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Applying Fixed Effects Panel Count Model to Examine Road Accident Occurrence

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Abstract: The most common probability models for modelling count data are the traditional Poisson and Negative Binomial model. This study focuses on modeling road accidents data using panel data analysis approach. The fixed-effects poisson and negative binomial (FENB) model is used to account for heterogeneity in the accident data on a panel of 14 states in Malaysia covering the period of 1996 to 2007. We examine various factors associated with road accidents occurrence. The factors considered are the monthly registered vehicle in the state, the amount of rainfall, the number of rainy day, time trend and the monthly effect of seasonality. Various model specifications are estimated including the pooled Poisson, Fixed Effects Poisson and Fixed Effects Negative Binomial model. Results revealed that road accident occurrence are positively associated with the increase in the number of registered vehicle, increase in the amount of rain and time. The effect of seasonality also indicates that accident occurrence is higher in the month of October, November and December.

Key words: Road accidents, panel count model, fixed effects negative binomial model, unobserved heterogeneity

INTRODUCTION

There has been a great amount of research conducted on modeling count data. Despite the various statistical models available for count data, further advancement has been made to improve the statistical model by using panel count data. The seminal work of Hausman *et al*. (1984) had introduced a variety of models when dealing with panel count data. Among which are the fixed effects and the random effects panel count regression model. Application on this technique has been widely used in modeling count data such as road accidents.

Recently, statistics on road accident in Malaysia is alarming and it is undeniable that road accident has been the main cause of deaths in Malaysia (Nhan, 2007). Thus, many researchers had tried to develop a statistical model that is capable to identify significant contributing factors on road accident occurrence. A number of statistical models ranging from time series model (Quddus, 2008), cross sectional model (Loeb, 1985) and panel count model (Law *et al*., 2009; Kumara and Chin, 2004; Karlaftis and Tarko, 1998) have been developed. This study focuses on modeling Malaysian road accident using panel data analysis approach. The objective of this paper is to determine factors that affect the number of road accidents in the last 12 years in 14 states.

Recent studies have found that the appropriate methodology to model accident count is based on counts model approach due to the nature of non-negative discrete integer value of accident data (Miaou *et al*., 1992; Kweon and Kockelman, 2004). Since, the road accidents are non-negative discrete and random event count, the use of conventional linear regression procedure has unsatisfactory statistical properties.

This leads to the development of statistical model for count data (Miaou and Lum, 1993). For instance, for cross sectional count data, the Poisson regression model is appropriate (Zlatoper, 1989). When count data exhibit overdispersion (i.e., variance greater than mean), the Negative Binomial (NB) regression model is used (Lord, 2006; Chin and Quddus, 2003). If accident count is collected over time, the Integer Valued Autoregressive (INAR) Poisson model is employed (Quddus, 2008).

Alternatively, when we have a combined time series and cross sectional data (also known as panel data) the appropriate count model is the Fixed Effects (FE) Poisson (or NB) model (Law *et al*., 2009; Kumara and Chin, 2004) or the Random Effects (RE) Poisson (or NB) model (Chin and Quddus, 2003). More detailed information of these different count models can be found in Cameron and Trivedi (1998, 2005). In this study, the accident data used are stacked in a form of panels (which is the 14 states) and investigation on modeling issues encountered for panel data model were highlighted.

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Much of the literature on panel count model is from the influential study of Hausman *et al*. (1984). Recent contribution on the application of panel count model can also be seen in varieties of application (Montalvo, 1997; Cincera, 1997). Following the development of panel count model by Hausman *et al*. (1984), the application of panel count model analysis has also been applied in modeling road accidents count. Hsiao (2003) and Karlaftis and Tarko (1998) highlighted the advantages of using panel count model over analysis based on cross section or time series data alone. In addition, this method can also account for possible existence of heterogeneity in count data. Some of the studies reviewed here had provided guidance on relevant explanatory variables for road accident.

Fridstrom and Ingebrigsten (1991) applied the Generalized Poisson Regression model assumption using pooled time series and cross section data on monthly personal injury road accidents and their severity for 18 Norwegian counties, covering the period 1974 to 1986. The explanatory variables involved in their study included road use (exposure), weather, daylight, traffic density, road investment and maintenance expenditure, accident reporting routines, vehicle inspection, law enforcement, seat belt usage, proportion of inexperienced drivers and alcohol sales. Their results showed that the expected number of casualties was positively associated with the amount of rainfall. While the more congested the road network in a given county resulted in fewer casualties.

