Examining injury severity in left turning crashes at intersections

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Abstract

In response to the increasing concerns and challenges for most frequently left-turn crashes at intersections, partial proportional odds models, for which some of the beta coefficients vary across variables, are proposed to examine and understand the influence of contributory factors (i.e. human attributes, traffic flow features, roadway geometrics, and environmental factors, etc.) on injury severity involved in left-turn crashes, using the selected 317 crash data over latest 6 years from Xian city. The results show that partial proportional odds model has better performance than general ordered logit or probit probability approach. Specifically, the aged and younger drivers are more prone to cause left-turn crashes, and the increasing effect of trucks involvement, impact points of both vehicles, environmental factors, safety belt usage, alcohol and/or drugs are also significantly associated with higher injury severities, which was underestimated or underreported in previous researches.

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1 Introduction

As the most dangerous locations of a roadway network, intersections have a poor safety performance compared with other road location groups [1]. According to the Harbin Traffic Police annual statistics report for 2008, motorcycle crashes constitute about 68.3% of fatal and about 56.9% of injury records at intersections controlled by traffic signals [2] and these observations are even more alarming in some hilly cities, such as Qingdao, Dalian, etc. Obviously, intersections are prone to be involved in traffic crashes due to the substantial causal factors, such as vehicular characteristics, driver attributes, pedestrian conflicts, roadway geometry features, environmental factors, etc [3, 4]. How these different factors affect the occurrence of crashes and severities, however, are still not clear, particular left-turn crashes.

There have been considerable research reports on the crash injury severity in the last two decades. A number of researchers have attempted to specify multinomial logit models into quantifying the effects of multiple alternatives (e.g. roadway, traffic, environmental, human and vehicular factors) on intersection related injury severity [5–7]. Chimba and Sando (2011) considered number of lanes, alcohol and drug use, high posted speed limit, curved areas, turning movements, ramps, and driving with no adequate daylight in their multinomial logit and multinomial probit analysis of independent variable effect on each injury severity [8]. Geedipally et al (2010) applied multinomial logit model to predict the proportion of crashes by collision type and to estimate crash counts by collision type and found it produced the best fit even for small sample size [9].

However, ordered nature of severity is inconsistent with the general logit model's assumption that alternatives or variables have independent errors. Hence, nested logit, mixed logit, or probit models can be applied to indentify the severity in terms of levels or grades from a modeling perspective. Young and Liesman (2007) applied the binary logit model to examine whether there was significant correlation between weather station wind data and the likelihood of freight vehicle involved overturning crashes [10]. Tay and Rifaat (2007) applied the ordinal probit model to determine the determinants (i. e., vehicle type,

road type, collision type, driver's characteristics and time of day, etc) of the severity of intersection crashes using 1992-2002 crash data in Singapore [11].Unfortunately, the assumption of the same coefficients of ordered probability models for different severity levels except for cut-off points is too arbitrary, and determining more parameters than necessary also causes some variables insignificant [12]. Wang and Abdel-Aty (2008) examined the left-turn crash injury severity using partial proportional odds models and reached a consistently better performance than ordered probability models with either logit or probit function [13], where parallel-lines constraint is violated only by one or a few of the included explanatory variables.

In summary, there have been numerous studies investigating crash injury severity. Unfortunately, only limited studies focused on left-turn crash injury severity at intersections specifically, and in previous studies, crash injury features are unable to be associated with contributory factors (i.e., turning movements, signal phase, traffic flow, roadway geometrics, environmental attributes, etc) that depend on sufficient crash data. However, it is difficult to collect crash data or even not available for most intersections. In this study, left-turn crash injury severity is estimated using partial proportional odds models, compared with ordered logit and probit models. Upon the urgent demand, the primary purpose of this research is to specify the effect of specific attributes on crash severity features using the surveyed 2005-2010 intersection crash data in Xi'an city, which enables researchers, engineers and decision-makers to identify and rank intersections for safety performance improvement needs.

