Modelling Malaysian Road Accident Deaths: An Econometric Approach

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ABSTRACT

A number of methods have been proposed for dealing with road accident death model. This paper uses econometric regression models to develop the road accident death model. By using this approach, this paper attempts to establish a statistical model to describe the relationship between the total road accident deaths and a range of explanatory macroeconomic variables. The macroeconomic factors used in the model include population, the number of registered vehicles, road length, technique of data coverage, system of data recording and Gross Domestic Product. The results suggest that the POP, ROAD, VEH and DR do not have any impact on road accident deaths. In contrast, the GDP and Technique of data Coverage were found to be highly significant (P < 0.05) in explaining the road accident deaths.

Keywords: Road accident death, econometric regression model, macroeconomic factors

Introduction

Road accident deaths in Malaysia are also considered as “global tragedy” with an ever-rising trend. The increase of these incidents are seldom being correlated with factors such as driving behaviors, traffic condition, vehicle condition and others. Nevertheless it cannot be denied that the macroeconomic factors also contribute in explaining the occurrence of road accidents deaths. Many researchers have reported an association between improved economic
conditions and increased in motor vehicle fatalities (Farmer, 1997). Over the last seven years from 1991 to 1997, the Malaysia economy had been growing at 7% annually. Between 1970 and 1997, the vehicle population had grown at an average growth rate of about 47% a year or 13 times more than in 1970 (HPU, 1998). This high economic growth rate had transcended into high accident figure over the same period where the road fatality figure had also grown. In 1996, the Malaysian government had committed to ensure that the road accident fatalities in the nation were to be reduced by at least 30 by the end of year 2000 (Hussain et al., 2002). Although much emphasis and funding in Malaysia have been directed towards road safety campaign in the media and during festive seasons and school holidays, the effectiveness of these campaigns is yet to be proven. In accordance with this scenario, many surveys and studies associated with traffic fatalities have been conducted in Malaysia. Most studies of traffic fatalities have been done to identify the factors that contribute to road incidents.

Problem Statement and Objectives

The purpose of the study is to establish an econometric model to describe the non-spurious relationship between the total road accident deaths and several macro econometric factors. The model developed from this study would help researchers to estimate the total road accident deaths using the prior information pertaining to the economic factors. This research was carried out with the aim of finding an econometric model that could best describe the Malaysian road accident death data. The objectives to be satisfied are to examine the trends and recent characteristics of total road accident deaths in Malaysia and to develop an econometric time series model that describes the relationship between road accident deaths and several economic factors.

Literature Review

Although traffic deaths are influenced by a large number of factors related to road user behavior, condition of vehicles, most death models are compounded by the "unexplained variable" into the error component of the model. This could be due to the unavailability of long data series or other macroeconomic factors.

As such, the most commonly used macroeconomic independent variables are population, number of registered vehicles, road lengths, technique of data coverage, the number of registered motocycles and Gross Domestic Product (Smeed, 1972, Hakim, 1991 Radin, 1996, Wagenaar, 1984 and Radin and Law, 2002). Previously there are many models being developed by taking into account these macroeconomic factors in predicting the road accident deaths (Hakim,
1991). One of the well-known models was introduced by Smeed in 1949. Smeed suggested an equation that relates the number of deaths with factors such as below.

\[
Death = 0.026 \text{ Population}^{0.7323} \text{ Vehicle}^{0.3372}
\]  

(1)

In Malaysia, there were two previous models being built. The first model was introduced by Rehan (1995). Rehan’s model is also similar to Smeed’s model with a forecast of 5073 total accident deaths by the year 2000. But still the capability and accuracy of traffic death model depends generally on the details and reliability of the data. The accuracy of a model can be significantly improved by means of suitable methods and incorporating more explanatory factors into the model. In view of this, Radin (1998) further improved the accuracy of Rehan’s (1995) model by considering more exposure variables and data structure to better suit developing country environment. Apart from that, the time series log-linear model with Poisson errors was established to explain the relationship between traffic deaths and traffic exposure. The exposure variables used were the population, registered vehicle, road length and interaction between population, registered vehicle and road length as a proxy to explain traffic exposure. Wagenaar (1984) has proven that a significant relationship existed between the unemployment rate, vehicle miles travelled and the number of accident deaths. This could be when the unemployment rate increases, the demand in vehicle miles traveled will decrease. Implicitly, as the vehicle miles travelled decreases the probability of accident occurrence will also decrease.

