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Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models

Xuesong Wang*, Mohamed Abdel-Aty

Department of Civil & Environmental Engineering, University of Central Florida, Orlando, FL 32816-2450, United States

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ABSTRACT

The purpose of this study is to examine left-turn crash injury severity. Left-turning traffic colliding with opposing through traffic and with near-side through traffic are the two most frequently occurring conflicting patterns among left-turn crashes (Patterns 5 and 8 in the paper, respectively), and they are prone to be severe. Ordered probability models with either logit or probit function is commonly applied in crash injury severity analyses; however, its critical assumption that the slope coefficients do not vary over different alternatives except the cut-off points is usually too restrictive. Partial proportional odds models are generalizations of ordered probability models, for which some of the beta coefficients can differ across alternatives, were applied to investigate Patterns 5 and 8, and the total left-turn crash injuries. The results show that partial proportional odds models consistently perform better than ordered probability models. By focusing on specific conflicting patterns, locating crashes to the exact crash sites and relating approach variables to crash injury in the analysis, researchers are able to investigate how these variables affect left-turn crash injuries. For example, opposing through traffic and near-side crossing through traffic in the hour of collision were identified significant for Patterns 5 and 8 crash injuries, respectively. Protected left-turn phasing is significantly correlated with Pattern 5 crash injury. Many other variables in driver attributes, vehicular characteristics, roadway geometry design, environmental factors, and crash characteristics were identified. Specifically, the use of the partial proportional formulation allows a much better identification of the increasing effect of alcohol and/or drug use on crash injury severity, which previously was masked using the conventional ordered probability models.

1. Introduction

Intersections are among the most dangerous locations of a roadway network. In the state of Florida, 43.1% of fatalities and serious injuries occurred at or were influenced by intersections (Florida Department of Transportation, 2006). In the U.S., although only around 10% of all intersections are signalized, in 2005, nearly 30% (2744) of intersection fatalities occurred at signalized intersections (Rice, 2007). Left-turn crashes occur frequently and they account for a high percentage of total crashes at signalized intersections. They are prone to be severe, possibly due to the relatively high conflicting speeds of involved vehicles and the angle of impact. In a sample of signalized intersections collected in Orange and Hillsborough counties in Florida, 64.2% of left-turn crashes involved injury, whereas the percentage of injury crashes was only 50.1% for all other crashes.

From 2002, a series of crash frequency studies have been conduced in Florida to identify the crash profiles for the major intersection types (Abdel-Aty and Wang, 2006; Wang and Abdel-Aty, 2006, 2007, 2008; Wang et al., 2006). In one study, Wang and Abdel-Aty (2008) investigated conflicting flows, intersection geometric design features, and traffic control and operational features on left-turn crash occurrence. Left-turn crashes were classified into distinct conflicting patterns (i.e., left-turn traffic colliding with opposing through traffic, or with near-side through traffic, etc.), and then the crash frequencies of different patterns were modeled. The studies indicate there are obvious differences in the factors which correlated with different left-turn collisions. However, crash frequency studies model accumulated crash counts, which ignores the difference of severe and minor crashes. Therefore, they are unable to investigate how specific features affect crash injury severity.

The left-turn crashes at signalized intersections result in a huge cost to society in terms of death, injury, lost productivity, and property damage. However, how the different factors affect left-turn

* Corresponding author at: Department of Civil & Environmental Engineering, University of Central Florida, Engr II, Room 301B, Orlando, FL 32816-2450, United States. Tel.: +1 407 8234902; fax: +1 407 8234676.
E-mail address: xuewang@mail.ucf.edu (X. Wang).

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crash severity is still not clear. For example, traffic volume has been identified as the most significant factor affecting crash occurrence (Wang and Abdel-Aty, 2008), but it is not clear whether traffic flow affects crash severity. Left-turn phase has been identified to be significant for left-turn crash occurrence, but no study investigates its influence on crash severity. The purpose of this study is to investigate how traffic characteristics, driver attributes, vehicular characteristics, roadway geometry features, environmental factors, and crash characteristics affect left-turn crash injury severity.

In police reports, crash injury is categorized into five levels based on the most serious injury to any person involved in a crash: no injury, possible injury, non-incapacitating injury, incapacitating injury and fatal injury. Multinomial logit models were specified for multiple alternatives of severity. Shankar and Mannering (1996) considered environmental, roadway, vehicular, and rider characteristics in their multinomial logit analysis of motorcycle-rider severity on single-vehicle motorcycle crashes. Carson and Mannering (2001) developed multinomial logit models to examine the effect of ice-warning signs on crash severity for different roadway functional classes. Ulfarsson and Mannering (2004) explored differences in severity between male and female drivers in single and two-vehicle collisions; separate multinomial logit models of severity were estimated for male and female drivers. However, the logit model's assumption of independent errors for each alternative is inconsistent with the fact that the alternatives for crash injuries are ordered. With ordered alternatives, one alternative is similar to those close to it and less similar to those further away (Train, 2003).

Nested logit, mixed logit, or probit models can be applied to account for the pattern of similarity and dissimilarity among different injury levels. Abdel-Aty (2003) compared the multinomial logit, nested logit, and ordered probit models for driver's injury severity at toll plaza and found that nested logit model produced the best fit. However, Train (2003) thinks such a specification does not actually fit the structure of the ordinal data.

