascar (63.4 percent), Niger (61.4 percent) and Burkina Faso (61.2 percent).

$2/Day measure of Poverty. The World Bank's measure of the percent of each country's population living on $2.08 or less per day is a less exclusive measure of economic poverty (less exclusive than the $1/day measure). Again, prices are measured in terms of 1993 purchasing power parity terms. (See World Development Report 2000/2001 Box 1.2 page 17 and Table 4 page 280 and 281.) The average value over our eighty countries is 43.15 percent. Nigeria shows the highest value of 90.8 percent; while several countries show values of less than two percent: Belarus, Czech Republic, South Korea, Portugal, Slovak Republic and Slovenia. Generally, African countries dominate the high end of this measure as Niger (85.3 percent), Rwanda (84.6 percent), Central African Republic (84 percent), Mali (90.6 percent), Burkina Faso (85.8 percent), Madagascar (89 percent) and Zambia (87.4 percent), in addition to Nigeria, are joined only by South Asia countries of India (86.2 percent), Pakistan (84.7 percent) and Nepal (82.5 percent) with percentages in excess of 80 percent. Other Asian countries, Eastern Europe and the Americas are not at the upper extreme in terms of this measure.

Undernourishment. The FAO measure of undernourishment is based on discrepancies between the minimum calories required for a population versus the calories available from local food consumption, trade and stocks (see FAO 2000 page 6 and table 1). The measure is the percentage of a country's population whose food intake falls below the minimum requirement. The data are for years 1996 – 1998. The average value over our eighty countries is 17.51 percent. Low observations on the index are the Eastern European countries and Portugal all having values less than 1 percent. Other low observations on this index are South Korea (<1 percent), Tunisia (<1 percent), Turkey (<1 percent) and South Africa (<1 percent). The high observation on undernourishment is 58 percent in Mozambique. Other high-end observations are noted for Burkina Faso (50 percent), Ethiopia (49 percent), Kenya (43 percent), Madagascar (40 percent), Mongolia (45 percent), Niger (46 percent), Sierra Leon (43 percent), Tanzania (41 percent) and

Zambia (45 percent). The Americas generally measure below 20 percent with respect to undernourishment, with the Dominican Republic at 28 percent, Guatemala at 24 percent and Bolivia at 23 percent being the highest measures in the western hemisphere. (Haiti is not part of our sample. It is part of the FAO study on undernourishment and has a value of 62 percent on this measure.)

Gini Index. Is the World Bank's estimate of the extent to which the distribution of income among individuals or households within a country deviates from equality. A value of 0 indicates equality across individuals or households. A value of 100 indicates the extreme of inequality. (See World Development Report 2000/2001 page 320 and Table 5 page 282 and 283.) The average value on this index for our eighty countries is 40.57. The lowest value (low level of income inequality) is observed for The Slovak Republic at 19.5. Other low values are observed for Belarus (21.6), The Czech Republic (26.6), Hungry (27), Latvia (27), Poland (27.2), Romania (25.5), Slovenia (28.2) and the Ukraine from eastern Europe. Rwanda at 28.9 is the low for Africa and Bangladesh at 28.3 the low for Asia. The high value for the Gini index is found in Brazil at 63.4. Other high-end countries with respect to income distribution are Chile (56.5), Columbia (51.3), Dominican Republic (50.5), El Salvador (50.8), Guatemala (59.6), Honduras (52.7), Mexico (50.3), Panama (56.6), Paraguay (57.7) and Venezuela (53.8), all from Latin America. Kenya (57.5), Botswana (50), Mali (50.5), Senegal (54.1), South Africa (58.4) and Zimbabwe (56.8) are the high-ranking (high levels of income inequality) countries from Africa. Russia, at 49.6, is the highest among the Eastern European countries.

Un-Freedom Index. The Heritage Foundation's Index of Freedom is used as a measure of overall freedoms. The index gives a rating of each country on nine aspects (categories) of "freedom:" International Trade, Fiscal Burden, Government Intervention, Monetary Policy, Foreign Investment, Banking and Finance, Wages and Prices, Property Rights and Regulation. Each country is provided a discrete measure of 1, 2, 3, 4 or 5 on each of these categories of freedom. The integer 1 indicates freedom with respect to a measure; a measure of 5 indicates no freedom with respect to a measure. Here we use an overall score, the simple average of scores on each of the nine attributes, rounded to tenths. The index is found at Web site: http://cf.heritage.org (accessed on April 5, 2001). The mean value on this index is 3.28. The Czech Republic is the lowest at 2.2 (most free in 1995). Several Latin American countries rank low on this measure (they measured as relatively free): Bolivia (2.7), Chile (2.55), Costa Rica (2.95), El Salvador (2.4), Guatemala (2.7), Jamaica (2.8), Panama (2.5), Paraguay (2.8) Peru (2.9), Trinidad and Tobago (2.6) and Uruguay (2.85). African countries showing low scores were Zambia (2.9), Tunisia (2.7), Namibia (2.9) and Morocco (2.85). Several European countries, in addition to the Czech Republic show low values on this index: Estonia (2.3), Latvia (2.85), Poland (2.9), Portugal (2.65) and Turkey (2.9). Asian countries showing low measures on this index are: Sri Lanka (2.8), Thailand (2.35) and South Korea (2.3). The highest value observed for the Un-Freedom index is 4.75, associated with Azerbaijan. Other countries scoring high (low degree of freedom) are: Belarus (4.0), PR Laos (4.45), Mozambique (4.1), Niger (4.0), Rwanda (4.3), Turkmenistan (4.2), Uzbekistan (4.5) and Yemen (4.1).

Agricultural Value Added Per Worker. This is the World Bank's measure of the output of the agricultural sector less the value of the intermediate inputs. Agriculture includes values from forestry, fishing and hunting, cultivation of crops and livestock production. Data are measured in 1995 constant U.S. dollars. The average value of this measure for our eighty countries is $2 226.38. The low value was observed in Mozambique at $121. Other countries achieving low levels of agricultural income are: Bangladesh ($273), Botswana ($473), Burkina Faso ($158), Central African Republic ($380), China ($316), Ethiopia ($136), Gambia ($233), India ($380), Kenya ($222), Madagascar ($187), Mali ($261), Mauritania ($444), Nepal ($185), Niger

($194), Rwanda ($326), Senegal ($317), Sierra Leon ($426), Tanzania ($176) Yemen ($369), Zambia ($210) and Zimbabwe ($312). The high value for Agricultural Income is observed as $29 860 for Slovenia. Other high agricultural income countries are: Bulgaria ($5 518), Chile ($5 658), South Korea ($8 914), Portugal ($6 695), Uruguay ($6 657) and Venezuela ($5 083).

GDP per capita. The World Bank's measure is defined as the domestic product divided by mid-year population in constant 1995 U.S. dollars. The average value for our sample is ($1 916.4). Ethiopia shows the lowest levels of 1995 income at $109.8. Other low-income achieving countries include: Burkina Faso ($244), Mali ($235), Mauritania ($258), Mozambique ($158), Nepal ($212), Niger ($205), Nigeria ($256), Rwanda ($221), Sierra Leon ($196), Tanzania ($180) and Yemen ($263). The high value of GDP per capita in our sample is $11 467 found in South Korea. Other countries showing high levels of GDP/capita are: Portugal ($11 202), Slovenia ($9 743), Uruguay ($5 975), Czech Republic ($5 288), Chile ($4 858), Brazil ($4 482), Hungry ($4 441) and Trinidad and Tobago ($4 356).

Illiteracy Rate. Here we use The World Bank's measure of the percentage of people ages 15 and older that cannot, with understanding, read and write a short straightforward declaration on their daily life. The average value of this measure is 25.99 percent. The lowest value for this measure is found at .14 for Kazakhstan. Most other countries of Eastern Europe or the former Soviet Union achieve low levels on this measure (high levels of literacy): Belarus (<1 percent), Czech republic (<1 percent), Estonia (<1 percent), Hungry (<1 percent), Latvia (<1 percent), Lithuania (<1 percent), Poland (<1 percent), Russia (<1 percent), Slovak Republic (<1 percent), Slovenia (<1 percent) and the Ukraine (<1 percent). The high value is found at 87 percent in Niger. Other countries having high rates of illiteracy include: Bangladesh (63 percent), Burkina Faso (81 percent), Central Africa Republic (61 percent), Cote d'Ivoire (61 percent), Ethiopia (68 percent), Gambia (70 percent), PR Lao (59 percent), Mali (68 percent), Mauritania (61 percent), Mozambique (62 percent), Nepal (65 percent), Senegal (68 percent) and Sierra Leon (60 percent). The Americas in our sample generally fall between 10 and 30 percent with low percentages found in Uruguay (2.8 percent), Chile (5.2 percent) and Costa Rica (5.3 percent).

Life Expectancy. The World Bank's measure of the number of years a newborn child would live if current patterns of mortality at the time of birth remain fixed throughout her/his life. The mean value of life expectation over our eighty countries is 63.3 years. The low value was observed for Sierra Leon at 35.2 years. Other countries showing low life expectancy include: Burkina Faso (45 years), Central Africa Republic (48 years), Cote d'Ivoire (48 years), Ethiopia (44 years), Mali (44 years), Mozambique (45 years), Niger (45.5 years), Rwanda (47.5 years), Tanzania (49 years) and Zambia (43 years). The high expectation of years of life was 76.5 in Costa Rica. Other countries showing high values for life expectancy include: the eastern European countries with life expectancies in the high 60s to low 70s years range. The Americas generally show high life expectancies, again, in the high 60-year to low 70-year range. Sri Lanka at 73 years sets the South Asia high mark, exceeding India at 63 years, Nepal at 56.3 years, Bangladesh at 58 years and Pakistan at about 61 years. Southeast Asia has Thailand at 68 years, Indonesia at about 66 years and PR Lao at 54 years. South Korea has a life expectancy of about 71 years.

Rural Population Percentage. This is the World Bank's measure of the percentage of a country's population living in rural areas. It is calculated from the difference between the total population and the urban population. The mean value of this measure over our eighty countries is 51.45 percent. The low value of this measure is 10 percent found in Uruguay. Other low values are found in Chile (16 percent), Venezuela (15 percent), Brazil (20 percent), South Korea (22 percent) and Russia (24 percent). The high value for this measure is found at 94.3 percent in Rwanda. Other countries having large percentages of rural populations are: Burkina Faso (85 percent), Ethiopia (85 percent), Nepal (90 percent), Niger (81 percent) and Thailand (80 percent). Eastern European countries generally have about 30 percent of their populations in the rural sectors: Estonia (30 percent), Latvia (31 percent), Czech Republic (26 percent), Hungry (37 percent), Russia (24 percent), Turkey (31 percent) and Ukraine (33 percent). The Americas, as we observed above, have some of the lowest percentages of population living in rural areas, but rates in the 25 – 40 percent range are not uncommon: Bolivia (39 percent), Columbia (28 percent), Ecuador (40 percent), Mexico (26 percent), Peru (29 percent) and Trinidad and Tobago (28 percent). Even higher rates of rural populations are observed in Guatemala (61 percent), Honduras (53 percent), Costa Rica (53 percent) Panama (45 percent) and Paraguay (48 percent). Southeast Asian countries are generally in excess of 60 percent on this measure: PR Laos (79 percent), Indonesia (60 percent) and Thailand (80 percent). South Asia shows similar numbers: Sri Lanka (78 percent), Pakistan (66 percent) and India (73 percent).

Child Mortality. We use the World Bank's measure of the probability that a newborn person will die before reaching age five if subject to current age-specific mortality rates. The number is expressed as a rate per 1 000 people. The mean value over our sample is 74.52 deaths per 1 000 population. The low observation across our 80 countries is 6.3 found in Slovenia. Other countries showing low levels of child mortality are: the Czech Republic (7.60/1 000), Portugal (8.20/1 000), Slovak Republic (10.40/1000), South Korea (11.30/1000), Hungry (11.80/1 000) and Poland (11.90/1 000). The high observation on Child Mortality is 286/1 000 in Sierra Leon. Other countries showing high rates of Child Mortality include: Burkina Faso (229/1 000), Mali (238/1 000), Mozambique (201/1 000), Niger (260/1 000) and Rwanda (202/1 000). Generally, Africa south of the Sahara shows death rates in excess of 100/1 000 people for children five and under. Exceptions include: Botswana at 62/1 000 and South Africa at 70/1 000. Namibia shows a death rate of 100/1 000. The Americas show Child Mortality rates generally less than 50/1 000, with Peru (55/1 000), Guatemala (57/1 000) and Bolivia (85/1 000) somewhat higher. Sri Lanka shows a much lower rate (19/1 000) than our other South Asia countries, Nepal (117/1 000), Pakistan (136/1 000) and India (95/1 000). Eastern Europe (as indicated above) shows low rates of Child Mortality, generally less than 25/1 000. Turkey at 50/1 000 is an exception. Southeast Asia shows considerable differences in Child Mortality rates. Thailand is at 34/1 000, Indonesia at 56/1 000 and PR Lao is at 170/1 000.