The changes in economic factor, such as inflation and other hidden factors were identified to be one of the contributing factors in explaining the rate of accident deaths. Joksh (1984) had proven that the rate of accident deaths was higher among the new cars compared to the old cars. The economic factors related to this situation is the inflation factor whereas the number of new cars sold decreases in the inflation year, the rate of accidents will also decrease. This phenomenon is also agreed by Hakim (1991), Wagenaar (1984) and Partyka (1984) who stated that the inflation factor is also one of the contributing factors in explaining the road accident death occurrence due to the changes in travel pattern. This was related to the inflation year that was expected to reduce the rate of accidents. Radin and Law (2002) used the Gross Domestic Product (GDP) to describe the Malaysian economic situation in modeling the road accident deaths. With the Box-Jenkins model approach, they found that the GDP, population and number of registered vehicles factors turned to be significant in influencing the road accident death pattern in Malaysia.

Paolo et al., (2004) reviewed the study done by Silva regarding the relationship between mortality due to traffic accidents, the number of registered motor vehicles and economic activity in Brazil from 1980 to 1999. The results indicated that the number of deaths in traffic accidents follow economic waves and showed a general tendency to decrease as the number of motor vehicles
per capita increases. Ameen and Naji (2001) proposed causal model for studying the road accident fatalities in Yemen.

With the multiple regression analysis using the first order difference of the original time series data approach, they measured the influence of a number of socio-economic variables on the number of fatalities. According to their model, to reduce the number of road accident fatalities either the population or the GNP or both would have to be reduced.

In studying the relationship between road accident deaths and economic factors, Radin and Law (2002) stated that traffic deaths could be influenced by a large number of factors related to traffic environment, vehicles and road user behavior. Dickerson, Peirson and Vickerman (1998) used econometric analysis to study the relationship between road accidents and traffic flows. They stated that most previous researchers have found a near proportional relationship between accident deaths and traffic flows. Beenstock and Gafni (1999) also used the approach of econometric analysis of time series to estimate the road accidents for Israel.

Scuffham and Langley (2002) applied the approach in time series econometric analysis to examine the changes in the trend and seasonal pattern in fatal crashes in New Zealand in relation to changes in economic condition. They used economic, demographic and road policy factors as independent variables. Finally, they found that most of the economic and demographic factors are not significant in the long run whereas the road policy variables all tend to be statistically significant to studying the fatal traffic crashes in New Zealand. Some good references regarding the importance of econometric time series modeling have been discussed by Charemza and Deadman (1992), Pindyck and Rubinfeld (1991) and Gujerati (1995) and Hill et al., (2000).

Scope of Study

The data used in this study were derived from four sources. First were the fatality and road lengths ('000 km) compiled by Polis Diraja Malaysia (PDRM) from 1972 to 2003. Data are available from a total of yearly series, which were geographically spread evenly throughout Malaysia. Exposure data, namely the number of registered vehicles was obtained from Jabatan Pengangkutan Jalan, Kementrian Pengangkutan Malaysia. These data were recorded from Laporan Perangkaan Kecelakaan Jalan Raya, Malaysia (PDRM 1997 - 2003). The third source was the size of population ('000 000) from the year 1972 to 2003 which were obtained from Jabatan Perangkaan Malaysia recorded from Laporan Perangkaan Ekonomi Malaysia Siri Masa, 2003. In addition, the Gross Domestic Product (GDP) Index (RM '000) during study period was collected from the Bank Negara Malaysia recorded from Laporan Sistem Akaun Negara (SAN).
Methodology

Econometric Model

In developing the econometric models, the formulation of equation with several variables is involved. The variables used in the construction of the econometric models may be categorized as dependent and independent variables. Generally, the dependent variable is placed on the left-hand side of the equation and the independent variables on the right hand side of the equation. The independent variables are also known as explanatory variables.

