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Path Modeling of Global warming with CO_2 Emission as a Surrogate

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Abstract: *Path Analysis is the statistical technique used to examine causal relationships between two or more variables; the technique was used to develop an exploratory Path model of global warming, using Carbon dioxide (CO_2) emission as a surrogate. Some factors which are assumed to have some causal relationship with CO_2 emission were considered. The correlation analysis result shows significant relationships between CO_2 emission and the selected factors which include; Energy consumption, Manufacturing output, Industrial output and Gross domestic product (GDP), at 5% significant level with the following correlation coefficients; r_1=0.892, r_2==0.935, r_3==0.986, r_5= 0.908 respectively). Path model developed shows that, energy consumption, manufacturing output and industrial output have both direct and indirect effects on global warming while GDP has only direct effect on global warming. This is a clear indication that GDP of any country could give an insight to the level of CO_2 being emitted by that country.*
Keywords: Causal relationship, CO_2 emission, Factors, Global warming and Path analysis,

I. Introduction

Path Analysis is the statistical technique used to examine causal relationships between two or more variables, and it is based upon a linear equation system. It could also be said to be a method for the decomposition and interpretation of relationships among variables in linear causal models using multiple regression or correlation procedures. It also aids in quantitative understanding of population genetics (Wright, 1921). However, little use was made of this technique until it was introduced to the social sciences by Duncan [2] Since then it has proved to be a useful approach in quantifying and interpreting causal theory. Path analysis is used mainly in an attempt to understand comparative strengths of direct and indirect relationships among a set of variables. In this way, it is unique from other linear equation models: In path analysis mediating pathways can be examined, and pathways in path models represent hypotheses of researchers, and can never be statistically tested for directionality [3] Path analysis is a subset of Structural Equation Modeling; a multivariate procedure which, as defined by Ullman [4], "allows examination of a set of relationships between one or more independent variables, either continuous or discrete, and one or more dependent variables, either continuous or discrete. In statistics, it is used to describe the direct dependencies among a set of variables, as such, its model is equivalent to any form of multivariate analysis. It is used in solving the problem of causal interpretation and provides information about indirect and direct effects on a dependent variable. It allows scientists to use their knowledge of the system under consideration by sequentially ordering the variables in a linear causal model which represents the causal processes assumed to operate among the variables in nature. However, it must be emphasized that path analysis is dependent on the availability of sufficient knowledge of the subject matter to construct realistic causal models and that the direction of assumed causal effects is determined entirely from an understanding of the processes under study. Hence, this study is interested in modeling Global warming, using Carbon dioxide (CO_2) emission as a surrogate. Carbon dioxide (CO_2) is recognized as a significant contributor to global warming and climatic change and it is the primary greenhouse gas emitted through human activities. In 2011, CO_2 accounted for about 84% of all U.S. greenhouse gas emissions from human activities [5]. It has been observed that due to rapid industrialization, energy demand and consequently CO_2 emission; owing to increased use of fossil fuels are expected to increase [6]. Though, CO_2 emissions come from a variety of natural sources but human-related emissions are responsible for the increase that has occurred in the atmosphere since the industrial revolution.[7]. Industrial activities, which includes manufacturing is among the major sources of CO_2 emission [5]. In this study, CO_2 emission and variables believed to be contributing to CO_2 emission were considered. We call these variables contributing variables.

II. Methodology

Using data collected from [8] on list of countries by their CO_2 emission and data on contributing variables collected from [9]; the method of Path analysis were applied. The data are shown on TABLE 1 below

Table 1: CO_2 Emission and Contributing Variables.