Foreign Aid. This is measured as official development assistance and net official aid record of international transfer of financial resources or of goods and services. The number is expressed as a percentage of gross national income for 1995. The mean value for our foreign aid measure over our eighty-country sample is 31.47 percent. The low value for this measure was South Korea at –2.57 percent. Other countries showing low levels of relative foreign aid are: Brazil (1.6 percent), Portugal (0 percent), Uzbekistan (1.2 percent), Venezuela (1.3 percent) and Nigeria (1.8 percent). The high value on foreign aid percentage was observed at 118.42 percent in Cote d'Ivoire. Other high observations on this measure are: Mauritania (117.97 percent), Rwanda (114.61 percent), Namibia (91 percent), Jordan (90 percent), Zambia (82 percent) and Mongolia (81 percent). Africa south of the Sahara shows a mixed picture with respect to foreign aid. Several countries receive aid in excess of 50 percent of their domestic product: Botswana (60 percent), Central Africa Republic (51 percent), Cote d'Ivoire (118 percent), Gambia (65 percent), Lesotho (62 percent), Mauritania (118 percent), Mozambique (78 percent), Namibia (91 percent), Rwanda (115 percent), Senegal (79 percent), Zambia (83 percent) and Zimbabwe (52 percent). However, there are many exceptions to this rule: South Africa (7.7 percent), Tanzania (34 percent), Nigeria (1.8 percent), Niger (43 percent), Mali (47 percent), Madagascar (22 percent), Kenya (26 percent), Ghana (33 percent), Ethiopia (20 percent) and Burkina Faso (44 percent). Eastern Europe generally shows low values on this measure, in a neighborhood of 5 to 20 percent. Notable exceptions on the high side of this range are Poland (47 percent), Armenia

(51 percent) and Georgia (33 percent). The Americas observed in this study generally show measures of foreign aid between 0 and 20 percent of GDP. Exceptions are Bolivia (79 percent), Honduras (53 percent) and El Salvador (55 percent). South Asia shows values of this measure less than 33 percent, with India low at 2.5 percent and Sri Lanka high at 33 percent. Southeast Asia shows low values in Indonesia at 9 percent and Thailand at 10 percent and a relatively high observation for PR Lao at 48 percent.

International Trade as a percentage of GDP. This measure uses the sum of exports and imports of goods and services as a share of gross domestic product for the year 1995. The average value of this measure over our eighty countries is 72 percent. The low value is observed as 16 percent in Brazil. Other countries achieving low percentages on this measure are: Peru (31 percent), Rwanda (32 percent) and Bangladesh (30 percent). The high value of this trade measure is 149.9 percent observed in Turkmenistan. Other high-end observations are found in: Estonia (145 percent), Lesotho (144 percent), Jordan (129 percent) and Moldova (129 percent). Generally, Africa south of the Sahara shows values of this measure less than 75 percent. Exceptions are Lesotho (as noted above at 144 percent), Botswana (91 percent), Cote d'Ivoire (86 percent), Gambia (113 percent), Mauritania (103 percent) and Namibia (123 percent). Eastern Europe and the former Soviet Republics generally show measures of this trade variable in excess of 100 percent. Notable exceptions to this rule are: Poland (50 percent), Turkey (49 percent), Russia (45 percent), Uzbekistan (63 percent), Romania (65 percent), Hungry (79 percent), Portugal (66 percent), Armenia (79 percent), Georgia (46 percent) and Azerbaijan (81 percent). The Americas generally show measures of this trade variable less than 80 percent; exceptions are Trinidad and Tobago (93 percent), Jamaica (108 percent), Honduras (99 percent) and Costa Rica (83 percent). South Asia, Southeast Asia and South Korea show measures less than 100 percent, with Thailand showing the largest Asia observation of 85 percent. North Africa and Middle East countries generally show less than 100 percent, with Jordan being an exception at 129 percent.

Birth Rate. This measure is the number of live births occurring during the year 1995, per 1 000 population estimated at midyear. The mean value of this measure for our sample of eighty countries is 27.06/1 000. The low value is observed as 8.6/1 000 in Bulgaria. Other countries showing low values for this measure are the Eastern European and former Soviet countries, all less than 15 live births for every 1 000 population. Exceptions to this rule are the Middle East/South Asia countries: Azerbaijan (18.9/1000), Turkmenistan (28.1/1 000), Kazakhstan (16.1/1000) and Uzbekistan (29.8/1000). The high value for birth rate was observed as 52.3 in Niger. Other countries showing high values for this measure are: Ethiopia (47/1 000), Mali (49/1 000) and Sierra Leon (47/1 000). Generally, Africa south of the Sahara shows birth rates in excess of 40 live births per 1 000 populations. Notable exceptions to this rule are South Africa (29/1 000), Zimbabwe (33/1 000), Namibia (37/1 000), Central Africa Republic (38/1 000), Cote d'Ivoire (38/1 000), Ghana (33/1 000) and Lesotho (36/1 000). The Americas in our sample of countries generally show birth rates in a neighborhood of 25/1 000. Paraguay (32/1 000), Guatemala (36/1 000) and Honduras (35/1 000) are somewhat higher. Trinidad and Tobago at 15/1 000 is noticeably lower than the general rule. South Asia shows Nepal and Pakistan in a neighborhood of 36/1 000; while India (28/1 000) and Sri Lanka (19/1 000) are lower. Southeast Asia shows PR Loa highest at 41 live births per 1 000 population, Indonesia (24/1 000) and Thailand (18/1 000) are considerably lower. China and South Korea are in a neighborhood of 16/1 000.

Prior justification for this set of variables comes from several recent studies in development. Sen (1981) offers discussion on the measurement of poverty and considers both economic and physical measures. He labels these the income method (the amount of money required to fulfill a minimum basket of survival needs) and the direct method (the actual consumption basket and its short-fall of some particular requirement). They are related: "… the income method can be seen as a way of approximating the results of the direct method. However, the income method can be seen as a way of taking note of individual idiosyncrasies without upsetting the notion of poverty based on deprivation" (Sen 1881, page 27). The World Bank's one and two dollars per day numbers are income measures that allow substitution possibilities (or idiosyncrasies) of the type to which the above quote refers. On the other hand, the FAO under-nourished index for each country allows us to consider a basic requirement for food and the extent that individuals in each country are able to meet that requirement. Requirements of other goods, such as medical care, while possibly part of one's general basic requirement set, are not part of the nutrition requirement (Sen 1981, page 168). The correlation between $2/day and percent undernourished in our eighty-country data set is .66, indicating a modestly strong positive association between the two measures.

Citing evidence from the Ethiopian famines it appears as if child mortality is a particularly strong result of famines. Sen writes: "In Ethiopian famines a high mortality level of under-five children seems to be a common characteristic." (Sen page 100 note 27). It is open to question whether or not this result from an environment of starvation carries-over to less extreme environments of poverty. Actually, child mortality might well be embedded in a causal chain that includes several of the measures described above: percent of people living on $1 or $2/day or less, under-nourishment, birth rate and life expectancy. However, there appears to be questions as to just where several of these should be placed in this "poverty chain." For example, should child mortality be a cause or an effect of birth rate? Empirical evidence suggests a cause, but the acceptance of the evidence is not unanimous (Williams [1977] and Olsen [1983]).

With respect to the child mortality and birth rate question, Berhrman and Deolalikar write: “ There are two mechanisms through which fertility is influenced by mortality: a replacement effect whereby a dead infant is replaced *ex post* by another birth, a hoarding effect whereby parents respond *ex ante* to anticipated deaths by bearing more children.” Berhrman and Deolalokar (1988 page 691). Others have suggested that the empirical evidence cannot necessarily be accepted because of spurious regression associated with micro mortality and fertility data. Additional evidence requires use of instrumental variable methods which, when applied with *a priori* instruments, in turn generates debate on the proper choice of instruments. Birdsall writes: “… at the family level high mortality and high fertility may be jointly determined, so that ordinary least squares estimates will be biased.” (Birdsall 1988, page 518) The use of instrumental variables requires that one find a set of variables that moves one of the jointly determined variables without moving the other. In short, use of instrumental variables requires a directed graph in which we can show that there is a clear partition on variables and their direction of influence on the jointly determined variables (mortality and fertility).

The nutrition-fertility link has been investigated by Menken et al. (1981). The latter write: “... little support is provided for the existence of a significant link between food intake and childbearing in situations of chronic or endemic malnutrition.” (Menken et al. 1981, page 425). Whether no link exists at more “normal” levels of poverty is open to question.

Life expectancy is a measure of poverty to which other measures in the above described poverty chain point. Policies related to reductions in under-nutrition, child mortality and the number of people living on $1 or $2 or less /day are expected (by policy makers) to ultimately manifest themselves in terms of increases in life expectancy. In the terms of a graphical representation, we expect to be able to change life expectancy by manipulating nutrition levels, child mortality and income levels of the extremely poor. Accordingly, we expect to see life expectancy at the end of the causal chain (the poverty chain) running from our measures of income levels of the extremely poor, nutrition, child mortality and, perhaps, the birth rate.

Our expectation is that several of our variables will precede (come before in a causal sense) the causal chain described above. GDP, agricultural income (Mellor 1995), freedom (Sachs and Warner [1997] and Haan and Siermann [1996]), illiteracy (Birdsall 1988, pages 514 - 516) and international trade (Bhagwati [1996] and Edwards [1993]) are expected to cause of one or more variables of the poverty chain so that one could conceivably manipulate anyone of these and change one or more of the variables in the chain. On the other hand, we expect that foreign aid may actually show-up as an effect of poverty. So, it seems that manipulation of one or more variables in the poverty chain may actually change the level of foreign aid that a country receives.

Placement of the measure on rural populations is somewhat uncertain as well. Evidence from famines, especially those in Ethiopia and the Sahel of the early 1970s, as discussed in Sen Chapters 7 and 8, indicates that pastoralists, cultivators and others living in agricultural environments were the largest group of destitutes (Sen 1981, pages 101 and 115). More recently, Rosenzweig writes: " . . . one important and pervasive characteristic of low-income countries is the large proportion of the labor force in agriculture." (Rosenzweig 1988, page 714). Finally, Demery (1999) shows that during the 1990s in several parts of Africa, rural poverty was more prevalent than urban poverty. In Burkina Faso, for example, rural poverty (as measured by the share of population living below the poverty line) is in the neighborhood of 50 percent (fifty percent of rural dwellers are below the poverty level); while urban poverty is closer to 10 to 15 percent. Similar measures for Zambia are rural dwellers at about 75 percent and urban about 33 percent (see World Bank table 1.3).

Mellor (1995) and Timmer (1988) argue that increases in real agricultural incomes are poverty reducing. Our two measures of agricultural activity, agricultural income and the percent of the population that is rural are expected to show different relationships to poverty. We expect that the former will contribute directly to poverty reduction. The role of the latter, as either a cause or an effect of poverty, seems open to question. Drought effects in an exogenously determined rural population would be described by the sentence "large rural populations → poverty." Or are large rural populations a consequence of poverty? Because of a high poverty rate poor people may relocate to the rural sectors, which would be consistent with the sentence "poverty → large rural populations."

Because our data are cross-section, we expect to see Foreign Aid to actually be an effect of one or more variables in that causal chain. Foreign Aid is not set using random assignment (we do not use experimental methods but observe it [all variables in our study] observationally). It is itself a function of information signals coming from the less developed world. To see the long-run effects of foreign aid we would need time series data over several decades.

Figure 1 gives scatter plots of each of twelve variables against the percentage of population living on two dollars or less per day. We observe from the figure that the Gini Index - $2/day scatter is quite wide, showing no clear positive or negative relationship between the two variables. Other visually unclear relationships are the Foreign Aid - $2/day plot and the Trade - $2/day plot. Positive relationships with our $2/day measure appear in the scatter plots with: the Index of Un-Freedom, Percentage of the Population that is Rural, Child Mortality, Illiteracy, Under Nourishment and Birth Rate. Negative relationships appear in the scatter plots between $2/day or less and Agricultural Income/person and GDP/person.

Figure 2 gives plots similar to Figure 1, except the y-ordinate on each plot is replaced by the percent of population living on one dollar or less per day. Generally, the plots in Figure 2 are similar to those of Figure 1, except the scatter is lower on the y-axis, reflecting the smaller percentages of people living on $1/day.

Below we apply TETRAD II to these same data to attempt to sort-out whether any of these visual relationships are causal.

Results

We present results for two different models. First we look at the World Bank's measure of the percentage of populations living on two dollars and less per day. This measure is studied with the twelve related variables discussed above. We then substitute the World Bank's percentage living on one dollar per day for the two dollar per day measure so our second set of results refer to the extreme poor. All other variables are the same in the two sets of results.

Results for Percentages Living on $2 or Less /Day

Our analysis of the two-dollar per day measure begins with the correlation matrix on the thirteen variables described above. The correlation matrix is the unconditional correlation between all thirteen variables. We list these in matrix equation (1), labeled V($2). The order in which the variables are listed is given across the top of the matrix using the abbreviations as follows: $2 = percent of population living on two dollars or less per day; GI = Gini Index; FR = Un-Freedom Index; AI = Agricultural Income; LE = Life Expectancy; RU = percent of population which is rural; CM = Child Mortality; GDP = Gross Domestic Product; IL = Illiteracy; FA = Foreign Aid; UN= percent of Under-nourished; BR = birth rate and IT = International Trade. The actual variable definitions are given above.

$$
(1)\qquad V(\$2) = \begin{array}{c}
\begin{array}{ccccccccccccc} \$2 & GI & FR & AI & LE & RU & CM & GDP & IL & FA & UN & BR & IT \end{array} \\
\begin{bmatrix}
1 & & & & & & & & & & & & \\
.19 & 1 & & & & & & & & & & & \\
.36 & -.20 & 1 & & & & & & & & & & \\
-.48 & -.13 & -.26 & 1 & & & & & & & & & \\
-.79 & -.09 & -.41 & .43 & 1 & & & & & & & & \\
.73 & -.03 & .38 & -.37 & -.68 & 1 & & & & & & & \\
.81 & .11 & .39 & -.40 & -.96 & .68 & 1 & & & & & & \\
-.61 & -.04 & -.54 & .72 & .53 & -.51 & -.51 & 1 & & & & & \\
.74 & .07 & .35 & -.40 & -.80 & .66 & .84 & -.49 & 1 & & & & \\
.39 & .08 & .16 & -.25 & -.51 & .31 & .53 & -.35 & .42 & 1 & & & \\
.66 & .17 & .39 & -.38 & -.71 & .62 & .70 & -.52 & ..56 & .43 & 1 & & \\
.82 & .35 & .30 & -.45 & -.83 & .68 & .87 & -.52 & .82 & .50 & .67 & 1 & \\
-.28 & -.19 & -.10 & .17 & .24 & -.15 & -.29 & .09 & -.34 & .15 & -.24 & -.29 & 1
\end{bmatrix}
\end{array}
$$

The correlations summarized in the first column of the matrix generally agree with our subjective interpretation of the scatter plots in Figure 1. Strong positive relationships are found between $2/day and Birth rate (BR) (.82), Child Mortality (CM) (.81), Rural Population (RU) (.73) and Illiteracy (IL) (.74). Negative relationships between $2/day and Agricultural Income (AI) (-.48) and domestic income (GDP) (-.61) are modestly strong. However, an even stronger negative relationship is seen between $2/day and life expectancy (-.79). As several large correlations are observed in other columns of equation 1 (other than column 1), we might well expect a rich set of causal flows between and among these variables.