Structurally, the model may take many forms. Some are simple involving only one independent variable whilst others are more complex involving more than one independent variables (Equation 1). In this research, an econometric model is developed involving more than one independent variable and including the lag of dependent variable acting as independent variables to overcome the serial correlation problem, which exists when developing the econometric model based on time series data. Consider the following regression model without lag variable:

\[ Y_t = \beta_0 + \beta_1 X_1 + \beta_2 X_{2t} + \beta_3 + \beta_4 X_{4t} + \beta_5 X_{5t} + \beta_6 X_{6t} + \varepsilon_t \]  

(2)

For the accident death data, the model with one dependent variable and more than one independent variable with lag dependent variable is used (Equation 2). The inclusion of lag dependent variable acting as independent variable is for the purpose of reducing the serial correlation problem that exists because this research deals with economic time series model. Consider the following economic time series regression model with lag variable:

\[ Y_t = \beta_0 + \beta_1 Y_{t-1} + \beta_2 X_{2t} + \ldots + \beta_6 X_{6t} + \varepsilon_t \]  

(3)

where \( Y_t \) is the dependent variable in period \( t \),

\( Y_{t-1} \) is the lag dependent variable in period \( t \)

\( X_{2t} \) is the \( i \)th independent variable in period \( t \), for \( i = 1, 2, \ldots, 6 \)

\( \beta_i \) is the error term in period \( t \) and is assumed identically, independent and normally distributed with mean, \( E(\varepsilon_t) = 0 \); variance \( E(\varepsilon_t^2) = \sigma^2 \); \( E(\varepsilon_t \varepsilon_{t-j}) = 0 \) for \( t \neq j \) and \( \beta_0, \beta_j \) for \( j = 1, 2, \ldots, 6 \) are unknown parameters to be estimated.

Therefore, the number of road accident deaths is assumed to depend on factors such as population size, number of registered vehicles, total of road length, technique of data coverage, data technique of recording and gross domestic product (Smeed, 1972, Hakim, 1991, Radin 1996, Wagenaar, 1984 and Radin and Law, 2002). The following are the variables used in this research.
<table>
<thead>
<tr>
<th>NO. VARIABLES</th>
<th>DESCRIPTION</th>
<th>TYPES OF VARIABLES</th>
<th>UNIT</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Death</td>
<td>Total number of death within 30 Days after the accident occurs Reported by PDRM</td>
<td>Dependent Quantitative</td>
<td>People</td>
</tr>
<tr>
<td>2. Population (POP)</td>
<td>Total number of population in Malaysia reported by Department of Statistic.</td>
<td>Independent Quantitative</td>
<td>Million People</td>
</tr>
<tr>
<td>3. Vehicle (VEH)</td>
<td>Total number of vehicles registered with JPJ in Malaysia.</td>
<td>Independent Quantitative</td>
<td>Million Vehicle</td>
</tr>
<tr>
<td>4. Road Length (ROADL)</td>
<td>Total road length in Malaysia Recorded by PDRM.</td>
<td>Independent Quantitative</td>
<td>Thousand Kilometers</td>
</tr>
<tr>
<td>5. Data Coverage (DC)</td>
<td>The effect of data coverage Recorded by PDRM.</td>
<td>Independent Qualitative</td>
<td>0 = Peninsular Malaysia only 1 = Peninsular, Sabah and Sarawak</td>
</tr>
<tr>
<td>6. Data Recording System (DR)</td>
<td>The effect of changes in data Recording system.</td>
<td>Independent Qualitative</td>
<td>0 = Trial form + Old form 1 = POL27 Pin1/91</td>
</tr>
<tr>
<td>7. Gross Domestic Product (GDP)</td>
<td>Gross Domestic Product obtained From Bank Negara Malaysia.</td>
<td>Independent Qualitative</td>
<td>Million RM</td>
</tr>
</tbody>
</table>

**Fitting an Econometric Model**

In order to build a good econometric model, this research initially applied general to specific modeling technique. Several testing procedures involved for the statistical validation consist of the General Fitness of the Model, testing on the signifianct of econometric coefficient, goodness of fit by looking at the R2, multicollinearity and serial correlation.

The major assumptions that have been followed thus far in this research are the error term has constant variance and the errors are normally distributed. The validity of these assumptions has been considered and the analyses to examine the adequacy of the model are conducted through checking on normality and heterocedasticity and Langrange Multiplier test.

**Results**

This section presents the output of SPSS programming for the road accident death model. In this study, six independent variables are used. Those variables are Population (POP), Number of registered vehicle (VEH), Road Length
(ROADL), Gross Domestic Product (GDP), Technique of data coverage (DC) and System of data recording (DR) while the dependent variable is Road Accident Deaths (Death).