Considering that severe crashes are comparatively less frequent (especially fatal crashes) and also for simplicity, some researchers collapsed the five level injury data into fewer levels. The binary logit or probit model can be used when severity is classified into two levels. Al-Ghamdi (2002) applied the binary logit model to examine the effect of crash characteristics on fatal and non-fatal injury and found that crash location and cause of crash were significant. Huang et al. (in press) and Obeng (2007) applied the binary logit to analyze crash injury of signalized intersections. But combining adjoining categories in ordered categorical regression could lose efficiency in estimating regression parameters (Train, 2003).

The main characteristic of crash injury data, from a modeling perspective, is that the responses are inherently ordered multiple-choice variables. Ordered logit and probit models have been commonly applied to fit the ordinal data structure of injury severity. By using the ordered probit model, O'Donnell and Connor (1996) investigated how variations in the attributes of road users can lead to variations in the probabilities of sustaining different levels of injury in motor vehicle crashes. Ma and Kockelman (2004) used the ordered probit model to predict severity based on factors including traffic, roadway and occupant characteristics and weather conditions at the time of a crash and type of vehicle. Khattak (2001) applied the ordered probit model to examine injury of multi-vehicle rear-end crashes. Abdel-Aty (2003) applied the ordered probit model to predict crash severity on roadway sections, signalized intersections and toll plazas by using the Florida crash database. Abdel-Aty and Keller (2005) created the ordered probit models by using roadway attributes and crash types for crashes occurred at the signalized intersections.

Ordered probability models are straightforward because they impose the restriction that regression parameters (except cut-off points) are the same for different severity levels. This is called parallel-lines assumption, or proportional odds assumption. However, for injury severity, it is not clear whether distances between adjacent injury levels are equal. It is too arbitrary to assume that coefficients of ordered probability models are the same except for cut-off points. The parallel-lines constraint can be relaxed for all variables, but estimating more parameters than necessary will also cause some variables to be insignificant. Considering that the assumption may be violated only by one or a few of the included variables, Peterson and Harrell (1990) proposed a partial proportional odds model, where parallel-lines constraint is relaxed only for those variables when it is not justified and allows non-proportional odds for a subset of the explanatory variables. To have more parsimonious layout, they used a gamma parameterization of partial proportional odds model.

Analyzing left-turning traffic is crucial for improving intersection operation and safety. Left-turn crashes are not all identical with respect to the maneuvers of the involved vehicles (vehicle movement and travelling direction). Left-turning traffic may collide with many other traffic flows at signalized intersections, and left-turn crashes have many distinct conflicting patterns in vehicle maneuvers before collisions. Wang and Abdel-Aty (2008) classified left-turn crashes into nine distinct conflicting patterns, and then the crash frequencies of different patterns were modeled. Pattern 5 is for those left-turn crashes of which one involved vehicle was turning left and another vehicle was going straight on the opposing approach. Pattern 8 is for left-turning vehicles colliding with vehicles going through from the near-side crossing approach. These are the most frequently occurring collision patterns, accounting for 72.5% and 14.1% of all left-turn crashes, respectively, and they are prone to be severe.

In summary, there have been numerous studies analyzing crash injury severity. However, only limited studies examined crash injury severity at signalized intersections (Abdel-Aty, 2003; Abdel-Aty and Keller, 2005; Huang et al., in press; Obeng, 2007), and in previous studies, crashes were not located to the exact sites they occurred. Therefore, the previous approach is unable to associate crash injury to features of related approaches. There is no study investigating injury severity for left-turn crashes specifically. In addition, most severity analyses depended on crash data in which most intersection attributes are not available (i.e., turning movements, signal phase, left-turn offset, etc.). However, these are the only viable factors traffic engineers have some control over. In this study, left-turn crash injury severity for Patterns 5 and 8, and total left-turn crashes are investigated using partial proportional odds models. Left-turn crashes are located to the crash sites where they occurred, which enables researchers to specify the effect of attributes of intersection geometric design features, traffic control and operational features, and traffic characteristics on crash severity.

2. Methodology: partial proportional odds models

Crash injury severity is categorized into five levels in increasing of severity and coded as: 1 = no injury, 2 = possible injury, 3 = non-incapacitating injury, 4 = incapacitating injury, and 5 = fatal injury. Note that level $j = 1$ is defined as the minimum value of the variable, no injury. Let Y_i denotes the recorded crash injury for crash i. Ordered logit and probit models can be derived based on the level of an unobserved variable (Train, 2003; Washington et al., 2003). A critical assumption of the ordered probability models is that the slope coefficients do not vary over different alternatives except the cut-off points. This parallel-lines assumption could be violated in many cases. A generalized ordered logit model can be specified to

relax parallel-lines assumption for all variables and the probability of crash injury for a given crash can be specified as

$$P(Y_i > j) = g(X_i'\beta_j) = \frac{\exp(\alpha_j - X_i'\beta_j)}{1 + \exp(\alpha_j - X_i'\beta_j)}, \quad j = 1, 2, 3, 4 \tag{1}$$

where X_i is a $p \times 1$ vector containing the values of crash i on the full set of p explanatory variables, β_j is a $p \times 1$ vector of regression coefficients, α_j represents cut-off point for the jth cumulative logit. The only difference between this model and the ordered logit model is that β is not fixed across equations.

