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Analysis of driver injury severity in wrong-way driving crashes on controlled-access highways

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ABSTRACT

For more than five decades, wrong-way driving (WWD) has been notorious as a traffic safety issue for controlled-access highways. Numerous studies and efforts have tried to identify factors that contribute to WWD occurrences at these sites in order to delineate between WWD and non-WWD crashes. However, none of the studies investigate the effect of various confounding variables on the injury severity being sustained by the at-fault drivers in a WWD crash. This study tries to fill this gap in the existing literature by considering possible variables and taking into account the ordinal nature of injury severity using three different ordered-response models: ordered logit or proportional odds (PO), generalized ordered logit (GOL), and partial proportional odds (PPO) model. The findings of this study reveal that a set of variables, including driver's age, condition (i.e., intoxication), seatbelt use, time of day, airbag deployment, type of setting, surface condition, lighting condition, and type of crash, has a significant effect on the severity of a WWD crash. Additionally, a comparison was made between the three proposed methods. The results corroborate that the PPO model outperforms the other two models in terms of modeling injury severity using our database. Based on the findings, several countermeasures at the engineering, education, and enforcement levels are recommended.

1. Introduction

Controlled-access highways are designed to provide high-speed vehicular traffic flows and maximize mobility by eliminating the potential conflicts between moving vehicles and driveways using grade-separated interchanges. Despite all the benefits in terms of vehicular throughput, this highway system is prone to a rare, but severe, kind of crash, which is caused by wrong-way driving (WWD). This type of crash happens when a driver, inadvertently or deliberately, drives against the main direction of traffic flow on a controlled-access highway. According to the National Transportation Safety Board (NTSB) Special Investigation Report, three possible mechanisms describe how a driver can end up driving in the wrong direction on controlled-access highways: (1) entering an exit ramp, (2) making a U-turn on the mainline, and (3) using an emergency turnaround through the median (NTSB, 2012). In addition to these mechanisms, a driver who crosses over the median and travels for some distance is also considered to make a WWD movement, despite accounting for a small number of WWD events. Even a short distance traveled means the movement is categorized separately from a cross-median crash where, instead, the driver collides with other vehicle(s) immediately after crossing over the median to an opposing traffic lane.

Regardless of the type of entrance, WWD crashes tend to be more severe and have a greater likelihood of resulting in death or injury when compared to other types of crashes on controlled-access highways. The reason is the high speed of traffic flow on these facilities and the nature of WWD crashes, which is mostly head-on. Past studies (Copelan, 1989; Cooner et al., 2004) showed that although a very small percentage of overall traffic crashes were caused by WWD, they result in a relatively large percentage of fatal crashes. In a recent study, Pour-Rouholamin et al. (2016) reported 1.34 fatalities per fatal WWD crashes in the U.S. from 2004 to 2013, while fatalities per fatal crash rate of 1.10 is observed for all other crash types during the same time period. Drivers and passengers in both wrong-way (WW) and right-way (RW) vehicles can be killed in WWD crashes. For example, of the 49 fatal WWD crashes on the New Mexico interstate highway system between 1990 and 2004, 35 drivers and 11 passengers in the WW vehicles were killed, and 18 drivers and 15 passengers in vehicles traveling in the correct direction were killed, as well (Lathrop et al., 2010). These statistics

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and accompanying safety issues corroborate the need for analyzing the injury severity of WWD crashes more in depth.

This study analyses the injury severity sustained by the WW (at-fault) drivers in a WWD crash considering the inherently ordered nature of injury severity. To this end, 398 WWD crashes[1] on controlled-access highways were investigated from the states of Illinois (10 years of data) and Alabama (5 years of data), based on the availability of the data. Three ordered-response models, including ordered logit, generalized ordered logit, and partial proportional odds models were nominated as possible analysis tools. A comparison between these three nominated models was also made to select the best modeling approach for WW driver injury severity analysis. Hence, the main objective of this study is to identify the factors that significantly affect the injury severity of WW drivers in such events. These factors fall under four major categories, which include responsible driver characteristics, temporal variables, vehicle information, and crash variables. The results of this study can provide useful insights into this safety issue and provide appropriate safety countermeasures to address this rare, particular traffic safety problem.