2 Data Collection

The data is sourced from the *Traffic Safety Statistics and Analysis Database* developed by Xi'an General Department of Transportation, which consists of data compiled from a sample of police-reported crashes that involve at least one motor vehicle traveling on a traffic road / street and resulting in property damage, injury, or death. A number of crash-related information on crash records, characteristics of the individuals involved, locations of crash, intersection geometric features and traffic control from 2005 to 2010 were obtained for 163 four-legged signalized intersections in Xi'an city. Details include the date of the occurrence, time of day, environment factors, involver age and gender, vehicle characteristics, entering traffic flow, roadway design attributes, and severity level in most observed crashes. According to the direction of vehicle movement including straight ahead, making right-turn and making left-turn, left-turn crashes could be considered as the crashes involved the making left turn vehicles.

Of the 1368 collisions at the selected intersections, 391 were left-turn collisions that account for 28.58% of all observed collisions at the selected locations. The injury severity of each individual involved in the crash record is collected on a five point ordinal scale in increasing of severity: 1 = no injury, 2 = possible injury, 3 = non-incapacitating injury, 4 = incapacitating in-

jury, and 5 = fatal injury [14]. Of the total 391 left turn crashes, 1.17% crashes are classified as fatal crashes, 52.63% are classified as injury crashes that at least one person was injured and the rest of them are property damage over CNY 5000 or no injury crashes.

Two approaches were used to select approximate variables for the severity estimation model. The first was to reference previous studies and find these similar reported variables [15, 16]. The second was to focus on local requirement and determine the specific variables that might have significant influence on injury crashes. It should be noted that some important variables such as AADT, intersection width, median exists were not chosen here because of the missing of necessary message in original crash reports. Therefore, 317 observations were finally explored to develop models retaining 9 variables in categories and the further descriptive lists of the corresponding variables were in Table 1, including type of vehicle, fault, crash geometry, safety belt equipment, light condition, age, weather, etc.

3 Model Specification

This study aims to evaluate the associations between driver injury severity and possible contributory factors. Since the severity of a crash is recorded in simple ordinal patterns such as fatal, injury and non-injury crashes, thus the ordered probit or logit model could be used to measure the crash involved severity because these approaches yield efficient and consistent estimates [17].

If the crash severity could be considered as an ordinal variable having m categories, Let j ($j = 1, 2, \ldots, m$-1) be an index to describe a severity level. The index j for severity level, for example, may take values of "no injury" ($j = 1$), "possible injury" ($j = 2$), "non-incapacitating injury" ($j = 3$), "incapacitating injury" ($j = 4$), and "fatal injury" ($j = 5$). Therefore, the probability of crash i having a severity level j will be specified through an ordered logit model (OLM) [18] as:

$$P\left(Y_i > j\right) = g\left(X_i \beta'\right) = \frac{\exp\left(X_i \beta' - \tau_j\right)}{1 + \exp\left(X_i \beta' - \tau_j\right)}, \quad (1)$$
$$j = 1, 2, \cdots, m - 1$$

where X_i is a $k \times 1$ vector of observed explanatory variables of crash i, β is a $k \times 1$ vector of under-determined regression parameters. The model parameter β and cut-point (τ_j) of crash i are estimated by maximum likelihood method [19].

It should be noted that the errors of Eq. (1) is assumed to be homoskedastic. However, such an assumption is violated, then the estimated parameters yield the inconsistency due to the aggregation bias assumption [20]. To overcome the shortcoming of unequal error variances, the heterogeneous choice model (HCM) is proposed [21] as:

$$P\left(Y_i > j\right) = g\left(\frac{X_i \beta'}{\sigma_i}\right) = \frac{\exp\left(\frac{X_i \beta'}{\sigma_i} - \tau_j\right)}{1 + \exp\left(\frac{X_i \beta'}{\sigma_i} - \tau_j\right)}, \quad (2)$$
$$j = 1, 2, \cdots, m - 1$$

Tab. 1. Driver-injury statistics and percentage distribution. Note: * AADT per lane > 5,000 pcu, based on the total number of 317 observations.