TETRAD II begins with the complete undirected graph in Figure 3. Here every variable is connected, without direction, to every other variable in the set. Accordingly, each variable has twelve lines connecting it with the other twelve variables. Lines are removed by way of tests that the correlation (covariance) between any two variables is not different from zero. If we cannot reject the hypothesis that a particular correlation (covariance) is zero at some pre-determined significance level, we remove the line connecting the two variables. TETRAD II considers all possible correlations between our thirteen variables. (There are n(n-1)/2 = 78 such correlations to consider here, which are given by the off diagonal lower triangular elements of equation (1).) Edges that remain are said to survive zero order conditioning (as we conditioned on no other variable to remove edges at this stage). Edges that are removed at zero order conditioning are given in Table 4, entries 1 through 14. Eight of these removed edges (lines) are with variables adjacent (connected in Figure 3) to the Gini Index. Four are with variable adjacent to Trade and two with variables adjacent to the Un-Freedom Index.

Edges (lines connecting variables) surviving these zero order tests are subjected to a series of first order conditioning tests. Here we condition edges between two variables on a third variable. If the conditional correlation between any two variables is not significantly different from zero we remove that edge, just as we did at zero order conditioning. Edges removed at first order conditioning are given in Table 4, entries 15 through 59. There are 45 edges removed at first order conditioning. Of these, 17 are from conditioning on Child Mortality, 9 from conditioning on GDP/Person, 6 each from conditioning on Birth Rate and Life expectancy, 5 from conditioning on percent Under Nourished and 2 from conditioning on percent Living on Two dollars or less per day. This suggests that Child Mortality is a primary player in understanding these data. To a somewhat lesser extent, GDP/Person shows itself important.

Continuing on, edges surviving tests of first order conditioning are subjected to tests of second order conditioning. These are given in Table 4, lines 60 – 65. Of the six edges removed at second order conditioning, four involve conditioning on birth rate.

TETRAD II cannot remove remaining edges at higher order (i.e. third order and higher) conditioning. It directs edges using *sepset* arguments discussed above. The resulting pattern is given in Figure 4. Arrows indicate direction of causation and a sign indicates whether an increase in the causal variable will increase (+) or decrease (-) the effect.

Here we see something very similar to what we labeled above as “the poverty chain” running down the center of the figure:

Illiteracy → Birth Rate → %<$2/day → % Pop Rural → % Under-nourished → Life Expectancy

Income variables (Ag Income/Person and GDP/Person) flow into this chain through their effects on percent<$2/day. Child Mortality enters the chain through its effect on Birth Rate and Life Expectancy. Un-Freedom and Income Distribution (Gini Index) enter through their influence on the Birth Rate. Un-Freedom enters as well through its effects on Income (GDP/Person). Foreign Aid and International Trade are disconnected from the poverty chain.

Agricultural Income is exogenous, apparently being influenced by the vagaries of nature (weather) and other (omitted) variables. It feeds directly (with a positive sign) into aggregate country income (GDP/Person), which in turn causes (with a negative sign) our income-based poverty measure (percent<$2/day). Both income measures reduce our income-based poverty measure (thus the negative sign on the edge GDP/Person → percent<$2/day). Income enters the poverty chain at a fairly low level, having no effect on Birth Rates, Child Mortality, or Illiteracy.

A few crucial edge directions require comment. The edge Child Mortality → Birth Rate has been discussed in the literature (see above). Here we see (Table 4) that the edge between the Gini Index (Income Distribution) and Child Mortality is removed at zero order conditioning, yet we cannot remove the edge running from the Gini Index to Birth Rate or that running between Child Mortality and the Birth Rate. Thus by the *sepset* argument, we direct the triple [Child Mortality, Birth Rate, Gini Index] as:

Child Mortality → Birth Rate ← Gini Index.

Heretofore, the evidence supporting this direction, Child Mortality → Birth Rate, has been based on time ordered observations. Behrman and Deolalikar write: “ Historically, declines in birth rates have followed periods of mortality decline. This phenomenon, called the Demographic Transition, took place in Europe during the eighteenth and nineteenth centuries and is evident in several countries of Latin America and Asia where crude and age-standardized fertility rates have been falling since the mid-1960s – some two to three decades after the onset of large mortality declines." (Behrman and Deolalikar 1989, pages 690-91). TETRAD II finds a similar, but not time delayed, direction in our cross section data as a result of vanishing unconditional correlation between Child Mortality and Income Distribution (Gini Index).

The lack of an edge between Life Expectancy and GDP/Person is worth additional comment as well. Wheeler (1980) studies cross section data and finds a significant effect of Life Expectancy on GDP using instrumental variables. His choices for instruments are earlier (initial) values of literacy, life expectancy, calorie availability, etc. He concludes that improvements in Life Expectancy yield (rather substantial) improvements in GDP. We find the edge between GDP/Person and Life Expectancy is removed by conditioning on Child Mortality. The p-value on our removed edge is .12. So we don't strongly reject that the edge he claims to exist (between GDP and Life Expectancy) is there. However, if the edge runs in the direction Wheeler suggests, we would see a directed cycle: GDP → Poverty Chain→ GDP. For cross section data (data measured at one point in time) this seems difficult to support; although, a dynamic pattern of feedback with these variables measured with time subscripts, $GDP_t \rightarrow$ Poverty $Chain_t \rightarrow GDP_{t+k}$, $k > 0$, is plausible.

Un-Freedom has an effect on the poverty chain through its causal effect on GDP/Person, which in-turn causes our income-based poverty measure (percent<$2/Day). Notice too that there is an undirected edge between the Un-Freedom Index and the Gini Index, suggesting the possibility that these variables are related. Actually in the footnote to Table 6 we report results on the use of Schwarz loss to provide evidence on the direction of this undirected edge. There we find evidence that the edge may be directed as Un-Freedom → Gini Index.

The unattached status of Foreign Aid is interesting. We remove all edges at rather high p-values, suggesting that the evidence is rather strong that Foreign Aid is not a major player in the poverty chain. Edges between Foreign Aid and Illiteracy, Child Mortality, Birth Rate, percent<$2/Day, percent Rural, percent Under-nourished and Life Expectancy are removed with partial correlations having p-values of .70, .20, .40, .82, .78, .36 and .78, respectively. Interestingly, the smallest p-value in the above list is that associated with the Child Mortality – Foreign Aid edge (p = .20). The correlation between these two variables is positive, indicating (if at all) that increases in Child Mortality lead to higher levels of Foreign Aid. The other small p-value associated with Foreign Aid, is that associated with the Foreign Aid – Un-Freedom Index. This edge is removed with a zero-order correlation having a p-value of .15. The sign on the edge is positive, indicating perhaps that higher levels of Un-Freedom cause higher levels of Foreign Aid, conceivably reflecting non-poverty related motivations associated with Foreign Aid (in any case TETRAD II drops the edge, suggesting that the edge is not a major player in the poverty chain).

International Trade is disconnected to the other variables. Two relatively low p-values on removed edges with International Trade are those associated with the Agricultural Income – International Trade edge at .12 and the Illiteracy – International Trade edge at .13. The former is associated with a positive relationship and the latter associated with a negative relationship. So, increases in Agricultural Income are associated with higher levels of International Trade and increases in Illiteracy are associated with decreases in International Trade. One might expect that if a causal path run between the latter two variables and carries a negative relationship, the path would run from Illiteracy to International Trade. But, in any case, at a 10 percent significance level we find no links to our measure of International Trade. We expected to see an edge running from International Trade to GDP/person (following standard trade theory – see Bhagwati (1996)). This expected edge may show-up in time series data or may be buried in aggregation over types of trade. The latter including considerations related to the well-known “Dutch Disease” an empirical observation that countries showing high rates of natural resource exports also show low rates of income growth (Bessler and Lopes 2001). Several countries in our sample rely heavily on natural resource exports; e.g. Nigeria, Venezuela and Trinidad.

Results for Percentages Living on $1 or Less /Day

We replicate the graph given above, substituting the $1/Day variable for the $2/Day variable. In population terms we are studying a much smaller percentage of world population. The correlation matrix summarizing the linear relationship among the thirteen variables, one of which is now percent of population living on one dollar or less per day is given in equation (2), labeled V($1):

$$(2)\qquad V(\$1) \;=\; \begin{array}{c} \begin{array}{ccccccccccccc} \$1 & GI & FR & AI & LE & RU & CM & GDP & IL & FA & UN & BR & IT \end{array} \\ \begin{bmatrix} 1 & & & & & & & & & & & & \\ .24 & 1 & & & & & & & & & & & \\ .24 & -.20 & 1 & & & & & & & & & & \\ -.37 & -.13 & -.26 & 1 & & & & & & & & & \\ -.80 & -.09 & -.41 & .43 & 1 & & & & & & & & \\ .62 & -.03 & .38 & -.37 & -.68 & 1 & & & & & & & \\ .83 & .11 & .39 & -.40 & -.96 & .68 & 1 & & & & & & \\ -.46 & -.04 & -.54 & .72 & .53 & -.51 & -.51 & 1 & & & & & \\ .68 & .07 & .35 & -.40 & -.80 & .66 & .84 & -.49 & 1 & & & & \\ .38 & .08 & .16 & -.25 & -.51 & .31 & .53 & -.35 & .42 & 1 & & & \\ .62 & .17 & .39 & -.38 & -.71 & .62 & .70 & -.52 & .56 & .43 & 1 & & \\ .79 & .35 & .30 & -.45 & -.83 & .68 & .87 & -.52 & .82 & .50 & .67 & 1 & \\ -.21 & -.19 & -.10 & .17 & .24 & -.15 & -.29 & .09 & -.34 & .15 & -.24 & -.29 & 1 \end{bmatrix} \end{array}$$

Notice, that except for the first column V($1) = V($2), twelve of the thirteen variables are the same. Comparing the first column of equation (1) with the first column equation (2), we see several interesting points. First, the signs on the correlations are the same. Measures that show a negative (positive) correlation with our $2/day income-based poverty measure show a negative (positive) correlation with our $1/day measure. However, seemingly large differences show up in the correlations between our income-based poverty measures and GDP/Person (.18), Un-Freedom (-.12), Agricultural Income (+.11) and percent of Population Rural (-.11). That is to say, country to country variation in the percentage of extreme poor (those living on $1/day or less) is associated less with country to country variation in GDP (-.43), than is the more well-to-do $2/day measure associated with variation in GDP (-.61). Similarly, variation in Un-Freedom and our $1/day measure is weaker than variation in Un-Freedom and our $2/day measure (by .12). Finally, Agricultural Incomes and Percentages of Populations that are Rural are less associated with our $1/day measure than our $2/day measure.

Figure 5 is the graph associated with equation (2). It is reflective of the differences in correlations between equation (2) and equation (1). The "poverty chain" found in Figure 4 is broken at the $1/day measure of poverty. The link to the poverty chain with income levels is broken also at the $1/day measure. We continue to see the links (edges or lines) between our non-income poverty variables. TETRAD II cannot direct these as it lacks sufficient information to provide direction. We still see the causal flows from Child Mortality, Illiteracy and Gini Index all to Birth Rate. However, in this graph (Figure 5) Birth Rate is a sink, information flows into Birth Rate but nothing flows out of it. Recall from Figure 4 that we did see a flow from birth rate to percent Living on $2/day. Via this link, in Figure 4, higher birth rates result in lower life expectancy. Whereas, in Figure 5 higher birth rates are not causes of lower life expectancy because the link at $1/day is broken.

Figure 5 generally shows that variation in the measure of extreme poor is detached from variations in our economic measures, GDP/Person and Agricultural Income/Person. The edge between GDP/Person and \$1/Day is removed by conditioning on Child Mortality (this conditional correlation is -.12 and has a p-value of .54). Similarly, the edge between Agricultural Income/Person and \$1/Day is removed by conditioning on Child Mortality (here the conditional correlation between Agricultural Income and percent\$1/Day is -.07, with a p-value of .55). These results suggest that the extreme poor are not helped by increasing incomes of the general population. A contrary result was found for variations in the \$2/day poverty measure (Figure 4). This measure of the more "well-to-do" poor was caused by variation in GDP/Person (and indirectly by variations in Agricultural Income and Freedom).

