Addressing Driving Actions of At-Fault Older Drivers: Bayesian Bivariate Ordered Probit Analysis

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ABSTRACT This study aimed to examine the driving actions of at-fault older drivers, and investigate the interrelations between the unobservable factors. To reach the goal, a Bayesian bivariate ordered probit model was proposed, which addressed the driving actions of different drivers simultaneously, and accommodated the interrelations between the unobservables by covariance. The data with 27 arterials from 2014 to 2017 were collected from ArcGIS open data site maintained by Nevada Department of Transportation (NDOT). Compared to individual Bayesian random parameter ordered probit model, the proposed model outperformed according to goodness-of-fit. Results revealed that injury severity and total vehicles were potentially significant factors for actions of at-fault older drivers, while total vehicle and vehicle condition were significant for actions of not-at-fault drivers. The findings can provide potential insights for practitioners to apply the new technology and remind the driving actions of older drivers.

INDEX TERMS Driving action, older driver, Bayesian bivariate ordered probit model, Bayesian seemingly unrelated bivariate ordered probit model, Bayesian random parameter ordered probit model.

I. INTRODUCTION

According to the standard of United Nation, the area with 7% population aged 65 years is considered as ageing society, which is one of the most significant social transformation and challenges in this century. With more and more countries and regions stepping into ageing society, this trend is expected to accelerate, and older drivers are regarded as one of most vulnerable and the highest risk road users in terms of crash-related severe injuries and fatalities [1]. Due to the declines of older drivers in the sensory, cognitive and decision-making abilities, these changes may cause the driving behavior to be risky and unpredictable. Accompanied with the progress of artificial intelligence, connected and autonomous vehicles (CAVs) technologies may substitute human drivers for the decision-making process for a variety of driving tasks [2], especially for older drivers. In this way, the injury due to ageing will be reduced significantly, and the potential benefits will bring a substantial payback. Therefore,

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if in the future the CAV technologies are mature adequately to be utilized, driving behavior will be changed completely and enormous safety improvements for the older drivers will be achieved. Based on this point, the objective of this study is to investigate the factors manipulating the driving behavior of the older drivers and avoid them possibly in the future with new technologies.

Among various driver behaviors, driving action plays an important role in crash injury severity including more than one driver. When the crash happens, drivers need to take different responsibilities, main or minor, especially for older drivers since the injury severity may be worse. The responsibility division can be helpful to clarify the drivers' liability and determine the corresponding personal status and actions. In the dataset from NDOT, the drivers with main responsibility are considered as at-fault, while the drivers with minor responsibility are as not-at-fault. Consequently, another objective of this study is to address the driving actions of at-fault older drivers so that the severity can be alleviated and less damage can be reached.

Various studies have shown that driving behavior is highly related to crashes and severe injury. At early stage, Dobson *et al.* [3] examined factors affecting driving behavior and accident rates in women Australia. A mail questionnaire on driver behavior and road accidents were completed, and the results showed that risky driving behavior for the young women were associated with stress and habitual alcohol consumption, while in the 45-50 years old group, poorer driver behavior were associated with higher levels of education, higher habitual alcohol consumption and lower life satisfaction. Paleti *et al.* [4] examined the impact of aggressive driving behavior on injury severity of drivers. Young drivers, not wearing seat belt, under the influence of alcohol, not having a valid license and driving a pick-up were found to be most likely to behave aggressively. From the gender difference, Jiménez-Mejías *et al.* [5] analyzed the distances travelled, driving behavior and the frequency of involvement in traffic accidents. During three consecutive years the questionnaire was completed, and the results revealed that men drove more kilometers, drove faster, used safety devices less frequently and were involved in risky driving behavior more often than women. Similar study by Lyu *et al.* [6] focused on the effect of gender, occupation and experience on behavior on freeway deceleration lane.