The rest of this paper is organized as follows: A review on the prior research on WWD crashes as well as methodological approaches is provided in Section 2. Section 3 elaborates on the databases used for analysis along with descriptive statistics of the multiple possible contributing factors. Ordered-response models (i.e., ordered logit, generalized ordered logit, and partial proportional odds model), their formulations, assumptions, and applications are discussed in Section 4. In Section 5, the proposed model is applied to the WWD crash dataset and parameter estimates and average direct pseudo-elasticities as well as model goodness-of-fit tests are presented. Finally, section 6 concludes this paper and provides safety recommendations.

2. Literature review

Previous research has focused on identifying which factors are correlated with the occurrence of WWD crashes on freeways. Many States have conducted studies on WWD crashes, including California, Texas, North Carolina, New Mexico, Michigan, Illinois, Alabama, and Florida. In addition to the studies in the U.S., other countries such as Finland, Switzerland, Netherlands, Japan, and France have also worked on WWD issues. The results of these efforts are summarized in Table 1.

Based on these studies, WWD crashes are more prevalent during non-daylight hours, particularly in the early morning. In Texas, 52% of all WWD crashes occurred during the six hours from 12:00 midnight to 6:00 a.m.; however, only 10.4% of overall freeway crashes occurred during that time period. Past studies (Copelan, 1989; Cooner et al., 2004; Braam, 2006; NTTA, 2009) indicated that WWD crashes occurred more frequently during the weekends; however, the monthly distribution of WWD crashes varies among different states (Braam, 2006; Cooner and Ranft, 2008; Pour-Rouholamin et al., 2016) and countries (ITARDA, 2002), showing no consistent trend.

Past research conducted in both Illinois (Zhou et al., 2012) and Texas (Cooner et al., 2004) found that WWD crashes occur in urban areas more often than in rural areas. Studies in Texas also found that most of the WWD collisions occurred in the inside lane of the correct direction and at locations with left-side exit ramps or one-way streets that transitioned into a freeway section. A study in the Netherlands from 1996 to 1998 found that 79% of WWD crashes took place on the main line of the freeway, 5% on merge/diverge lanes, and 17% on ramps (SWOV, 2009).

The characteristics of WW drivers, such as driver sobriety, age, and gender, have been discussed in many past studies. A significant portion of WWD crashes on freeways was caused by those who were driving under the influence (DUI) of alcohol or drugs. Most past studies concluded that young drivers and older drivers are overrepresented in the WWD crashes. Most of the crashes caused by drivers in the young and middle-age range occurred because of distraction (Haendeler et al., 2014; Pour-Rouholamin et al., 2016), while most crashes caused by drivers in the senior age range occurred because of some physical illnesses such as dementia or confusion (ITARDA, 2002). The findings of a study by Gibbons et al. (2012) established a relationship between aging and nighttime driving behaviors, signifying that older drivers have more difficulty detecting objects than younger drivers when the roadway is not lit well. An overwhelming majority of WWD crashes involved male drivers, and most of the female drivers were in young age groups (ITARDA, 2002).

Despite all the efforts to characterize WWD crashes and delineate between these types of crashes and the others, there is no research into the factors that affect the driver's injury severity within the WWD domain. Along with recognizing the factors that affect the probability of WWD crashes, it is also crucial to identify the extent to which these factors might affect the severity of injuries sustained by the WW driver in terms of safety implications. To this end, several methods have already been used whether they consider the ordered nature of severities or not.

Over the past years, numerous disaggregate modeling approaches have been employed to quantify the effect of several contributing factors on various levels of injury severity. Given the ordered nature of the injury severity in crashes (representing an ordinal outcome), these methodological approaches generally fall under two main categories (based on whether this nature is considered or not): ordered-response models and unordered-response models. Ordered logit/probit (Khattak and Rocha, 2003; Lee and Li, 2014), generalized ordered logit (Wang and Abdel-Aty, 2008; Abegaz et al., 2014), and mixed generalized ordered logit (Eluru and Bhat, 2007; Eluru et al., 2008) models are among the models that do consider the ordered nature of crash severity. However, there is an increasing tendency towards using unordered response models, as well. Nested logit (Haleem and Abdel-Aty, 2010; Hu and Donnell, 2010), multinomial logit (Celik and Oktay, 2014; Xie et al., 2012), and mixed logit models (Kim et al., 2013; Klassen et al., 2014) have also been used to provide in-depth insight into significant contributing factors to crash injury severities. This study considers the ordered nature of crash injury severity; thus, it employs ordered-response models to examine the effect of various contributing factors to the driver injury severity in WWD crashes on controlled-access highways (freeways, expressways, Interstate highways).

