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IPAT MODEL ANALYSIS FOR AIR POLLUTION MANAGEMENT IN MALAYSIA

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Abstract

Air pollutants can be either gases or aerosols with particles or liquid droplets suspended in the air. They change the natural composition of the atmosphere, can be harmful to humans and other living species and can cause damage to natural water bodies and the land. Anthropogenic specifically due to the human causes that in this study, it has been identified that Population, Gross Domestic Product (GDP) and Manufacturing Industry adaptive from IPAT Model, are the major contributors to the emission of carbon dioxide. The air pollution measurement was adapting from the model being developed by Cramer (1998), Dietz and Rosa (1997), Shi (2003) and York et al. (2003a, b) and the application is based on a stochastic and non-tautological version of the famous IPAT model that originated from a dispute between Commoner, Corr and Stamler (1971) and Ehrlich and Holdren (1971). The IPAT model acknowledges the effects of population magnitude on the environment. However, according to Fischer-Kowalski & Amann (2001), T is a rather fuzzy category that might involve variations other than population and affluence.

Keywords: Air Pollution, IPAT Model, Population, GDP, Manufacturing Industry, Polution management

INTRODUCTION

A change in economic structure, which is seen as the growth of the manufacturing industry, affects the amount carbon emissions. This happens as a particular economy shifts from subsistence to an agricultural economy and later, to an industrial economy. In this case pollution levels increase as the result the significant as well as instrumental changes in the manner of the production processes. Moreover, the trade policy which comes under the major activity in Gross Domestic Product (GDP) stipulates that the more open an economy, the greater the possibilities for importing and exporting pollution intensive commodities, and to another end, the lower or higher the domestic pollution levels. Another matter that warrants attentions is the condition of economic scale. It considers the magnitude of a population; the bigger the economy, the greater the pollution, and this happens as everything else remains constant. These three questions describe the problem statement of this following research. This research investigates the impacts of population density, Gross Domestic Product (GDP) and the manufacturing industry with regards to the links between the growth of population and the environment.

Furthermore, such investigation also contributes to the argument that the size of the population and other determinants must be given due consideration in the forecasting of air pollutant emissions. This study is therefore, very much related to the vast and dynamic literature related to the Environmental Kuznets Curve (EKC). The EKC states that pollution with regards to the environment increases and decreases along the rise in per capita income levels. Examples of this can found in the research done Cole, Rayner & Bates (1997), Grossman & Krueger (1995) all of whom analyzed the impacts highlighted. Population is often included only as a scale variable in EKC studies.

There are very few systematic quantitative empirical studies on the relationship between population and pollution that are explicitly examined. Cramer (1998, 2002) along with Cramer and Cheney (2000) studied the effects of population magnitude on the level of air pollution in the U.S state of California came up with conclusion that some sources of emissions are closely related to the population while others not. However, the global implications of Cramer's and Cramer and Cheney's work are not adequate; this is due to them limiting their attention on only one state in a developed country as the U.S and as such, their main result is far from robust. Dietz and Rosa (1997), together with York, Rosa and Dietz (2003a, b) in their studies which focus on the emissions of CO2 and energy use, investigated the roles played by population, affluence and technology by adopting the Impact-Population-Affluence-Technology (IPAT) model. They found out that the ratio of change between energy use and CO2 emissions is bordering on unity. For example, it was estimated that an approximately one percent increase in CO2 emissions is the result of one percent increase in population. But, Dietz and Rosa (1997), along with York, Rosa and Dietz (2003a, b) did not make projections as to how such elasticity might differ with population levels. Moreover, these results are derived from a one year- cross-sectional study. Shi (2003), utilizing IPAT model too, employs a group of cross-sectional and time series data for similar investigation. Shi found the population elasticity for CO2 to be around 1.41 and 1.65. But, he also did not study how different population size might affect the kind of result that is to be obtained from such study.