Through the wrist breaking, Mussewhite *et al.* [7] investigated the changes of people's travel behavior. The questionnaire was performed, and it was found that wearing the plaster cast didn't compromise safety, although compensatory behaviors took place. Ma *et al.* [8] analyzed the effect of aggressive driving behavior on driver's injury severity at highway-rail grade crossings. Mixed logit model was proposed and younger male drivers and driving during peak-hours were found to be significant factors for high level injury severity with aggressive driving behavior. Focusing on taxi drivers, Ba *et al.* [9] developed a negative-binomial regression model to forecast the risk of personal injury collisions. The risky driving behaviors (e.g. disregarding red lights, speeding, aggressive driving, fatigue driving, etc.) were highly concerned with the risk of personal injury collisions. Similar study by Wang *et al.* [10] explored the relation between working conditions, aberrant driving behavior and crash propensity among taxi drivers in China. A hybrid bivariate model of crash involvement was specified to capture the unobserved traits and unobserved correlation between error terms. The findings revealed that heavy workload was correlated with the higher propensity of crash involvement, as well as covariate of fatigue and aberrant driving behavior. From the perspective of psychophysical conditions, García-Herrero *et al.* [11] estimated the variations in injury severity and distraction probability based on drivers' behavior. Combining the driver fatigue, gender, with distracted driving, Fountas *et al.* [12] provided further insights on perceived and observed aggressive driving behavior. The correlated grouped random parameters bivariate probit modeling framework was employed, and the results showed that the effect of socio-demographic and behavioral factors on

perceived and aggressive driving behavior may vary across the groups of drivers in terms of magnitude and directional effect. Similarly, Oviedo-Trespalacios *et al.* [13] proposed the grouped random parameters random threshold ordered model to initiate risk-compensating behavior. Panagopoulos and Pavlidis [14] proposed a method forecasting markers of habitual driving behaviors associated with crash risk. An extreme gradient boosting algorithm was fed; alerting drivers when distractions and aggressiveness have taken hold on them can provide sobering awareness, provided that people drift into these states subconsciously. The research above provides some foundation for our study.

Driving behavior may have relation with certain vehicle type. Wenzel and Ross [15] examined the effect of vehicle type and driver behavior on risk. It was found that the higher aggressivity of SUVs and pickup trucks imposed much greater risk than cars on drivers, and more subtle differences in drivers and the driving environment by vehicle type may cause more risks, which provides some insights of our study. Dandona *et al.* [16] explained the risky behavior of drivers for motorized two wheeled vehicles in India, and drivers over 16 years were interviewed at petrol filling stations. The results showed that driver license ownership, use of helmet, lower education gender were significant factors.

Behaviors of older drivers (due to the frailty and high fatality) have been paid much attention. Charlton *et al.* [17] described characteristics of older drivers who adopted self-regulatory driving behaviors. Logistic regression modeling revealed that those most likely to adopt avoidance behavior were female, 75 years and older reported vision problem and lower confidence ratings. Sargent-Cox *et al.* [18] provided health literacy of older drivers and the importance of health experience for self-regulation of driving behavior. A telephone interview was completed with drivers aged 65 years and over, and the results showed that being older and having more than one medical condition was found to increase the likelihood of self-regulation of driving, but health knowledge was less important for predicting driving behavior than health experience. Continuously, Hassan *et al.* [19], [20] explored the process of self-regulation and driving cessation among older drivers over 70 years. The findings suggested that further elaboration of the precaution adoption process model was required to take into account the role of insight and feedback on the process of self-regulation among older drivers. Devlin and McGillivray [21] explored self-regulatory driving behavior amongst older drivers in terms of cognitive status. Telephone interviews were conducted and self-regulation was found to be common with the majority of drivers aged 65 years and above, i.e. the largest discrepancy between passenger and driver reports of self-regulation behavior was found for the drivers with cognitive impairment.

Using a portable driving simulator, Devlin *et al.* [22] investigated driving behavior of older drivers with mild cognitive impairment (MCI). The simulation displayed that MCI patients performed more poorly than controls across a number of variables, but the trends failed to reach

statistical significance. From the visual search behavior, Dukic and Broberg [23] identified to what degree the visual behavior could explain older driver's involvement in intersection accidents. The results showed that the older drivers looked more at lines and markings on the road to position them in the traffic.