Our result on the \$1/Day measure and Income measures of the general population don't support a "rising tide lifts all boats" interpretation of the macro-income poverty interface – although simple regressions may suggest otherwise. Consider the following regressions. Equation (3) is a heteroskedastic-consistent regression (see RATS, Doan 1995) of the percentage living on one dollar or less per day from country i (percent One_i) on GDP/person from country i and a constant. The estimated coefficients, standard errors and R^2 are given in usual regression format.

$$(3)\quad \%\ One_i = \underset{(2.65)}{27.45} - \underset{(.0009)}{.004}\ (GDP/Person)_i \quad ; \quad R^2 = .60$$

Here the estimated coefficient associated with GDP/Person is indeed large relative to its estimated standard error – a t-statistic of 4.65, suggesting at a very low level of significance that GDP/Person is an important variable in understanding our measure of the extreme poor (percent One dollar or less per day). The negative sign on the estimated coefficient might well be interpreted as "when GDP/Person in country i increases, the percentage of the population in country i living in extreme poverty declines." Furthermore, one could well design policy to rely on such a response when world incomes are increasing or decreasing. However, a regression, similar to equation (3), but including Child Mortality on the right-hand-side, yields the following heteroskedastic-consistent result:

$$(4)\quad \%\,\text{One}_i = \underset{(2.82)}{2.75} - \underset{(.0006)}{.0004}\,(\text{GDP/Person})_i + \underset{(.022)}{.237}\,(\text{Child Mort.})_i\ ;\ R^2 = .84$$

Focus again on the estimated coefficient on GDP/person and its standard error. The estimate falls in absolute value relative to the corresponding coefficient from equation (3). Furthermore, the t-statistic associated with this estimate suggests that at usual levels of significance the coefficient is not different from zero. Based on results reported in equation (4), we conclude that the extreme measure of poverty (percent Living on One Dollar or less per day) is not responsive to changes in GDP/Person.

It is interesting to contrast the results from equations (3) and (4) with analogous regression equations on the two dollar and less per day poverty measure. Equations (5) and (6) give corresponding estimated regressions for the Two-dollar per day measure.

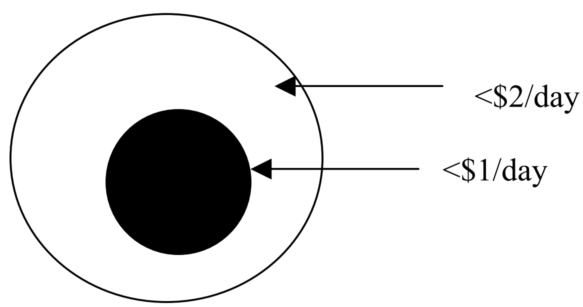
$$(5)\quad \%\,\text{Two}_i = \underset{(3.39)}{57.96} - \underset{(.001)}{.007}\,(\text{GDP/Person})_i\ ;\ R^2 = .81$$

$$(6)\quad \%\,\text{Two}_i = \underset{(4.223)}{28.481} - \underset{(.0007)}{.0033}\,(\text{GDP/Person})_i + \underset{(.0341)}{.287}\,(\text{Child Mort.})_i\ ;\ R^2 = .91$$

Here the coefficient associated with GDP/Person for country i is significantly different from zero in both equations (5) and (6). Although its magnitude falls in absolute value in equation (6), it remains significant (t-statistic of 4.83 in equation (6)). Differences between these last two regression equations and those found using the one dollar per day measure (equation 3 and 4) show-up in our directed graphs (Figures 4 and 5) by an arrow running from GDP/person to \$2/day in Figure 4 and no arrow between GDP/person and \$1/day in Figure 5.

Returning to our discussion of Figure 5, we see that variation in the measure of the extreme poor do not cause variations in the urban/rural population mix, suggesting that the extreme poor are not primarily characteristic of rural populations, as are people included in the \$2/day measures. Recall from figure 4 that the \$2/day measure is a cause of the percentage of population living in the rural sector.

The differences between the "extreme poor" and the "moderate poor" are trivially illustrated in the Venn diagram below. Our results suggest that the inner core (<\$1/day) is not responsive to improvements in the general economic climate of a country. The less extreme poor, as represented by the outer band, do respond to such improvements. Those in the outer band move in and out of our poverty classification in response to general economic conditions; whereas those in the inner core appear to be not responsive to such macro-economic changes.



Furthermore, members of the inner core are less associated with rural environments than are their less extremely positioned siblings. Both measures of economic poverty are positively related to Child Mortality, with the \$1/day measure showing slightly higher correlation. Recall that the \$2/day measure is indirectly caused by Child Mortality by way of the Birth Rate measure while the \$1/day measure is associated with Child Mortality. TETRAD cannot assign a causal path. The Child Mortality → \$1/day possibility is probably less believable than the reverse possibility Child Mortality ← \$1/day, although an investment view of children may suggest otherwise.

Differences between results found from \$2/day and \$1/day measures of poverty suggest the inner core of poverty is a "hard core", showing little possibilities for "manipulation" via policy, whereas the outer layer does appear to offer opportunities via changes in (manipulations in) literacy rates, birth rates, freedom, agricultural incomes, general economic conditions and income distribution.

More Regressions (Elasticities)

As is apparent from the regressions on poverty measures and GDP/Person that we reported above, if one is interested in a measure of the influence of one or more causal variables on poverty measures, he/she must be sure to condition on the appropriate set of right-hand side variables.[8] If, for example, we want to measure the effect of agricultural income per capita on our \$2 or less per day poverty measure and we use the graph given in Figure 4 as a guide for specification, we can perform ordinary least squares regression of \$2/day on a constant and agricultural income, because the latter is exogenous in our thirteen variable model. That is, there is no backdoor path from agricultural income to our \$2/day poverty measure. There are no other variables to be conditioned on (given our causally sufficient set of thirteen variables) for unbiased estimation of the effect of agricultural income per capita on the \$2/Day poverty measure. We must be careful, however, not to condition on variables that are the effects of Agricultural Income. That is, we should not include GDP and Agricultural Income on the right hand side of a regression equation in order to measure the effect of Agricultural Income on \$2/Day.

Equation (7) gives the ordinary least squares regression estimates of the effects of Agricultural Income/Person on the \$2/Day poverty measure:

[8] Pearl addresses this point of proper specification in regression models through his analysis of the adjustment problem (see Pearl 2000, pages 78 – 84 and 353 – 357).

$$\text{(7)} \quad \$2/\text{Day} = \underset{(4.34)}{51.73} - \underset{(.0018)}{.0038}\ \text{Ag Income/Person} \ ; \quad R^2 = .23$$

At usual levels of significance (.05 or .10) we would reject the hypothesis that the coefficient associated with Agricultural Income is zero. However, if we add GDP/Person to the right hand side of equation (7), we see that the coefficient associated with Agricultural Income is not significantly different from zero:

$$\text{(8)} \quad \$2/\text{Day} = \underset{(3.60)}{57.99} - \underset{(.0014)}{.0007}\ \text{Ag Income/Person} - \underset{(.0018)}{.0068}\text{GDP/Person} \ ; \quad R^2 = .37$$

Equation (8), if interpreted without the advantage of the causal model given in Figure 4, suggests that agricultural income per person is not important for changing poverty levels. Of course the reason for the weak measured influence of Agricultural Income/ Person on $2/Day in this equation is that the former is a cause of GDP/Person, which in turn causes $2/Day. So conditioning on GDP/Person blocks the measured affect of Agricultural Income/Person on $2/Day. Equation (8) is not properly specified for measuring the effect of agricultural income on poverty; while equation (7) is properly specified.

Our estimate of the effect of GDP/person on the $2/day measure requires either the Un-Freedom index, the Gini Index or Birth Rate be included on the right-hand-side of an ordinary least squares equation for unbiased estimation of the effect of GDP/Person on the $2/day poverty measure because there is an unblocked backdoor path running from GDP/person to $2/day through the Un-Freedom index, the Gini Index and the birth rate. This path has no converging arrows on it (→Xi ←). Conditioning on either the Gini Index, the Un-Freedom Index or Birth Rate will block the path from GDP/Person to the $2/Day poverty measure.

In Table 6 we give the estimated coefficients associated with ordinary least squares regression of \$2/Day on each of its "causal" variables. The table gives coefficient estimates, estimated standard errors (in parentheses), the coefficient of determination (R^2) and elasticity estimated with respect to changes of each of the "causal" variables identified in Figure 4. These elasticities are calculated as follows:

$$\eta_{\$2,Xi} = \%\Delta \$2/\text{day} \; / \; \%\Delta X_i = (b_i)(\text{mean } X_i)/(\text{mean } \$2/\text{day}),$$

where b_i is the estimated coefficient associated with the regression of \$2/day on the variable X_i. The X_i are: the Gini Index, Un-Freedom Index, Illiteracy Rate, Birth Rate, GDP/Person, Agricultural Income/Person and Child Mortality Rate.

Because there are two undirected edges in Figure 4, we considered alternative regressions to measure several of the causal effects, depending on the direction of the causal flow in these undirected edges (see the footnote to Table 6 for more details). From the table we see that the highest elasticity (indicating the most influential causal variable) is associated with the Un-Freedom index. That is to say, \$2/day poverty measure is most responsive to changes in the Un-Freedom (UF) index. Our two estimates (a. $\eta_{\$2,UF} = 1.48$ and b. $\eta_{\$2,UF} = 1.70$, depending on how we treat the undirected edge between Un-Freedom and the Gini Index) are interpreted as the percentage change in the percent of a population living on \$2 or less per day due to a one percent change increase in the Un-Freedom index.[9] As the estimates are greater than one, this suggests that the \$2/day poverty measure is quite responsive to changes in the freedom levels.

The \$2/day poverty measure is also elastic with respect to changes in the birth rate (BR) ($\eta_{\$2,BR} = 1.16$). A 1 percent increase in birth rate results in a 1.16 percent increase in the percentage of a country's population living on two dollars or less per day.

[9] Based on the Schwarz-loss metrics reported in the footnote to Table 6, we recommend using the regressions (elasticities) associated with the Un-Freedom → Gini Index and Illiteracy → Child Mortality edges.

The order of importance of other variables on the two dollar measure is given as: Gini Index (GI) ($0_{\$2,GI}$ • .64), Child Mortality (CM) ($0_{\$2,CM}$ •.52), GDP per person ($0_{\$2,GDP}$ •-.37), Illiteracy Rate (IR) ($0_{\$2,IR}$ • .33) and Agricultural Income per person (AI) ($0_{\$2,AI}$ • -.21). Here we report the simple averaged estimated elasticity in cases where we estimated two values to account for undirected edges in Figure 4 (see Table 6).

The elasticity on Illiteracy Rate is interesting. Note from Figure 4 that TETRAD II cannot direct the edge between Child Mortality and Illiteracy. If we direct this edge as Illiteracy Rate → Child Mortality, then the simple regression of $2/day on Illiteracy Rate is appropriate and gives us a coefficient associated with illiteracy of .87. Evaluating the elasticity at the mean values on $2/day and Illiteracy Rate (43.15 and 25.99, respectively) gives us an estimated elasticity of .52 ($0_{\$2,IR}$ • .52). If we direct the edge between Child Mortality and Illiteracy Rate as Child Mortality → Illiteracy Rate, then a backdoor path exist from Illiteracy Rate to $2/day, because Child Mortality is a cause of $2/Day through Birth Rate (see Figure 4). This requires us to condition our estimate of the effect of Illiteracy Rate on $2/day on Child Mortality, giving us an estimated coefficient on Illiteracy Rate of .25 (and an estimated standard error of .17). Again, we see, as we did on the $1/Day regressions discussed above, that the differences in coefficient estimates (Table 6) and estimated elasticities are not trivially related to what variables we put on the right-hand-side in our regression equations. In this last case our subjective view and the Schwarz-loss measures reported in the footnote to Table 6 suggest the flow of causality on this edge runs from Illiteracy Rate to Child Mortality.

Summary and Conclusions

We use recently developed methods of directed acyclic graphs to help sort-out causal patterns among a set of thirteen measures deemed relevant to the incidence of world poverty. Recently available cross section measures of the percent of population living on one and two dollars or less per day from eighty low income countries are exposed to a battery of tests of conditional independence with respect to measures of economic and political freedom, income inequality, income per person, agricultural income, child mortality, birth rate, life expectancy, relative size of rural population, illiteracy rate, foreign aid as a percentage of national income, international trade as a percentage of national income and percent of population which is under nourished. Results are that our measures of economic and political freedom, income inequality, illiteracy and agricultural income are exogenous movers of poverty. Results on foreign aid and international trade show both to be not connected to other variables in the graph.

Differences in the resulting graphs when our measure of poverty is $2/day, as opposed to $1/Day, indicate that extreme poverty is less accessible to manipulation through intervention. Furthermore, extreme poverty appears not to be, particularly, a rural phenomenon. Our graphs support early literature in finding Child Mortality as a cause of Birth Rates and not finding a relationship between Under-nutrition and Birth Rates.

Our results are based on cross section data from a sample of 80 less developed countries. Such analysis assumes a basic exchangeability between observations across countries. We argue that such an assumption is reasonable, at least at first glance. Human beings under similar circumstances, whether in country A or B, react basically the same way. A preferred approach would be to allow country differences, so that we could measure whether people in country (culture) A react differently than people in country B to changes in one or more of our thirteen poverty related variables. Time series data on our poverty measures would allow us to say more relative to such questions.

We used recent advances in modeling directed acyclic graphs. These advances have been built on a tripod of assumptions discussed in the body of the paper: The Causal Sufficiency Condition, The Causal Markov Condition and the Faithfulness Condition. While all three may be violated in any particular application, it is the first condition that gives us concern. In a study of an issue as enormous as "world poverty", the assumption that we have a list of thirteen causally sufficient variables is controversial. Yet, in the final analysis some type of causal sufficiency assumption must be made if we are to make progress with observational data.

This brings us to the discussion offered at the beginning of our paper.   Even if we agree that understanding cause and effect is important, and thus we are willing to move beyond an agnostic view of poverty as explained in our opening paragraph, there is a message to be communicated. To identify and measure the relative strengths of causes one must consider the causal mechanism behind their settings. Indeed if each is set according to some random assignment process, then there is no need for the graphical methods applied here (as discussed in Holland 1986). However, if randomization is not used to set values of our casual variables (and our correlation tests strongly suggest that it is not), then inference and policy analysis requires that we understand the causal mechanism behind all variables we study! Here we need to condition any inference and subsequent policy on a fully sufficient set of casual variables. This point is clearly illustrated in our analysis of the causal mechanism behind the $1/day poverty measures. A causal path running from GDP/Person to percent living on $1 or less /day is shown to be highly unlikely when we condition on Child Mortality. A policy recommendation based on such a causal path (GDP/Person → $1 or less/day) may suggest that the extremely poor will benefit from improvements in the general economy, through, perhaps, some 'trickle down process'. Such a suggestion (if based solely on this path) is likely specious.