S/N	Countries	CO2emission in thousand metric tons	GDP in $ bn	Industrial output in $ bn	Export output in $ bn	Consumption of energy in million tones	Manufacturing output $ bn
1	United States	6,049,435	11711.8	2,271	12.06	2,280.8	1,523
2	China	5,010,170	1,931.7	893	5.33	1,409.4	889
3	Russia	1,524,993	581.4	182	1.69	639.7	138
4	India	1,342,962	691.2	171	1.14	553.4	101
5	Japan	1,257,967	4,622.8	1,308	5.91	517.1	894
6	Germany	808,767	2,740.6	721	9.33	347.1	495
7	Canada	639,403	978.0	285	3.21	260.6	177
8	United kingdom	587,261	2,124.4	496	6.20	232.0	319
9	South Korea	465,643	691.2	247	2.43	205.3	174
10	Italy	449,948	1,677.8	417	3.85	181.0	294
11	Mexico	438,022	676.5	162	1.63	160.0	111
12	South Africa	437,032	212.8	61	0.47	118.6	38
13	Iran	433,571	163.4	67	0.38	136.4	18
14	Indonesia	378,250	257.6	113	0.72	161.6	73
15	France	373,693	2,046.6	399	5.08	271.3	255
16	Brazil	331,795	604.0	211	0.88	193.2	57
17	Spain	330,497	1,039.9	274	2.35	136.1	153
18	New-Zealand	31,570	98.9	25	0.24	100.1	25
19	Australia	326,757	637.3	124	1.00	112.6	57
20	Saudi Arabia	308,393	250.6	147	533.7	136.1	25
21	Poland	307,238	242.3	96	0.77	93.7	41
22	Thailand	268,082	161.7	70	0.93	88.8	56
23	Turkey	226,125	302.8	56	0.74	79.0	35
24	Algeria	194.001	84.6	44	0.35	55.4	25
25	Malaysia	177,584	118.3	60	116	56.7	37
26	Venezuela	172,623	110.1	41	0.43	50.5	19
27	Egypt	158,237	78.8	27	0.38	126.1	24
28	United Arab Emirates	149,188	104.2	57	0.77	68.5	58
29	Netherlands	142,061	579.0	132	3.49	80.8	68
30	Argentina	141,786	153.0	50	0.38	59.9	34
31	Pakistan	125,669	96.1	58	1.14	69.3	63
32	Czech Republic	116,991	107.0	37	0.62	60.3	25
33	Nigeria	114025	58	40	0.47	41.8	40
34	Belgium	100716	352.3	80	2.73	97.3	49
35	Greece	96,695	205.2	42	0.41	27.5	18
36	Israel	71,247	116.9	60	0.42	27.5	17
37	Austria	69,846	292.3	81	1.42	107.5	45
38	Chile	62,418	94.1	38	3.56	87.7	58
39	Hungary	57,183	100.7	35	0.53	50.5	22
40	Colombia	53634	97.7	27	0.87	159	58
41	Sweden	53,033	346.4	87	1.52	104.7	44
42	Denmark	52,956	241.4	51	0.98	105.1	29
43	Singapore	52,252	106.8	35	1.22	100	29
44	Switzerland	40,457	357.5	76	1.99	108.0	53
45	Hong Kong	37,411	163.0	78	0.98	100	24
46	Norway	87,602	250.1	87	0.96	135.1	19
47	Philippines	80,512	84.6	27	0.43	56.5	20
48	Finland	65,799	185.9	50	0.64	103.1	32
49	Portugal	58,906	167.7	39	0.46	27	22
50	Ireland	42,353	181.6	56	1.53	103.8	42

From TABLE 1 above, the data were classified as exogenous (independent) and endogenous (dependent) variables. In path analysis the exogenous variables are those that are predetermined, that is, whose total variation is assumed to be caused by variables outside the set under consideration. No attempt is made to explain their variability. Endogenous variables are those whose variation is assumed to be determined by some linear combination of the variables under consideration; all are ultimately determined by the exogenous variables in the system. The endogenous variables requires the construction of a linear causal model, written as a set of structural equations representing the causal processes assumed to operate among the variables in nature. It is assumed that each relationship in the model is linear and that the model is recursive, implying that there are no reciprocal effects or feedback loops. The model used in this study is represented in Fig.1 below in a simplified form.

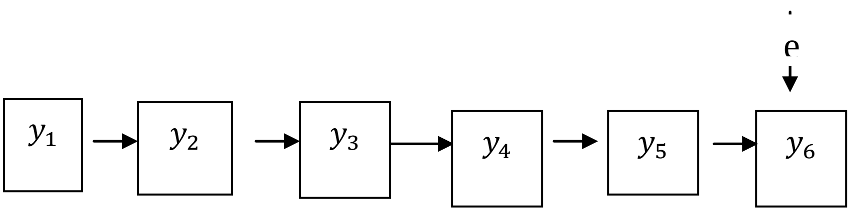

Figure1. path diagram of the exogenous and endogenous variables

Each endogenous variable enters the pathway sequentially from left to right. Once entered, each variable is assumed to have an effect on every other endogenous variable added subsequent to it. Each disturbance variable represents all the unmeasured and residual causes of an individual endogenous variable which are not explicitly identified in the model; the disturbance variables are assumed to be uncorrelated with each other and with the exogenous variable. One of the important applications of path analysis is the analysis of correlation into various components. Within a given causal model it is possible to determine what part of a correlation between two variables is due to the direct effect of a cause and what part is due to indirect effects through other variables. It involve a technique for dealing with a complex system of interrelated variables, which, from the theoretical point of view and prior knowledge, are considered as affecting the behaviour of some other variables. Its primary role, is therefore, not merely to provide a format for presenting conventional calculations for predictive purposes as does regression analysis, but to render an interpretation for a complex system of relationships. In Path analysis the ordering of the independent variables is not arbitrary, but is determined by the theoretical considerations that generated the model under study. The Variables are defined according to assumed causes. In view of these, the following relationships were generated among the selected variables based on the assumed theoretical causal relationship.