Explanatory variables	No injury		Possible injury/non-incapacitating injury		Incapacitating injury/fatal		Total	%
Driver features of left-turning vehicle								
Very Young (age ≤ 18)	2	100	0	0	0	0	2	0.63
Young (18 < age < 24)	13	72.2	4	22.2	1	5.6	18	5.68
Old (age>65)	21	63.6	8	24.2	4	12.1	33	10.41
Alcohol/drug impaired	45	56.3	22	27.5	13	16.3	80	25.24
Trapped/extracted	14	51.9	7	25.9	6	22.2	27	8.52
Illness/fatigured	9	39.1	11	47.8	3	13.0	23	7.26
Asleep/fainted	17	54.8	10	32.3	4	12.9	31	9.78
Safety belt not used	136	59.4	54	23.6	39	17.0	229	72.24
Driver features of entering vehicle								
Very Young (age ≤ 18)	1	50.0	1	50.0	0	0	2	0.63
Young (18 < age < 24)	8	61.5	4	30.8	1	7.7	13	4.10
Old (age>65)	25	64.1	11	28.2	3	7.7	39	12.30
Alcohol/drug impaired	107	59.8	49	27.4	23	12.8	179	56.47
Trapped/extracted	31	58.5	14	26.4	8	15.1	53	16.72
Illness/fatigured	13	36.1	17	47.2	6	16.7	36	11.36
Asleep/fainted	12	34.3	14	40.0	9	25.7	35	11.04
Safety belt not used	121	52.4	63	27.3	47	20.3	231	72.87
Vehicle characteristics								
Both vehicles in large size	13	65.0	5	25.0	2	10.0	20	6.31
Motorcycle involved	46	61.3	20	26.7	9	12.0	75	23.66
Impact point of left-turning vehicle								
Back right	69	62.2	31	27.9	11	9.9	111	35.02
Back	47	71.2	15	22.7	4	6.1	66	20.82
Back left	53	49.1	39	36.1	16	14.8	108	34.07
Front left	15	78.9	3	15.8	1	5.3	19	5.99
Other	11	84.6	2	15.4	0	0.0	13	4.10
Impact point of entering vehicle								
Front right	72	59.5	34	28.1	15	12.4	121	38.17
Back right	53	60.9	26	29.9	8	9.2	87	27.44
Back and back left	66	77.6	16	18.8	3	3.5	85	26.81
Other	17	70.8	5	20.8	2	8.3	24	7.57
Roadway characteristic								
Heavy traffic*	77	58.8	35	26.7	19	14.5	131	41.32
Average daily percent of trucks	34	48.6	21	30.0	15	21.4	70	22.08
Posted speed limit 40 km/h	87	46.3	58	30.9	43	22.9	188	59.31
Traffic signal	46	62.2	20	27.0	8	10.8	74	23.34
Stop sign/flasher	184	65.5	76	27.0	21	7.5	281	88.64
Environmental influence								
Wet road surface	66	72.5	17	18.7	8	8.8	91	28.71
Snow/slush road surface	41	53.9	25	32.9	10	13.2	76	23.97
Ice road surface	24	44.4	13	24.1	17	31.5	54	17.03
Fog/smoke/haze	9	28.1	12	37.5	11	34.4	32	10.09
Severe cross wind	5	71.4	1	14.3	1	14.3	7	2.21
Time of day								
AM rush hour (7:00-9:00)	36	44.4	14	17.3	31	38.3	81	25.55
PM rush hour (17:00-19:00)	53	57.6	26	28.3	13	14.1	92	29.02
Light condition								
Dawn or dusk	16	69.6	5	21.7	2	8.7	23	7.26
Dark-lighted	52	72.2	8	11.1	12	16.7	72	22.71
Dark-unlighted	35	59.3	18	30.5	6	10.2	59	18.61
Sunglare	13	56.5	7	30.4	3	13.0	23	7.26
Total	176		82		59		317	
Percentage	55.52		25.87		18.61		100	

Generally, the OLM regression approach follows the proportional odds / parallel lines assumption and the estimated parameters remain the same for different severity levels. However, this parallel-lines assumption could be violated in many cases. We therefore employ a generalized ordered logit model (GOLM), which would not impose the constraint of parallel regression assumption and allow the effect of the explanatory variables to differ for each category of dependent alternatives [22], which could be specified as:

$$P\left(Y_i > j\right) = g\left(X_i\hat{\beta}'\right) = \frac{\exp\left(X_i\hat{\beta}' - \tau_j\right)}{1 + \exp\left(X_i\hat{\beta}' - \tau_j\right)}, \quad (3)$$
$$j = 1, 2, \cdots, m - 1$$