**Univariate Analysis of the Terms**

Table 1 below summarizes the univariate analysis of road accident deaths. For the exploratory stage, it can be seen that all terms are significant at 5 level. The significance of the terms was assessed by the i) overall model fit (F test) and ii) testing the individual coefficient (T test) which are both highly significant.

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory Variable</th>
<th>Parameter Estimates</th>
<th>Standard Error</th>
<th>Degree of Freedom</th>
<th>T-value</th>
<th>F-value</th>
<th>P = 0.05</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Constant POP</td>
<td>-1986.67</td>
<td>277.683</td>
<td>30</td>
<td>7.154</td>
<td>492.192</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>POP</td>
<td>0.344</td>
<td>0.016</td>
<td></td>
<td>22.185</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>Constant VEH</td>
<td>1980.37</td>
<td>156.077</td>
<td>30</td>
<td>12.688</td>
<td>246.872</td>
<td>Yes*</td>
</tr>
<tr>
<td></td>
<td>VEH</td>
<td>0.4</td>
<td>0.025</td>
<td></td>
<td>15.712</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>Constant ROADL</td>
<td>1097.54</td>
<td>203.885</td>
<td>30</td>
<td>5.383</td>
<td>249.624</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>ROADL</td>
<td>0.067</td>
<td>0.004</td>
<td></td>
<td>15.799</td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>Constant GDP</td>
<td>2311.201</td>
<td>127.234</td>
<td>30</td>
<td>17.250</td>
<td>297.559</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.012</td>
<td>0.001</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>5.</td>
<td>Constant DC</td>
<td>2323.00</td>
<td>347.564</td>
<td>30</td>
<td>6.684</td>
<td>32.723</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>DC</td>
<td>2345.174</td>
<td>409.964</td>
<td></td>
<td>5.720</td>
<td></td>
<td></td>
</tr>
<tr>
<td>6.</td>
<td>Constant DR</td>
<td>2999.2</td>
<td>151.949</td>
<td>30</td>
<td>19.738</td>
<td>117.677</td>
<td>Yes</td>
</tr>
<tr>
<td></td>
<td>DR</td>
<td>2691.717</td>
<td>248.132</td>
<td></td>
<td>10.848</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

**Fitting an Econometric Model**

The following results are an extension of findings in Table 1. Since it is proven that individually all the six explanatory variables significantly contributed to the accident death occurrence, thus the next step is to fit the econometric model. In this study, a general to specific general to specific approach is adopted for estimating the models where the entire variables are simultaneously entered, then ‘tested down’. The result below show the multivariate analysis of road accident deaths and the corresponding theoretical model which is,

\[ Y_i = \beta_0 + \beta_1 X_{1i} + \beta_2 X_{2i} + \beta_3 X_{3i} + \beta_4 X_{4i} + \beta_5 X_{5i} + \beta_6 X_{6i} + \varepsilon \]

Table 2 show the models and their respective terms included in the models. Model 1 shows the full model to explain the total road accident deaths per year. Even though in univariate analysis it is shown that all terms are significant at
5% level, the POP, ROADL and DR still appear to be not significant in the full model. The preliminary analyses suggest that there had been some slight multicollinearity problems between population, vehicle and recording data. Inspection on correlation matrix between independent variable is done. Omitting the variables that had a strong correlation between independent variable would help to reduce the multicollinearity problem (Montgomery et al., 2001). The correlation in the trend between POP and between VEH and GDP is 0.992 (Table 3). Therefore, in model 2, ROADL and VEH is 0.921 and the model with the hope to reduce the effect of multicolinearity. Even though ROADL was no longer in the model, the results still showed POP and DR were not significant at 5% level.

Model 3 shows the reduced model with the POP, ROADL and DR terms removed from the model. All terms were found to be highly significant at 5% level. The $R^2$ was very high with 96.5% of all variation in road accident deaths, which is explained by VEH, GDP and DC.