Anthropogenic air pollution sources can be categorized based on different criteria. One criterion categorizes the source in terms of its mobility, whether it is mobile or otherwise. The former refers to traffic-related sources, which includes ground traffic (buses, private vehicles, taxis, etc.), underground traffic (metro or subway) and air traffic, the latter mainly referring to industrial, commercial or personal emissions. Traffic related sources of air pollution are becoming an increasing concern among interested exposure assessors, epidemiologists, as well as toxicologists. Ground level traffic vehicles in urban areas are typically natural gas fuelled, gasoline or diesel fuelled. Both physical and chemical characteristics are different, with reference to specific regions, in terms of benzene content (Verma and Tombe, 2002), making it complex for the findings of one location to be generalized to others. This complexity in generalization across studies in further complicated by different meteorological conditions, different percentages of heavy polluters; for example the increase in the composition of motorcycles in developing countries, design of motorways; graded or non-graded, driving habits, difference in maintenance as well as quality of and control measures for vehicles, and exposure profiles of people (Gwilliam, 2003). Compared to the large volume and variety of study carried out in developed nations, exposure assessment studies in developing nations are relatively scarce. Despite revised emission standards and technical improvements in pollution control measures, expanding industrialization and increase in traffic volumes of developing nations will drastically increase total emissions of many air pollutants, as predicted by a study on air pollutant trends of East Asian countries (Klimont et al., 2001).

LITERATURE REVIEW

The scope of the literature is limited to three variables based on the IPAT Model proposed by Commoner, Corr and Stamler (1971) and Ehrlich and Holdren (1971). Most of the researchers claimed their models to be the best and come with minimum error. The IPAT model is based on the equation I = f (P, A, T), in which I represents environmental impact with *P, A* and *T* represented by the variables population, affluence and technology respectively. However, given the limitation in terms of the availability of data, the variables are modified with I referring to Air Pollution Index (API), *P*referring to Population and A being affluence. The manufacturing Industry, on the other hand is the agent for *T*. However, most of the economists, environmentalists and scientists do not give due consideration to the importance of IPAT Model in their study.

The IPAT model acknowledges the effects of population magnitude on the environment. Occasionally, according to Daily and Ehlirch (1992) given the complications in determining the *A* and *T*, the amount of energy (per capita) used is often adopted as a proxy for their result. Dietz and Rosa (1994) found that some researchers equate the role of T to that of the impact *(I)* of an economic activity, whereas for the researchers like Fischer-Kowalski and Amann (2001), T is a rather fuzzy category that might involves variations other than population and affluence. The IPAT equation first came to being in the early 1970s, being the result of the study done by Ehrlich, Holdren and Commoner. This impact equation was initially mentioned in a paper by Ehrlich and Holdren in 1971 in the early form of *I* = *P.F*, with F being the function that estimates the per capita impact. However, they showed considerable concern when a number of analysts undermine the importance of population increase. Such concern can be summarized in two points:

Firstly, mistakes are easy to make when it comes to calculating the changes in the composition of resource demand or the increases of environmental impact per capita, which pointed to the underestimation the role of population growth. Ehrlich and Holdren (1971) countered that those changes in the components of the total energy budget created huge increase in electricity consumption. Electricity made up of only 12 per cent of the energy use in the U.S in the year 1940. However, this number rose to 22 per cent by 1970. Effect-wise, the main concern is not on the change in electricity consumption. Instead, it is about the change in the total energy use. Given that the main objective of this study is to establish the link between population changes and the air pollution, electricity consumption is one of the signals that are associated with the population activity. Acknowledgement of this contributes to less dramatic and traumatic increase than electricity consumption of 140 percent. Ehrlich and Holdren (1971) concluded that from this, only 38 per cent growth in energy consumption can be related to population increase.

Secondly, in certain circumstances, commentators also failed to realize that population size affects energy use as well as related the impact on the environment. In addition, the impact can increase either faster or slower with population size. It is found that whenever the law of diminishing returns operates, impact can increase faster than population. The best example to illustrate this is related to fisheries. When the richest fishery stocks are reduced, more energy is needed to preserve the supply as the amount of yield per unit effort drop. The same law is found to be relevant to other sectors such as agriculture, mining and the consumption of renewable water supplies.