Considering that the parallel-lines assumption may be violated only by one or a few variables, a partial proportional odds model can be specified, for which one or more βs differ across equations and others can be the same for all equations. Peterson and Harrell (1990) proposed a gamma parameterization of partial proportional odds model with logit function as below:

$$P(Y_i > j) = g(X_i'\beta_j) = \frac{\exp[\alpha_j - (X_i'\beta_j + T_i'\gamma_j)]}{1 + \exp[\alpha_j - (X_i'\beta_j + T_i'\gamma_j)]} \tag{2}$$

where T_i is a $q \times 1$ vector, $q \leq p$, containing the values of crash i on that subset of the p explanatory variables for which the proportional odds assumption is not assumed, and γ_j is a $q \times 1$ vector of regression coefficient associated only with the jth cumulative logit. In the model, each explanatory variable has one β coefficient, $k-2\gamma$ coefficients, where k is the number of alternatives (in this study, $k = 5$). There are $k-1\alpha$ coefficients reflecting cut-off points. The γ coefficients represent deviations from proportionality. This gamma parameterization combines all the features of the traditional ordered models while allowing for non-proportionality in some or all of the variables in the model. If all the gammas are equal to zero, it is actually a proportional odds model. The gamma parameterized partial proportional odds model with a probit function can be expressed as

$$P(Y_i > j) = g(X_i'\beta_j) = \Phi[\alpha_j - (X_i'\beta_j + T_i'\gamma_j)] \tag{3}$$

Partial proportional odds models can be fitted by a user-written program gologit2 (Williams, 2006). It should be cautious for interpreting the coefficients of intermediate categories. The sign of β does not always determine the direction of the effect of the intermediate outcomes (Washington et al., 2003; Wooldridge, 2002). The marginal effects are useful for interpretation of the variables. In Stata (2005), for continuous variables, the derivative is calculated numerically; for dummy variable, a difference rather than the derivative is computed. Ordered probability models and partial proportional odds models with different functions (logit or probit) are not nested. Pseudo R^2 measure $R^2 = 1 - (\ln L/\ln L_0)$ and Akaike's information criterion AIC = $-2\ln L + 2p$ are applied to evaluate models' performance, where $\ln L$ and $\ln L_0$ are the log-likelihood in the fitted and intercept-only models, and p is the number of parameters estimated. Pseudo R^2 coincides with an interpretation of linear model R squared (Cameron and Trivedi, 1998). Smaller AIC indicates a better-fitting model (Stata, 2005).

3. Data preparation

Information on intersection geometry design features, traffic control and operational features, traffic flows, and crashes from 2000 to 2005 were obtained for 197 four-legged signalized intersections from Orange and Hillsborough counties in the Central Florida area. Geometric design features for the intersection approach include the number of through lanes, the number of left-turn lanes and whether they were exclusive, the presence of median, whether it had exclusive right-turn lanes, the types of left-turn lane offset (negative, zero, or positive offset), the direction of each intersection roadway, and the angle of intersecting roadways. Traffic control and operational features were retrieved by inspecting signal plans provided by the county traffic engineering departments. The types of left-turn control include "permissive", "compound" ("permissive/protected" or "protected/permissive"), and "protected". The key factors for signal phases, i.e., yellow time, and all-red time for through and left-turn (if protected) movements were retrieved. The speed limit for each approach was also obtained.

In both counties, the approach movements (right-turn, through, and left-turn) for both morning and afternoon peak hours were counted for a year during the study period. The approach daily turning movements were derived from the approach AADT and the proportion of approach turning movements. The real traffic volume in the hour of collision is not available currently for signalized intersections in the state. Instead, left-turn, through, and right-turn movements in the crash hour of each approach were converted from approach daily turning movements considering daily, weekly, monthly variations, and the growth rates over the study period.

The Crash Analysis Reporting (CAR) system maintained by the Florida Department of Transportation (FDOT) Safety Office was used to retrieve the crash data for the selected intersections. There were a total of 13,218 collisions for the selected intersections over the 6-year period. The crash site location (e.g., at intersection), the initial crash type (e.g., left-turn), the vehicle movement (e.g., straight ahead, making left-turn), the direction of travel (e.g., west), and the contributing cause (e.g., failed to yield right-of-way, disregarded traffic signal) for both at-fault and innocent vehicles/drivers are stored in the crash database. Left-turn crashes in this study are defined as the crashes that occurred at the intersection when at-least one involved vehicle was turning left before the collisions. Only vehicular crashes were considered. Other variables from crash database include driver's age, gender, estimated speed, impact point, ejection, crash safety equipment usage, light condition for both left-turning vehicle and another vehicle (might go through, turn left, or turn right).