Causal paths identified in this paper (Figures 4 or 5) may vanish as well if other variables are added to our (assumed) causally sufficient set. This conclusion puts us on weak ground with respect to edges that remain. (Removed edges, however, remain detached if we add other variables to our causally sufficient set.). Yet, we see no alternative, short of making overconfident statements about what we know and why we know it. The wisdom in Pratt and Schlaifer's advice when assessing the evidence on the ill effects of smoking is worth recalling:

> The estimates of the effects of smoking were shown to remain almost unchanged when one concomitant after another was introduced into the analysis, until finally it became much easier to believe that smoking in fact had the effects it seemed to have than to believe that it was merely proxying for some other, as yet undiscovered variable or variables." (Pratt and Schlaifer 1988 page 45)

A similar evolution of beliefs on the causes and effects of observational poverty is currently underway. This evolution will involve tolerance with respect to many possible concomitants. Variables not studied here but certainly worthy of consideration include access to clean water, aggregate expenditures on health care, agricultural investment and aggregate financial health; the list of possibilities is seemingly endless. Nevertheless, the *a priori* rejection of a subset of variables or the prior assignment of causal flow may inappropriately mask the underlying causal flows that are present in the data.

Table 1. Hypothetical values of X, Y and U under passive observation and policy settings on X

Passive Observations			Forced or Policy Induced		
X = GDP/person	Y = % \$2/Day	U = Other Variables	X_f = Forced =200	$U_{Xf=200}$ = Other Vars.	$Y_{Xf=200}$ = % \$2/Day
\$100	40	-50	200	-50	30
\$100	50	-40	200	-40	40
\$100	60	-30	200	-30	50
\$200	30	-50	200	-50	30
\$200	40	-40	200	-40	40
\$200	50	-30	200	-30	50

$Y = 100 - .1\ X + U.$

Table 2. Hypothetical values of X, Y, V and U under passive observation and policy settings on X

V= Freedom	X = GDP/person	Y = % $2/Day	U = Other Variables	$X_f = 200$	$U_{Xf=200}$ = Other Variables	$Y_{Xf=200}$ = % $2/Day
5	$100	65	-25	200	-25	55
5	$100	65	-25	200	-25	55
5	$100	65	-25	200	-25	55
4	$200	60	-20	200	-20	60
4	$200	60	-20	200	-20	60
4	$200	60	-20	200	-20	60

$Y = 100 - .1X + U$; $X=600-100V$; and $U = -5V$.

Table 3. **Countries studied**

Algeria	Honduras	Paraguay
Armenia	Hungry	Peru
Azerbaijan	India	Poland
Bangladesh	Indonesia	Portugal
Belarus	Jamaica	Romania
Bolivia	Jordan	Russia
Botswana	Kazakhstan	Rwanda
Brazil	Kenya	Senegal
Bulgaria	Korea South	Sierra Leon
Burkina Faso	Lao Peoples Demo. Republic	Slovak Republic
Central African Republic	Latvia	Slovenia
Chile	Lesotho	South Africa
China	Lithuania	Sri Lanka
Columbia	Madagascar	Tanzania
Costa Rica	Mali	Thailand
Cote d'Ivoire	Mauritania	Trinidad
Czech	Mexico	Tunisia
Dominican Republic	Moldova	Turkey
Ecuador	Mongolia	Turkmstan
Egypt	Morocco	Ukraine
El Salvador	Mozambique	Uruguay
Estonia	Namibia	Uzbekistan
Ethiopia	Nepal	Venezuela
Gambia	Niger	Yemen
Georgia	Nigeria	Zambia
Ghana	Pakistan	Zimbabwe
Guatemala	Panama	

Countries listed in this table were selected from 2001 World Bank Development Indicators for which $1/day and $2/day population figures were available; see World Development Report 2000/2001, Table 4, pages 280-81.

Table 4. Edges removed on graph construction with percent living on $2 or less per day, correlation or partial correlation and p-values on Ho: value equals zero

Edge Removed	Correlation or Partial Correlation	Value	Probability on Ho:
Gini -- Ag Inc	rho(Gini, Ag Inc)	-0.1266	0.2612
Gini – Life Exp	rho(Gini, Life Exp)	-0.0920	0.4157
Gini -- % Rural	rho(Gini, % Rural)	-0.0298	0.7921
Gini -- Child Mort	rho(Gini, Child Mort)	0.1103	0.3283
Gini -- GDP/Person	rho(Gini, GDP/Person)	-0.0416	0.7131
Gini -- Illiteracy	rho(Gini, Illiteracy)	0.0709	0.5315
Gini -- Foreign Aid	rho(Gini, Foreign Aid)	0.0829	0.4637
Gini – Under-nourish	rho(Gini, Under-nourish)	0.1736	0.1222
Unfree – Foreign Aid	rho(Unfree,Foreign Aid)	0.1619	0.1501
Unfree -- Trade	rho(Unfree, Trade)	-0.1005	0.3734
Ag Inc -- Trade	rho(Ag Inc, Trade)	0.1749	0.1193
% Rural -- Trade	rho(% Rural, Trade)	-0.1487	0.1867
GDP/Person -- Trade	rho(GDP/Person,Trade)	0.0920	0.4155
Foreign Aid -- Trade	rho(Foreign Aid, Trade)	0.1484	0.1873
Life Exp -- Birth Rate	rho(Life Exp, Birth rate | Child Mort)	0.0093	0.9347
Life Exp -- Illiteracy	rho(Life Exp, Illiteracy | Child Mort)	0.0312	0.7842
Life Exp -- <$2/Day	rho(<$2/Day, Life Exp | Child Mort)	-0.1199	0.2906
Life Exp -- % Rural	rho(Life Exp, % Rural | Child Mort)	-0.1183	0.2973
GDP/Person -- Birth rate	rho(GDP/Person, Birth rate | Life Exp)	-0.1674	0.1388
GDP/Person -- % Rural	rho(GDP/Person,% Rural | <$2/Day)	-0.1314	0.2464
Life Exp -- Foreign Aid	rho(Life Exp, Foreign Aid | Child Mort)	-0.0317	0.7808
Child Mort -- GDP/Person	rho(Child Mort, GDP/Person | Birth rate)	-0.1385	0.2217
GDP/Person -- Illiteracy	rho(GDP/Person, Illiteracy | Life Exp)	-0.1284	0.2574
<$2/Day -- Ag Inc	rho(<$2/Day, Ag Inc |GDP/Person)	-0.0838	0.4619
Ag Inc -- Birth rate	rho(Ag Inc, Birth rate | GDP/Person)	-0.1285	0.2571
Unfree -- Life Exp	rho(Unfree, Life Exp | Child Mortality)	-0.1292	0.2544
Ag Inc -- Child Mort	rho(Ag Inc, Child Mort | GDP/Person)	-0.0574	0.6138
Ag Inc -- Illiteracy	rho(Ag Inc, Illiteracy | GDP/Person)	-0.0731	0.5213
Ag Inc -- % Under-nourish	rho(Ag Inc, % Under-nourish |GDP/Person)	-0.0117	0.9180
Ag Inc -- % Rural	rho(Ag Inc, % Rural | GDP/Person)	-0.0021	0.9852
GDP/Person -- Foreign Aid	rho(GDP/Person, Foreign Aid | Life Exp)	-0.1050	0.3551
Illiteracy -- Trade	rho(Illiteracy, Trade | Child Mort)	-0.1731	-0.1256
Child Mort -- Trade	rho(Child Mort, Trade | Birth rate)	-0.0874	0.4428
Birth rate -- Trade	rho(Birth rate, Trade | Child Mort)	-0.0745	0.5134
<$2/Day -- Trade	rho(<$2/Day, Trade | Birth rate)	-0.0698	0.5399

Table 4. Cont.

Edge Removed	Correlation or Partial Correlation	Value	Probability on Ho:
Unfree -- Ag Inc	rho(Unfree, Ag Inc | % Under-nourish)	-0.1289	0.2556
Ag Inc -- Foreign Aid	rho(Ag Inc, Foreign Aid | GDP/Person)	-0.0023	0.9839
% Under-nourish –Trade	rho(% Under-nourish, Trade | Child Mort)	-0.0544	0.6330
Gini – Trade	rho(Gini, Trade | Birth Rate)	-0.0994	0.3816
<$2/Day – Gini	rho(<$2/Day, Gini | Birth Rate)	-0.1632	0.1495
Life Exp – Trade	rho(Life Exp, Trade | % Under-nourish)	0.1066	0.3481
Unfree – Birth rate	rho(Unfree, Birth rate | % Under-nourish)	0.0632	0.5794
% Rural -- Foreign Aid	rho(% Rural, Foreign Aid | <$2/Day)	0.0313	0.7832
Unfree – Illiteracy	rho(Unfree, Illiteracy | % Under-nourish)	0.1794	0.1119
<$2/Day – Illiteracy	rho(<$2/Day, Illiteracy | Child Mort)	0.0940	0.4086
Unfree -- % Rural	rho(Unfree, % Rural | Child Mort)	0.1675	0.1385
Unfree -- Child Mort	rho(Unfree, Child Mort | % Under-nourish)	0.1772	0.1168
Unfree -- % Under-nourish	rho(Unfree, % Under-nourish | GDP/Person)	0.1506	0.1839
<$2/Day -- Foreign Aid	rho(<$2/Day, Foreign Aid | Birth rate)	-0.0254	0.8232
Illiteracy -- Foreign Aid	rho(Illiteracy, Foreign Aid | Child Mort)	-0.0441	0.6988
% Under-nourish – Foreign Aid	rho(% Under-nourish ,Foreign Aid | Child Mort)	0.1036	0.3618
Ag Inc -- Life Exp	rho(Ag Inc, Life Exp| GDP/Person)	0.0788	0.4887
Foreign Aid – Birth rate	rho(Foreign Aid, Birth rate | Child Mort)	0.0955	0.4012
Child Mort -- Foreign Aid	rho(Child Mort, Foreign Aid | Life Exp)	0.1454	0.1995
Life Exp -- GDP/Person	rho(Life Exp, GDP/Person | Child Mort)	0.1749	0.1218
Illiteracy -- % Under-nourish	rho(Illiteracy, % Under-nourish | Child Mort)	-0.0606	0.5949
% Under-nourish – Birth rate	rho(% Under-nourish, Birth rate | Child Mort)	0.1745	0.1228
% Rural -- Child Mort	rho(% Rural, Child Mort | Life Exp)	0.1530	0.1770
Child Mort -- % Under-nourish	rho(Child Mort, % Under-nourish | Life Exp)	0.0926	0.4155
GDP/Person -- % Under-nourish	rho(GDP/Person,%Under-nourish| Ag Inc, <$2/Day)	-0.1795	0.1142
% Rural – Illiteracy	rho(% Rural, Illiteracy | <$2/Day, Birth Rate)	0.1858	0.1017
<$2/Day -- % Under-nourish	rho(<$2/Day, % Under-nourish | Birth Rate, % Rural)	0.1660	0.1450
% Rural – Birth rate	rho(% Rural, Birth rate | <$2/Day, % Under-nourish)	0.1350	0.2364
<$2/Day – Illiteracy	rho(<$2/Day, Illiteracy | Birth Rate, Child Mort)	0.0656	0.5673
<$2/Day – Child Mort	rho(<$2/Day, Child Mort| Birth Rate, Life Exp)	0.0694	0.5449

Table 5. Edges removed on graph construction with percent living on $1 or less per day, correlation or partial correlation and p-values on Ho: value equals zero

Edge Removed	Correlation or Partial Correlation	Value	Probability on Ho:
Gini -- Ag Inc	rho(Gini, Ag Inc)	-0.1266	0.2612
Gini – Life Exp	rho(Gini, Life Exp)	-0.0920	0.4157
Gini -- % Rural	rho(Gini, % Rural)	-0.0298	0.7921
Gini -- Child Mort	rho(Gini, Child Mort)	0.1103	0.3283
Gini -- GDP/Person	rho(Gini, GDP/Person)	-0.0416	0.7131
Gini -- Illiteracy	rho(Gini, Illiteracy)	0.0709	0.5315
Gini -- Foreign Aid	rho(Gini, Foreign Aid)	0.0829	0.4637
Gini – Under-nourish	rho(Gini, Under-nourish)	0.1736	0.1222
Unfree – Foreign Aid	rho(Unfree,Foreign Aid)	0.1619	0.1501
Unfree -- Trade	rho(Unfree, Trade)	-0.1005	0.3734
Ag Inc -- Trade	rho(Ag Inc, Trade)	0.1749	0.1193
% Rural -- Trade	rho(% Rural, Trade)	-0.1487	0.1867
GDP/Person -- Trade	rho(GDP/Person,Trade)	0.0920	0.4155
Foreign Aid -- Trade	rho(Foreign Aid, Trade)	0.1484	0.1873
Life Exp -- Birth Rate	rho(Life Exp, Birth rate | Child Mort)	0.0093	0.9347
Life Exp -- Illiteracy	rho(Life Exp, Illiteracy | Child Mort)	0.0312	0.7842
Life Exp -- <$1/Day	rho(<$1/Day, Life Exp | Child Mort)	-0.0601	0.5976
Life Exp -- % Rural	rho(Life Exp, % Rural | Child Mort)	-0.1183	0.2973
GDP/Person -- Birth rate	rho(GDP/Person, Birth rate | Life Exp)	-0.1674	0.1388
GDP/Person -- % Rural	rho(GDP/Person,% Rural | <$1/Day)	-0.1314	0.2464
Life Exp -- Foreign Aid	rho(Life Exp, Foreign Aid | Child Mort)	-0.0317	0.7808
Child Mort -- GDP/Person	rho(Child Mort, GDP/Person | Birth rate)	-0.1385	0.2217
GDP/Person -- Illiteracy	rho(GDP/Person, Illiteracy | Life Exp)	-0.1284	0.2574
<$1/Day – GDP/Person	rho(<$1/Day, GDP/Person |Child Mort|)	-0.0706	0.5354
Ag Inc -- Birth rate	rho(Ag Inc, Birth rate | GDP/Person)	-0.1285	0.2571
Unfree -- Life Exp	rho(Unfree, Life Exp | Child Mortality)	-0.1292	0.2544
Ag Inc -- Child Mort	rho(Ag Inc, Child Mort | GDP/Person)	-0.0574	0.6138
Ag Inc -- Illiteracy	rho(Ag Inc, Illiteracy | GDP/Person)	-0.0731	0.5213
Ag Inc -- % Under-nourish	rho(Ag Inc, % Under-nourish |GDP/Person)	-0.0117	0.9180
Ag Inc -- % Rural	rho(Ag Inc, % Rural | GDP/Person)	-0.0021	0.9852
<$1/Day – Ag Inc	Rho(<$1/Day, Ag Inc | Child Mortality)	-0.0682	0.5493
GDP/Person -- Foreign Aid	rho(GDP/Person, Foreign Aid | Life Exp)	-0.1050	0.3551
Illiteracy -- Trade	rho(Illiteracy, Trade | Child Mort)	-0.1731	-0.1256
Child Mort -- Trade	rho(Child Mort, Trade | Birth rate)	-0.0874	0.4428
Birth rate -- Trade	rho(Birth rate, Trade | Child Mort)	-0.0745	0.5134

Table 5. Cont.