y_6= F(y_1, y_2, y_3, y_4, y_5)
y_5 = F($y_1, y_2, y_3, y_4,$)
y_4,= F($y_1, y_2, y_3,$)
y_3, = F(y_1, y_2) (1)
y_2, = F(y_1)

From the relationship above, the following equation apply;

y_6, =b_{6o} + $b_{61}y_1$, + $b_{62}y_2$, + $b_{63}y_3$, +$b_{64}y_4$, +$b_{65}y_5$,
y_5, =b_{5o} + $b_{51}y_1$, + $b_{52}y_2$, + $b_{53}y_3$, +$b_{54}y_4$,
y_4, =b_{4o} + $b_{41}y_1$, + $b_{42}y_2$, + $b_{43}y_3$,
y_3, =b_{3o} + $b_{31}y_1$, + $b_{32}y_2$, (2)
y_2, =b_{2o} + $b_{21}y_1$,
y_1, =b_{1o}

Wherey_1=Energy consumption, y_2 = Manufacturing output, y_3 = Industrial output,y_4 = Export output,y_5 = Gros s
domestic product y_6=CO_2 emission.
The endogenous variable is y_6 =CO_2 emission while the exogenous variables are;
y_1=Energy consumption, y_2 = Manufacturing output, y_3 = Industrial output, y_4= Export output, y_5 = Gross domestic product (GDP)

2.2. Assumptions: The assumptions for the type of path analysis that will be employed in this study are as follows

1. All relations are linear and additive. The casual assumptions are shown in the path diagram.
2. The residuals are uncorrelated with the variables in the model and with each other.
3. The casual flow is one-way

To build the Path model, we obtain the partial derivatives of (2) above in other to obtain the direct and indirect effects of the various variables; thus

$\frac{\delta y_6}{\delta y_1} = b_{61}\ \frac{\delta y_1}{\delta y_1} + b_{62}\ \frac{\delta y_2}{\delta y_1} + b_{63}\ \frac{\delta y_3}{\delta y_1} + b_{64}\ \frac{\delta y_4}{\delta y_1} + b_{65}\ \frac{\delta y_5}{\delta y_1}$

Therefore the total effect of y_1 on y_6 is given as

$\therefore B_{61} = b_{61} + b_{62}.b_{21} + b_{63}.b_{31} + b_{64}.b_{41} + b_{65}.b_{51}$ which implies

Total = Direct + Indirect (3)

Where B_{61} is the total effect of y_1 on y_6, b_{61} is the direct effect of y_1(independent variable) on y_6 (dependent variable), the cross products $b_{62}.b_{21}$, $b_{63}.b_{31}$, $b_{64}.b_{41}$, $b_{65}.b_{51}$.are the indirect effects of y_1 on y_6

Taking partial derivative again with respect to y_2

$\frac{\delta y_6}{\delta y_2} = b_{61}\ \frac{\delta y_1}{\delta y_2} + b_{62}\ \frac{\delta y_2}{\delta y_2} + b_{63}\ \frac{\delta y_3}{\delta y_2} + b_{64}\ \frac{\delta y_4}{\delta y_2} + b_{65}\ \frac{\delta y_5}{\delta y_2}$

But $\frac{\delta y_1}{\delta y_2} = 0$ since $y_2 \neq y_1$ meaning that the variable y_2 does not affect the variable y_1

Therefore the total effect of y_2 on y_6 is given as

$\therefore B_{62} = b_{62} + b_{63}.b_{32} + b_{64}.b_{42} + b_{65}.b_{52}$ which implies

Total = Direct + Indirect (4)

Where B_{62} is the total effect of y_2 on y_6. b_{62} is the direct effect of y_2(independent variable) on y_6(dependent variable), the cross products $b_{63}.b_{32}$, $b_{64}.b_{42}$, & $b_{65}.b_{2}$.are the indirect effects.