Of the 13,281 collisions at the selected intersections, 3098 were left-turn collisions. This accounts for 23.4% of all police reported vehicle collisions at the selected intersections. These collisions can be classified into nine different patterns (Wang and Abdel-Aty, 2008). Patterns 5 and 8 are the most frequently occurring collision types, accounting for 72.5% and 14.1% of all left-turn crashes, respectively, and they contributed all 32 left-turn fatal crashes as shown in Table 1, which summarized left-turn crash severity for Patterns

Table 1
Left-turn crash injury severity distribution by conflicting patterns for the selected intersections

Injury severity levels	Pattern 5 crashes	Pattern 8 crashes	All left-turn crashes
None	694 (31.18%)	126 (28.90%)	1129 (35.90%)
Possible	547 (24.57%)	96 (22.02%)	730 (23.21%)
Non-incapacitating	651 (29.25%)	130 (29.82%)	845 (26.87%)
Incapacitating	313 (14.06%)	73 (16.74%)	409 (13.00%)
Fatal	21 (0.94%)	11 (2.52%)	32 (1.02%)
Total	2226 (100.00%)	436 (100.00%)	3145 (100.00%)

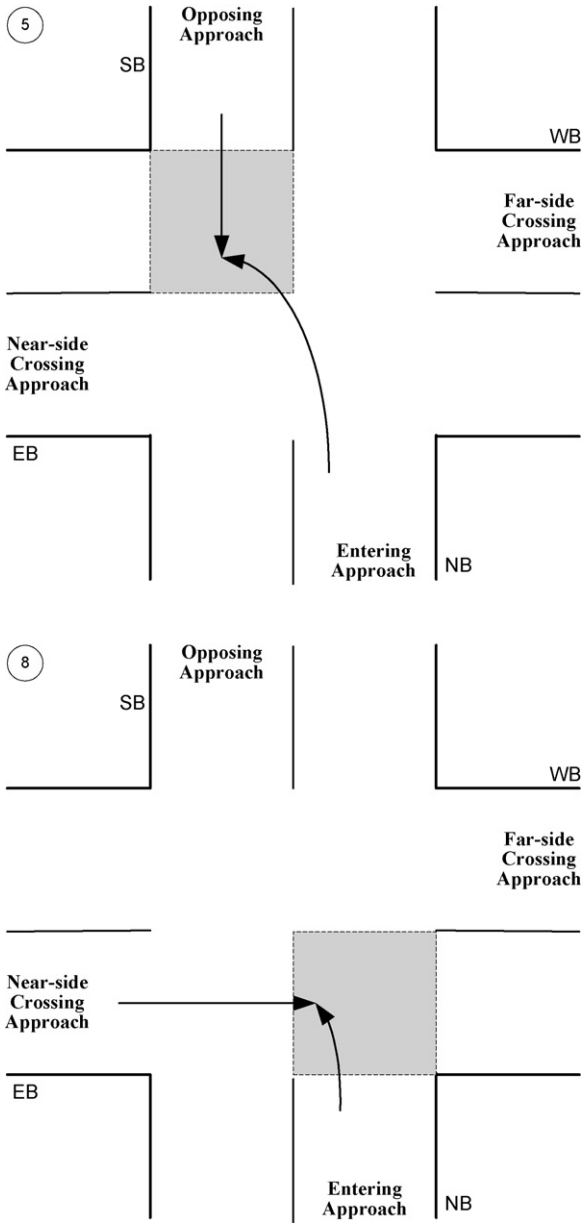

Fig. 1. Collision diagram and data arrangement for Patterns 5 and 8 left-turn crashes.

5 and 8 and entire left-turn crashes. Based on vehicle movements (e.g., straight ahead, making left-turn) and direction of travel of both involved vehicles, left-turn crashes were assigned to the approach from which the left-turning vehicles turned. The approach level intersection-related explanatory variables were arranged as entering, near-side crossing, far-side crossing, and opposing approaches as illustrated in Fig. 1 for Patterns 5 and 8. All of the crash related data were assembled with intersection related data.

4. Estimation results

Partial proportional odds models with both logit and probit functions were developed for Patterns 5 and 8, and total left-turn crash injury severity. Partial proportional odds models were fitted by a user-written program gologit2 (Williams, 2006). For comparison, ordered logit and probit models were also fitted.

4.1. Pattern 5 left-turn crashes

The ordered logit model had better performance than the ordered probit model (AIC = 5935.64 vs. 5941.97). Parallel-lines assumption for each variable was tested using a series of Wald tests to see whether its coefficients differ across equations. The variable, crash alcohol/drug involved, violated parallel-lines assumption (p-value = 0.0066). Partial proportional odds models with both logit and probit functions were fitted with this variable changing across equations while other variables were imposed to have their effects meet parallel-lines assumption. The partial proportional odds model with a logit function performed better than that with a probit function (AIC = 5931.86 vs. 5934.54; pseudo R^2 = 0.0466 vs. 0.0454). The estimations for the ordered logit model and the partial proportional odds model with logit function are presented in Table 2, and the marginal effects are reported in Table 3.