3. Data

The WWD crash records in this study mainly come from the results of two major WWD studies in Illinois (Zhou et al., 2012, 2015; Zhou and Pour-Rouholamin, 2015) and Alabama (Zhou et al., 2016). The Illinois crash data was accessed through the Illinois Department of Transportation (IDOT) crash database. This database combines the crash data from three separate text files (crash, person, and vehicle). Crash records in these three files can be linked together using a numerical variable unique to each crash record, called the Illinois Case Number (ICN). The Alabama crash data was also accessed through the Critical Analysis Reporting Environment

[1] While the sample size might look small, it should be noted that several studies have already used small sample sizes mainly because of the rareness of this kind of crash. For instance, Kemel (2015), Zhou et al. (2012), and Lathrop et al. (2010) used sample sizes of 266, 217, and 49 for their analyses, respectively.

Table 1
Summary of some of the studies on WWD.

State	Study Period	Contributing Factors	References
Conducted in the U.S.			
California	1983–1987	Darkness; Intoxicated drivers; Time of the day; Urban areas; Interchanges with short sight distance; Partial cloverleaf interchanges; Half and full diamond interchanges; Trumpet interchanges; Slip ramps; Buttonhook ramps; Scissors exit ramp; Left-side exit ramp; Five-legged intersections near exit ramps	Copelan (1989)
Texas	1997–2000	Early morning hours; Male drivers; Drivers less than 34 years old; Intoxicated drivers; Left-side exit ramps; Urban areas; One-way street transitioned into freeway	Cooner et al. (2004)
North Carolina	2000–2005	Alcohol-related; Younger drivers; Older drivers; Interstate routes; Rural areas; Time of day (midnight to 5:59 am); Months of February and June; Two-quadrant parclo interchanges; Full diamond interchanges	Braam (2006)
New Mexico	1990–2004	Darkness; Intoxicated drivers; Older drivers; Male drivers; Passenger cars; Month of November; Non-Hispanic and native Americans	Lathrop et al. (2010)
Michigan	2005–2009	Darkness; Intoxicated drivers; Time of the day (late night and early morning); Younger drivers; Older drivers; Male drivers; Parclo interchanges; Trumpet interchanges; Tight diamond interchanges	Morena and Leix (2012)
Illinois	2004–2009	Darkness; Older Driver; Younger drivers; Male drivers; Local drivers; Intoxicated drivers; Time of day (midnight to 5:00 am); Head-on crashes; Weekends; Urban areas; Type of interchange; Passenger cars; Single-occupant vehicles;	Zhou et al. (2012)
Alabama	2009–2013	Time of the day (evening and afternoon); Older drivers; Intoxicated drivers; Physically impaired drivers; Driver residency distance (local drivers); Vehicles older than 15 years; Roadway condition; Months of March, May, and November	Pour-Rouholamin et al. (2016)
Florida	2003–2010	Driver age; Driver gender; Driver condition (eyesight, fatigue, illness, seizure, epilepsy); Intoxicated drivers; Time of the day; Urban areas; Darkness; Rainy and foggy weather; Vehicle use; Day of week; AADT	Ponnaluri (2016)
Conducted in Other Countries			
Finland	1999–2002	Younger drivers; Older drivers; Darkness; Intoxicated drivers; Ramp configuration; Making a U-turn at the end of exit ramp;	Karhunen (2003)
Switzerland	2003–2005	Younger drivers; Intoxicated drivers; Older drivers; Time of day; Female drivers; Lighting condition	Scaramuzza and Cavegn (2007)
Netherlands	1996–1998	Older drivers; Younger drivers; Inexperienced drivers; Intoxicated drivers	SWOV (2009)
Japan	2005–2009	Older drivers; Younger drivers; Darkness; Type of interchange; Making a U-turn on carriageway; Dementia; Time of day (4:00 pm to 10:00 pm);	Xing (2014)
France	2009–2012	Darkness; Older drivers; Intoxicated drivers; Local drivers; Driving older vehicles; Passenger cars; Single-occupant vehicles; Unlicensed drivers	Kemel (2015)

software, also known as CARE (CARE, 2015). This database encompasses three major levels of crash characteristics including person, vehicle, and environment, along with corresponding crash severity. The crash severity used in both the IDOT and CARE databases is in the 5-level scale of KABCO in which fatality is coded as “K”, incapacitating injury as “A”, non-incapacitating injury as “B”, possible (but not evident) injury as “C”, and no injury as “O”. For both databases, if a driver dies within 30 days of a crash due directly to that crash, the severity is defined as a fatality and must be coded as “K”.

