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USE OF MIXED LOGIT MODELS IN THE PERCEPTION OF ACCIDENT RISK

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ABSTRACT

Traffic fatalities are high in ages between 15 and 29 years, where the human factor causes 70% and 80% of accidents. According to the above, the institutions in charge of preventing traffic fatalities must have the tools to make decisions that promote safer driving habits and thus reduce the number of accidents. The research goal is to identify how drivers behave at risk of traffic fatalities using the mixed logit models. The variables analyzed were: a) speeding, b) driving in the wrong direction, c) overtaking on curves, and d) being under the influence of alcohol. The results show that speed can vary according to driving maneuvers.

INTRODUCTION

The global accident rate is not encouraging; according to the World Health Organization, traffic fatalities claim 1.24 million lives and cause injuries to people between 20 and 50 million. In addition, it is the leading cause of death in the 15-29 age group. Pedestrians, cyclists, and motorcyclists account for 50% of reported fatalities, making them the most vulnerable road users. Low and middle-income countries account for 53% of the world's vehicle fleet and 92% fatalities (World Health Organization, 2013). Traffic fatalities will become the fifth leading cause of death.

Mixed logit (ML) models have been widely used in safety research. Some of the cases have covered the effect of road safety belt use (Gkritza & Mannering, 2008), crash injury severity (Kim et al., 2013; Wu et al., 2014), and pedestrian crossing safety at intersections (Anciaes & Jones, 2018). This background provides literature support for the use of ML in this study. Similarly, the perception of accident risk when driving a vehicle has been a widely addressed phenomenon (Agrawal & Mudgal, 2021; Li et al., 2021; Lidestam et al., 2021; Măirean & Diaconu-Gherasim, 2021).

This paper attempts to answer the question: whether, using mixed logit models, it is possible to determine whether the effects of the parameters vary significantly in people's perception of the risk of an accident?

The rest of the paper is organized in the following sections: Chapter 2 presents the modeling approach, emphasizing the mixed logit. Chapter 3 examines the nature of the data covering the survey design. Chapter 4 shows and discusses the results of the model. Finally, Chapter 5 presents the main contributions and conclusions of the research.

METHODOLOGY

Mixed Logit Methodological Approach

One modeling alternative is ML (Bolduc & Ben-AkiWand, 1996; Brownstone & Train, 1998). The randomness incorporated in the model and the handling of correlation or heteroskedastic effects make it possible to extract virtues and potentialities associated with Logit and Probit models. However, the practical application of these models requires simulation (Munizaga & Álvarez, 2000). This type of specification assumes that random coefficients vary in the population, reflecting possible variations in tastes (Ortúzar S. & Willumsen, 2011).

The ML model assumes a utility function (U_{in}) consisting of a deterministic component (V_{in}), a random component independent (ε_{in}) and identically distributed, and one or more additional random terms. These error terms can be grouped into an additive term η_{in}, which can be a function of the observed data, allowing the presence of correlation and heteroskedastic to be captured. Thus, the utility function is defined as:

$$U_{in} = V_{in} + \eta_{in} + \varepsilon_{in} \qquad (1)$$

Since ε_{in} is iid Gumbell, the conditional probability on η_{in} that individual n chooses alternative i corresponds to the Multinomial Logit or Simple Logit model:

$$P_n(i/\eta) = L_{in}(\eta) = \frac{e^{V_{in}+\eta_{in}}}{\sum_{j \in A(q)} e^{V_{jn}+\eta_{jn}}} \qquad (2)$$

Thus, the probability of choice P_{in} can reach a closed-form overall value of η_{in}:

$$P_{in} = \int L_{in}(\eta) f(\eta / \theta^*) d\eta \qquad (3)$$

Can use it with a utility function with the following specification:

$$U_{in} = \beta^t x_{in} + \mu_{in}^t z_{in} + \varepsilon_{in} \qquad (4)$$

Survey Data and Design

To obtain the perceptions associated with drivers' risk and the influence of their driving behavior. The data were obtained from applying a survey in the city of Ocaña (Colombia). A Declared Preferences (PD) instrument was designed, where participants were confronted with two hypothetical driving scenarios and asked to choose one of them.