The estimated partial proportional odds model had one beta coefficient for each variable, three gamma coefficients for the variable violating parallel-lines assumption, and four alpha coefficients reflecting the cut-off points. The gamma coefficients for Gamma_2 through Gamma_4 were highly significant; p-values were 0.023, 0.051, and 0.005, respectively. The Gamma_2 value for the variable crash alcohol/drug involved (0.3359) was added to beta estimate (0.0618) to yield the value for the coefficient of this variable in the second equation. The same process was used to get the coefficient in the third equation (0.5215 = 0.4597 + 0.0618) and in the fourth equation (0.9532 = 0.8914 + 0.0618). Therefore, the estimated coefficients were increasing, which was masked using the ordered probability models as shown in Table 2. The marginal effects also showed that alcohol or drugs had positive effects on severe and fatal crashes (0.0299 and 0.0243).

Traffic volume was identified to be the most significant factor for crash occurrence. In this study, the different forms of traffic volume were tested for investigating their effect on crash injury severity, which include traffic of the entire intersection, traffic of entering approach, traffic of opposing approach, left-turning traffic, and opposing through traffic. The results showed that having heavy opposing through traffic, specifically in the hour of collision, Pattern 5 crashes tended to be more severe (Coef. = 0.0148; p-value = 0.0055). These results were confirmed by the positive marginal effects for serious, severe, and fatal injuries as shown in Table 3. From the crash data, 81.6% of Pattern 5 crashes were left-turning vehicles at-fault. Generally, more opposing through traffic meant shorter gaps for left-turn vehicles and therefore there was less time and space after crash occurred for both vehicles to react to reduce injury severity.

Among the geometric design features, left-turn lane offset was identified to be significant (Coef. = −0.1813; p-value = 0.02). Providing positive offset will mitigate the sight restriction for vehicles turning left from opposing left-turn lanes (Joshua and Saka, 1992; McCoy et al., 1992). With better visibility, both drivers would be better able to react and to lower crash severity.

Protected left-turn phase was associated with less severe crashes (Coef. = −0.1169); however, compound phase was not significant and it was combined with permissive phase. One obvious reason is that at a compound signal left-turning and opposing through traffic is usually higher than that for a permissive signal. In addition, compound is the most complicated phasing. Crash records indicated that left-turn crashes occurring under protected left-turn phases typically resulted as left-turn vehicles were not cleared from the intersection upon the onset of the opposing through vehicle's green signal. Of these crashes, left-turn vehicles collided with vehicles which just entered intersections and therefore the through vehicles' speeds were low, while under permissive left-

Table 2
Models for pattern 5 left-turn crashes

Variables	Ordered logit estimates		Generalized ordered logit estimates	
	Coef.	S.E.	Coef.	S.E.
Beta				
Logarithm of the opposing through traffic in the crash hour	0.0148	0.0042	0.0148	0.0042
Positive left-turn lane offset (vs. zero or negative left-turn lane offset)	−0.1804	0.0784	−0.1813	0.0784
Protected left-turn phasing on entering approach (vs. compound or permissive left-turning)	−0.2586	0.0882	−0.2608	0.0882
Standardized all-red time for opposing through movement	−0.6615	0.2501	−0.6642	0.2500
Crash alcohol/drug involved (vs. no)	0.2146	0.1829	−0.1093	0.2166
Left-turning driver age (base: 25 ≤ age ≤ 79)				
Very young (≤19)	−0.4098	0.1107	−0.4136	0.1109
Young (20 ≤ age ≤ 24)	−0.1290	0.1085	−0.1301	0.1085
Old (≥80)	0.5743	0.2276	0.5809	0.2284
Impact point of through vehicle (base: is front)				
Front left	−1.1913	0.1125	−1.1898	0.1125
Front right	−0.2991	0.0970	−0.2983	0.0970
Back	−1.6884	0.2963	−1.6876	0.2967
Back left and right	−0.9875	0.1596	−0.9900	0.1596
Speed ratio of opposing through vehicle (estimated speed/speed limit)	0.1831	0.1065	0.1849	0.1065
Safety equipment in use vs. not used	−0.6708	0.1206	−0.6672	0.1203
Gamma_2				
Crash alcohol/drug involved vs. no	–	–	0.3725	0.1671
Gamma_3				
Crash alcohol/drug involved vs. no	–	–	0.5249	0.2617
Gamma_4				
Crash alcohol/drug involved vs. no	–	–	1.7161	0.5439
Alpha				
Constant 1	−1.7359	0.2042	−1.7482	0.2042
Constant 2	−0.6055	0.2014	−0.5981	0.2013
Constant 3	1.0092	0.2027	1.0276	0.2031
Constant 4	3.9801	0.2916	4.1800	0.3159
Summary statistics				
Number of observations	2226		2226	
Log likelihood at convergence	−2949.82		−2944.92	
AIC	5935.64		5931.86	
Pseudo R^2	0.0440		0.0466	

Note: dash (–) indicates data not applicable or unavailable.

