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Social or Economic Variables? Which One Reduces Poverty? A Causality Approach

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In this paper, we used the Social Progress Index (SPI) and the Global Competitive Index (GCI) as main variables, in order to identify the causal relationship between social and economic variables and the impact on poverty in the world. We used a powerful and recent econometric technique: Directed Acyclic Graphs, we conclude that SPI and GCI have an important causal relationship and is the GCI and the Gini Index the main causes of poverty, from here is possible to identify efficient public policies to eradicate poverty in the world.

I. INTRODUCTION

How do we measure development? This is still one of the most important questions in public policy analysis, if the main goal is to improve citizens' wellbeing in any country. We also wonder, what is the relationship between economic development and social progress? The general wisdom has been that economic development measured mainly by GDP per capita will lead to social progress, however this is not always the case. Also, we need to consider that sometimes social progress influences economic development.

In order to understand the relationship between economic development and social progress we used the Global Competitiveness Index as the summit of many economic variables on one hand, and the Social Progress Index as a social indicator on the other. Our main goal is to understand the relationships among these variables and their impact on poverty levels, for this, we used an econometric technique to identify causality: Directed Acyclic Graphs.

Directed Acyclic Graph methods are a new area of analysis that has emerged in the last few decades. These techniques may shed light on causality in applied econometrics. The basic or fundamental result from these efforts is embedded in the notion of *d-separation*, which formalizes notions of conditional independence between variables. The objective of this paper is to identify how Directed Acyclic Graphs perform in identifying causal relationships between economic variables, social variables and poverty levels.

This paper is organized as follows: In the first section, we present the concept of Directed Acyclic Graphs and *d-separation* and suggest why they may be used in causality. Section two describes the data used. In the third section, we present the results using a simple regression model and a Directed Acyclic Graph model, results show how the general wisdom may be misleading and how directed graphs can improve estimations of causal relationships. At the end we will give some general conclusions and recommendations.

II. DEFINITIONS

A Directed Acyclic Graph is a picture representing the causal flow among a set of variables. More formally, it is an ordered triple <**V**,**M**,**E**> where **V** is a non-empty set of variables, **M** is a non-empty set of symbols attached to the end of undirected edges, and **E** is a set of ordered pairs. Each member of **E** is called an edge. Variables connected by an edge are said to be adjacent. If we have a set of variables {**A**,**B**,**C**,**D**,**E**}: (a) the undirected graph contains only undirected edges (e.g., **A-B**); (b) a directed graph contains only directed edges (e.g., $\mathbf{B} \rightarrow \mathbf{C}$); (c) an inducing path graph contains both directed edges and bi-directed edges (e.g., $\mathbf{C} \leftrightarrow \mathbf{D}$), and (d) a partially oriented inducing path graph contains

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directed edges ($\rightarrow$), bi-directed edges ($\leftrightarrow$), non-directed edges (o-o) and partially directed edges (o$\rightarrow$). A Directed Acyclic Graph is a directed graph that contains no directed cyclic paths (an acyclic graph contains no variable more than once).

Directed Acyclic Graphs are designs for representing conditional independence as implied by the recursive product decomposition:

$$pr(x_1, x_2, x_3, \ldots, x_n) = \prod_{i=1}^{n} pr(x_i \mid pa_i) \tag{1}$$

where *pr* is the probability of vertices $x_1, x_2, x_3, \ldots x_n$ and pa_i is the realization of some subset of the variables that precede (come before in a causal sense) x_i in order ($x_1, x_2, x_3, \ldots x_n$). Pearl (1995) proposed *d-separation* as a graphical characterization of conditional independence. That is, *d-separation* characterizes the conditional independence relations given by equation (1). If we formulate a Directed Acyclic Graph in which the variables corresponding to pa_i are represented as the parents (direct causes) of x_i, then the independencies implied by equation (1) can be read off the graph using the notion of *d-separation* (defined in Pearl (1995)):