Table 2: Multivariate Analysis of Malaysia Road Accident Death

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory Variable</th>
<th>Estimates</th>
<th>Standard Error</th>
<th>Value</th>
<th>P = 0.05</th>
<th>DW</th>
<th>VIF</th>
<th>R2</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.</td>
<td>Constant</td>
<td>-816.254</td>
<td>1921.571</td>
<td>-0.425</td>
<td>No</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>VEH</td>
<td>-0.523</td>
<td>0.197</td>
<td>-2.664</td>
<td>Yes</td>
<td>179.875</td>
<td>R2 = 0.97</td>
<td></td>
</tr>
<tr>
<td></td>
<td>ROADL</td>
<td>-0.022</td>
<td>0.018</td>
<td>-1.224</td>
<td>No</td>
<td>1.073</td>
<td>55.173</td>
<td>R\ = 0.963</td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.017</td>
<td>0.006</td>
<td>2.766</td>
<td>Yes</td>
<td>210.399</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DC</td>
<td>831.118</td>
<td>270.512</td>
<td>3.072</td>
<td>Yes</td>
<td>5.814</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DR</td>
<td>341.434</td>
<td>290.407</td>
<td>1.176</td>
<td>No</td>
<td>7.769</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Constant</td>
<td>1136.545</td>
<td>1081.193</td>
<td>1.051</td>
<td>No</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2.</td>
<td>POP</td>
<td>0.1</td>
<td>0.091</td>
<td>1.105</td>
<td>No</td>
<td>140.332</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>VEH</td>
<td>-0.411</td>
<td>0.175</td>
<td>-2.344</td>
<td>Yes O500</td>
<td>210.170</td>
<td>R^0.988</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.017</td>
<td>0.006</td>
<td>2.701</td>
<td>Yes .077</td>
<td>5.708</td>
<td>R = 0.962</td>
<td></td>
</tr>
<tr>
<td></td>
<td>DR</td>
<td>375.196</td>
<td>291.85</td>
<td>1.286</td>
<td>No</td>
<td>54.018</td>
<td></td>
<td></td>
</tr>
<tr>
<td>3.</td>
<td>Constant</td>
<td>2363.673</td>
<td>133.562</td>
<td>17.697</td>
<td>Yes</td>
<td>80.139</td>
<td>R=0.961</td>
<td></td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.026</td>
<td>0.004</td>
<td>6.478</td>
<td>Yes</td>
<td>2.304</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DC</td>
<td>1168.187</td>
<td>175.157</td>
<td>6.669</td>
<td>Yes</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>4.</td>
<td>Constant</td>
<td>2009.344</td>
<td>121.967</td>
<td>16.475</td>
<td>Yes</td>
<td>R@0.976</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.010</td>
<td>0.001</td>
<td>14.903</td>
<td>Yes</td>
<td>1.555</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>DC</td>
<td>777.894</td>
<td>176.707</td>
<td>4.368</td>
<td>Yes</td>
<td>1.555</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

However, note that the sign on VEH coefficient parameter indicates an inverse relationship. Inspection on the wrong sign of coefficient of parameter for vehicle suggesting a slight multicolinearity exists in the third fitted model. The inspection on VIF values for independent variables also shows value more than 10 which concludes the presence of multicollinearity. Thus, the last model was fitted by removing the vehicle variable from the model.
Model 4 shows GDP and DC variable are both significant. The VIF value of 1.555 which is less than 10 also indicates that there is no more multicollinearity problem in the fitted model. However, Model 4 still cannot be the best econometric model to explain the road accident deaths. Once a final model is obtained, it is subjected to diagnostic tests for serial correlation (the Durbin-Watson (DW)). Note that the Durbin Watson statistics value in Model 4 was very poor with 0.468. It shows a serious serial correlation problem exists in the model. The results for Durbin Watson Test for the entire four models respectively are as in Table 4.

<table>
<thead>
<tr>
<th>POP</th>
<th>VEH</th>
<th>ROADL</th>
<th>GDP</th>
<th>DC</th>
<th>DR</th>
</tr>
</thead>
<tbody>
<tr>
<td>POP</td>
<td>1.000</td>
<td>0.977</td>
<td>0.978</td>
<td>0.973</td>
<td>0.731</td>
</tr>
<tr>
<td>VEH</td>
<td>0.977</td>
<td>1.000</td>
<td>0.921</td>
<td>0.992</td>
<td>0.651</td>
</tr>
<tr>
<td>ROADL</td>
<td>0.978</td>
<td>0.921</td>
<td>1.000</td>
<td>0.923</td>
<td>0.744</td>
</tr>
<tr>
<td>GDP</td>
<td>0.973</td>
<td>0.992</td>
<td>0.923</td>
<td>1.000</td>
<td>0.597</td>
</tr>
<tr>
<td>DC</td>
<td>0.731</td>
<td>0.651</td>
<td>0.744</td>
<td>0.597</td>
<td>1.000</td>
</tr>
<tr>
<td>DR</td>
<td>0.863</td>
<td>0.850</td>
<td>0.838</td>
<td>0.890</td>
<td>0.485</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Model</th>
<th>DW</th>
<th>DU</th>
<th>4-DU</th>
<th>Results</th>
<th>Serial Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>1.073</td>
<td>2.310</td>
<td>Reject Ho</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.899</td>
<td>1.352</td>
<td>2.403</td>
<td>Reject Ho</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>0.995</td>
<td>2.572</td>
<td>Reject Ho</td>
<td>Yes</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0.465</td>
<td>2.648</td>
<td>Reject Ho</td>
<td></td>
<td></td>
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</tbody>
</table>