Table 3
Marginal effects and standard errors (in parentheses) for Pattern 5 crashes based on generalized ordered logit model

Variables	Crash injury severity				
	None injury	Possible injury	Non-incapacitating injury	Incapacitating injury	Fatal
Logarithm of the opposing through traffic in the crash hour	−0.0031 (0.0009)	−0.0005 (0.0002)	0.002 (0.0006)	0.0016 (0.0005)	0.0001 (0.00004)
Positive left-turn lane offset (vs. zero or negative left-turn lane offset)	0.0379 (0.0164)	0.0065 (0.0029)	−0.0238 (0.0103)	−0.0194 (0.0084)	−0.0012 (0.0006)
Protected left-turn phasing on entering approach (vs. compound or permissive left-turning)	0.0556 (0.0192)	0.0078 (0.0024)	−0.0348 (0.012)	−0.0269 (0.0088)	−0.0017 (0.0007)
Standardized all-red time for opposing through movement	0.1389 (0.0523)	0.0242 (0.0097)	−0.0873 (0.0331)	−0.0713 (0.0269)	−0.0045 (0.002)
Crash alcohol/drug involved (vs. no)	0.0233 (0.047)	−0.0886 (0.0388)	0.0111 (0.0447)	0.0299 (0.0323)	0.0243 (0.0138)
Left-turning driver age (base: 25 ≤ age ≤ 79)					
Very young (≤19)	0.0909 (0.0254)	0.008 (0.0021)	−0.0562 (0.0155)	−0.0402 (0.0098)	−0.0025 (0.0008)
Young (20 ≤ age ≤ 24)	0.0277 (0.0235)	0.004 (0.0029)	−0.0173 (0.0147)	−0.0135 (0.0109)	−0.0008 (0.0007)
Old (≥80)	−0.107 (0.0362)	−0.0372 (0.02)	0.0638 (0.0188)	0.0752 (0.0349)	0.0052 (0.0029)
Impact point of through vehicle (base: is front)					
Front left	0.2745 (0.0268)	−0.0122 (0.008)	−0.1586 (0.0148)	−0.0978 (0.008)	−0.0059 (0.0014)
Front right	0.0643 (0.0215)	0.0079 (0.0022)	−0.0401 (0.0134)	−0.0302 (0.0093)	−0.0019 (0.0007)
Back	0.3983 (0.0635)	−0.0846 (0.0306)	−0.2065 (0.026)	−0.1014 (0.0096)	−0.0058 (0.0014)
Back left and right	0.2322 (0.0393)	−0.0154 (0.0111)	−0.1341 (0.0206)	−0.0781 (0.0094)	−0.0046 (0.0012)
Speed ratio of opposing through vehicle (estimated speed/speed limit)	−0.0387 (0.0223)	−0.0067 (0.004)	0.0243 (0.014)	0.0198 (0.0115)	0.0013 (0.0008)
Safety equipment in use vs. not used	0.124 (0.0196)	0.0413 (0.0104)	−0.0739 (0.0109)	−0.0854 (0.0181)	−0.0059 (0.0019)

Table 4
Models for Pattern 8 left-turn crashes

Variables	Ordered logit estimates		Generalized ordered logit estimates	
	Coef.	z	Coef.	z
Beta				
Logarithm of the near-side crossing through traffic in the crash hour	0.1517	0.0770	0.1532	0.0762
Left-turn lane offset of entering approach (base: negative)				
Zero offset	−0.7168	0.3657	−0.6746	0.3646
Positive offset	−0.6473	0.3596	−0.5982	0.3582
Driver ejected vs. no	1.9194	0.6529	1.9246	0.6524
Crash alcohol/drug involved vs. no	1.3422	0.4597	0.4518	0.5315
Gamma_2				
Crash alcohol/drug involved vs. no	–	–	0.2609	0.3953
Gamma_3				
Crash alcohol/drug involved vs. no	–	–	1.1922	0.4988
Gamma_4				
Crash alcohol/drug involved vs. no	–	–	2.1689	0.7802
Alpha				
Constant 1	−0.5425	–	−0.5131	0.5966
Constant 2	0.4216	–	0.4617	0.5996
Constant 3	1.8879	–	1.9865	0.6038
Constant 4	4.2123	–	4.5611	0.7050
Summary statistics				
Number of observations	436		436	
Log likelihood at convergence	−616.43		−612.37	
AIC	1250.86		1248.74	
Pseudo R^2	0.0215		0.0279	

Note: dash (–) indicates data not applicable or unavailable.

turn phase, left-turn vehicles usually collided with high speed opposing through traffic.

Another key variable for signal control is all-red time for opposing through traffic. In the state of Florida, FDOT recommends an all-red interval of 1 s for approach speeds up to 50 mph, and 2 s for approach speeds above 50 mph (Traffic Engineering Manual, 2007). At each intersection, all-red times could be increased as necessary to fit the specific conditions. The safety effects of the standardized all-red time (defined as the all-red time divided by the crossing distance) and the differences between the real values and the standard values for all-red intervals have been explored in the models. The result showed that providing longer standardized clearance time tended to reduce crash severity (Coef. = −0.6642). For the approach with permissive left-turn phase, left-turners might sneak into intersections on a permissive green waiting to make a left-turn, and they might use the clearance interval if there were not enough gaps. Under protected left-turn phase, left-turners might beat red-light and they were probably unable to clear from intersections. In both situations, if the crash occurred with more all-red time drivers would have more time to react and therefore to reduce crash severity.