In order to improve the accuracy of analysis and the quality of the results, and based on the data availability, a 10-year crash data collection (2004–2013) from Illinois and a 5-year crash data collection (2009–2013) from Alabama were compiled. Before running any analysis, WWD crashes need to be identified using defined criteria specific to each database and verified based on the crash reports (with especial emphasis on the diagrams and narratives) as well as existing online maps. The time-consuming process of identification and verification for Illinois and Alabama crash data are further explained in details in Zhou et al. (2012) and Pour-Rouholamin et al. (2016), respectively. After filtering out non-WWD crashes and screening out a few verified WWD crash records with insufficient information and obviously incorrect values for the studied parameters, altogether 398 WWD crash records (305 records in Illinois and 93 records in Alabama) were collected for further severity analysis.

A review on the severity of injuries sustained by drivers in these crashes revealed that 212 drivers were not injured, 9 drivers were possibly injured, 61 complained about minor injuries, 74 incurred incapacitating injuries, and 42 perished either at the scene or within 30 days of the crash. In this study, due to the severe nature of WWD crashes and in order to ensure a sufficient number of observation in each crash severity category, the 5-level scale of KABCO was converted to a 3-level scale of no injury to the driver (comprising property damage only crashes) (53.27%), minor injury comprising C- and B-level injuries (17.59%), and severe injuries (comprising A-injuries and fatalities) (29.15%). The explanatory variables used in this severity study are cross-tabulated with these 3-level injury severities and are presented in Table 2. It should be noted that the Other/Unknown categories for the variables are not presented in this table; therefore, the total number for some variables under the columns may not sum up to the corresponding injury severity frequency.

4. Method

4.1. Econometric model

According to Boes and Winkelmann (2006) the “ordered-response models” is a general terms that is assigned to discrete statistical models in which the dependent variable represents an ordinal outcome and can be explained by a number of arbitrar-

Table 2
Description of explanatory variables.

Explanatory Variable	No Injury		Minor Injury		Severe Injury		Total
Total	212	53.27%	70	17.59%	116	29.15%	398
Responsible Driver Characteristics							
Age							
Young (Less than 24)	39	46.43%	15	17.86%	30	35.71%	84
Middle-aged (25–64)	112	51.14%	38	17.35%	69	31.51%	219
Older (65 and over)	56	62.22%	17	18.89%	17	18.89%	90
Gender							
Male	129	48.13%	54	20.15%	85	31.72%	268
Female	50	52.08%	16	16.67%	30	31.25%	96
Condition							
Normal	50	60.24%	17	20.48%	16	19.28%	83
DUI	104	49.29%	36	17.06%	71	33.65%	211
Seatbelt Status							
Used	152	54.87%	58	20.94%	67	24.19%	277
Not used	8	22.22%	5	13.89%	23	63.89%	36
Temporal Variables							
Season							
Spring	50	47.17%	23	21.70%	33	31.13%	106
Summer	36	46.75%	12	15.58%	29	37.66%	77
Autumn	63	57.27%	19	17.27%	28	25.45%	110
Winter	63	60.00%	16	15.24%	26	24.76%	105
Day of Week							
Weekday	114	50.22%	43	18.94%	70	30.84%	227
Weekend	98	57.31%	27	15.79%	46	26.90%	171
Time of Day							
Morning	23	57.50%	7	17.50%	10	25.00%	40
Afternoon	23	62.16%	8	21.62%	6	16.22%	37
Evening	56	52.83%	21	19.81%	29	27.36%	106
Night	110	51.16%	34	15.81%	71	33.02%	215
Vehicle Information							
Number of Vehicles							
One	47	67.14%	13	18.57%	10	14.29%	70
Two	133	53.20%	39	15.60%	78	31.20%	250
Three and more	32	41.03%	18	23.08%	28	35.90%	78
Type							
Passenger Car	140	53.44%	45	17.18%	77	29.39%	262
Pickup	29	48.33%	10	16.67%	21	35.00%	60
SUV	19	48.72%	8	20.51%	12	30.77%	39
Van/Minivan	7	41.18%	5	29.41%	5	29.41%	17
Age							
Less than 5	45	47.87%	17	18.09%	32	34.04%	94
5 to 14 years	117	50.65%	44	19.05%	70	30.30%	231
15 years and over	23	51.11%	8	17.78%	14	31.11%	45
Airbag Status							
Not deployed	49	74.24%	10	15.15%	7	10.61%	66
Deployed	50	29.07%	42	24.42%	80	46.51%	172
Crash Variables							
Type of Setting							
Urban	160	55.75%	48	16.72%	79	27.53%	287
Rural	52	46.85%	22	19.82%	37	33.33%	111
Weather Condition							
Clean/Cloudy	169	52.00%	54	16.62%	102	31.38%	325
Rain	30	61.22%	10	20.41%	9	18.37%	49
Surface Condition							
Dry	158	50.32%	55	17.52%	101	32.17%	314
Wet	43	61.43%	15	21.43%	12	17.14%	70
Lighting Condition							
Daylight	45	60.81%	14	18.92%	15	20.27%	74
Dawn/Dusk	5	55.56%	2	22.22%	2	22.22%	9
Dark–Not Lit	62	44.93%	23	16.67%	53	38.41%	138
Dark–Lit	98	56.00%	31	17.71%	46	26.29%	175
Head-on Crash?							
No	160	72.07%	36	16.22%	26	11.71%	222
Yes	52	29.55%	34	19.32%	90	51.14%	176