Based on Table 4, all the four models estimated have a serious serial correlation problem. For this reason, it is advisable to solve this serial correlation problem before concluding on the final model.

In order to overcome the serial correlation problem, Hill et al., (2001) proposed a correction technique by introducing the lag dependent variable as the new independent variable in the model. The corresponding theoretical model is,

$$ Y_1 = \beta_0 + \beta_1 X_{1t} + \beta_2 X_{2t} + \beta_3 Y_{1t-1} + \beta_4 Y_{1t-2} + \varepsilon $$

(4)

This method will help to improve and eliminate the serial correlation problem in the model.
Corrected Models for Serial Correlation

As mentioned, Model 4 in Table 2 shows GDP and DC are the last two independent variables that are significant after solving the multicollinearity. Incidentally the value of DW is poor and indicates a serious serial correlation problem exists in the fitted model. To further refine the model, lag one of dependent variable (Death) is introduced into the model to overcome the serial correlation problem.

Model 1 in Table 5 is estimated with lag one of dependent variable (Death$_{t-1}$) included in the model. The result shows that the GDP and DC variables turn out to be not significant at 5 level. This might be due to the presence of serial correlation problem. The inclusion of Death$_{t-1}$ still may not be sufficient to solve the serial correlation problem.

<table>
<thead>
<tr>
<th>Table 5: Corrected Models for Serial Correlation</th>
</tr>
</thead>
<tbody>
<tr>
<td>Model</td>
</tr>
<tr>
<td>-------</td>
</tr>
<tr>
<td>1.</td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td></td>
</tr>
<tr>
<td>2.</td>
</tr>
<tr>
<td></td>
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</tbody>
</table>

To confirm this, Langrange Multiplier (LM) Test was carried out to test on the coefficient of e. Model 1A in Table 6 shows the results of LM test with Death, in the model. Since the coefficient on was significant with p-value lesser than 0.05, it meant at 5 significance level, the LM test rejected the null hypotheses of no correlation. Thus the conclusion on Model 1A was that the serial correlation problem still existed in the model 1A.

Hence, the final step was performed to further improve the model. At this stage, lag two of the dependent variable (Death,\textsuperscript{2}) was introduced into the model. Referring to Model 2 in Table 5, all the terms were found to be highly significant at 5 even after the correction of serial correlation problem. The F and T test were highly significant and so does the R\textsuperscript{2} of 98.2.

Again, to further refine the model, the LM test was done for model 2A to test on the serial correlation problem. Based on Model 2A in Table 6 the coefficient on e.i was not significant with p value greater than 0.05. This means, at 5 significant levels the LM test failed to reject the null hypotheses of no correlation.
Table 6: Model of Langrange Multiplier Test

<table>
<thead>
<tr>
<th>Model</th>
<th>Explanatory Variable</th>
<th>Estimates</th>
<th>Standard Error</th>
<th>T Value</th>
<th>P = 0.05</th>
<th>L.M Test</th>
</tr>
</thead>
<tbody>
<tr>
<td>1A.</td>
<td>Constant</td>
<td>1264.193</td>
<td>276.784</td>
<td>4.567</td>
<td>Yes</td>
<td>Reject Ho</td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.006</td>
<td>0.001</td>
<td>4.072</td>
<td>Yes</td>
<td>(Autocorrelation exist)</td>
</tr>
<tr>
<td></td>
<td>DC</td>
<td>461.778</td>
<td>130.614</td>
<td>3.535</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Death1-1</td>
<td>0.417</td>
<td>0.133</td>
<td>3.131</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td></td>
<td>e-i</td>
<td>0.762</td>
<td>0.208</td>
<td>3.670</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td>2A.</td>
<td>Constant</td>
<td>899.093</td>
<td>263.037</td>
<td>3.418</td>
<td>Yes</td>
<td>Accept Ho</td>
</tr>
<tr>
<td></td>
<td>GDP</td>
<td>0.004</td>
<td>0.001</td>
<td>3.310</td>
<td>Yes</td>
<td>(No Autocorrelation)</td>
</tr>
<tr>
<td></td>
<td>DC</td>
<td>358.481</td>
<td>130.110</td>
<td>2.755</td>
<td>Yes</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Death1-i</td>
<td>-0.372</td>
<td>0.268</td>
<td>3.5</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Death1-2</td>
<td>0.249</td>
<td>0.336</td>
<td>-1.49</td>
<td>No</td>
<td></td>
</tr>
<tr>
<td></td>
<td>e. -i</td>
<td>0.336</td>
<td>0.336</td>
<td>1.0</td>
<td>No</td>
<td></td>
</tr>
</tbody>
</table>