Different from the parameter β in OLM, vector $\hat{\beta}$ could differ across equations in GOLM. Considering the homoscedasticity assumption might be violated only by one or a few variables, a gamma parameterization of partial proportional odds model with logit function could be proposed [23] as:

$$P\left(Y_i > j\right) = \frac{\exp\left(X'_{1i}\beta' + X'_{2i}\beta'_j - \tau_j\right)}{1 + \exp\left(X'_{1i}\beta' + X'_{2i}\beta'_j - \tau_j\right)} \quad (4)$$

where the parameter β related to variables X_{1j} would be the same across all equations with respective to different severity level j and the parameter β_j associated with other variables X_{2j} would vary across some severity level j. In the model, each explanatory variable has one β coefficient, $k - 2$ β_j coefficients, where k is 9 as the number of alternatives. There are $k - 1$ τ coefficients reflecting cut-off points.

4 Estimation Results and Analysis

This study analyzed police-reported intersection crashes from the city of Xi'an, China, from 2005 to 2010, involving only left turning observations. This yields a total of 317 samples. OLM, HCM, GOLM approaches and partial proportional odds model with logit function for both unsignalized intersections and signalized intersections were developed for comparison in case of the quantitative estimation of total left-turn crash injury severity using the proposed nine variables reported in Table 3, which includes some goodness-of-it statistics as well, such as log-likelihood at zero, log-likelihood at convergence, and Akaike information criterion "AIC".

GOLM approach has better performance than the ordered logit model and probit one due to the largest Pseudo R^2(0.0285) and the smallest AIC (1063.67). Parallel-lines assumption for each variable was tested through Wald tests to check whether its coefficients differ across injury levels. The variables, safety belt / alcohol involved and environmental influence, are identified to be against the parallel-lines assumption (p-value < 0.01). The p-values of the Wald test derived from other variables satisfy the parallel-lines assumption for the final model [13].

Traffic flow related variables (i. g., traffic volume, traffic composition, driving behavior, vehicle features, etc.) are identified to be among the most significant factors for left turning crash occurrence. In this study, the effects of different forms of traffic flow on crash injury severity are checked including driver features of left-turning vehicle, driver features of entering vehicle, vehicle characteristics, impact point of left-turning vehicle, impact point of entering vehicle. The results show that very young drivers tend to be involved in more severe crash (Coef. < 0.05; p-value < 0.01), specifically during the rush hour and under the foggy / rainy driving environment. From the total crash data, more than 60 percent are left-turning vehicles at-fault, such as unsafe turning, primarily turning with insufficient headway. On the other hand, more opposing through traffic also causes less time and space for left-turn vehicles due to shorter gaps and therefore cause crashes between two vehicles.

Among the roadway features, average daily percent of trucks is identified to be significant (Coef. < 0.04; p-value < 0.04). Too more trucks will bring poor visibility and decreased capacity of overall intersection and positive restriction of trucks would be better able to provide driving visibility for both drivers and then mitigate the occurrence of left turning crashes as well as lower crash severity. Driver's age also has significant effect on crash injury severity. Compared to middle aged drivers, older than 65 people and young people of age group 18–24 are both more likely to be involved in left-turn crashes due to weak physical conditions and poor driving experiences and very young people are more prone to be get severe injuries and fatalities, which is consistent with previous studies [12, 13].

Of the crash related variables, the points of impact of both left turning vehicles and entering vehicles affect crash severity significantly. Coefficients of the factors back right, back, back left, front left are all negative, which indicate that the front of both involved vehicles is the most dangerous impact point, due to the greater colliding forces translated from excessive speed [13]. The difference of variable speeds of both vehicles was marginally significant to affect crash injury and seat-belt use would relieve automatically shock in collision and reduce crash severity to a greater extent (Coef. < -0.1; p-value < 0.03).