Taking partial derivative again with respect to y_3

$\frac{\delta y_6}{\delta y_3} = b_{61}\ \frac{\delta y_1}{\delta y_3} + b_{62}\ \frac{\delta y_2}{\delta y_3} + b_{63}\ \frac{\delta y_3}{\delta y_3} + b_{64}\ \frac{\delta y_4}{\delta y_3} + b_{65}\ \frac{\delta y_5}{\delta y_3}$

but $\frac{\delta y_1}{\delta y_3}$ and $\frac{\delta y_2}{\delta y_3} = 0$, $\frac{\delta y_3}{\delta y_3} = 1$

Meaning that the variable y_3 does not affect the variable y_1 and the variable y_3 does not affect the variable y_2

Therefore the total effect of y_3 on y_6 is given as

$B_{63} = b_{63} + b_{64}.b_{43} + b_{65}.b_{53}$ which implies

Total = Direct + Indirect (5)

Where B_{63} is the total effect of y_3 on y_6, b_{63} is the direct effect of y_3 (independent variable) on y_6 (dependent variable), the cross products $b_{64}.b_{43}$, & $b_{65}.b_{53}$,.are the indirect effects

Taking partial derivative again with respect to y_4

$\frac{\delta y_6}{\delta y_4} = b_{61}\ \frac{\delta y_1}{\delta y_4} + b_{62}\ \frac{\delta y_2}{\delta y_4} + b_{63}\ \frac{\delta y_3}{\delta y_4} + b_{64}\ \frac{\delta y_4}{\delta y_4} + b_{65}\ \frac{\delta y_5}{\delta y_4}$

but $\frac{\delta y_1}{\delta y_4} = 0$, $\frac{\delta y_2}{\delta y_4} = 0$, $\frac{\delta y_2}{\delta y_4}{}_3 = 0$

Therefore the total effect of y_4 on y_6 is given as

$B_{64} = b_{64} + b_{65}.b_{54}$ which implies

Total = Direct + Indirect (6)

Taking partial derivative again with respect to y_5

$\frac{\delta y_6}{\delta y_5} = b_{61}\ \frac{\delta y_1}{\delta y_5} + b_{62}\ \frac{\delta y_2}{\delta y_5} + b_{63}\ \frac{\delta y_3}{\delta y_5} + b_{64}\ \frac{\delta y_4}{\delta y_5} + b_{65}\ \frac{\delta y_5}{\delta y_5}$

But $\frac{\delta y_1}{\delta y_5} = 0$, $\frac{\delta y_2}{\delta y_5} = 0$ $\frac{\delta y_3}{\delta y_5} = 0$ $\frac{\delta y_4}{\delta y_5} = 0$

Meaning that the variable y_5 does not affect the variable y_1, the variable y_5 does not affect the variable y_2, the variable y_5 does not affect the variable y_3 , and the variable y_5 does not affect the variable y_4 .

$\therefore B_{65} = b_{65}$
Total = Direct (7)

Where B_{65} is the total effect of y_5 on y_6 ,b_{65} is the direct effect of y_5 (independent variable) on y_6 (dependent variable).

To develop the Path model, it requires the correlation coefficients as contained in TABLE 2 below;

Table 2. Correlation Analysis of CO_2 Emission and Contributing Variables.

	y_1	y_2	y_3	y_4	y_5	y_6
y_1	1	0.799	0.847	-0.012	0.982	0.892
y_2	0.799	1	0.972	-0.027	0.863	.935
y_3	0.847.	0.972	1	-0.006	0.884	0.986
y_4	-0.012.	-0.027	-0.006	1	-0.020	-0.044
y_5	0.982.	0.863	0.884	-0.020	1	0.908
y_6	0.892	0.935	0.986	0.044	0.908	1

The interpretation of the results of path analysis in this study was based on the methods of Alwin & Hauser [10] and Duncan [11].A zero-order correlation coefficient expresses the degree of linear relationship between two variables and it can be regarded as a measure of their total association, made up of 3 distinct components:
(a) Direct effect being that effect not transmitted via intervening variables but remaining when all other variables have been held constant - measured by the path coefficient;
(b) Indirect effects being those effects mediated through intervening variables, each given by the product of the path coefficients in the appropriate indirect pathways;
(c) 'Spurious' correlations being those correlations due to joint dependence on an antecedent variable (i.e. common 'cause') and to correlated exogenous variables. Based on these interpretations, the following path model applies;