Distracted and aggressive driving also plays an important role in older drivers' behavior. Charlton et al. [24] examined older driver engagement in distracting behavior at intersections. Drivers between 65 and 83 years drove an instrumented vehicle on their regular trips for about two weeks, and the most frequently observed distracting behavior were scratching/grooming. At intersection the key variables in distracting behavior were intersection complexity, vehicle status and traffic density. Speeding behavior can be one characterization of aggressive driving. Chevalier et al. [25], [26] explored the older drivers' speeding behavior. The results suggested that older drivers with poorer cognition and visual attention may drive more cautiously. Kidd and Buonarosa [27] compared distracting behaviors among different age groups, teenagers and young, middle-aged, and older adult drivers. The results showed that collision warnings were not related to significant increase or decreases the overall likelihood of distracted driving for teen and adult drivers.

From the perspective of route choice, Payyanadan et al. [28] developed a route risk measure, and quantified the risk of driving challenges using older driver crash statistics. Results showed that the low-risk alternative reduced risk for 77.7% of the older drivers' trips on average by 61.4%. Similarly, Payyanadan et al. [29] used trip diaries to mitigate route risk and risky driving behavior among older drivers.

Summarized from the literature above, there have been various methods and approaches about the driving behavior and behavior of older drivers. However, there are no specific studies focusing on the driving actions and there may exist interrelations between the unobservables of at-fault older drivers and not-at-fault drivers. Therefore, the purpose of this study is to estimate the driving actions and to control for interrelations with bivariate ordered probit models in Bayesian framework, which can address driving actions of both drivers simultaneously, and accommodate the interrelations between the unobservables by covariance, so that the findings can provide some potential insights for the application of CAV technologies in the future to improve the driving actions of older drivers.

II. METHODOLOGY
A. BIVARIATE ORDERED PROBIT MODEL

It is assumed that two ordered dependent variables $Y_j (j = 1, 2)$ are the outcome of a joint decision, while the decisions depend on individual characteristics of each probit equation and the two equations' errors are correlated. Thus, the model can be described as:

$$y_{i1}^* = x_{i1}'\beta_1 + \varepsilon_{i1} \quad y_{i2}^* = x_{i2}'\beta_2 + \varepsilon_{i2} \tag{1}$$

where y_{ij}^* represents latent variables denoting a threshold for choosing one alternative to the other, in which $i = 1, \ldots n$, is the number of observations. x_{ij} represents individual specific covariates, and β_j denotes the regression coefficients. Here ε_{ij} are normally distributed errors correlated with a correlation parameter ρ. Specifically, y_{i1}^* and y_{i2}^* here denote the driving behavior of older drivers with main responsibility and that of drivers involved in the same injury, respectively, and x_{i1} and x_{i2} include various influencing factors, injury severity, driver conditions, vehicle conditions, and environmental conditions.

The observed ordered dependent variable follows the rule by:

$$Y_{ij} = \begin{cases} 1 & \text{if } y_{ij}^* = backingup \\ 2 & \text{if } y_{ij}^* = changing\ lanes \\ 3 & \text{if } y_{ij}^* = going\ straight \\ 4 & \text{if } y_{ij}^* = making\ U-turn \\ 5 & \text{if } y_{ij}^* = passing\ other\ vehicle\ /speeding \\ 6 & \text{if } y_{ij}^* = stopped \\ 7 & \text{if } y_{ij}^* = turning\ left \\ 8 & \text{if } y_{ij}^* = turning\ right \\ 9 & \text{if } y_{ij}^* = other \\ 0 & \text{if } y_{ij}^* = unreported \end{cases} \tag{2}$$

In the bivariate probit model, however, the joint response as a bivariate standard normal cdf is modeled. More details about bivariate probit model and estimation can be referred to Zhou et al.[30] and Yuan et al. [31].