Driver's age had significant effect on crash injury severity. Compared to people in middle age, very old people (age ≥ 80) were more likely to be involved in severe left-turn crashes, while very young (age ≤ 19) and young people (19 < age ≥ 24) were more likely to sustain severe injuries, which is consistent with previous literature (Evans, 2004). For very old drivers, their weak physical condition might explain the higher probability of injury and fatality. Rice (Rice, 2007) summarized that approximately 27% (or 2450) of intersection fatalities involved people age 65 years or older. According to 2001 National Household Travel Survey, the elderly had the highest fatal crash rate (fatalities per 100 million vehicles miles of travel), around 4.2 and 11 for age group 80–84 and older than 85, respectively (Liss et al., 2001).

Of the crash related variables, the points of impact of both vehicles were the most significant variables to affect crash severity. Coefficients and marginal effects of severe injuries (non-incapacitating injury, incapacitating injury, and fatal) for the factors front left, front right, back, back left and right were all negative, which showed that crashes were more likely to involve severe injury if a through vehicle was struck at the front. The energy of involved vehicles was translated into greater forces being exerted

Table 5
Marginal effects and standard errors (in parentheses) for Pattern 8 crashes based on generalized ordered logit model

Variables	Crash injury severity				
	None injury	Possible injury	Non-incapacitating injury	Incapacitating injury	Fatal
Logarithm of the near-side crossing through traffic in the crash hour	−0.0311 (0.0184)	−0.0072 (0.0047)	0.0156 (0.0097)	0.0201 (0.0118)	0.0026 (0.0020)
Left-turn lane offset of entering approach (base: negative)					
Zero offset	0.1404 (0.0940)	0.0263 (0.0152)	−0.0709 (0.0488)	−0.0848 (0.0528)	−0.0109 (0.0088)
Positive offset	0.1202 (0.0893)	0.0282 (0.0232)	−0.0588 (0.0429)	−0.0791 (0.0617)	−0.0105 (0.0105)
Driver ejected vs. no	−0.2344 (0.0630)	−0.1478 (0.0478)	−0.0354 (0.0852)	0.3300 (0.1068)	0.0877 (0.0915)
Crash alcohol/drug involved vs. no	−0.0833 (0.2089)	−0.0896 (0.1334)	−0.1706 (0.0928)	0.1836 (0.1263)	0.1599 (0.0995)

Table 6
Models for total left-turn crashes

Variables	Ordered logit estimates		Generalized ordered probit estimates	
	Coef.	*z*	Coef.	*z*
Beta				
Left-turn crash conflicting pattern (base: Pattern 6)				
Pattern 5	1.5535	0.3613	0.8858	0.1943
Pattern 8	1.9124	0.3794	1.1122	0.2056
Patterns 1–4, 7 and 9	0.8874	0.3667	0.4942	0.1969
Conflicting vehicle types (base: other combination)				
Both vehicles in large size	−0.3482	0.1120	−0.1951	0.0655
Motorcycle involved	0.8471	0.2750	0.5057	0.1637
Lighting condition: dark with street light vs. others	−0.2610	0.0757	−0.1474	0.0444
Maximum of speed ratios (estimated speed/speed limit) of two involved vehicles	0.1729	0.0865	0.1029	0.0509
Driver ejected (vs. no)	0.6871	0.2851	0.3882	0.1618
Safety equipment in use (vs. not used)	−0.4669	0.1038	−0.2656	0.0613
Crash alcohol/drug involved (vs. no)	0.6982	0.2503	0.0618	0.1717
Point of impact of entering left-turning vehicle (base: front and front right)				
Back right	−0.6947	0.1014	−0.4053	0.0602
Back	−1.3157	0.2265	−0.7727	0.1290
Back left	−0.9233	0.1960	−0.5543	0.1169
Front left	−0.2208	0.1032	−0.1371	0.0607
Other	−0.7372	0.1961	−0.4989	0.1202
Point of impact of another vehicle (base: front and front left)				
Front right	−1.0130	0.0980	−0.6053	0.0576
Back right	−0.5116	0.0885	−0.2907	0.0522
Back and back left	−1.8358	0.2056	−1.0473	0.1181
Other	−1.0140	0.1350	−0.5900	0.0798
Driver age of left-turning vehicle (base: age ≥ 25)				
Very young (≤19)	−0.4238	0.0963	−0.2446	0.0566
Young (20 ≤ age ≤ 24)	−0.2225	0.0955	−0.1503	0.0565
Driver age of another vehicle (base: 20 ≤ age ≤ 64)				
Very young (≤19)	−0.2271	0.1028	−0.1441	0.0611
Old (≥65)	0.2473	0.1421	0.1500	0.0843
Gamma_2				
Crash alcohol/drug involved vs. no	–	–	0.3359	0.1174
Point of impact of another vehicle: other vs. base case	–	–	0.1607	0.0974
Gamma_3				
Crash alcohol/drug involved vs. no	–	–	0.4597	0.1869
Point of impact of another vehicle: other vs. base case	–	–	0.4342	0.1632
Gamma_4				
Crash alcohol/drug involved vs. no	–	–	0.8914	0.2726
Point of impact of another vehicle: other vs. base case	–	–	0.4342	0.1632
Alpha				
Constant 1	−0.4553	–	−0.3155	0.2076
Constant 2	0.6766	–	0.3766	0.2081
Constant 3	2.2959	–	1.3606	0.2080
Constant 4	5.1588	–	2.7590	0.2200
Summary statistics				
Number of observations	3145		3145	
Log likelihood at convergence	−3962.19		−3956.88	
AIC	7978.38		7977.75	
Pseudo R^2	0.0816		0.0829	