5 Conclusions

A large number of previous studies have applied ordered-response logit / probit models to examine injury severity in relation to human factors, vehicle attributes, and roadway geometrics and environmental effects. These approaches have implicitly assumed the model's independent errors for alternatives that are actually inconsistent with the fact that crash injuries are ordered. The parallel-lines or proportional odds assumption is generally too restricting as well and it may be violated only by one or a few of input variables.

Different from other crash patterns, left-turn crash has its own conflicting features and possibly other specific related factors. This study attempts to estimate the effects of the parameters or

Tab. 2. Driver-injury severity estimation for left turning crashes. Note: dash (—) indicates data not applicable or unavailable.

Variables	OLM		HCM		GOLM	
	Coef.	S.E.	Coef.	S.E.	Coef.	S.E.
Beta						
Driver features of left-turning vehicle						
Very Young (age ≤ 18)	0.0471	0.0036	0.0463	0.0036	0.0411	0.0036
Young (18 < age < 24)	-0.1706	0.7812	-0.1726	0.7739	-0.1633	0.7667
Old (age>65)	-0.2548	0.0883	-0.2601	0.0875	-0.2409	0.0867
Alcohol/drug impaired	-0.5013	0.2601	-0.4936	0.2577	-0.5098	0.2553
Trapped/extracted	0.2145	0.1837	0.2126	0.1820	0.2073	0.1803
Illness/fatigured	-0.1831	0.0784	-0.1872	0.0777	-0.1786	0.0770
Asleep/fainted	-0.0726	0.2917	-0.1839	0.2891	0.0711	0.3364
Safety belt not used	0.2503	0.0273	-0.0763	0.0269	-0.1396	0.0266
Driver features of entering vehicle						
Very Young (age ≤ 18)	0.0487	0.0107	0.0430	0.0106	0.0481	0.0105
Young (18 < age < 24)	-0.1583	0.7347	-0.1601	0.7279	-0.1515	0.7211
Old (age>65)	-0.2064	0.0819	-0.2513	0.0811	0.2235	0.2967
Alcohol/drug impaired	-0.4851	0.2413	-0.4579	0.2391	-0.4729	0.3369
Trapped/extracted	0.1990	0.1904	-0.1972	0.1886	-0.1923	0.1868
Illness/fatigured	-0.1699	0.0727	-0.1837	0.0720	-0.1657	0.0713
Asleep/fainted	0.1674	0.2706	-0.1706	0.2681	-0.0660	0.2956
Safety belt not used	-0.2322	0.0253	-0.1908	0.0251	-0.1295	0.0249
Vehicle characteristics						
Both vehicles in large size	-1.4987	0.2137	-1.4744	0.2164	-1.4794	0.1102
Motorcycle involved	-0.9239	0.3083	-1.0082	0.3071	1.5281	0.4204
Impact point of left-turning vehicle						
Back right	-0.2087	0.0748	-0.1977	0.0708	-0.2170	0.0777
Back	-0.1762	0.0822	-0.1869	0.0779	-0.2052	0.0855
Back left	-0.2596	0.0764	-0.2649	0.0724	-0.2908	0.0795
Front left	-0.6635	0.2703	-0.6884	0.2560	-0.7557	0.2810
Other	0.2143	0.1928	0.1630	0.1826	-0.1789	0.2005
Impact point of entering vehicle						
Front right	-1.1762	0.1135	-1.1098	0.1132	-1.2183	0.1121
Back right	-1.6776	0.0791	-1.5417	0.0791	-1.6925	0.0776
Back and back left	-0.8709	0.2647	-0.8561	0.2647	-0.9398	0.2617
Other	0.1281	0.0623	0.1106	0.0623	0.1214	0.0609
Roadway characteristic						
Heavy traffic	0.6137	0.1046	0.7208	0.1041	0.7345	0.1039
Average daily percent of trucks	-0.4813	0.0374	-0.4275	0.0284	-0.4223	0.0261
Posted speed limit 40 km/h	-1.0471	0.0747	-0.9741	0.0733	-0.9622	0.0725
Traffic signal	-1.6109	0.0651	-1.5093	0.0617	-1.1336	0.0616
Stop sign/flasher	0.9235	0.2833	0.9346	0.2568	1.1232	0.2607
Environmental influence						
Wet road surface	-0.3805	0.3598	-0.3976	0.3642	-0.4048	0.3962
Snow/slush road surface	0.7342	0.3524	0.7431	0.3568	0.7523	0.3871
Ice road surface	-0.5303	0.6430	-0.5369	0.6509	-0.5435	0.7083
Fog/smoke/haze	-0.1335	0.4523	-0.1351	0.4579	-0.1368	0.4966
Severe cross wind	-0.4807	0.3758	-0.4866	0.3804	-0.4926	0.4135
Time of day						
AM rush hour (7:00-9:00)	-0.4089	0.1337	-0.4136	0.1029	-0.4379	0.0933
PM rush hour (17:00-19:00)	-0.1293	0.1158	-0.1308	0.1086	-0.1536	0.1017
Light condition						
Dawn or dusk	-1.3651	0.4275	-1.3336	0.4162	-1.3028	0.4068
Dark-lighted	-1.0037	0.3311	-0.9805	0.3268	-0.9579	0.3207
Dark-unlighted	0.4309	0.4637	0.4209	0.4597	0.4112	0.4515
Sunglare	0.2298	0.6872	0.2245	0.6804	0.2193	0.6933