ily scaled independent variables. Since crash severity is ordinal in nature (Savolainen et al., 2011) recognizing this feature is an important consideration in selecting the appropriate analysis tool, necessitating the use of ordered-response models. In this study, driver injury severity was considered as a 3-level ordinal outcome from the lowest, which is No Injury, to the highest, which is Severe Injury. There are three different ordered-response models that have previously been used in the literature. These models are ordered logit (or proportional odds -PO) model, generalized ordered logit (GOL) model, and partial proportional odds (PPO) model.

When the dependent variable in a regression model is ordinal (i.e., an ordered-response model is being developed—which is the case in this work), then specific attention should be given to the parallel regression (proportional odds) assumption. This assumption says, in PO model (the simplest form of the three ordered-response models), the coefficients that describe the odds of being in the lowest level (here, No Injury) compared to all higher categories of the dependent variable are the same as those that explain the odds between the second lowest level (here, Minor Injury) and all higher categories. Accordingly, just one set of coefficients will be calculated for all odds of the variables being modeled. As a result, the effect of that particular variable on the injury severity would be linear (i.e., each variable may either increase or decrease the likelihood of higher injury severities). However, that may not be the case in real world. For example, crashes happened in rural areas might not make a significant difference between No Injury and Minor Injury, while making a significant difference between Minor Injury and Severe Injury. In other words, the effect of rural areas on severe injuries might be more pronounced compared to other injury levels. The difference between these three ordered-response models lies here and comes from the parallel regression assumption and how these models handle it. To be more specific, PO model holds this assumption for all variables, GOL model violates this assumption for all variables, and PPO model holds this assumption for those variables that are found not to violate the assumption based on some statistical tests (e.g., Brant test). These models are explained more in detail in the following.

The simplest form of these three ordered-response models is the PO model. If j denotes the crash severity level (1 = no injury; 2 = minor injury; 3 = severe injury) and J represents the number of severity levels (here J = 3), then the standard form of the conventional ordered logit or PO model is as follows:

$$Pr\left(Y_i > j\right) = \frac{exp\left(X_i\beta - \alpha_j\right)}{1 + \left[exp\left(X_i\beta - \alpha_j\right)\right]} j = 1, 2, \ldots, J-1 \quad (1)$$

where Y_i represents the observed severity for crash i, X_i is a vector of explanatory variables, β is a vector of the corresponding parameter estimations, and α_j is the cutoff term for the thresholds in the model. This model tries to estimate $\beta\langle errorimage\rangle$'s and $\alpha_j\langle errorimage\rangle$'s values (Long, 1997), while assumes $\beta\langle errorimage\rangle$'s are constant across different severity levels for each variable and the only difference between J-1 regression lines is the parameter α., which is called parallel regression assumption, as explained earlier.