B. SEEMINGLY UNRELATED BIVARIATE ORDERED PROBIT MODEL

Different from bivariate ordered probit model, the seemingly unrelated bivariate ordered probit model can be expressed as follows:

$$y_{i1}^* = x_{i1}'\beta_1 + \delta\left(y_{i2}^*\right) + \varepsilon_{i1} \quad y_{i2}^* = x_{i2}'\beta_2 + \varepsilon_{i2} \tag{3}$$

where all the variables represent the same meaning as Equation (1), and the Wald test can provide evidence on the correlation between the unobserved explanatory variables of both equations so that if $\rho = 0$ then y_{i2}^* is exogenous for the second equation.

The bivariate probit model can be estimated by full-information maximum likelihood or Bayesian approach. Bayesian estimation has more advantages over other methods [30], which considers both prior distribution and posterior density. In this study, Markov Chain Monte Carlo (MCMC) is conducted to compute the joint posterior distribution. In order to determine the significance, the results consider Bayesian credible interval (BCI) as a probability statement about the parameter itself, i.e. a 95% BCI involves the true parameter value with ∼95% certainty. If the 95% BCI of the posterior mean does not involve 0, it indicates that this impact is statistically significant at the 95% level [30].

For model comparison, as provided by previous studies under the Bayesian [31], [32], the Deviance Information Criterion (DIC) is employed to make the comparison, meanwhile Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are adopted to assess the goodness-of-fit for maximum likelihood, thus, DIC is utilized to compare the models abovementioned:

$$DIC = D\left(\bar{\theta}\right) + 2p_D = \bar{D} + p_D \qquad (4)$$

where $D\left(\bar{\theta}\right)$ is the deviance evaluated at $\bar{\theta}$, the posterior mean of the parameter of interest, p_D is the effective number of parameter in the model, and $\bar{D}$ is the posterior mean of the deviance statistic $D\left(\bar{\theta}\right)$. The lower the DIC, the better the model is. Usually differences in DIC of more than 10 definitely rule out the model with the higher DIC, and differences between 5 and 10 are considered substantial, while the difference less than 5 reveals that the models are not statistically different.

III. DATA DESCRIPTION

ArcGIS open data site maintained by Nevada Department of Transportation (NDOT) from 2014 to 2017 was considered as the data source, and 27 major and minor arterials in the metropolitan Las Vegas area were the target population selected in this study, which included City of Las Vegas, City of North Las Vegas, City of Henderson, and Clark County. Four main aspects were collected and considered: the driver features, the vehicle profiles, roadway characteristics and the injury features and environment.

According to Charlton *et al.* [24] and Devlin and McGillivray [21], drivers aged 65 and more are regarded as older drivers. As described, 27 arterials were elaborately selected, in which driving action observations of at-fault older drivers reach 2,302. In order to examine the correlation between driving action of at-fault older drivers and that of not-at-fault drivers involved in the same injury, the dependent variables in the proposed model were considered as bivariate, and the driving action from Equation (2) was considered as ordered, which can estimate the equation less complicated than multinomial model, therefore, the dependent variables can be matched with bivariate ordered probit model.