Air pollution modeling is a numerical tool used to describe the causal relationship between emissions, meteorology, atmospheric concentrations, deposition, and other factors. Air pollution measurements provide vital, quantitative information in relation to ambient concentrations and deposition, but can only describe air quality at specific locations and times, without giving clear guidance on the identification of the causes of the air quality problem. Air pollution modeling, instead, can provide a more complete deterministic description of the air quality problem, including an analysis of factors and causes (emission sources, meteorological processes, and physical and chemical changes), and some guidance on the implementation of mitigation measures. Air pollution models play an important role in science, because of their capability to assess the relative importance of the relevant processes. Air pollution models are the only method that quantifies the deterministic relationship between emissions and concentrations or depositions, including the consequences of past and future scenarios, and the determination of the effectiveness of abatement strategies. This makes air pollution models indispensable in regulatory, research, and forensic applications.

METHODOLOGY

Like Cramer (1998), Dietz and Rosa (1997), Shi (2003) and York et al. (2003a, b) the current researcher adopts a stochastic and non-tautological version of the popular IPAT equation that are derived from the dispute between Commoner, Corr and Stamler (1971) and Ehrlich and Holdren (1971):

$$I = f\,(P, A, T) \quad (1)$$

where I is environmental impact, P is population, A is affluence and T is technology. The IPAT model is most famous in its tautological or definitional identity formulation, which follows from Equation (2) if one defines A as consumption C per capita and T as pollution per unit of consumption:

$$I \equiv P \times A \times T \quad (2)$$

However, the IPAT Model alone cannot cater the following criteria's such as comprehensibility, parsimony, modularity, best dealing with uncertainty, parallelism and robust.

Empirical Model for time Series Analysis

The empirical model or model regression that involve in this study consists three versions which are, original equation adopted from IPAT model, after the log and increase the robustness after fuzzy the model.

General equation:

$$Y_{jt} = B_0 + B_1 x_{1t} + B_2 x_{2t} + B_3 x3_t + e_t \quad (3)$$

Adaptive equation:

$$C0_2 = B_0 + B_1 Pop_t + B_2 GDP_t + B_3 Man_t + e_t \quad (4)$$

After log:

$$\text{Log } C0_2 = B_0 + \text{Log } B_1 Pop_t + \text{Log } B_3 Man_t + e_t) \quad (5)$$

In which, y_{jt} represent the Air Pollution trend represented by Carbon Emission that involve in this study which are Pollution, Gross Domestic Product and Manufacturing Industry. In the time series analysis, this study will conducting several important tests and choose the best model estimator to explore the impact of Pollution-Affluence-Technology (PAT) variables structures on carbon emission.

Multiple Linear Regression (MLR) Model

The Multiple Linear Regression (MLR) has been widely applied to a large number of situations including air pollution analysis, especially ozone estimation and prediction. We are interested in how the meteorological factors affect air pollutant concentrations, so pollutant concentrations can be treated as responses; and meteorological variables as predictors. The MLR model is given as:

$$X_t = a_0 + a_1 M_{1,t} + a_2 M_{2,t} + ... + a_k M_{k,t} + \varepsilon_t \qquad (6)$$

Whereby *Xt* is the pollutant concentration at the time *t*, *{Mi,t}* stands for the meteorological variables at time *t*, *{ai}* are regression coefficients, and *!t* is the random error at time *t*. Ideally, all the explanatory variables in the MLR model should be independent of each other. However, certain variables may be exactly, or very nearly, are in linear combinations with other variables. Technically, this is known as multicollinearity (Maindonald and Braun, 2007). For each multicollinear relationship, there is one redundant variable. In the presence of multicollinearity, the estimate of one variable's impact in response to controlling others, tend to be less precise than if predictors were uncorrelated with one another. To detect multicollinearity, the formal criterion is variance inflation factor (VIF) which measures the impact of multicollinearity among the explanatory variables in a regression model in the precision of estimation. It expresses the degree to which multicollinearity among the predictors degrade the precision of an estimate. Typically a VIF value greater than 10 is of concern (Dirk and Bart, 2004).