Definition: Let X, Y and Z be three disjoint subsets of vertices in a directed acyclic graph G, and let p be any path between a vertex in X and a vertex 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: (a) w has converging arrows along p, and neither w nor any of its descendants are on Z, or (b) w does not have converging arrows along p, and w is in Z. Further, Z is said to d-separate X from Y on graph G, written $(X \perp\!\!\!\perp Y|Z)_G$, *if and only if Z blocks every path from a vertex in X to a vertex in Y.*

Geiger, Verma and Pearl show that there is a one-to-one correspondence between the set of conditional independencies, $X \perp\!\!\!\perp Y|Z$, implied by equation (1) and the set of triples (X, Y, Z) that satisfy the *d-separation* criterion in graph G. In other words, given a causal graph G, the concept of *d-separation* will help to decide whether a set of variables X is independent of another set Y, given a third set Z. The criterion associates "dependence" with "connectedness" if a connecting path exists.

A path in a causal graph is defined as any consecutive sequence of arrows, disregarding their directionalities. A connecting path can be traced without traversing a pair of arrows that collide head to head, since arrows that meet head to head do not constitute a connection for the purpose of passing information. Following Spirtes, Glymour and Scheines we can view a causal graph as a pipeline carrying information flow (water). Each vertex (variable or set of variables) represents a valve, which is either closed or open. Consider three such vertices: X, Y and Z. A variable (or set of variables) is a collider if arrows converge on it: $X \rightarrow Y \leftarrow Z$. Here information on X cannot get through to Z, as the valve is closed at Y. The vertex Y is a collider and, X and Z are *d-separated*, given the null set. However, if we condition on Y, we open the valve and information is able to flow from X to Z. If information flow is characterized by diverging arrows, then the *d-separation* conditions are different. If we now have $A \leftarrow B \rightarrow C$. Here the unconditional correlation between A and C will be non-zero, as they have a common cause B. If we condition on B, the association between A and C disappears. Conditioning on common causes, blocks the flow of information between common effects. In an unconditional sense, A and C are *d-connected*, while conditioning on B, variables A and C are *d-separated*. Finally, if our causal path is one of a chain, so that D causes E and E causes F we have $D \rightarrow E \rightarrow F$. 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

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middle vertex (E) makes the end points *d-separated*.

Spirtes, Glymour, and Scheines have incorporated the notion of *d-separation* into an algorithm (PC algorithm) for building Directed Acyclic Graphs, using the notion of *sepset*. Essential for this connection is the following result: If G is a Directed Acyclic Graph with vertex set V, A and B are in V, and H is also in V, then G linearly implies the correlation between A and B conditional on H=0 if and only if A and B are *d-separated* given H.

The PC algorithm is an ordered set of commands which 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 (1993, p. 117).

Advanced versions (refinements) are described as the modified PC algorithm, the causal inference algorithm, and the fast causal inference algorithm. As the basic definition of a *sepset* is used in all and PC algorithm is the most basic, we restrict our discussion to PC algorithm. Briefly, one forms a complete undirected graph G on the variable set **V**. The complete undirected graph shows an undirected edge between every variable of the system. Edges between variables are removed sequentially based on zero correlation or partial correlation (conditional correlation). 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). 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 $\rightarrow$ Y $\leftarrow$ Z if Y is not in the *sepset* of X and Z. If X $\rightarrow$ 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 $\rightarrow$ Z. If there is a directed path from X to Y, and an edge between X and Y, then direct (X-Y) as: X $\rightarrow$ Y.