As stated above, the explanatory variables here include the vehicle, roadway, injury and environment. In accordance with the classification by NDOT, when the crash happens, if there are two or more vehicles included, the at-fault vehicle is regarded as vehicle 1, while the not-at-fault vehicle is considered as vehicle 2, in this way the at-fault and not-at-fault drivers can be sorted out from the dataset. Followed this category, the vehicle-related variables include the total vehicle, vehicle types, vehicle direction, vehicle action (e.g. changing lanes, making U-turn, passing other vehicles, etc.), vehicle conditions (e.g. hit-and-run, mechanical defects, driving too fast, etc.), vehicle driver's age and driver's conditions (e.g. normal, fatigue, physical impairment, distracted, etc.) for at-fault and not-at-fault drivers.
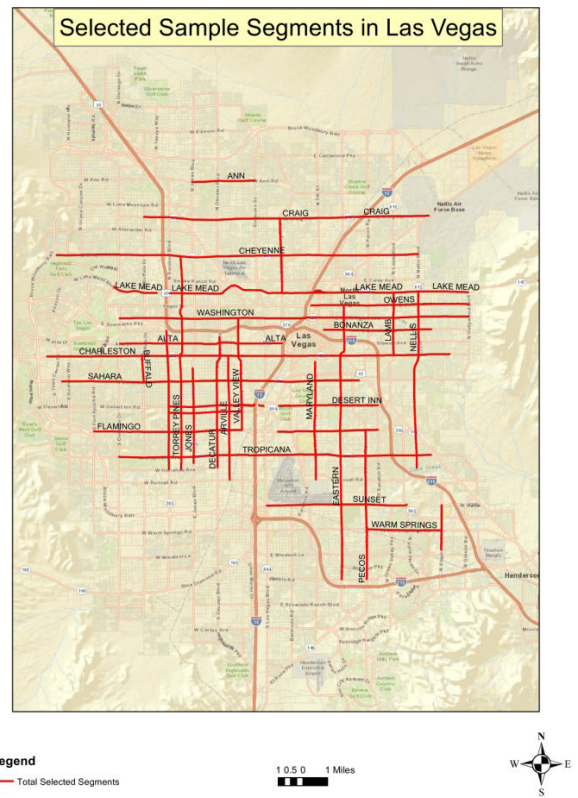

FIGURE 1. Selected arterials in las vegas.

The roadway characteristics include the number of vehicle lanes, roadway conditions (e.g. dry, wet, ice, snow, etc.), while the injury includes the time, location, severity and the environment involves the weather, lighting conditions, and first harm (e.g. median, fence, pedestrian, etc.)

In order to assess the proposed models in Stata software, the categorical parameters are digitalized and standardized, and all the parameters categorized are listed and summarized in Table 1 with the proportions of each parameter.

IV. RESULTS

Based on the variables selected from the four components, the correlation between main influencing factors needs to be examined before running the model. The Pearson correlation test was performed to avoid the co-linearity among the independent variables. Shown from the test result, crash type is highly related to total vehicle, thus, in the final results the crash type and total vehicle may not occur at the same time.

The Bayesian bivariate ordered probit and Bayesian seemingly unrelated bivariate ordered probit models are proposed to assess the actions of at-fault older drivers and that of not-at-fault drivers. In order to make the comparison, the individual Bayesian random parameter ordered probit model is performed to examine whether the single or bivariate model is more suitable for this problem. Table 2 and Table 3 give the results of single and bivariate models.

TABLE 1. Summary of parameters.

Variable	Description	Count (proportion)
i) Dependent variables		
Action of at-fault older drivers	1-Backingup	16(0.6%)
	2-Changing lanes	149(6.5%)
	3-Going straight	1041(45.2%)
	4-Making U-turn	60(2.6%)
	5-Passing other vehicles/racing	6(0.3%)
	6-Stopped	26(1.1%)
	7-Turning left	635(27.5%)
	8-Turning right	188(8.2%)
	9-Other	8(0.3%)
	0-Unreported	173(7.5%)
Action of not-at-fault drivers	1-Backingup	1(0.01%)
	2-Changing lanes	6(0.3%)
	3-Going straight	1433(62.2%)
	4-Making U-turn	2(0.04%)
	5-Passing other vehicles/racing	4(0.2%)
	6-Stopped	576(25.0%)
	7-Turning left	146(6.3%)
	8-Turning right	39(1.7%)
	9-Other	9(0.2%)
	0-Unreported	90(3.9%)
ii) Independent variables		
Crash type	1-Angle	1372 (59.6%)
	2-Backing	22(0.9%)
	3-Head-on	16 (0.6%)
	4-Rear-end	657 (28.5%)
	5-Sideswipe	141 (6.1%)
	6-Non-collision	84(3.6%)
	0-Unknown	9(0.3%)
Injury severity	0-Property Damage Only (PDO)	625(27%)
	1-Injured +Fatality	1677(73%)
Vehicle 1 type	1-Car	1384 (60.2%)
	2-Truck/bus	487 (21.1%)
	3-Motorcycle	14 (0.6%)
	4-Other	15 (0.6%)
	5-Pickup/van	402 (17.5%)
Vehicle 1 driver condition	1-Apparently normal	1936 (84.1%)
	2-Driving under influence(DUI)	70 (3.0%)
	3-Drowsiness, fatigue, fainted etc.	15 (0.7%)
	4-Illness/physical impairment	56(2.4%)
	5-Inattentio/distracted	76 (3.3%)
	6-Obstructed view	10 (0.4%)
	7-Other	63 (2.7%)
	0-Unknown	76 (3.3%)

TABLE 1. *(Continued.)* Summary of parameters.