Edge Removed	Correlation or Partial Correlation	Value	Probability on Ho:
Unfree -- Ag Inc	rho(Unfree, Ag Inc | % Under-nourish)	-0.1289	0.2556
Ag Inc -- Foreign Aid	rho(Ag Inc, Foreign Aid | GDP/Person)	-0.0023	0.9839
% Under-nourish –Trade	rho(% Under-nourish, Trade | Child Mort)	-0.0544	0.6330
<$1/Day -- Trade	Rho(<$1/Day, Trade | Child Mortality)	0.0585	0.6077
Gini – Trade	rho(Gini, Trade | Birth Rate)	-0.0994	0.3816
<$1/Day – Gini	rho(<$1/Day, Gini | Birth Rate)	-0.0672	0.5551
<$1/Day – Unfree	rho(<$1/day, Unfree |Child Mort)	-0.1562	0.1676
Life Exp – Trade	rho(Life Exp, Trade | % Under-nourish)	0.1066	0.3481
Unfree – Birth rate	rho(Unfree, Birth rate | % Under-nourish)	0.0632	0.5794
% Rural -- Foreign Aid	rho(% Rural, Foreign Aid | Child Mort)	-0.0862	0.4490
Unfree – Illiteracy	rho(Unfree, Illiteracy | % Under-nourish)	0.1794	0.1119
Unfree -- % Rural	rho(Unfree, % Rural | Child Mort)	0.1675	0.1385
<$1/Day – Foreign Aid	rho(<$1/Day, Foreign Aid | Child Mort)	-0.1190	0.2944
Unfree -- Child Mort	rho(Unfree, Child Mort | % Under-nourish)	0.1772	0.1168
Unfree -- % Under-nourish	rho(Unfree, % Under-nourish | GDP/Person)	0.1506	0.1839
Illiteracy -- Foreign Aid	rho(Illiteracy, Foreign Aid | Child Mort)	-0.0441	0.6988
% Under-nourish -- Foreign Aid	rho(% Under-nourish ,Foreign Aid | Child Mort)	0.1036	0.3618
Ag Inc -- Life Exp	rho(Ag Inc, Life Exp| GDP/Person)	0.0788	0.4887
Foreign Aid – Birth rate	rho(Foreign Aid, Birth rate | Child Mort)	0.0955	0.4012
Child Mort -- Foreign Aid	rho(Child Mort, Foreign Aid | Life Exp)	0.1454	0.1995
Life Exp -- GDP/Person	rho(Life Exp, GDP/Person | Child Mort)	0.1749	0.1218
Illiteracy -- % Under-nourish	rho(Illiteracy, % Under-nourish | Child Mort)	-0.0606	0.5949
<$1/Day – % Rural	rho(<$1/Day, % Rural | Child Mort)	0.1381	0.2228
<$1/Day – %Under-nourish	rho(<$1/Day, %Under-nourish | Child Mort)	0.1198	0.2912
% Under-nourish – Birth rate	rho(% Under-nourish, Birth rate | Child Mort)	0.1745	0.1228
<$1/Day – Illiteracy	rho(<$2/Day, Illiteracy | Child Mort)	-0.0376	0.7413
% Rural -- Child Mort	rho(% Rural, Child Mort | Life Exp)	0.1530	0.1770
Child Mort -- % Under-nourish	rho(Child Mort, % Under-nourish | Life Exp)	0.0926	0.4155
GDP/Person -- % Under-nourish	rho(GDP/Person,%Under-nourish | %Rural, Life Exp)	-0.1840	0.1053
% Rural – GDP/Person	rho(% Rural, GDP/Person | Illiteracy, % Under-nourish)	-0.1760	0.1218
% Rural -- Illiteracy	rho(< % Rural, Illiteracy| Child Mort, Birth Rate)	0.1560	0.1713
% Rural – Birth rate	rho(% Rural, Birth rate | <$2/Day, % Under-nourish)	0.1350	0.2364
% Rural – Birth Rate	rho(%Rural, Birth Rate | Child Mort, Illiteracy)	0.1630	0.1526
<$1/Day – Birth Rate	rho(<$1/Day, Birth Rate| Child Mortality, Gini Index)	0.1513	0.1845

Table 6. Regressions of percentage living on two dollars or less per day on alternative causal (independent) variables

Causal Sub-Graph	Independent Variables		R^2	Elasticity at Mean (with respect to variable listed first)
Gini → $2/Day	Gini			
	.56		.04	.53
	(.29)			
Gini → $2/Day	Gini	Un-Freedom		
	.80	22.39	.21	.75
Un-Freedom	(.25)	(5.98)		
Un-Freedom → $2/Day	Un-Freedom			
	19.50		.13	1.48
	(6.28)			
Un-Freedom → $2/Day	Un-Freedom	Gini		
	22.39	.80	.21	1.70
Gini	(5.89)	(.25)		
Ag Income → $2/Day	Ag. Income			
	-.0038		.23	-.21
	(.0018)			
GDP/Person → $2/Day	GDP/Person	Un-Freedom		
	-.0074	2.74	.37	-.37
Un-Freedom	(.0015)	(6.54)		
Illiteracy → $2/Day	Illiteracy			
	.869		.54	.52
	(.076)			
Illiteracy → $2/Day	Illiteracy	Child Mort .		
	247	.266	.66	.15
Child Mort.	(.168)	(.063)		

Table 6. Cont

Causal Sub-Graph	Independent Variables		R^2	Elasticity at Mean (with respect to variable listed first)
Child Mort → \$2/Day	Child Mort. .339 (.033)		.65	.59
Child Mort → \$2/Day ↑ ↗ Illiteracy	Child Mort. .266 (.063)	Illiteracy .247 (.168)	.66	.45
Birth Rate → \$2/Day ↑ ↗ Un-Freedom	Birth Rate 1.851 (.15)	Un-Freedom 6.899 (4.16)	.68	1.16

The entries in the table refer to ordinary least squares regression estimates of the parameters associated with the independent variables listed in under the heading "Independent Variables". Under each variable is listed the coefficient estimate and its estimated standard error (the latter in parentheses). The column headed by the label "R^2" gives the coefficient of determination associated with the regression summarized in the particular row of the table. The column labeled "Elasticity at the Mean" gives the estimate of the %) \$2/Day/ %)X_i , where X_i is the variable listed first under the column "Independent Variables" when reading from left to right. The determining factor on whether there are one or more sub-graphs to represent the causal graph between \$2/Day and each independent variable is how we treat the undirected edges from Figure 4: Un-Freedom – Gini Index and Illiteracy Rate – Child Mortality. To illustrate the reason we need two "pictures" on say estimating the effect of Gini Index on \$2/Day, consider: if the edge between Gini Index and Un-Freedom runs from Gini to Un-Freedom (Gini → Un-Freedom) then to estimate the effect of Gini Index on \$2/Day we need only simple (ols) regression. However if the edge is reversed (Un-Freedom → Gini), then there is a backdoor path Gini ←Un-Freedom ← GDP/Person → \$2/day, which is not blocked by converging arrows. To estimate the effects of Gini on \$2/Day, we condition on either Freedom or GDP/Person in the regression of \$2/Day on the Gini Index. Of course, there is also the possibility that these undirected edges reflect more subtle causal relationships involving omitted variables (Lauritzen and Richardson (2002)).

Following Haigh and Bessler (2003) we scored the causal graph given in Figure 4 under all four alternative directed orderings on the two ambiguous edges found using TETRAD II: Illiteracy – Child Mortality and Un-Freedom – Gini Index. Using a modified Schwarz-loss metric we find the following:

SL_1(Illiteracy → Child Mortality and Un-Freedom → Gini Index) = 1337.9039998
SL_2(Child Mortality → Illiteracy and Un-Freedom → Gini Index) = 1337.9193124
SL_3(Illiteracy → Child Mortality and Gini Index →Un-Freedom) = 1337.9040202
SL_4(Child Mortality → Illiteracy and Gini Index →Un-Freedom) = 1337.9193329

Here $SL_i = (T)\times Log(Trace(G_i)) + (\text{number of regressors})\times log(T)$, i=1,2,3,4; where T is the number of observations used to fit the alternative models (80) and G_i is the residual variance/covariance matrix associated with model i; see Doan page 5-18 for details on the SL measure in general. As we want to minimize SL, the first metric SL_1 indicates the best model for these data.

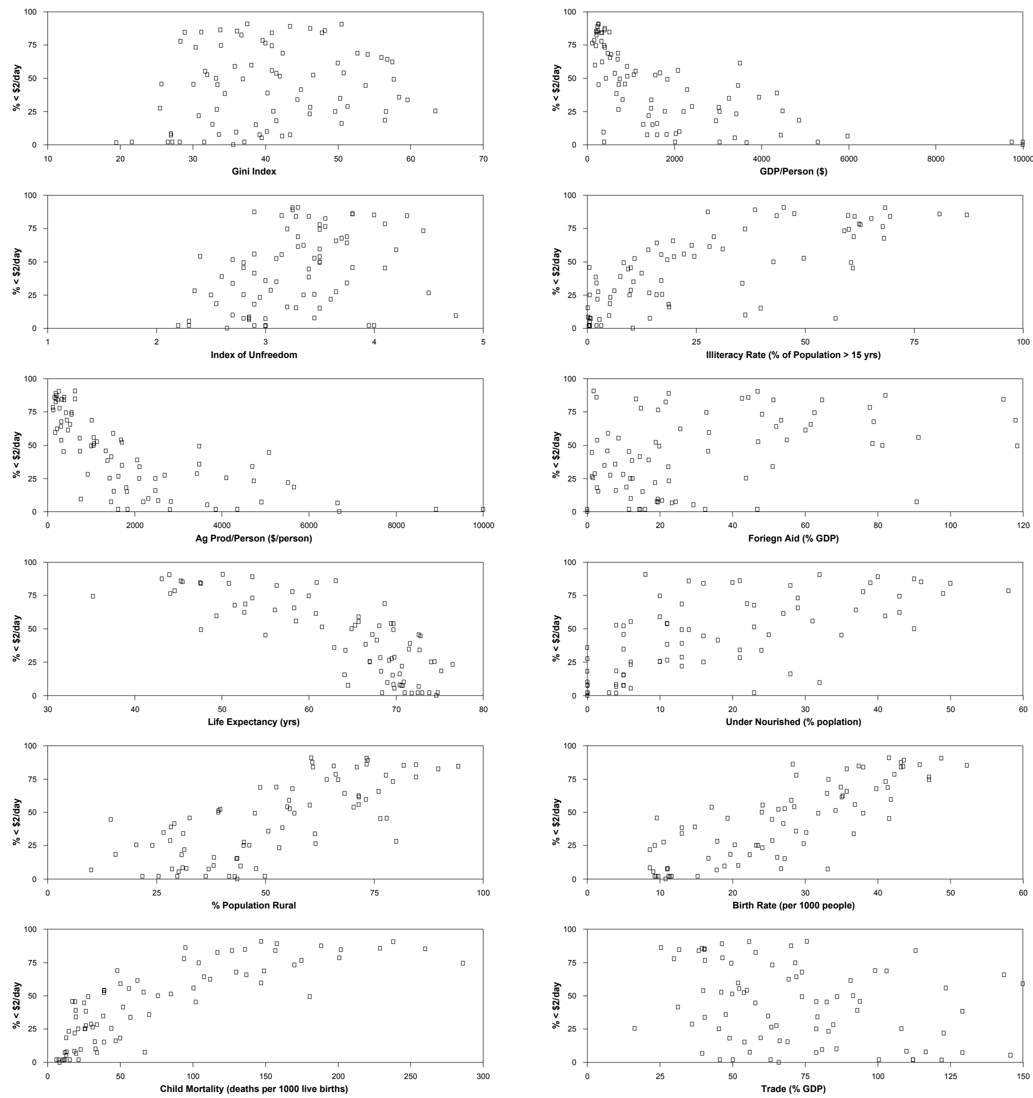


Figure 1. Scatter plots of twelve development-relevant variables and the percentage of populations living on two dollar per day or less from 80 less developed countries