Fisher's z is used to test whether conditional correlations are significantly different from zero, where

$$z(\rho(i,j\,|\,k)n) = 1/2(n-|k|-3)^{1/2} x \ln\{(|1+\rho(i,j\,|\,k)|) x (|1-\rho(i,j\,|\,k)|)^{-1}\}$$

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. PC algorithm and its more refined extensions are marketed as the software TETRAD V (Scheines et al., 1994).[1]

Following this line of thought, Papineau described an asymmetry in causal relations. Consider three variables in Figure 1: X, Y and Z, where X causes Y and Z. Here the unconditional association between Y and Z is nonzero (as both Y and Z have a common cause in X), but the conditional association between Y and Z given knowledge of the common cause X, is zero: a common cause screens off associations between its joint effects. Let X be the level of health consciousness in the population, Y be the number of overweight persons in the population and Z be the frequency of heart disease. We can use the level of overweight persons to forecast the incidence of heart disease. That is since P(Z|Y) >P(Z) we can say that Y helps in the forecasting of Z. However, if we are able to measure the level of health consciousness in the population, the influence of the variable "overweight" disappears in the estimation of diseases: P(Z|Y,X)=P(Z|X) so we can estimate the direct relationship of X on Z, and we don't need a proxy of Y. This is an example of the common cause screening off associations between the effects. We need to condition on X to get *d-separation*. The causal structure in Figure 1 is sometimes refered as a "causal fork." We need to condition on the common cause of the fork to get *d-separation*.

[1] Notice that using the PC algorithm to define a later model to estimate could generate the problem of pre-test bias.

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On the other hand, in Figure 2 we define the case where X and Z cause Y. Here the unconditional association between X and Z is zero, but the conditional association between X and Z given the common effect Y is not zero: a common effect does not screen off association between its joint causes. If we now define X as nutrition, Y as health and Z as exercise, and we assume that nutrition and exercise are independent events, i.e. P(X|Z)=P(X), it is not useful to have information about exercise when we want to predict nutrition. However, if we know that the population has very poor health and that they exercise, we can say something about the level of nutrition, i.e. P(X|Y,Z)<P(X|Y). Here we do not need to condition on Y to get *d-separation* between X and Z. The causal structure illustrated in Figure 2 is sometimes refered to as an "inverted causal fork." We do not need to (or want to) condition on the common effect to obtain *d-separation*.

Hausman and Woodward suggest that it is false to say simply that common causes screen off their effects, and that what is relevant is to condition on all the parents of the effect. Also, in order to define the correct association between variables one needs the correct variables and the correct level of analysis. As an illustration of the problems created by not using the right variables, suppose that one finds the following results from a study of the effectiveness of a new treatment (taken from Hausman and Woodward (1999)).

From Table 1 we can see that treatment and recovery are strongly correlated, yet it could be the case that when one analyses the data further one finds the following. Among men and among women there is no correlation between treatment and recovery. The correlation in the aggregate data results from the fact that women are more likely to recover and that a larger proportion of the women than the men in the sample are treated. If the relevant cause of treatment -gender- had been included, there would be no conditional probabilistic dependence between treatment and recovery, as shown in Table 2.

The concept of conditional correlation was pointed out by Simpson and is now known as Simpson's Paradox. Any statistical relationship between two variables may be reversed or negated by including additional factors in the analysis. This means that a non-zero correlation between two variables could exist $Corr(X,Y)\neq 0$, but when we condition this correlation on another variable Z, this correlation becomes zero $Corr(X,Y\mid Z)=0$. Simpson's Paradox says that it is possible to have $P(X\mid Y)<P(X)$ and have at the same time both $P(X\mid YZ)>P(X)$ and $P(X\mid YZ')>P(X)$. This could be expressed as Y is unfavorable to X, but if we include in these analysis the effect of having Z and not having Z then Y becomes favorable to X.

For the case when we need to define the right level of analysis, consider an example due to Salmon (1985). A cue ball collides with two other billiard balls. Call the variable that measures whether or not a collision occurs C, the variable that measures whether or not the first ball goes into the corner pocket A and the variable that measures whether or not the second ball goes in the corner pocket B. Each variable can take values a, ~a; b, ~b; c, ~c. Because of the conservation of momentum, conditional on whether or not the collision (c or ~c) occurs, whether or not the first ball goes into a corner pocket (a, ~a) provides additional information about whether the second ball does (b, ~b). Hence, although C is a common cause of A and B and A and B are not related as cause and effect, C fails to screen off A from B. A more precise and informative specification of the collision event (call it C*) 'the exact momentum of the cue ball on striking the two target balls' will be a screening off common cause.