The first part of the questionnaire sought to obtain socioeconomic information about the respondent, such as:

- Sex.
- Age.
- Job.
- Level of education.
- Marital status.
- Type of incapacities.
- Ownership of driver's license.
- The seniority of the driver's license.
- Personal monthly salary.
- You’re current job involves driving a vehicle.
- You have been involved in a traffic accident.

Next, four perception indicators were solicited, asking the respondent to answer the question assigned to the indicator based on the possible responses (constantly, frequently, sometimes, and never). Each indicator was denoted by a number, with the associated question shown below:

a) Do you do any other activities during driving (Check the gas level, check the speedometer level)?
b) Do you use a cell phone while driving? (Answering or chatting).
c) Do you drive in sub-optimal conditions? (For example: under the influence of drugs, injuries, sleep, stress).
d) Do you use seat belts or helmets in case of motorcycles while driving?
The PD survey consisted of presenting hypothetical driving scenarios with two alternatives each. Four attributes characterized the other options:

- Driving speed.
- Driving in the wrong direction.
- Overtaking a vehicle in a curve.
- Driving under alcohol and drugs.

The participant was asked to select the one considered most prone to accidents.

RESULTS

The proposed ML model is a function of the explanatory variables and the interactions between the socio-economic variables. The driving speed variable has a random parameter associated with it. The ML model, references the following items:

- The number of observations used in the estimation.
- Log-likelihood of convergence (L (θ)).
- The rho-squared index (ρ^2).

Calculating the separate t-test for each estimated coefficient, from which can test statistical significance. Table 1 shows the results of the ML model.

The values of the main explanatory variables are all significant at a 95% confidence level (except for the parameter associated with the speed with a 90% confidence level) and show signs consistent with microeconomic theory. The ML model adequately reproduces the risk perception of accidents when people increase their driving speed. The same effect is generated when an individual drives the wrong way, overtakes a vehicle on a curve, or drives while intoxicated or under drugs. The significance of the parameter associated with the standard deviation of driving speed (σ_{vel}) indicates that the effects of speed on the risk perception process differ significantly between individuals. The estimation of the parameters associated with the interactions between effects is performed in the model. The interactions tested correspond to the variables $\theta_{vel*gen}$ and $\theta_{avc *age3}$. The results indicate that men perceive a higher risk of accidents at higher speeds than women. The model shows that overtaking maneuvers in curves is more dangerous when between 36 and 45 years of age. For both interactions, the statistical significance of the parameters stands out.

Table 1: ML parameter estimation

Variable	Description	ML	
		Value	***t-test***
Explanatory variables			
θ_{avc}	Overtaking in curves	1.47	3.95
θ_{ccv}	Driving the wrong way	1.37	5.35
θ_{cad}	Driving under the influence of alcohol or drugs	3.11	5.96
θ_{vel}	Driving speed	0.00947	1.71
$\theta_{vel*gen}$	Interaction between driving speed and gender	0.015	2.07
$\theta_{avc *age3}$	Curve overtaking interaction and age3	1.43	2.73
σ_{vel}	DS of the variable driving speed	0.0604	3.3
General Report			

N	Number of observations	
$L(\theta)$	Log-likelihood	-608.811
ρ^2	Rho squared index	0.451

CONCLUSION

The configuration of mixed logit models is essential for understanding crash risk perception. The ML model provides evidence of inter-individual variability in driving risk perception.

The estimated models identified the attributes considered in the experiment, such as:

- Driving speed.
- Driving in the opposite direction.
- Overtaking in curves.
- Driving under alcohol or drugs influences the perception of accident risk that affects drivers.

The ML model showed that the variable driving under alcohol and/or drugs had a higher incidence than the attribute driving speed (significant at 90% confidence level). The variables showed the expected values, and their performance verifies the theoretical basis.

The ML model produces consistent and expected results for its estimation. From it, we can highlight the evidence obtained on how driving speed is perceived differently among drivers. It could also be determined that speed produces a greater sense of risk in men and that overtaking maneuvers on curves is more dangerous for individuals between 36-and 45 years. The above is essential and may become an extension of the work, as many countries have high accident rates associated with speeding.

Future research could focus on performing similar experiments in simulators and comparing the results to accept or refute the findings of this study. Likewise, it would be interesting to consider the effect of other types of vehicles, such as motorcycles, light vehicles, and cargo vehicles, among others. The hypothesis, in this case, is that the perception of accident risk in drivers is different according to the type of vehicle.

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