In order to overcome the issue that arose from parallel line assumption, the GOL model is developed that relaxes this assumption for all the variables in the model. This model can be formulated as follows:

$$Pr\left(Y_i > j\right) = \frac{exp\left(X_i\beta_j - \alpha_j\right)}{1 + \left[exp\left(X_i\beta_j - \alpha_j\right)\right]} j = 1, 2, \ldots, J-1 \quad (2)$$

where β_j is the vector of parameter estimations that, despite the PO model, do vary across equations for different crash severities (Williams, 2006). The other factors were previously introduced. However, the adoption of this method may result in an unnecessary increase in the number of calculated $\beta\langle errorimage\rangle$'s as not all the variables in the model will violate this assumption. In other words, just one or more variables in the model may necessitate considering varying $\beta\langle errorimage\rangle$'s across those severity levels. This situation has appropriately been handled in the PPO model. The PPO model accounts for the fact that not every single variable will violate the parallel line assumption and is specified as:

$$Pr\left(Y_i > j\right) = \frac{exp\left(X_{1i}\beta_1 + X_{2i}\beta_2 - \alpha_j\right)}{1 + \left[exp\left(X_{1i}\beta_1 + X_{2i}\beta_2 - \alpha_j\right)\right]} j = 1, 2, \ldots, J-1 \quad (3)$$

where β_1 and β_2 are the vectors of parameter estimations that do and do not violate the parallel line assumption, respectively. The corresponding vector of independent variables that do and do not violate this assumption are X_{1i} and X_{2i}, respectively. This model, which has previously been employed by some studies (Quddus et al., 2010; Kaplan and Prato, 2012; Pour-Rouholamin and Zhou, 2016), can be fitted by the gologit2 program in Stata (Williams, 2006).

The identification of the variables that violate the parallel regression assumption can be fulfilled using several tests, such as the likelihood ratio test, the Wolfe Gould test, or the Brant test. In this study, a Brant test (Brant, 1990) is proposed prior to model estimation in order to determine whether any of the variables violates this assumption. This test estimates the coefficients for the underlying binary logistic regressions and examines the equality of all parameter estimates for individual variables using a chi-square statistic. The statistical significance of the test statistic is the indication of an assumption violation for that particular variable.

4.2. Elasticity

Elasticities can be calculated in order to quantify the effect of significant variables on the probability of severities. This is because the interpretation of the results from ordered-response models needs more attention as the sign and value of the $\beta\langle errorimage\rangle$'s do not always determine the direction and magnitude of the effect of the intermediate levels for crash severity (Kaplan and Prato, 2012). It is worth mentioning that elasticities are applicable to continuous variables, whereas—given the nature of explanatory variables in this study that are dummy variables taking the value of 0 or 1—direct pseudo-elasticities can instead be used for each injury severity and each crash record. This measure is calculated as the change in the percentage of the crash severity probability when the dummy variable is switched from 0 to 1 or vice versa. Direct pseudo-elasticity can be computed as (Kim et al., 2013):

$$E_{x_{jnk}}^{Pr(Y_i>j)} = \frac{Pr\left(Y_i > j\right)\left[Givenx_{jnk} = 1\right] - Pr\left(Y_i > j\right)\left[Givenx_{jnk} = 0\right]}{Pr\left(Y_i > j\right)\left[Givenx_{jnk} = 0\right]} \quad (4)$$

where $Pr\left(Y_i > j\right)$ is defined by Eqs. (1), (2), or (3) (whichever applies) and x_{jnk} is the k^{th} explanatory variable associated with the injury severity j for the individual crash n. The average direct pseudo-elasticities can then be calculated for each injury severity to represent the whole dataset (Kim et al., 2010).

4.3. Model comparison

After selecting the appropriate model based on the Brant test results, the other two models can also be fit on the same dataset and a performance assessment study can be conducted. To this end, three different criteria are proposed to check the performance of the ordered-response models used. These criteria, which are employed to compare maximum likelihood models, include log-likelihood of the full model with statistically significant explanatory variables (LL_{Full}), Akaike Information Criterion (AIC), and Bayesian Information Criterion (BIC). The latter two are formulated as follows:

$$AIC = -2LL_{Full} + 2k \quad (5)$$

$$BIC = -2LL_{Full} + \ln(N) \times k \quad (6)$$

where, k is the number of parameters estimated in the model, and N is the number of observation (398). In addition to comparing the model fit, these two measures can account for the complexity of the model by penalizing the criterion for the number of explanatory variables included in the model. This penalization is carried out by either $2k$ or $\ln(N) \times k$ terms in the equations. Having the models fit on the same dataset, the model with lower LL_{Full}, AIC, and BIC is considered to outperform the others.