From the mathematical definition of cause and effect, we know that if we identify that X causes Y, then we can wiggle Y by wiggling X, while when one wiggles Y, X remains unchanged. Causes are viewed as levers that can be used to manipulate their effects, and it is also assumed that effects can be controlled through their causes.

A political or social scientist would be tempted to identify the causes that could guide to the desired effect in some economic or social variable. In fact,

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economic theory tries to identify this relationship while the objective of government policy makers is to identify the causes in order to apply programs that directly affect consequences like poverty level. These programs or interventions need to satisfy certain requirements in order to be effective.

Hausman and Woodward identify the characteristics that an intervention on the cause must satisfy in order to be effective on the desired effect. In addition to causing a change in the variable X, an intervention on X must not directly change the value of Y. This seems obvious, if the intervention changes Y directly we don't need to identify the cause of Y, for example reducing poverty just giving money to all poor people. However, we can think of a situation where the program is designed to generate an indirect effect. In addition, the process that changes the value of X must not also cause a change in other causes of Y, and the change in the value of X must not be correlated with such changes. If these conditions are not met, a change in the value of X could be accompanied by a change in the value of Y even though X doesn't cause Y. So, we need to define the effect of Y only through X and not via some other causal route. It is important to remember that causal claims hold even when interventions are not feasible, or are not being carried out by human beings. Even though X causes Y, interventions that change the value of X 'too much' may cause the relationship between X and Y to break down. It could be real life situations that X causes Y, but in which there is no physically possible process that will satisfy the conditions for an intervention on X. Considering the advantage of the Directed Acyclic Graph method to identify causality among variables, we used it to identify causes of poverty from the economic and social perspective, the data is described in the next section.

III. DATA STUDIED

The *World* Bank offers poverty indicators from a large number of countries, however since our main interest is to find the causal relationship among the Social Progress Index and the Global Competitive Index and their effect on poverty levels, we end up using a date set from 68 countries with available data. The list of countries studied is on Table 3.

The variables we study are as follows:

Poverty headcount ratio at national poverty lines (% of population). Source: World Bank. National poverty headcount ratio is the percentage of the population living below the national poverty lines. National estimates are based on population-weighted subgroup estimates from household surveys. Since there is not available data for all countries and all years, we estimate an average from 2005 to 2015.

Global Competitiveness Index (GCI). Source: World Economic Forum. As an economic indicator GCI "assesses the competitiveness landscape of 140 economies, providing insight into the drivers of their productivity and prosperity." We used date for 2015 and 2016.

Social Progress Index (SPI). Source: Social Progress Imperative. We used data for the year 2015. "The Social Progress Index offers a rich framework for measuring the multiple dimensions of social progress, benchmarking success, and catalyzing greater human wellbeing."

Happiness Index. Source: World Happiness Report 2016, The Sustainable Development Solutions Network from United Nations. "The World Happiness Report is a landmark survey of the state of global happiness, it describes how measurements of well-being can be used effectively to assess the progress of nations." We calculate data average from 2013 to 2015.

Gini Index. Source: World Bank. "Gini index measures the extent to which the distribution of income (or, in some cases, consumption expenditure) among individuals or households within an economy deviates from a perfectly equal distribution. A Lorenz curve plots the cumulative percentages of total income received against the cumulative number of recipients, starting with the poorest individual or household. The Gini index measures the area between the Lorenz curve and a hypothetical line of absolute equality, expressed as a percentage of the maximum area under the

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line. Thus a Gini index of 0 represents perfect equality, while an index of 100 implies perfect inequality." The data available to use in this study is an average from 2005 to 2013.

GDP per capita, PPP (constant 2011 international $). Source: World Bank. "GDP per capita based on purchasing power parity (PPP). PPP GDP is gross domestic product converted to international dollars using purchasing power parity rates." In this case we used the average from 2005 to 2014, which is the data available.