Variable	Description	Count (proportion)
Vehicle 2 driver age	1-less than 18 years	102 (4.4%)
	2-18- 65 years old	1432(62.3%)
	3-more than 65 years old	768(33.3%)
Vehicle 2 driver condition	1-Apparently normal	2176 (94.5%)
	2-Driving under influence(DUI)	8 (0.3%)
	3-Drowsiness, fatigue, fainted etc.	5(0.2%)
	4-Illness/physical impairment	1 (0.04%)
	5-Inattentio/distracted	0 (0.0%)
	6-Obstructed view	0 (0.0%)
	7-Other	3 (0.1%)
	0-Unknown	109 (4.7%)
Vehicle 2 condition	1-Disregarded traffic signs/signals/road markings	7 (0.3%)
	2-Driving too fast	4 (0.1%)
	3-Failed to yield right of way	6 (0.3%)
	4-Failure to keep in proper lane or running off road	4(0.1%)
	5-Follwed too closely	9 (0.4%)
	6-Hit and run	8 (0.3%)
	7-Made an improper turn	2 (0.08%)
	8-Mechnical defects	3 (0.1%)
	9-Other improper driving	30 (1.3%)
	0-Unknown	2229 (96.8%)
Vehicle 2 type	1-Car	1250 (54.3%)
	2-Truck/bus	468(20.3%)
	3-Motorcycle	75(3.3%)
	4-Other	145 (6.3%)
	5-Pickup/van	364(15.8%)
Vehicle 1 condition	1-Disregarded traffic signs/signals/road markings	222(9.6%)
	2-Driving too fast	64(2.8%)
	3-Failed to yield right of way	805(34.9%)
	4-Failure to keep in proper lane or running off road	110 (4.8%)
	5-Follwed too closely	273 (11.8%)
	6-Hit and run	33 (1.4%)
	7-Made an improper turn	93 (4.0%)
	8-Mechnical defects	3(0.1%)
	9-Other improper driving	367(15.9%)
	0-Unknown	332 (14.4%)

TABLE 1. *(Continued.)* Summary of parameters.

First harm	1-Cross median/centerline	1 (0.04%)
	2-Fence/wall	0 (0.0%)
	3-Light/luminary support	0(0.0%)
	4-Motor vehicle in transport	544 (23.6%)
	5-Pedal cycle/pedestrian	0(0.0%)
	6-Ran off road left/right	2 (0.09%)
	7-Slow/stopped vehicle	49 (2.1%)
	8-Other fixed/movable object	2 (0.09%)
	9-Other non-collision	2 (0.09%)
	0-No data	1702(73.9%)
Road conditions	1-Dry	2254 (97.9%)
	2-Wet	38 (1.7%)
	0-Unknown	10 (0.4%)
Weather conditions	1-Clear	1963(85.3%)
	2-Cloudy	290 (12.6%)
	3-Rain	31 (1.3%)
	4-Blowing sand, soil, dirt, snow	4 (0.2%)
	5-Other	2 (0.09%)
	0-Unknown	12 (0.5%)
Lighting conditions	0-Daylight	1824 (79.2%)
	1-Dark	478(20.7%)

iii) Continuous variables		Mean	S.D	Min	Max
Total vehicle	Total vehicles involved	2.13	0.51	2	8