Table 3
Estimation results and sverage firect pseudo-elasticities.

Explanatory Variable	Parameter Estimates		Average Direct Pseudo-Elasticities		
	Threshold 1	Threshold 2	No Injury	Minor Injury	Severe Injury
Responsible Driver Characteristics					
Age					
Older[a]	−0.298**	−0.646**	13.90%	21.00%	−45.90%
Condition					
DUI	0.394**	0.394**	−18.40%	9.50%	27.90%
Seatbelt Status					
Not used	1.195***	1.201***	−55.60%	28.90%	85.40%
Temporal Variables					
Time of Day					
Afternoon	−0.263*	−0.263*	11.70%	−7.00%	−18.70%
Night	0.340**	0.340**	−15.10%	9.20%	20.70%
Vehicle Information					
Airbag Status					
Deployed[a]	1.272***	1.272***	−59.20%	31.30%	90.50%
Crash Variables					
Type of Setting					
Rural	0.375**	0.375**	−17.40%	9.20%	26.70%
Surface Condition					
Wet	−0.499**	−0.499**	23.20%	−12.30%	−35.50%
Lighting Condition					
Dark – Not Lit	0.492**	0.492**	−22.90%	12.10%	35.00%
Dark – Lit	0.179*	0.179*	−8.30%	4.40%	12.70%
Head-on Crash?					
Yes[a]	1.491***	1.695***	−69.40%	20.00%	120.60%
Constant	−1.455***	−2.561***	–	–	–
Number of Observations	398				
Wald Chi^2 (14)	113.58				
Log-likelihood at Constant	−370.42				
Log-likelihood at Convergence	−284.75				
McFadden's Pseudo R^2	0.2313				
AIC	601.500				
BIC	665.283				

Notes: *** Significant at the 99% confidence interval. ** Significant at the 95% confidence interval. * Significant at the 90% confidence interval.
[a] Explanatory variable violating parallel line assumption.

5. Results and discussion

Before estimating the parameters, calculating the associated average direct pseudo-elasticities, and interpreting the results, the first step is to examine the parallel regression assumption to determine the appropriate ordered-response model to use (PO, GOL, and PPO). As mentioned earlier, in this study, a Brant test was employed to examine whether the entire model (all the variables) or any of the variables violate the parallel regression assumption. The results of the Brant test demonstrated that three variables (older drivers, deployed airbag, and head-on collision) violate this assumption, hence requiring the development of PPO model. Table 3 summarizes the results of the developed PPO model, including parameter estimates as well as the average direct pseudo-elasticities. Furthermore, the Wald chi-square statistic of 113.58 with 14 degrees of freedom—which is substantially larger than the respective chi-square values at any reasonable confidence level—demonstrates that the presence of exogenous variables significantly improves the quality of the model's estimation. The McFadden's pseudo R-square of 0.2313 indicates the model enjoys a very good predictive strength. According to Louviere et al. (2000), a model with a McFadden's pseudo R-square value between 0.2 and 0.4 represents a high predictive power.

The same dataset was used to fit the other two ordered-response models, which were PO and GOL, to make a comparison between the performances of these models. As previously mentioned, log-likelihood of the full models (LL_{Full}) along with AIC and BIC were used to this end. These three parameters were calculated and presented in Table 4. While comparing models obtained from maximum likelihood approach, the lower LL_{Full} can be used as a sign of outperformance, given that fitted models have the same sample and dependent variable (Finch et al., 2014). As can be seen in Table 4, the PPO model provides the lowest LL_{Full}; therefore, it outperforms the other two models. In addition to the lowest LL_{Full}, PPO provides lowest AIC and BIC values compared to the other two models in this study that further corroborate the outperformance of the PPO model over the other two. Based on these numbers, the PPO model evidently provides better fit than both PO and GOL models in analyzing the driver injury severity in WWD crashes.

Table 4
LL at Convergence, AIC, and BIC of PO, GOL, and PPO Models.