Agriculture, value added (% of GDP). Source: World Bank. "Agriculture corresponds to ISIC divisions 1-5 and includes forestry, hunting, and fishing, as well as cultivation of crops and livestock production. Value added is the net output of a sector after adding up all outputs and subtracting intermediate inputs. It is calculated without making deductions for depreciation of fabricated assets or depletion and degradation of natural resources. The origin of value added is determined by the International Standard Industrial Classification (ISIC), revision 3. Note: For VAB countries, gross value added at factor cost is used as the denominator." In this case we used average data from 2005 to 2014.

Merchandise trade (% of GDP). Source: World Trade Organization, and World Bank GDP estimates. "Merchandise trade as a share of GDP is the sum of merchandise exports and imports divided by the value of GDP, all in current U.S. dollars." We used average data from 2005 to 2014.

Government Expenditure as a percentage of GDP. Source: World Economic Forum. This is an indicator on how important are the actions and the intervention of the government in the general condition of the economy. In this case, we used data for the year 2015.

There are many other social variables considered crucial by literature in order to explain poverty, some of them are undernourishment, illiteracy rate, life expectancy and child mortality, these variables are not explicitly analyzed here since they are already included in the SPI. Remember that our main goal is to separate social and economic variables in order to identify, which one is more important to reduce poverty.

From a general analysis of the variables considered we notice many coincidences between SPI and GCI, for example: primary school enrollment, internet users, life expectancy, private property rights, corruption and number of globally ranked universities. However the correlation coefficient among this two variables is 0.68. This is not the highest correlation among the variables analyzed, the highest one is between agricultural value added and SPI with 0.81. The correlation matrix is in Table 4. The correlation matrix is an input in the TETRAD V, which uses directed acyclic graph to identify causation among variables.

IV. RESULTS

In order to analyze the relationship between social and economic variables and the impact on poverty reduction, in a statistical manner, we first use a simple regression method using poverty as dependent variable and agricultural, international trade, Gini index, government expenditure, GDP per capita, Happiness Index, Global Competitive Index and Social Progress Index as independent or explanatory variables. Our results show that the main variables related with poverty using this method are the Gini Index, Global Competitiveness Index and GDP per capita. The results are shown on table 5. We will focus our attention for the moment on the GDP per capita, is possible to jump to the conclusion that improvements on the general condition of the economy could decrease the percentage of population living in poverty, since there is a negative sign between this variables. Increases in GDP per capita reduces poverty, as it has been the general wisdom in the last few decades on poverty studies. Also, the results show that if inequality increases, measured by the Gini Index, the percentage of people living in poverty will increase. Finally, an improvement in the GCI is possible to reduce poverty. However we should remember that simple regression uses simple correlations among variables, the inclusion or deletion of some variables could change the estimate performance of the variable. This is the reason why becomes necessary to use methods

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like Directed Acyclic Graph to identify causes of poverty from economic and social variables with the software TETRAD V.

As explained in the first section, and following the directions from Bessler (2004), TETRAD V begins with the complete undirected graph, every variable is connected, without direction, to every other variable in the set. Lines are removed by way of tests that the correlation between any two variables is not different from zero. If we cannot reject the hypothesis that a particular correlation is zero at some pre-determined significance level, we remove the line connecting the two variables. TETRAD V considers all possible correlations between our nine variables.

Edges that remain are said to survive zero order conditioning (as we conditioned on no other variable to remove edges at this stage). 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. Continuing on, edges surviving tests of first order conditioning are subjected to tests of second order conditioning. TETRAD V 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 3. Arrows indicate direction of causation and a sign indicates whether an increase in the causal variable will increase (+) or decrease (-) the effect. At 5% significance level.

Our expectation is that several variables will precede, or come before in a causal sense, the variables that we want to explain which are poverty and Happiness Index. In this analysis, we allow all the variables to precede in the causal sense the two last variables that we want to explain, is possible to specify this conditions on TETRAD V.