Shown from Table 2 and Table 3, significant variables of Bayesian random parameter ordered probit model are little different from those of Bayesian bivariate ordered probit model and seemingly unrelated bivariate ordered probit model. Injury severity is significant for both random parameter ordered probit models, but is only significant for actions of at-fault older drivers in bivariate models. The covariances ρ of both models are not equal to 0 and both are significant, implying that correlation indeed exists between the actions of at-fault older drivers and that of not-at-fault drivers. Moreover, the absolute value ρ (0.344) from Bayesian bivariate ordered probit models is larger than that (0.336) from Bayesian seemingly unrelated bivariate ordered probit model. Furthermore, the DIC values (1419.021 and 1432.931) from bivariate models are much smaller than those (6754.678 and 4462.689) from single models, and the difference is beyond 10, which indicates the models are statistically different. Combined the two criteria, the goodness-of-fit of bivariate models performs better, whereas the Bayesian bivariate ordered probit model

is a little better than the corresponding seemingly unrelated bivariate one, thus the explanation would concentrate on the Bayesian bivariate ordered probit model.

As for the actions of at-fault older drivers, injury severity and total vehicle are significant variables, while as for the actions of not-at-fault drivers total vehicle and vehicle 2 condition are significant. As seen, injury severity is positively associated with actions of at-fault older drivers, indicating that the severe injury may cause the older drivers in going straight action to convert into turning left or right. This is in agreement with common sense. Making right or left turning requires more decision-making process than going straight, thus leading to more chances of running into severe injury. It can be calculated that the actions changing probability may rise 22.9% if the injury severity changes from PDO to injured and fatality.

Total vehicles involved play a positive role in actions of at-fault older drivers, i.e. the more number of total vehicles involved, the more actions the older drivers need to make, which is understandable. Among all the older drivers' actions, going straight and turning left occur frequently, accounting for about 45.2%, and 27.5%, respectively. When more vehicles are included during driving, the older drivers need to determine whether going straight or making turns. The possibility of changing from going straight to turning left is increased 19.9% when one more vehicle is added during driving.

Similarly, total vehicles have positive association with actions of not-at-fault drivers with the same injury, and compared to the at-fault older drivers, the possibility of changing from going straight to turning left or stopped is increased over 400 percent when one more vehicle is added, which indicates that the actions of not-at-fault drivers would definitely change.

Another significant variable, the vehicle 2 condition (i.e. the vehicle with the same injury) is positively related to drivers' actions, which indicates that when the vehicle conditions vary from ''failed to yield right-of-way'' and ''hit and run'' to ''other improper driving'', the actions of drivers with the same injury is changed from going straight to turning left or stopped, and the possibility is increased 22.9% during this variation.

V. DISCUSSION

As stated above, there have been various methods and approaches about the driving behavior analysis of older drivers. However, most of the studies address the behavior of older drivers generally and individually, and there may exist interrelations between the unobservables of at-fault older drivers and not-at-fault drivers with the same injury. In this study, in order to estimate the two (seemingly unrelated) driving actions and to control for interrelations between their unobservables, the Bayesian bivariate probit models are proposed, which can address the driving actions of at-fault older drivers and that of not-at-fault drivers simultaneously, and accommodate the interrelations between the unobservables.

TABLE 2. Estimation results of Bayesian random parameter ordered probit models.

Variable	Mean	Std. Dev.	MCSE	95% BCI
Actions of at-fault older drivers				
Injury severity	0.200*	0.051	0.002	(0.104, 0.297)
Total vehicle	-0.179*	0.037	0.005	(-0.248, -0.107)
Vehicle 1 condition	-0.059*	0.008	0.001	(-0.074, -0.043)
Sigma^2	0.015	0.008	0.001	(0.005, 0.038)
DIC	6754.678			
Actions of drivers involved in the same injury				
Injury severity	-0.107*	0.051	0.006	(-0.208, -0.014)
Crash type	0.154*	0.015	0.002	(0.125, 0.183)
Vehicle 2 driver condition	-0.367*	0.018	0.001	(-0.402, -0.330)
Sigma^2	0.023	0.012	0.001	(0.006, 0.053)
DIC	4462.689			

Note: * denotes significance at 95% confidence interval.

TABLE 3. Results for Bayesian bivariate probit and Bayesian seemingly unrelated bivariate probit models.