Karlaftis and Tarko (1998) addressed the importance of the issue of heterogeneity in panel data analysis when developing models to estimate crashes for urban and suburban arterial of 92 counties in Indiana for the period of 1988 to 1993. The fixed effects model for both Poisson and negative binomial was adopted to develop the panel model. Their findings indicated increased in the number of accidents are associated with higher vehicle miles travelled, population, the proportion of city mileage and the proportion of urban roads in total vehicle miles travelled.

Noland (2003) applied the fixed effects negative binomial regression models to analyze the impact of road infrastructure variables on traffic-related fatalities and injuries using the panel data for 50 US states from the period 1984 to 1997. In order to account for heterogeneity, the researcher used the fixed effects over dispersion model assumption by conditioning the joint probability of the count for each group upon the sum of the counts for the group. The results of this study rejected the hypothesis that the infrastructure improvements had been effective in reducing total fatalities and injuries. Chin and Quddus (2003) examined the relationship between traffic accident frequencies and the geometric, traffic and regulatory control characteristics of a total of 52 four-legged signalized intersections. They developed the Random Effects Negative Binomial (RENB) panel model to take into account the location-specific effects and serial correlation in time of the accident counts. The findings indicated that the total approach volumes, right-turn volumes, the uncontrolled left-turn lane, median width above 2 m, the presence of bus stop, intersection sight distance together with the presence of surveillance camera and the number of phases per cycle were highly associated with higher total accident occurrence.

Kweon and Kockelman (2004) investigated the safety effects of the speed limit increase on crash count measure in Washington State using the panel regression methods of both the fixed-effects and random effects model assumption. To develop models for the number of fatalities, injuries, crashes, fatal crashes, injury crashes, and Property-Damage-Only (PDO) crashes, the initial standard Poisson models for pooled count data were used followed by the more complex panel model of fixed-effect and random effects Poisson and negative binomial model specification. The estimated model was based on the conditional likelihood estimation process as described in Hausman *et al*. (1984) and Cameron and Trivedi (1998, 2005). The findings showed that the fixed-effects negative binomial model performed best for injury count while for fatalities, injuries, PDO crashes and total crashes, the pooled negative binomial model was a better choice.

Noland and Quddus (2004) presented an analysis on a panel of regional pedestrian and bicycle road accident for 20 years covering 11 region of United Kingdom. They used the fixed and random effects negative model derived by Hausman *et al*. (1984) to model panel data. Their results revealed that high pedestrian and bicycle road accident were associated with lower income areas, increases in road network, increases in alcohol expenditure and total population.

Kumara and Chin (2004) found that road network per capita, gross national product, population and number of registered vehicles were positively associated with fatal accident occurrence. They analyzed accident data from the period of 1980 to 1994 across 41 countries in the Asia Pacific region. By using the fixed effects negative binomial panel model, they found that socio economic and infrastructure factors had significant effects on fatal accidents.

Recently, Law *et al*. (2009) examined the effect of motorcycle helmet law, medical care, technology improvement, and the quality of political institution on motorcycle death. They applied the fixed effects negative binomial model on a panel of 25 countries from the period of 1970 to 1999. Their findings revealed that implementation of road safety regulation, improvement in the quality of political institution and medical care and technology developments showed significant effect in reducing motorcycle death.

MATERIALS AND METHODS

Pooled poisson regression model: A simple pooled Poisson model was first employed in this study, given the non-negative discrete nature of accident data. The basic Poisson probability specification is:

$$P(y_{it}) = f(y_{it}) = \frac{e^{-\lambda_{it}}\lambda_{it}^{y_{it}}}{y_{it}!}, \quad i = 1,2,...,N \quad t = 1,2,...,T \tag{1}$$

where y_{it} is the number of road accident deaths observed in state i for month t and that $\log\lambda_{it}=x_{it}'\beta$ (Cameron and Trivedi, 2005). In the basic Poisson count data model, the assumption of independent observations over individual units and across time still holds true with strong assumptions that $E(Y_{it})=Var(Y_{it})=\lambda_{it}$. However, the property for time independence permits a possible weakness of the serial correlation of residuals in the model specification that needs further investigation. Nevertheless, this model will be used as a benchmark model:

$$\begin{aligned}\log\lambda_{it} &= \gamma_i + \beta_1 LOGVEH_{it} + \beta_2 A\_RAIN_{it} + \beta_3 RAINY\_D_{it} \\ &+ \beta_4 TIME_{it} + \varphi_m \sum_{M-1}^{12} DMONTH_m + \varepsilon_{it}\end{aligned} \tag{2}$$

where, λ_{it} is the expected number of accidents occur during month t in state i , VEH is the number of registered vehicle, A_RAIN is the amount of rain, RAINY_D is the number of rainy day, TIME is the time trend and DMONTH is the seasonal dummy variables (a technique adopted from Diebold (2007) to account for the differences in accident occurrence across month) and γ_i, β_1, β_2, β_3, β_4, φ_m are unknown parameters to be estimated. In order to account for differences among cross-sectional unit, two basic approaches can be used by negative binomial model; using fixed effects or random effects. The random effects model assumed the individual effects are independent, identically distributed and uncorrelated with the observed effect. This method will produce inconsistent estimator if the unobserved individual heterogeneity specific effect is correlated with explanatory variables. In which the fixed effects estimators will be more appropriate.

Fixed effects poisson model: Suppose that we have panel count data for i states, each state observed a total of T_i times (Hu, 2002). Let η_{it} be the count variable for individual i at time t. Then the expected value of η_{it} is linked to asset of regressors by:

$$\begin{aligned}E(\eta_{it}) = \tilde{\lambda}_{it} &= \exp(d_i + x_{it}'\beta) \quad i = 1,2,...,N, \\ &= \alpha_i\lambda_{it} \qquad\qquad\quad t = 1,2,...,T\end{aligned} \tag{3}$$

where, d_i are state specific dummies, $\alpha_i=e^{d_i}$ is the individual specific effect, x_{it} is a vector of regressors. The conditional maximum likelihood method is used to estimate the model parameters (Hausman *et al*., 1984; Green, 2000). As y_{it} follows the Poisson distribution, the sum of accidents:

$$\sum_{i=1}^{T_i} y_{it}$$

also follows the Poisson distribution with parameters:

$$\sum_t \tilde{\lambda}_{it} = \alpha_i \sum \lambda_{it}$$

The parameters will be estimated by obtaining the joint distribution of $(y_{i1},...,y_{iT})$ conditional on their sum (Green, 2000). According to Hausman *et al.* (1984), the distribution of y_{it} conditional on:

$$\sum_{i=1}^{T_i} y_{it}$$

gives a multinomial distribution of:

$$f\left(y_{i1},...,y_{iT} \mid \sum_t y_{it}\right) = \frac{\left(\sum_t y_{it}\right)!}{\prod_t y_{it}!} \cdot \prod_t \left[\frac{\tilde{\lambda}_{it}}{\sum_t \tilde{\lambda}_{it}}\right]^{y_{it}} = \frac{\left(\sum_t y_{it}\right)!}{\prod_t y_{it}!} \cdot \prod_t \left[\frac{e^{X_{it}\beta}}{\sum_t e^{X_{it}\beta}}\right]^{y_{it}} \tag{4}$$

Fixed effects negative binomial model: In this study, the number of road accidents are monthly figures for individual state with defined socioeconomic and development characteristics. Thus, when cross sectional heterogeneity exists, the fixed effects model is more appropriate. Based on the fixed effects negative binomial formulation of Hausman *et al.* (1984) the accident model is expressed as:

$$\log\lambda_{i,t} = \alpha_i + \beta x_{i,t} \quad i = 1,2,...,n \text{ and } t = 1,...,T \tag{5}$$

where, $\lambda_{i,t}$ is the expected number of accidents in state i in year t, α_i is the fixed effects associated with i, and β vectors of parameters to be estimated for the vector of explanatory variables x_{it}. To illustrate the fixed effect negative binomial model, Hausman *et al.* (1984) add individual specific effects of α_i and the negative binomial overdispersion parameter of ϕ_i into the model replacing $\theta_i=\alpha_i/\phi_i$. Here, the number of accident, y_{it} for a given time period, t is assumed to follow a negative binomial distribution with parameters $\alpha_i\lambda_{it}$ and ϕ_i, where $\lambda_{it}=\exp(x_{it}'\beta)$ giving y_{it} has a mean $\alpha_i\lambda_{it}/\phi_i$ and variance $(\alpha_i\lambda_{it}/\phi_i)\times(1+\alpha_i/\phi_i)$ (Cameron and Trivedi, 1998). This model allows the variance to be greater than mean. The parameter α_i is the individual-specific fixed effects and the parameter ϕ_i is the negative binomial overdispersion parameter which can take on any value and varies across individuals. Obviously α_i and ϕ_i can only be identified as the ratio of α_i/ϕ_i and this ratio has been dropped out for conditional maximum likelihood. To show this, let:

$$y_{it} \sim NB\left[\frac{\alpha_i\lambda_{it}}{\phi_i},\left(\frac{\alpha_i\lambda_{it}}{\phi_i}\right)\left(1+\frac{\alpha_i}{\phi_i}\right)\right] \quad (6)$$

then the negative binomial mass function is given by:

$$f(y_{it})=\frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)}\left(\frac{1}{1+\frac{\alpha_i}{\phi_i}}\right)^{\lambda_{it}}\left(\frac{\frac{\alpha_i}{\phi_i}}{1+\frac{\alpha_i}{\phi_i}}\right)^{y_{it}} \quad (7)$$

Thus, when y_{it} follow negative binomial distribution, then $\Pr[y_i,\ldots,y_T]$ is the product of negative binomial densities where

$$\sum y_{it} \sim NB\left[\frac{\alpha_i\sum\lambda_{it}}{\phi_i},\left(\frac{\alpha_i\sum\lambda_{it}}{\phi_i}\right)\left(1+\frac{\alpha_i}{\phi_i}\right)\right] \quad (8)$$

Consequently, the conditional joint density for this observation is

$$\Pr\left[y_1,\ldots,y_T\middle|\sum_{t=1}^{T}y_{it}\right]=\frac{\Gamma\left(\sum_t\lambda_{it}\right)\Gamma\left(\sum_t y_{it}+1\right)}{\Gamma\left(\sum_t\lambda_{it}+\sum_t y_{it}\right)}\times\prod_{t=1}^{T}\frac{\Gamma(\lambda_{it}+y_{it})}{\Gamma(\lambda_{it})\Gamma(y_{it}+1)} \quad (9)$$

This distribution yields the negative hypergeometric distribution (Johnson and Kotz, 1969). The estimation of vector $\hat{\beta}_{NBFE}$ is done using the maximum likelihood method by maximizing the log likelihood function given by:

$$\begin{aligned}L_i=\sum_{i=1}^{N}\Bigg\{&\log\Gamma\left(\sum_{i=1}^{T}\lambda_{i,t}\right)+\log\Gamma\left(\sum_{t=1}^{T}y_{i,t}+1\right)\\&-\log\Gamma\left(\sum_{i=1}^{T}\lambda_{i,t}+\sum_{t=1}^{T}y_{i,t}\right)+\sum_{t=1}^{T}\Big[\log\Gamma(\lambda_{i,t}+y_{i,t})\\&-\log\Gamma(\lambda_{i,t})-\log\Gamma(y_{i,t}+1)\Big]\Bigg\}\end{aligned} \quad (10)$$

Significance testing: In the development of statistical models, it is important to decide whether one model is significantly better than another when additional explanatory variable is added or excluded from the model. The quality of model goodness of fit between the fitted and the observed values y_i were measured using various statistics. To confirm on the suitability of the fitted model, the Akaike information criterion (AIC) is first applied to identify the best model among various model examined. The AIC statistic is given by AIC = $-2[L(\beta)]+2k$ where $L(\beta)$ is the log-likelihood function of candidate model evaluated under β by using observation and k is the number of unknown parameters. Then, the resulting model is subjected to the log-likelihood value where $L(\beta)$ is log-likelihood at convergence and $L(0)$ is log-likelihood in the zero model.

The data: The data used in this study comprised of the monthly Malaysian road accident data from January 1996 to December 2007. The monthly total road accidents or road crash used referred to the total figure of their occurrences on public or private roads due to the negligence or omission by any party concerned (on the aspect of road users conduct, maintenance of vehicle and road condition), environmental factor (excluding natural disaster) resulting in a collision (including "out or control" cases and collision of victims in a vehicle against object inside or outside the vehicle e.g. bus passenger) which involved at least one moving vehicle whereby damage or injury was caused to any person, property, vehicle, structure, or animal was the other. The data were collected from the Royal Malaysian Police, Headquarters in Kuala Lumpur (RMP, 2007). Data on the number of registered vehicles (VEH) were taken from the Department of Road Transport in the Malaysian Ministry of Transportation. The number referred to the total number of vehicles (private and public) that was registered with the Department of Road Transport. It included all vehicles using either petrol or diesel which are motorcycles, motorcars, buses, taxis and hired cars, goods vehicle and other vehicles. However, the figure did not include army vehicle. While, data for climatic variables were collected from the Malaysian Metereologist Department. The climate factor considered is the amount of monthly rainfall (in millimeter) for a particular month. The data were captured from 14 selected weather stations in the respective 14 states. This factor had been most commonly used in previous work in road safety modeling literature (Fridstrom *et al*., 1995). Another climate factor considered was the number of rainy days (in days) for a particular month. The data were also captured from the same 14 weather stations. The number of rainy days was also considered in previous studies of its relationship with road accident crash (Fridstrom *et al*., 1995).