Thus, the conclusion for Model 2A was, there was no more serial correlation problem in the model. Based on the criteria of F test, R^2, correction for multicolinearity and serial correlation problem, Model 2 could thus be considered as the best fit to describe road accident deaths in Malaysia.

Model Adequacy Checking

As discussed, it is proven that model with GDP and Technique of data coverage (DC) with Death1., and Death ^ (to allow for serial correlation) was the best model to explain the road accident deaths in Malaysia. However, it was subjected to diagnostic checking on model adequacy for normality, heterocedasticity and stationarity. Based on the normal probability plot, the normality assumption for the final model with GDP and DC variable was considered fulfilled. Checking on the assumption of constant variance (homocedasticity) is also an important criterion that needs to be done. For this study, inspection on the residual plot was done. Referring to the residual plot, the least square residual exhibited no obvious pattern of non-constant variance depicted from the graph.

Conclusion

Various econometric models are estimated to describe the road accident deaths using the least square (OLS) method. Models were tested for the satisfactions of regression assumption. Attempts were then made in rectifying any violation of fundamental assumptions such as homocedasticity, non-autocorrelation, normality and linearity. Models with significant serial correlation are corrected by including the lag dependent variable. The Durbin Watson statistics is used to detect the presence of autocorrelation. A subsequent analysis of Langrange
Multiplier test is carried out when the DW test is inapplicable. The best model to describe the road accident deaths is found to be Model 2 in Table 5. The model gives the best $R^2$ of 0.982. The final model including GDP and dummy variable of Technique of Data Coverage accounts for 98.2 of the variability in total road accident deaths from 1972 to 2003. The two terms included are highly significant ($p < 0.05$). The estimated model obtained from the model is quite consistent with small standard error. Detailed analysis on multicollinearity and correction for serial correlation also indicates that the model serves the best to describe the relationship between accident death occurrence and several macroeconomic variables significantly identified to be GDP and Data Coverage. Based on the model adequacy checking, this final model also has fulfilled the normality assumption and homoscedasticity assumption of the error term from the residual plot. The yearly road accident deaths predicted by the model showed a reasonable good match. The fit generally followed the same pattern as the actual death counts. Hence, based on the above argument, it can be concluded that the best model to explain the yearly road accident death is

\[ \text{Death} = 867.41 + 0.004 \text{GDP} + 310.674 \text{Z5C} + 1.1 \text{SO Death}_{t-1} - 0.570 \text{Death}_{t-2}. \]

Thus GDP is an important variable to reflect the road accident deaths. The term is positively significant with an increase of about 0.004 deaths per year. Or in other words, for every RM 1000 million increase in GDP, the number of road accident deaths is expected to increase by 4 people subject to the other variable held constant. Other than GDP variable, the technique of data coverage done by PDRM has not only improved the quality of data, but the quantity of the data collected. An increase of about 310 deaths of road accident deaths was observed after the adjustment of data coverage in 1981. The inclusion of this factor is important in interpreting the effectiveness of technique of data coverage.

**Recommendation**

Recent development in the econometric analysis of the time series is used to estimate the road accident deaths. But this econometric approach is somehow only suitable for the purpose of developing a model and identifying the factors that significantly contribute to the model. One of the disadvantages of using this approach is that it may not truly represent the actual pattern when doing forecasting for future values due to the stationarity characteristics of the data series. Thus, it is recommended that the modeller should consider the Error Correction Mechanism Approach for future research.
References