Tab. 3. Driver-injury severity estimation for left turning crashes. Note: dash (—) indicates data not applicable or unavailable.

Variables	OLM		HCM		GOLM	
Gamma_2						
Safety belt / alcohol involved vs. No	—	—	—	—	0.3275	2.4617
Gamma_3						
Safety belt / alcohol involved vs. No	—	—	—	—	0.5163	2.7704
Gamma_4						
Safety belt / alcohol involved vs. No	—	—	—	—	0.8819	3.1386
Alpha						
Constant 1	-0.4448	–	-0.3874	–	-0.3082	0.2073
Constant 2	0.6154	–	0.5463	–	0.3679	0.2498
Constant 3	2.2429	–	1.8347	–	1.3292	0.2249
Constant 4	5.0396	–	3.9703	–	2.6953	0.2188
Summary Statistics						
Number of observations	317		317		317	
Log likelihood at convergence	-498.72		-486.36		-471.84	
AIC	1081.25		1070.18		1063.67	
Pseudo R^2	0.0207		0.0226		0.0285	

variables on crash severity, and also compares parametric insights on key roadway geometrics, vehicle, environmental and driver related factors through the application of OLM, HCM, GOLM and partial proportional odds model with logit function approaches when accounting for injury study, aiming at providing reasonable basis to potentially reduce left turning injury severity through advancing the state-of-the-art of injury mitigation strategy, facility manufacturing and policy-making.

Left-turn crashes are located to the crash sites where they occur, which enable to specify the effect of contributory factors on injury severity. The partial proportional odds model has better performance for left-turn crashes, compared with ordered logit or probit model. By using three proposed statistical models, the interpretation of 9 group variables yields greater insight concerning contributing effects of included variables on injury severity. For example, it reveals the aged or younger drivers are more likely to cause left-turn crashes and percentage of trucks involvement also affects the crash occurrence frequency strongly and significantly and increases the injury severity as well. Meanwhile, the points of impact of both vehicles, environmental conditions, safety belt usage, alcohol and/or drugs are found to be strongly associated with higher severities, and all these risk factors should be considered strategically in any future traffic management.

This study is the first step in the statistical estimation of the size of variables affecting injury severity in left-turn crashes. Similar to most previous studies, this approach also has some limitations, such as the fact that small sample data from a single Xi'an city database in Western China, the fact that limited available types of traffic flow related variables from the database, and the fact that traditional statistical models are compared. Future studies with multiple data from different databases and more comprehensive analysis models and methods are strongly encouraged and conducted to confirm the efficiency of the estimator for large-scale analysis for left-turn crashes.

References

1 **Oosthuizen P, Nienaber H**, *The status of talent management in the South African consulting civil engineering industry in 2008: a survey*, Journal of the South African Institution of Civil Engineering **52** (2010), no. 2, 41–47.

2 **Wang Y G, Bai H, Xiang W S**, *Traffic safety performance assessment and multivariate treatments for intersection locations*, The Baltic Journal of Road and Bridge Engineering **6** (2011), no. 1, 30–38.