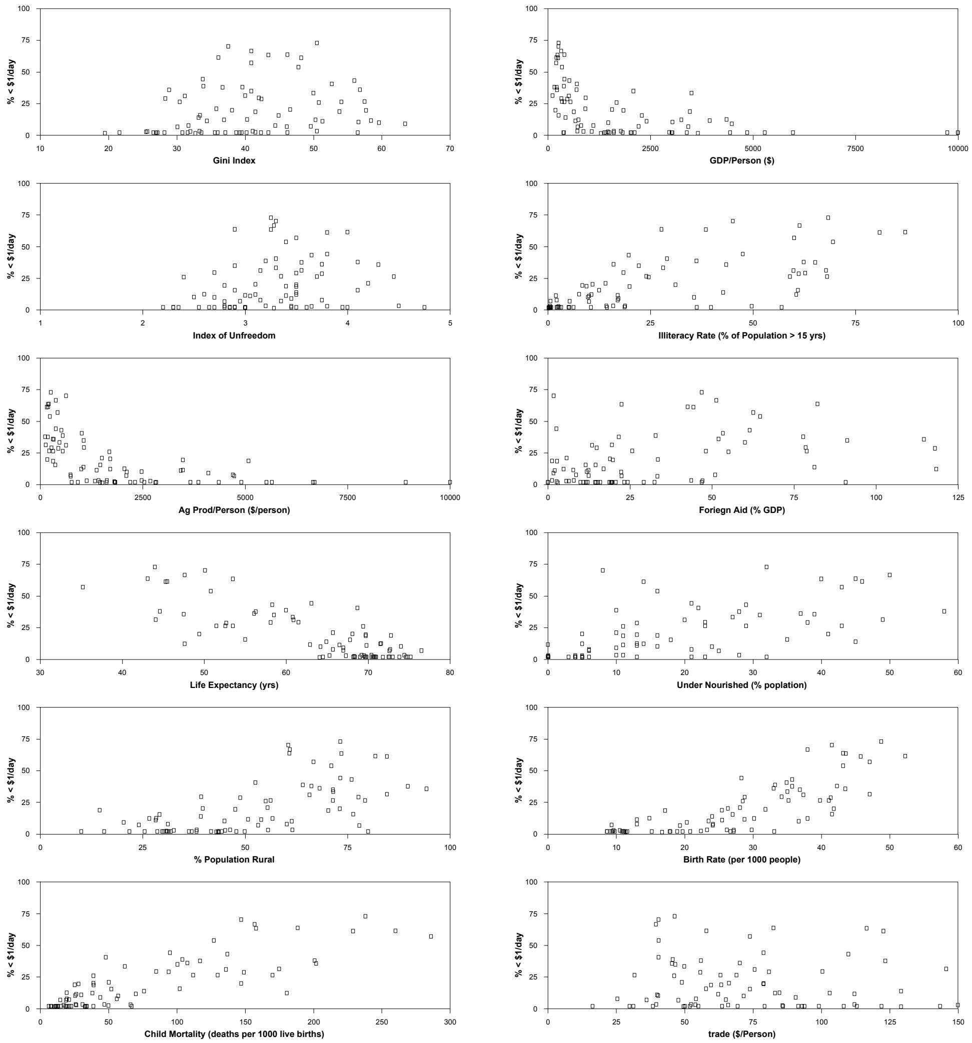


Figure 2. Scatter plots of twelve development-relevant variables and the percentage of populations living on one dollar or less per day from 80 less developed countries

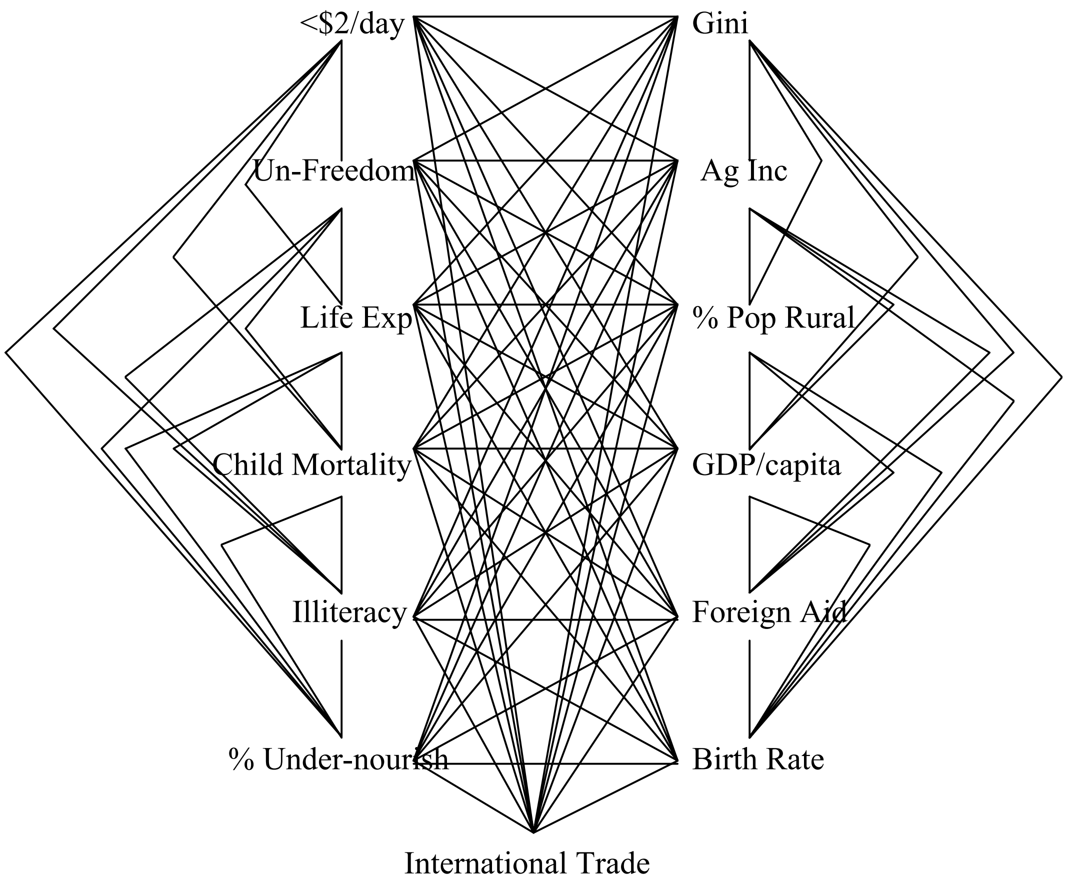


Figure 3. Complete undirected graph on thirteen development related variables

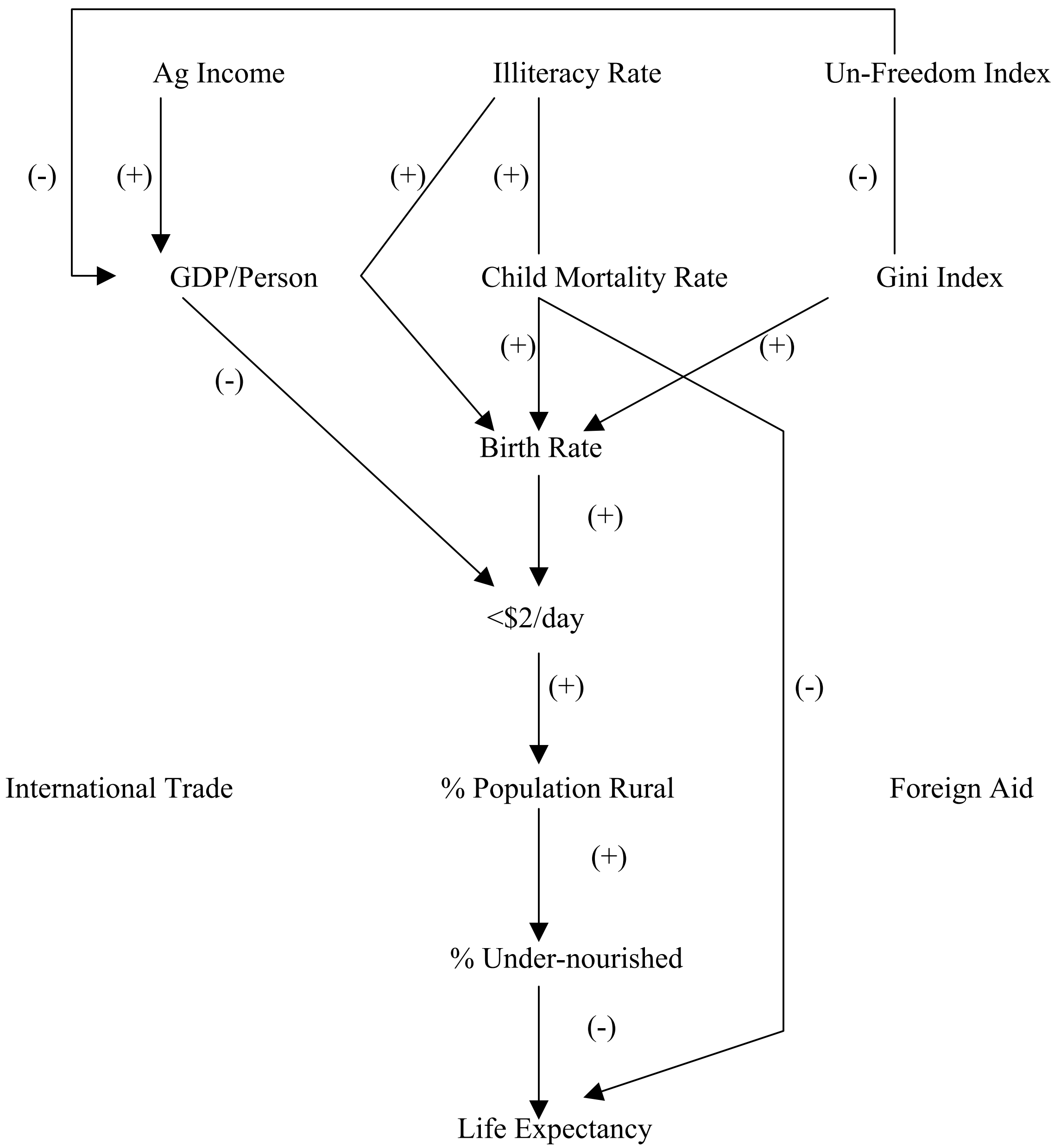


Figure 4. Pattern on thirteen development related variables including percentage of population living on two dollars and less per day, found with TETRAD II algorithm on mid-1990's data from eighty less developed countries

(The 10 percent significance level is applied for edge removal; the plus or minus (+ or -) associated with each edge is the algebraic sign on the unconditional correlation between the variables (vertices) associated with each edge.)

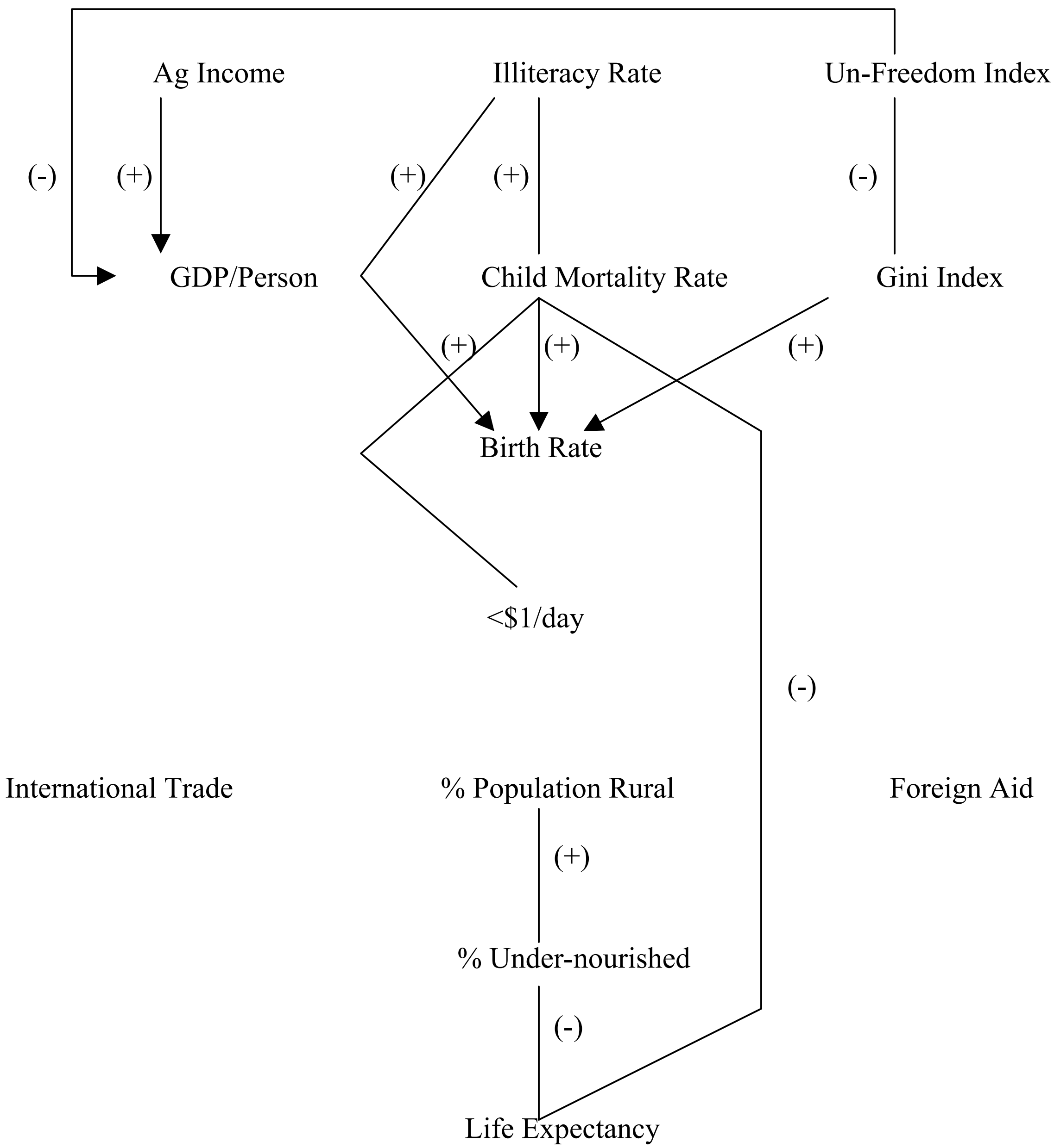


Figure 5. Pattern on thirteen development related variables, including percentage of population living on one dollar and less per day, found with TETRAD II algorithm on mid-1990's data from eighty less developed countries

(The 10 percent significance level is applied for edge removal; the plus or minus (+ or -) associated with each edge are the algebraic sign on the unconditional correlation between the variables (vertices) associated with each edge.)