RESULTS AND DISCUSSION

Exploratory analysis: Graphical analysis was done to observe the relationship between the monthly number of road accidents and vehicle volume for 14 states for each of twelve years from 1996 to 2007. Figure 1 provides a plot of original data on the number of accidents against the vehicle volumes using data for all states in all years.

Inspection on the relationship between the number of accidents occurrence and the vehicles volume suggest a non-linear relationship. Figure 2 shows a plot of the ln(accidents) against ln(vehicles) for all 14 states in all years. The number of accidents clearly increases with the vehicles volume. This type of relationship can be analyzed by separating it into cross-section and time-series component using panel data model such as fixed effects model. For most of the months under study, the average monthly rainfall is about 160.36 mL ranging from 0.2 to 1471.1 mL across 14 states in Malaysia while the average number of rainy days is about 5 to 6 days per month.

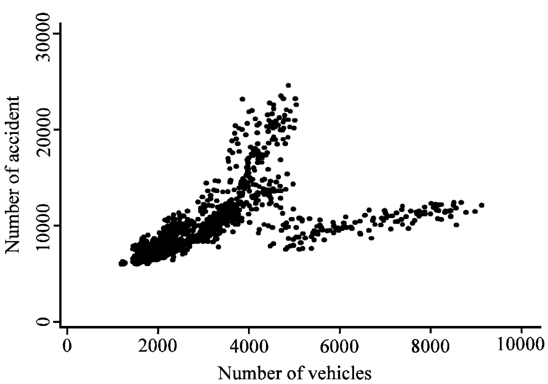

Fig. 1: Plot of road accidents and registered vehicles: pooled (overall) regression

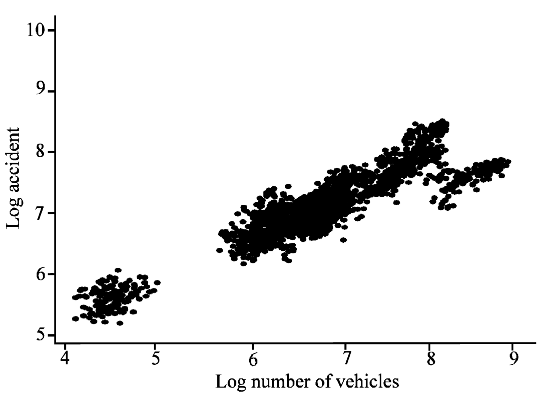

Fig. 2: Plot of log road accidents and registered vehicles: pooled (overall) regression

Panel model: In modeling nonlinear panel model, several nonlinear panel models were estimated. Starting with a saturated model that involves all the possible explanatory variables considered in this study, a procedure of eliminating insignificant variables using backward and stepwise method are undertaken and the most parsimonious model was obtained on the basis of minimizing the AIC value. Table 1 presents the coefficient estimates of the final model for Pooled Poisson regression, Poisson fixed effects and Negative Binomial fixed effects model. The explanatory variables included in the analysis are the number of registered vehicle, the amount of rain and the number of rainy days. The time trend is also added to the analysis to capture the effects of other unobserved exogenous time dependent variables such as improvement in better and safer manufactured vehicle and road due to technological change that may have some influence on road accident occurrence or even severity reduction (Kumara and Chin, 2004; Umar *et al*., 1996; Broughton and Stark, 1986). The effects of seasonality on road accidents occurrence was investigated by introducing dummy variable for the 12 months.