Note: dash (–) indicates data not applicable or unavailable.

on the occupants of involved vehicles when they collided. The variable speed ratio of through vehicle was marginally significant to increase crash injury (Coef. = 0.1849; *p*-value = 0.0850), which is consistent with the previous studies (Kweon and Kockelman, 2003). The result also showed that using the seat belt would reduce crash severity significantly (Coef. = −0.6672; *p*-value <0.0001).

4.2. Pattern 8 left-turn crashes

There were 436 Pattern 8 left-turn crashes, which account for 14% of total left-turn crashes, while more than 30% of left-turn fatal crashes were from this pattern. The partial proportional odds model with logit function had better performance (AIC = 1248.74). The estimates and the marginal effects are presented in Tables 4 and 5, respectively. The variable crash alcohol/drug involved was identified to have varying coefficients for different injury levels. Near-side crossing through traffic in the crash hour, zero or positive left-turn lane offset of entering approach, and crashes with drivers ejected were also identified to be significant.

4.3. Total left-turn crashes

The total number of left-turn crashes was 3145 for the selected intersections over the period of study. Both crash alcohol/drug involved and point of impact of another vehicle were identified to

violate parallel-lines assumption, with p-values 0.003 and 0.041 in the Wald test, respectively. Partial proportional odds models with either logit or probit function were fitted with these two factors differing across injury levels. The p-value of the Wald test for parallel-lines assumption for the final model was 0.8120, which indicated that the final model did not violate the parallel-lines assumption. The partial proportional odds model with probit function had better performance with the largest Pseudo R^2 (0.0829) and the smallest AIC (7977.75) as shown in Table 6.

Results showed that Pattern 5 was more severe than Pattern 6 (conflicting with opposing right-turn vehicle. Coef. = 0.8858), and Pattern 8 was the most severe left-turning conflicting pattern (Coef. = 1.1122). Crashes occurred at night but with street light and safety equipment in use will reduce crash injury level, Coef. = −0.1474 and −0.2656, respectively. Crashes involved motorcycle, with drivers ejected from vehicle, and higher speed ratio of involved vehicle tend to produce more severe left-turn crashes, Coef. = 0.5057, 0.3882, 0.1029, respectively. For both involved vehicles, the front is the most dangerous impact point. Previous studies showed that young drivers were more likely involved in crashes, however, the negative coefficients −0.2446 and −0.1441 indicated that they were less likely to be injured.

5. Summary and discussion

This paper presents a series of crash injury severity models for left-turn crashes. Crash injury severity is categorized into five levels in increasing of severity. The literature suggests that the logit model's assumption of independent errors for alternatives is inconsistent with the fact that the crash injuries are ordered. The parallel-lines assumption (or proportional odds assumption) of commonly applied ordered probability models is usually too restricting. This assumption may be violated only by one or a few of the included variables. A partial proportional odds model where the parallel-lines constraint is relaxed only for those variables when it is not justified is applied in this study.

Partial proportional odds models were developed for left-turning traffic colliding with opposing through traffic (Pattern 5) or with near-side through traffic (Pattern 8), and all of the left-turn collisions that occurred at 197 signalized intersections in the Central Florida area over 6 years. A massive data collection effort was undertaken for these intersections including intersection approach geometric design features, traffic control and operational features (with signal plan), traffic characteristics (with turning movements), and crash data. Left-turn crashes were located to the crash sites where they occurred, which enables the researchers to specify the effect of attributes of intersection approach features on crash severity. The partial proportional odds models perform consistently better for Patterns 5 and 8, and total left-turn crashes. By using partial proportional odds models, the interpretation of the parameters yields greater insight concerning contributing factors, i.e., it revealed the increasing crash injury severity due to alcohol and/or drugs.

Of traffic characteristics, the estimated opposing through traffic and the near-side crossing through traffic in the hour of crash are identified to be significant for Patterns 5 and 8 crash injury, respectively. Traffic volume has been identified as the most significant factor influencing crash occurrence. This study found that neither the total approach volume, nor the entire intersection volume, but rather the specific vehicle movements affected crashed injury significantly. With the real traffic volume at the time of crash available in the future, a more realistic relationship can be established.

Of intersection geometric design features, left-turn offset has been identified to be significant for both Patterns 5 and 8. Of traffic control and operational features, protected left-turn signal and all-red time on opposing through movements have significant influences on Pattern 5 crash injury. Crashes occurred at night at intersections with street lights are associated with lower left-turn crash injury level. All these are viable factors that traffic engineers have some control over. Therefore, based on these findings more efficient countermeasures can be developed to mitigate left-turn crash severity. Many crash related variables were identified to be significant which include: alcohol/drug use, vehicle type, driver age, impact point, speed ratio, safety equipment, and driver ejection.

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