As we can see in Figure 3 there are some exogenous variables in the explanation of poverty, this are international trade and government expenditure. In the case of the first variable we can infer that the degree of openness of the economy is not direct related with poverty conditions, although this conclusion could be very difficult to accept for an international trade specialist, we have to remember that we only have a sample of the total country number in the world with poverty indicators. The second variable could be more shocking in this result, even with many of the public policy programs used by governments in social aspects, there is no direct relationship with one of the most important wellbeing conditions of any population which his poverty. We can argue that government expenditure is directed to economic variables, like fixing market imperfections, in most countries.

The variables with direct impact on poverty are Gini index and Global Competitiveness Index (GCI), there is no direct causal relationship found between Social Progress Index (SPI) and poverty. However, we found a high causation between SPI and GCI, which can be interpreted as an indirect causal relationship from the SPI to poverty with a negative coefficient, which implies that SPI could reduce poverty in an indirect manner, as Hausman and Woodword pointed out in the characteristics of an intervention discussed in the first section. The main difference with a simple regression model is the lack of direct causation between GDP per capita and Poverty, this is a radical difference to the general wisdom on development theory, from this technique we make an inference that just an improvement in the general conditions of the economy reflected on the general population is not necessarily going to decrease poverty conditions.

There is a week relationship between agriculture value added and GDP per capita, and there is a causal direct relationship between agriculture and SPI which is a direct cause on the Happiness Index with a positive sign, meaning that and increase in social conditions increase happiness as we can expect. The other direct cause on happiness is GDP per capita also with a positive sign.

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V. CONCLUSION

In order to identify the relevance on poverty reduction by social or economic variables, we used the Global Competitiveness Index (GCI) and the Social Progress Index (SPI) with the econometric technique of Directed Acyclic Graphs. Our results shows that contrary to the general wisdom GDP per capita is not the main causation on poverty, the main causations are Gini Index and GCI. Also, there is a strong relationship between GCI and SPI which could be a good start for future research, is possible to disaggregate each one of the indicators of these indexes and their influences on poverty in the world. Another possibility is to analyze these variables by region; we will be able to prove the hypothesis that different states of the economy and social development, and different regions could generate causal impacts on poverty levels, from there is possible to propose efficient public policies on poverty reduction.

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Table 1: Treatment and Recovery

	Recovers	Does not recover
Treated	240	140
Untreated	260	350

Table 2: Treatment and Recovery by Sex

		Recovers	Does not recover
Women	Treated	200	60
	Untreated	100	30
Men	Treated	40	80
	Untreated	160	320

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Table 3: Countries used

Albania	Guatemala	Nicaragua
Armenia	Guinea	Nigeria
Azerbaijan	Honduras	Pakistan
Bangladesh	India	Panama
Benin	Indonesia	Paraguay
Bolivia	Jordan	Peru
Bosnia and Herzegovina	Kazakhstan	Philippines
Botswana	Kenya	Rwanda
Brazil	Kyrgyz Republic	Senegal
Cambodia	Lao PDR	Serbia
Cameroon	Macedonia, FYR	South Africa
Chad	Madagascar	Sri Lanka
Chile	Malawi	Tajikistan
Colombia	Malaysia	Tanzania
Costa Rica	Mali	Thailand
Croatia	Mauritania	Tunisia
Dominican Republic	Mexico	Turkey
Ecuador	Moldova	Uganda
Egypt, Arab Rep.	Mongolia	Ukraine
El Salvador	Montenegro	Uruguay
Ethiopia	Morocco	Venezuela, RB
Georgia	Namibia	Zambia
Ghana	Nepal	