The model estimation procedure begins with the standard pooled Poisson model with assumption of

Table 1: Panel model estimator

	Model		
Variable	Pooled poisson	Poison FE	Negative binomial FE
LogVeh	0.77576**	0.09474**	0.06878**
	(0.000674)	(0.00256)	(0.0104)
LogA_Rain	0.090492**	0.016379**	0.01390**
	(0.000742)	(0.0007543)	(0.0028)
Time	0.001492**	0.004444**	0.00451**
	(0.0000133)	(0.000017)	(0.00007)
Constant	0.323813**		3.681211**
	(0.006754)	-	(0.09087)
Sample size	2016	2016	2016
Group (number of states)	14	14	14
AIC	855,590.6	43,716.77	24,509.72
Log likelihood L(β)	-427,788.29	-21,852.38	-12,247.86

*p-value<0.05,**p-value<0.01, Note: Panel standard error estimates for the slope coefficients are in parentheses independent observations. However, the deviance value of the Poisson model of 837,844.6 indicates a serious overdispersion problem exists in the data. This implies the importance of correcting for overdispersion in the Poison model, the Negative Binomial fixed effects model would be more appropriate. The resulting negative binomial model fixed effects model yields a minimum AIC value of 24,509.72 with improved log likelihood value which indicates that the model has a reasonably good fit. The parsimonious model shows four significant variables that affect the number of road accidents occurrence in Malaysia that includes the number of registered vehicle, the amount of rainfall, time and the month dummy variables. In Table 1 results for dummy variables are omitted for brevity. The level of significance is indicated by the ratio of the parameter estimate, β to the standard error of estimates.

The number of registered vehicles ($p<0.0001$) has a significant positive effect on the likelihood of road accidents occurrence. This implies that the accident count is expected to increase with an increase in the number of vehicles in the country. This positive effect is in accord with the findings on the traffic accident study done by Kumara and Chin (2004) and Jessie and Yuan (1998). The hypothesis is that increment in the number of vehicle volume leads to increases in the distance travel and thus gives greater exposure for accident occurrence. The time trend factor is also estimated in the model. This variable is used as a proxy to describe the technological change that may also reflect the increase in the population volume and the development of road network over the time (Kumara and Chin, 2004; Umar *et al*., 1996) as these monthly data are not available for Malaysian. The time variable in the FE Negative Binomial model indicates an upward trend in the number of road accidents in Malaysia.

The weather condition is found to have a significant impact on accident count. In this study, the rainfall amount (in mm) and the number of rainy days were used to examine such effect on accident count. It was found that the rainfall amount measured during the period of study revealed a positive significant effect in affecting the number of accident occurrence. However, the latter was not significant to capture this effect. This suggests that the accident is expected to increase with an increase in the amount of rainfall. Several interpretations are possible, for example, the surface of road might be slippery during the rainy month that might affect the safety effect (Fridstrom *et al*., 1995). This is in agreement with the findings obtained in the research done by Fridstorm and Ingebrigtsen (1991). To account for factors that vary according to season considering Malaysia as one of the tropical countries, a full set of dummy variables for month was included in the analysis. Based on the Negative Binomial Fixed Effect model, the estimated model yielded significant coefficient estimated of dummy for the month of October, November and December. This suggests that the causal effect is channeled through the seasonal dummies implying more accident is likely to occur in the month of October, November and December compares to the month of January. In other words, these months are particularly prone to accidents. Interestingly, the explanation behind this is unique for Malaysia to revial. This positive effect might be due to the increase in the traveling activity during the unique multicultural and religious activity and school holiday in Malaysia. This common variable has been used in the study done by Umar *et al*. (1996). It is common for Malaysian to take a long holiday during this seasonal holidays to visit their relatives and parents and thus resulting in the increase of traffic volume on all roads nationwide.

CONCLUSION

The application of fixed effects panel count model developed by Hausman *et al*. (1984) has been widely used in modeling road accident count data. This nonlinear panel methodology is appropriate for panel (longitudinal) data. It has several advantages in measuring both cross-sectional and time-series effect particularly in modeling the road accident between states as well as over the time. By using the fixed effects model, our main findings are as follows. First, the number of vehicles has significant effect in accident count. The accident is expected to increase with the increase in the volume of vehicles. Secondly, the weather condition has a significant influence on the accident occurrence. Here, the amount of rainfall has a positive significant effect on accident count. Thirdly, the number of accidents increases with time. Finally, to capture the seasonality effect, the month dummy variable reveals a significant effect on accident occurrence suggesting the months of October, November and December are particularly prone to accident.

Thus, based on the outlined findings, the fixed effects negative binomial panel model approach has successfully modelled the road accident occurrence with correction for overdispersion. This modeling technique can be used to model any non-negative integer count data in a form of panel structure in future research.

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