To avoid multicollinearity, the redundant variable whose effect is already accounted for by other variables need to be removed. There are two methods that can be applied to select efficient regression models. The simplest approach is called forward selection. In this approach, variables are added to the model one at a time. At each step, each variable that is not already in the model is tested for inclusion in the model. The most significant of these variables is added to the model, so long as its P-value is below a certain pre-set level. Thus we begin with a model including the variable that is most significant in the initial analysis, and continue adding variables until none of remaining variables are 'significant' when added to the model.

An alternate approach is the backward selection. Under this approach, one starts with fitting a model with all the variables of interest. Then the least significant variable is dropped, so long as it is not significant at our chosen critical level. We continue by successively re-fitting reduced models and applying the same rule until all remaining variables are statistically significant.

EMPIRICAL FINDINGS

MLR Model

The correlation of carbon emission concentrations and each independent variables show that the carbon emission concentrations tend to positively correlated with Gross Domestic Product (GDP) and Manufacturing Industry (MAN) and negatively correlated with total number of Population. From the MLR coefficients table (Table 1) for all the three variables, we can see that there are only two variables significant at level 5%: GDP and MAN. Same as Population and GDP, multicollinearity still are of concern (Table 2).

Table 1: MLR Coefficients of CO with all three predictors.

	Estimate	Std. Error	t-Statistic	Pr (> |t|)
Intercept	-16.2819	6.2673	-2.5980	0.0133
POP	-1.4904	4.2590	-0.3499	0.7283
GDP	3.2432	0.3039	10.671	0.0000
MAN	8.7317	1.4598	5.9816	0.0000

Re-fitting the significant predictors in Table 1 to the detrend and deseasonalized CO concentrations, the MLR model is (Table 3)

$$X_t = -18.2493 + 3.1436 M_{1,t} + 8.9594 M_{2,t} \qquad (7)$$

where *Xt* is the pollutant concentration at time *t*, $M_{1,t}$ stand for GDP, $M_{2,t}$ stand for MAN. From the equation 7, it can be explain that RM 1 million increase in GDP will increase 3.1436% of COppm concentration and increase 1 number of Manufacturing Industry will increase in 8.959% of COppm concentration. The R^2 is 0.96. It shows that 96% of each independent variable can be explained by dependent variable. The other 0.04% is not included in the model.

Table 2: Table of VIF for the MLR model of CO with all three predictors

Predictors	VIF
POP	11.9259
GDP	10.3250
MAN	1.5842

Table 3: MLR coefficients of CO with GDP and Manufacturing Industry

	Estimate	Std. Error	t-Statistic	Pr (> |t|)
Intercept	-18.2493	2.7380	-6.6652	0.0000
GDP	3.1436	0.1054	29.835	0.0000
MAN	8.9594	1.2920	6.9348	0.0000

The information given from Table 1, 2 and 4 indicates that the MLR model may not be a good choice for CO with Population, GDP and Manufacturing Industry. For MLR the MSE value is 15.65 and the value of AIC is 5.73

CONCLUSION

Generally, the three variables, Population, Affluence and Technology affect the impact of human populations on the environment. Since it is clear that man's impact on the globe is already far too great, it would be logical to seek ways to reduce the magnitude of all three variables P, A and T in the impact equation, in every country across the globe. All the information derived in this study is undeniable and most importantly informative.

Concerning the traditional quantitative methods, this research introduces an alternative method of the environmental performance evaluation system. Further research in this area is needed to develop a method for relating membership values to linguistic variables in environmental performance evaluation, as well as testing the sensitivity of membership values and their impact on the outcome. This paper provides a simple-to-use fuzzy logic model for establishing a more meaningful environmental Performance evaluation system. This study develops an evaluation approach to measure environment performance. Many factors are subjective and difficult to quantify in the environment evaluation process. Fuzzy logic enables the evaluator or the decision maker to incorporate information in the environment evaluation system which is both vague and subjective.

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