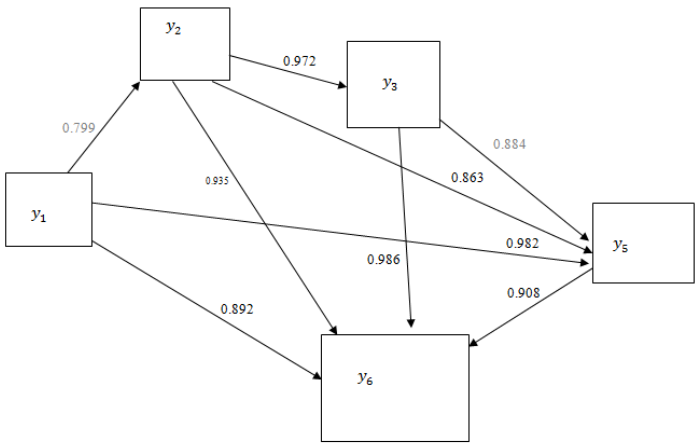

Figure 2 path model of global warming

In the model above, the exogenous variables (y_1,y_2,y_3 and y_5) are modeled as being correlated and as having direct effects on y_6 (the dependent or 'endogenous variable. In most real models, the endogenous variables are also affected by factors outside the model (including measurement error). The effects of such extraneous variables are depicted by the 'e' or 'error' terms in the model as shown in figure 2 above. Also, from: (3) – (6), the total effects are decomposed into direct and indirect effect, but in: (7) the total effect is just direct on y_6. This is implies that the effect of GDP is direct on CO_2 emission. This is understandable since the GDP of any country is measured by all the economic activities that goes on in that country which in turn amounts to their level of CO_2 emission that contributes to global warming. It is pertinent to mention that y_4 was not included in the model because the result of the analysis indicates that it is not a good predictor.

III. Conclusion

The Path model developed in Fig.2 above based on this study could be used to estimate global warming since all the variables considered have an average of 80% effect on CO_2 emission which is used as a surrogate of global warming. According to the correlation analysis on TABLE 2, the selected variables were statistically significant at 5% significant level. This indicates that based on this study, the variation in CO_2 emission could be traceable to these variables. According to path analysis result, the correlation coefficient of 0.892, 0.935, 0.986 and 0.908 respectively were due to direct effect of the selected variables on CO_2 emission which causes global warming, while 0.799, 0.972 and 0.884 respectively were due to indirect effect of the selected variables on global warming. The highest percentage for the direct effect was due to industrial output (y_3) with 0.986, which shows that global warming increases with increase in industrial activities. As a matter of fact one would not advocate for reduction in industrial activities in other to reduce global warming rather an alternative approach should be thought of. Therefore this study suggests that industries should adopt a symbiotic method of operation by also engaging in activities that requires the use of CO_2.

References

[1] WRIGHT, S. (1921).Correlation and causation. *Journal of Agricultural Research 20*, 557-85.
[2] Duncan, O.D.(1966).Path analysis: sociological examples. *American Journal of Sociology 72,* 1-16.
[3] Shipley, B. (1997). Exploratory path analysis with applications in ecology and evolution. *The American Naturalist. 149 (6)*,1113-1138.
[4] Ullman. J.B. (1996). Structural equation modeling: Using *Multivariate Statistics*.3, (B.G. Tabachnick and L.S. Fidell, Edition, HarperCollins College Publishers, New York) 709-819.
[5] United States Environmental Protection Agency, Carbon Dioxide Emission.*http://www.epa.gov/climatechange/ghgemissions/gases/co2.html Assessed 14th January,2014*.
[6] Ang,B.W Ang (2004)Growth curves for long term global CO_2 emission reduction analysis, *Energy policy 32*, 2004, 1569-1572
[7] NRC (2010). Advancing the Science of Climate Change. *National Research Council. The National Academies Press, Washington, DC, USA*
[8] CDIAC (2006) List of Countries by Carbon dioxide emissions. Data collected by the US Deprtment of Energy's Carbon Dioxide Analysis Center (CDIAC). *http://en.wikipedia.org/wiki/list-of-countries-by-carbon-dioxide-emissions-per-capita.*
[9] *The Economist fact book* (2007) List of countries by their GDP, Industrial output, manufacturing output, Energy consumption, and export output
[10] Alwin, D. F. and Hauser, R. M. (1975).The decomposition of effects in path analysis. *American Sociological Review. 40*, 37-47.
[11] Ducan, O. D. (1975**).** *Introduction to Structural Equation Mode1s*. (New York: Academic Press).