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Appendix Table 1. Data

Country	$2/day	GIx	Free	Ag.Inc	L.Exp	%Rur	CldMor
Algeria	15.1	38.7	3.5	1820.00	69.60	43.40	39.00
Armenia	34	44.4	3.75	4698.00	72.70	31.10	19.50
Azerbaijan	9.6	36	4.75	767.00	69.00	44.30	22.80
Bangladesh	77.8	28.3	3.5	273.00	58.10	77.70	94.00
Belarus	2	21.6	4	3860.00	68.40	29.80	15.30
Bolivia	51.4	42	2.7	1072.00	61.50	39.30	85.00
Botswana	61.4	50	3.3	473.00	60.80	71.50	62.00
Brazil	25.4	63.4	3.45	4099.00	67.00	20.40	44.00
Bulgaria	21.9	30.8	3.6	5518.00	70.70	31.40	18.70
Burkina	85.8	48.2	3.8	158.00	45.30	84.60	229.00
C. Afr.Rep.	84	40.9	3.28	380.00	47.60	60.90	157.00
Chile	18.4	56.5	2.55	5658.00	75.20	15.60	13.00
China	53.7	41.5	3.5	316.00	69.70	70.30	39.10
Columbia	28.7	51.3	3.05	3426.00	69.80	28.20	30.00
Costa Rica	23.3	46.1	2.95	4733.00	76.50	53.20	14.80
Cote Divor	49.4	36.9	3.5	1004.00	47.60	56.70	180.60
Czech	2	26.6	2.2	4357.00	73.80	25.50	7.60
Dominican Rep.	16	50.5	3.2	2472.00	70.40	38.20	47.00
Ecuador	52.3	46.6	3.1	1710.00	68.10	39.70	39.00
Egypt	52.7	32	3.45	1133.00	65.30	55.60	66.10
El Salvador	54	50.8	2.4	1690.00	69.40	55.00	39.00
Estonia	5.2	39.5	2.3	3664.00	69.80	30.10	13.00
Ethiopia	76.4	40	3.55	136.00	44.10	84.60	175.00
Gambia	84	47.8	3.4	233.00	50.80	71.00	127.00
Georgia	2	37.1	3.95	1833.00	72.50	41.70	21.30
Ghana	74.6	33.9	3.2	554.00	60.00	64.10	104.00
Guatemala	33.8	59.6	2.7	2111.00	64.20	61.40	57.00
Honduras	68.8	52.7	3.3	1018.00	68.70	52.50	48.00
Hungry	7.3	27	3	4906.00	70.60	37.00	11.80
India	86.2	33.8	3.8	380.00	63.10	73.20	95.00
Indonesia	55.3	31.7	3.15	742.00	65.70	60.20	56.00
Jamaica	25.2	41.1	2.8	1426.00	74.40	46.30	26.00
Jordan	7.4	43.4	2.8	1458.00	70.80	28.60	34.00
Kazakhstn	15.3	32.7	3.28	1522.00	64.10	43.60	32.60
Kenya	62.3	57.5	3.35	222.00	52.60	71.40	112.00
Korea s.	2	31.6	2.3	8914.00	71.00	21.80	11.30
Lao Pdr.	73.2	30.4	4.45	554.00	53.50	79.30	170.00
Latvia	8.3	27	2.85	2540.00	69.70	31.00	18.50
Lesotho	65.7	56	3.65	516.00	58.30	76.00	137.00
Lithuania	7.8	33.6	3.45	2833.00	70.40	31.90	13.20
Madagascar	89	43.4	3.25	187.00	53.50	73.50	158.00
Mali	90.6	50.5	3.25	261.00	44.00	73.20	238.00
Mauritania	68.7	42.4	3.75	444.00	52.70	48.80	149.00
Mexico	34.8	50.3	3.1	1705.00	71.50	26.60	38.40
Moldova	38.4	34.4	3.4	1376.00	66.50	53.90	26.50
Mongolia	50	33.2	3.5	1054.00	64.90	39.20	76.00
Morocco	7.5	39.2	2.85	2197.00	64.50	47.90	67.00
Mozambique	78.4	39.6	4.1	121.00	44.60	66.20	201.00
Namibia	55.8	40.9	2.9	1062.00	58.50	71.40	100.50
Nepal	82.5	36.7	3.55	185.00	56.30	89.70	117.00

Country	$2/day	GIx	Free	Ag.Inc	L.Exp	%Rur	CldMor
Niger	85.3	36.1	4	194.00	45.50	81.80	260.00
Nigeria	90.8	37.5	3.3	629.00	50.10	60.50	147.00
Pakistan	84.7	31.2	3.15	632.00	60.90	65.70	136.00
Panama	25.1	56.6	2.5	2475.00	74.00	45.00	25.70
Paraguay	49.3	57.7	2.8	3484.00	69.70	47.60	28.00
Peru	41.4	44.9	2.9	1465.00	67.80	29.10	52.00
Poland	2	27.2	2.9	1622.00	73.00	36.30	11.90
Portugal	0	35.6	2.65	6695.00	74.60	43.60	8.20
Romania	27.5	25.5	3.65	2692.00	69.50	45.10	26.40
Russia	25.1	49.6	3.35	2105.00	67.00	24.10	21.20
Rwanda	84.6	28.9	4.3	326.00	47.50	94.30	202.00
Senegal	67.8	54.1	3.7	317.00	51.50	56.20	130.00
Sierra Leone	74.5	40.9	3.5	426.00	35.20	66.70	286.00
Slovak rep	1.7	19.5	3	2814.00	71.80	43.00	10.40
Slovenia	2	28.2	3	29860.00	74.80	49.90	6.30
So Africa	35.8	58.4	3	3486.00	62.90	50.70	70.00
Sri Lanka	45.4	30.1	2.8	746.00	72.60	77.90	19.00
Tanzania	59.7	38.1	3.5	176.00	49.40	73.10	147.00
Thailand	28.2	46.2	2.35	922.00	68.20	80.00	34.00
Trinidad	39	40.3	2.6	2057.00	71.60	28.30	19.40
Tunisia	10	40.2	2.7	2310.00	70.90	38.10	33.00
Turkey	18	41.5	2.9	1808.00	68.30	30.80	50.00
Turkmenistan	59	35.8	4.2	1506.00	65.70	55.50	50.20
Ukraine	45.7	25.7	3.8	1337.00	67.30	32.60	17.10
Uruguay	6.6	42.3	2.85	6657.00	72.60	10.00	19.80
Uzbekistan	26.5	33.3	4.5	1624.00	69.20	61.50	31.10
Venezuela	44.6	53.8	3.4	5083.00	72.80	14.50	25.20
Yemen	45.2	33.4	4.1	369.00	55.00	76.40	102.00
Zambia	87.4	46.2	2.9	210.00	43.10	60.80	188.50
Zimbabwe	64.2	56.8	3.75	312.00	56.10	68.20	107.70

Country	GDP/Per	Illt.	For Aid	Und.Nour	BR	Trade	$1/day
Algeria	1498.82	39.8	15.255	5	27.18	54.113	2
Armenia	809.75	2.13	51.035	21	13	79.23	7.8
Azerbaijan	377.68	5	19.401	32	18.9	80.897	2
Bangladesh	326.21	62.7	14.858	38	28.78	29.78	29.1
Belarus	2013.14	0.6	11.552	0.01	9.8	100.409	2
Bolivia	919.80	18.4	78.559	23	34.2	49.856	29.4
Botswana	3502.09	28.1	60.074	27	35.06	90.603	33.3
Brazil	4482.16	17.2	1.608	10	20.32	16.301	9
Bulgaria	1409.47	2.3	18.727	13	8.6	122.708	2
Burkina	244.09	80.9	44.351	14	45.8	39.464	61.2
C. Afr.Rep.	321.11	61.4	51.328	50	37.98	38.363	66.6
Chile	4858.29	5.2	10.801	4	19.7	59.645	2
China	630.19	19.9	2.706	11	17.12	39.903	18.5
Columbia	2403.14	10	2.046	13	25.5	36.044	11
Costa Rica	3419.72	5.3	22.453	6	24.1	83.071	6.9
Cote Divor	746.89	60.6	118.42	14	38	86.003	12.3
Czech	5288.01	0.6	14.343	0.01	9.3	112.129	2
Dom. Rep.	1607.97	18.8	7.865	28	26.16	66.224	3.2
Ecuador	1563.93	10.9	18.864	5	26.32	53.909	20.2
Egypt	1065.82	49.7	47.137	4	27.18	46.136	3.1
El Salvador	1669.42	24.6	54.991	11	28.52	55.007	26
Estonia	3387.42	0.6	29.266	6	9.1	145.704	2
Ethiopia	109.78	67.8	19.512	49	47.08	40.542	31.3
Gambia	340.73	69.5	64.704	16	43.2	113.014	53.7
Georgia	387.39	2.13	32.529	23	11.6	45.706	2
Ghana	385.80	36.2	32.81	10	33.24	71.558	38.8
Guatemala	1473.15	35.6	22.35	24	36.7	40.393	10
Honduras	705.55	29	53.383	22	34.94	99.107	40.5
Hungry	4441.04	0.8	19.539	0.01	11	78.799	2
India	399.51	47.5	2.544	21	28.3	25.363	44.2
Indonesia	1105.46	17	8.586	6	24.14	52.265	7.7
Jamaica	1782.69	15.9	43.69	10	23.27	108.239	3.2
Jordan	1607.98	14.4	90.784	5	33.1	129.194	2
Kazakhstn	1285.43	0.14	3.032	5	16.7	68.99	1.5
Kenya	342.13	24	25.67	43	35.2	69.362	26.5
Korea s.	11467.4	3.2	-2.57	0.01	15.2	63.116	2
Lao Pdr.	398.42	59.03	48.125	29	41.12	63.757	26.3
Latvia	2035.13	0.2	20.625	4	8.6	109.888	2
Lesotho	521.15	19.7	61.506	29	35.74	143.461	43.1
Lithuania	1819.39	0.6	19.175	0.02	11.1	116.527	2
Madagascar	235.30	38.48	22.393	40	43.62	46.324	63.4
Mali	258.38	68.4	46.918	32	48.76	55.785	72.8
Mauritania	470.88	61.2	117.971	13	41.4	103.032	28.6
Mexico	3250.63	10.6	4.745	5	30.177	62.255	12.2
Moldova	672.94	1.9	12.332	11	13	129.184	11.3
Mongolia	425.16	42.74	81.281	45	24.04	91.591	13.9
Morocco	1378.73	57	24.342	5	26.7	55.927	2
Mozambique	157.87	62.4	77.815	58	42.32	46.594	37.9
Namibia	2080.34	22.2	91.247	31	36.88	123.424	34.9
Nepal	212.10	65.2	21.582	28	35.72	58.013	37.7
Niger	205.40	87.1	42.621	46	52.28	40.409	61.4
Nigeria	256.06	45.1	1.76	8	41.56	75.59	70.2

Country	GDP/Per	Illt.	For Aid	Und.Nour	BR	Trade	$1/day
Pakistan	506.82	59.9	13.443	20	37.4	40.302	31
Panama	3039.76	9.7	11.829	16	23.5	78.874	10.3
Paraguay	1842.69	8.4	19.79	13	31.82	73.86	19.5
Peru	2293.10	12.5	14.525	18	27	31.24	15.5
Poland	3037.90	0.3	46.851	0.01	11.2	50.129	2
Portugal	11202.8	10.5	0	0.01	10.8	65.887	2
Romania	1466.32	2.5	6.328	0.01	10.5	65.107	2.8
Russia	2209.39	0.6	12.453	6	9.3	45.359	7.1
Rwanda	221.37	43.5	114.612	39	43.54	31.688	35.7
Senegal	549.71	68.1	78.911	23	39.82	73.942	26.3
Sierra Leone	196.37	60	62.61	43	47.06	49.594	57
Slovak rep	3652.90	0.6	14.671	4	11.4	122.011	1.7
Slovenia	9743.52	0.4	15.949	3	9.5	112.113	2
So Africa	3943.33	17	7.696	0.01	28.74	47.724	11.5
Sri Lanka	727.00	10	33.315	25	19.3	78.874	6.6
Tanzania	180.21	31.1	33.527	41	41.84	51.881	19.9
Thailand	3017.38	6.2	9.916	21	17.9	84.712	2
Trinidad	4356.33	7.61	16.92	13	14.85	92.946	12.4
Tunisia	2118.57	36.3	12.035	0.01	20.8	85.784	2
Turkey	2955.34	18.7	2.668	0.01	22.4	48.986	2.4
Turkmenistan	914.23	14	5.674	10	28.1	149.991	20.9
Ukraine	863.43	0.5	5.582	5	9.6	93.857	2.9
Uruguay	5975.21	2.8	23.264	4	17.8	39.642	2
Uzbekistan	716.45	14.21	1.241	11	29.8	63.437	3.3
Venezuela	3461.78	9.4	1.263	16	25.45	57.841	18.7
Yemen	263.33	61	11.499	35	41.6	82.509	15.7
Zambia	401.47	27.7	82.151	45	43.22	70.187	63.7
Zimbabwe	697.66	16	52.007	37	33.04	72.005	36