Table 4: Correlation matrix from the data used

	pov	*agri*	*gini*	*trade*	*SPI*	*GCI*	*Happy*	*gov*	*gdppc*
pov	1.00								
agri	0.34	1.00							
gini	0.41	(0.22)	1.00						
trade	(0.19)	(0.19)	(0.05)	1.00					
SPI	(0.49)	(0.81)	0.18	0.24	1.00				
GCI	(0.54)	(0.58)	0.08	0.25	0.68	1.00			
Happy	(0.27)	(0.61)	0.22	0.15	0.71	0.50	1.00		
gov	(0.28)	(0.35)	(0.11)	0.28	0.39	0.06	0.13	1.00	
gdppc	(0.54)	(0.76)	0.11	0.19	0.77	0.65	0.67	0.30	1.00

Where pov is poverty level, agri is agricultural value added, gini is the Gini index, trade is the percentage of trade in the country, SPI is the Social Progress Index, GCI is the Global Competitive Index, Happy is the happiness index, gov is the government expenditure as a percentage of GDP and gdppc is GDP per capita.

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Table 5: Simple regression model

Dependent Variable: POV					
Included observations: 68					
Variable	Coefficient	Std. Error	t-Statistic	Prob.	
C	88.51073	21.45585	4.125249	0.000	
AGRI	-0.33297	0.20758	-1.604054	0.114	
TRADE	0.014168	0.053219	0.266228	0.791	
GINI	0.742396	0.140985	5.265798	0.000	signigicant
GOV	-0.18287	0.166866	-1.095913	0.278	
GDPPC	-0.000839	0.000342	-2.452943	0.017	signigicant
GCI	-12.27249	4.509167	-2.721675	0.009	signigicant
SPI	-0.373056	0.265198	-1.406704	0.165	

Where pov is poverty level, agri is agricultural value added, gini is the Gini index, trade is the percentage of trade in the country, SPI is the Social Progress Index, GCI is the Global Competitive Index, gov is the government expenditure as a percentage of GDP and gdppc is GDP per capita.

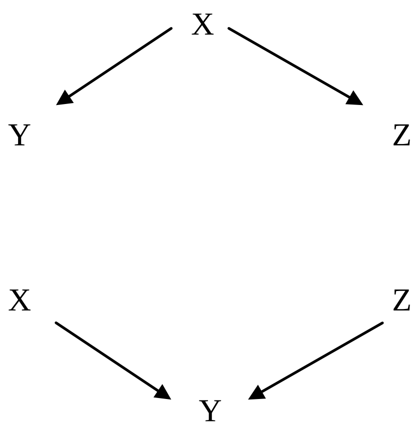

Figure 1: Causal Fork

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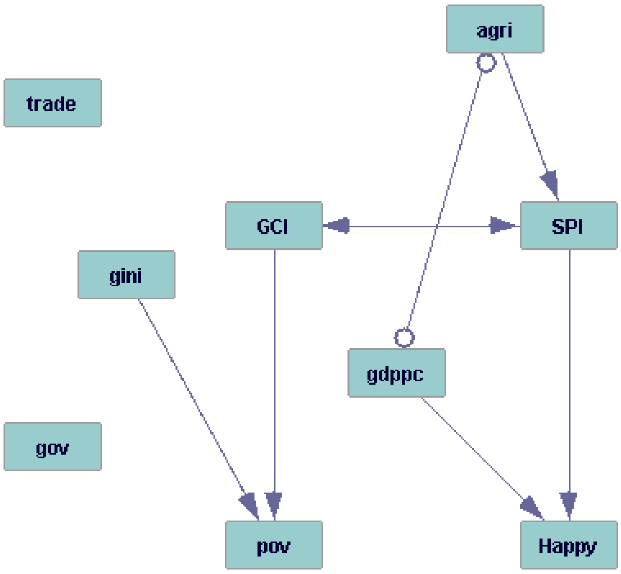

Figure 2: Inverted Causal Fork

Figure 3: DAG on nine social an economic variables

Where pov is poverty level, agri is agricultural value added, gini is the Gini index, trade is the percentage of trade in the country, SPI is the Social Progress Index, GCI is the Global Competitive Index, gov is the government expenditure as a percentage of GDP and gdppc is GDP per capita.

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