Variable	Bayesian bivariate ordered probit				Bayesian seemingly unrelated bivariate ordered probit			
	Mean	Std. Dev.	MCSE	95%BCI	Mean	Std. Dev.	MCSE	95%BCI
Actions of at-fault older drivers								
Injury severity	0.229*	0.087	0.003	(0.052,0.406)	0.226*	0.079	0.003	(0.070,0.383)
Total vehicle	0.199*	0.093	0.003	(0.030,0.393)	0.193*	0.084	0.003	(0.022,0.359)
Vehicle 2 condition	0.059	0.039	0.002	(-0.024, 0.132)				
Constant	0.279	0.441	0.019	(-0.566, 1.173)	0.878*	0.181	0.005	(0.521, 1.238)
Actions of drivers involved in the same injury								
Injury severity	0.193	0.191	0.010	(-0.182,0.555)				
Total vehicle	4.388*	0.308	0.015	(3.855,5.058)	3.318*	0.404	0.014	(2.567,4.165)
Vehicle 2 condition	0.229*	0.041	0.001	(0.148,0.309)	-0.132*	0.046	0.002	(-0.218,-0.035)
Constant	-8.723*	0.770	0.039	(-10.417,-7.305)	-4.111*	0.853	0.029	(-5.925, -2.546)
Goodness-of-fit								
ρ	0.344*	0.114	0.002	(0.113, 0.569)	0.336*	0.113	0.002	(0.115,0.558)
No. of observations		2302				2302		
Log marginal likelihood		-763.936				-759.413		
DIC		1419.021				1432.931		

Note: Std. Dev.=Standard Deviation; MCSE=Monte Carlo Standard Error; BCI=Bayesian credible interval; * denotes significance at 95% confidence interval.

Shown from Table 2 and 3, the closer examination of the estimated results displays some similarities and differences between individual and bivariate models. First, the similarity lies in that among all the influencing variables injury severity is of significance for actions of at-fault older drivers, and vehicle 2 condition is significant for not-at-fault actions of drivers. This indicates that injury severity is critical for the older drivers' actions, and not-at-fault drivers involved in the same injury needs to pay more attention to vehicle 2 condition. Second, the difference is that significant variable of bivariate models are fewer than those of single models, and the correlations are highlighted. This implies that the actions of at-fault older drivers are associated with themselves as well as not-at-fault drivers involved in the same injury risk.

In accordance with the results obtained, for the at-fault older drivers empirically, injury severity should be reduced

as much as possible and if in the future CAVs are realized, it would be decreased to a great extent. Moreover, the number of vehicles involved will be reduced if CAV technologies were employed; as for the not- at-fault drivers, keeping vehicle itself condition is the emphasis, and under autonomous driving condition the vehicles may avoid this situation and select other routes in advance.

VI. CONCLUSION

In this study Bayesian bivariate probit model was presented to examine the driving actions of at-fault older drivers, in which driving actions were addressed by bivariate ordered probit model simultaneously within Bayesian framework, and the interrelations between the unobservables were accommodated by covariance. The results revealed that injury severity and total vehicles were potentially significant factors for

driving actions of at-fault older drivers, while total vehicles and vehicle 2 condition were significant for not-at-fault drivers.

Two main findings can be obtained from the results of the work. First, there does exist correlation between actions of at-fault older drivers and that of not-at-fault drivers, compared to individual random parameter ordered probit models. Second, Bayesian bivariate ordered probit model can address the driving actions simultaneously, and accommodate the interrelations between the unobservables, which expands the range of bivariate probit analysis.

Some drawbacks may need to be considered in the future. More variables related to older drivers' characteristics need to be collected, such as driver personal status (e.g. gender), physical and psychological status, education level, driving habits (passive or aggressive) etc., and with those variables the driving behavior can be reflected completely. Another weakness is that the results of the work are founded on the dataset from Las Vegas, and it is worthy of employing different data sources to ascertain the findings and transferability in the future work. Further study may consider the space and time, so that spatial and temporal issues can be addressed concretely.

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