3 **Abdel-Aty M, Salkapuram H, Lee C, Brady P A**, *A simplistic, practical approach to identify traffic crash profiles at signalized intersections*, ITE Journal **76** (2006), no. 4, 28–33.

4 **Pulugurtha S S, Sambhara V R**, *Pedestrian crash estimation models for signalized intersections*, Accident Analysis and Prevention **43** (2011), no. 1, 439–446.

5 **Xie Y C, Zhang Y L, Liang F M**, *Crash injury severity analysis using Bayesian ordered probit models*, Journal of Transportation Engineering **135** (2009), no. 1, 18–25.

6 **Rana T A, Sikder S, Pinjari A R**, *Copula-based method for addressing endogeneity in models of severity of traffic crash injuries: Application to two-vehicle crashes*, Transportation Research Record (2010), no. 2147, 75–87.

7 **Kim J K, Ulfarsson G F, Shankar V N, Kim S**, *Age and pedestrian injury severity in motor-vehicle crashes: a heteroskedastic logit analysis*, Accident Analysis and Prevention **40** (2008), no. 5, 1695–1702.

8 **Chimba D, Sando T**, *Multinomial probability assessment of motorcycle injury severities*, Advances in Transportation Studies (2010), no. 21, 73–80.

9 **Geedipally S R, Patil S, Lord D**, *Examination of methods to estimate crash counts by collision type*, Transportation Research Record (2010), no. 2156, 12–20.

10 **Young R K, Liesman J**, *Estimating the relationship between measured wind speed and overturning truck crashes using a binary logit model*, Accident Analysis and Prevention **39** (2007), no. 3, 574–580.

11 **Tay R, Rifaat S M**, *Factors contributing to the severity of intersection crashes*, Journal of Advanced Transportation **41** (2007), no. 3, 244–265.

12 **Quddus M A, Noland R B, Chin H C**, *An analysis of motorcycle injury and vehicle damage severity using ordered probit models*, Journal of Safety Research **33** (2002), no. 3, 445–462.

13 **Wang X S, Abdel-Aty M**, *Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models*, Accident Analysis and Prevention **40** (2008), no. 5, 1674–1682.

14 **Tollazzi T, Rencelj M, Rodosek V, Zalar B**, *Traffic safety of older drivers in various types of road intersections*, Promet – Traffic & Transportation **22** (2010), no. 3, 194–201.

15 **Kornelija R**, *Model for the substantiation of road safety improvement measures on the roads of Lithuania*, The Baltic Journal of Road and Bridge Engineering **4** (2010), no. 2, 116–123.

16 **Schuchmann G**, *Road network vulnerability-evaluation of measures in ranking damages and developments*, Periodica Polytechnica – Civil Engineering **54** (2010), no. 1, 61–65.

17 **Nassiri H, Edrissi A, Alibabai H**, *Estimation of the logit model for the online contraflow problem*, Transport **25** (2010), no. 4, 433–441.

18 **Yannis G, Antoniou C, Vardaki S, Kanellaidis G**, *Older drivers' perception and acceptance of in-vehicle devices for traffic safety and traffic efficiency*, Journal of Transportation Engineering **136** (2010), no. 5, 472–479.

19 **Arentze T A, Ettema D, Timmermans H J P**, *Estimating a model of dynamic activity generation based on one-day observations: method and results*, Transportation Research Part B: Methodological **45** (2011), no. 2, 447–460.

20 **Quddus M A, Wang C, Ison S G**, *Road traffic congestion and crash severity: econometric analysis using ordered response models*, Journal of Transportation Engineering **136** (2010), no. 5, 424–435.

21 **Srinivasan K K, Naidu G M, Sutrala T**, *Heterogeneous decision rule model of mode choice incorporating utility maximization and disutility minimization*, Transportation Research Record (2009), no. 2132, 59–68.

22 **Srinivasan K K**, *Injury severity analysis with variable and correlated thresholds: ordered mixed logit formulation*, Transportation Research Record (2002), no. 1784, 132–142.

23 **Tien F F, Fu T T**, *The correlates of the digital divide and their impact on college student learning*, Computers and Education **50** (2008), no. 1, 421–436.