Model	Criterion		
	LL_{Full}	AIC	BIC
PO	−299.975	627.949	683.760
GOL	−286.224	612.449	692.178
PPO	−284.750	601.500	665.283

Considering the specific estimation results in Table 3, the parameter age is found to significantly affect the injury severity of drivers in WWD crashes with varying effects across injury severity levels. Accordingly, compared to middle-aged drivers as the reference group, older drivers (65 years and older) are less affected by severe injuries. Specifically, the probability of incurring severe injuries for this age group shows a decrease of 45.9%, while the probability of no injuries and minor injuries are increased by 13.9% and 21.0%, respectively. This finding can be explained so that as the drivers grow older, they follow more cautious and conservative driving behaviors by driving at safer speeds. Researchers have reported various findings on the effect of drivers' ages on the sustained severity by types of crashes. For example, some studies (Lee and Li, 2014; López et al., 2014) have shown that young drivers are more likely to be severely injured in single-vehicle crashes compared to older drivers, as they are more likely to make errors and get involved in single-vehicle crashes. On the other hand, Russo et al. (2014) identified older drivers as more likely to suffer from more severe injuries in multi-vehicle crashes due to their physiological characteristics and attributes.

Driving under the influence was found as another significant parameters affecting the injury severity of WW drivers. It was determined that driving while intoxicated increases the probability of severe injuries by 27.9%, minor injuries by 9.5%, and decreases the probability of no injuries by 18.4%. Interestingly, more than half of the at-fault drivers in WWD crashes were identified as DUI. Wu et al. (2014) indicated that drivers who were DUI showed delayed perception and reaction times that made them more likely to suffer fatality when getting involved in crashes, including WWD. Stübig et al. (2012) demonstrated that alcohol-intoxicated road users experience higher injury severities due to the higher impact speed difference compared to sober drivers. Additionally, intoxicated drivers may be less likely to take proper evasive/corrective actions at the moment of the crash, which subsequently increases the severity of the crash (Behnood and Mannering, 2015). This result is consistent with the findings by Khorashadi et al. (2005) and Zhang et al. (2000). However, Behnood and Mannering (2015) also noted that DUI driving has been associated with reduced hospital stays and lower injury-mortality rates in some medical literature. It can be explained by the fact that intoxicated persons tend to be more relaxed at the moment of crash, which distributes the force of impact over larger areas of the person's body and, consequently, reduces the severity of injury. This can justify the less pronounced effect of DUI driving in this study.

Two safety features installed in the vehicles, including the seatbelt and airbag, were both found to significantly affect the severity of injuries sustained by the at-fault drivers in WWD crashes. The sign of the parameter estimates for seatbelt use as well as the associated elasticities in Table 3 obviously highlight the critical role of wearing a seatbelt in reducing the severity of WWD crashes. Based on the results, not wearing a seatbelt considerably increases the likelihood of experiencing minor and severe injuries by 28.9% and 85.4%, respectively. Abu-Zidan et al. (2012) remarked that seatbelt usage not only reduces the severity of the vehicle occupant's injury, but also reduces the hospitalization duration as well as the likelihood of operations on vehicle occupants. Furthermore, seatbelt usage prevents ejection of drivers from the vehicles after the crash, which is believed to be one of the main causes of higher injury severities (Abu-Zidan and Eid, 2015), including WWD (Zhou et al., 2015), although driver ejection was not considered in this study due to its incomplete/inaccurate attributes in the database. Airbag deployment, however, shows varying effects on injury levels. Interestingly, deployed airbags was found to be associated with increased probability for both minor and severe injuries by 31.3% and 90.5%, respectively. A decrease of 59.2% in the probability of no injuries is also reasonable, as the airbag itself may cause some minor injuries (Savolainen and Ghosh, 2008). It should be noted that out of 80 severe crashes that caused airbag deployment, 24 resulted in fatalities and 56 in A-injuries. This means that the direction of this parameter estimate and the associated obtained elasticity toward a severe crash category in the model is due mainly to A-injury crashes. Airbags are designed to work efficiently in combination with the three-point seatbelts. If there is no such seatbelt in use, airbag deployment can itself permit otherwise preventable injuries that may explain the increase in the probability of minor and severe injuries (Wallis and Greaves, 2002). Cummins et al. (2011) conducted a comprehensive study on the role of seatbelt use and airbag deployment in the severity outcome of crashes using a database of around 185,000 patients involved in crashes between 1988 and 2004. The analysis of the data identified that the use of seatbelts and airbag deployment reduced the mortality rate by more than 50% and 32%, respectively.

The obtained results indicate the significant effect of the time of day on the driver injury severity in WWD crashes. It is determined that the occurrence of a WWD crash during afternoon and nighttime conditions have various effects on injury severity so that the former decreases the probability of severe injuries while the latter shows an inversed effect. This change in the severity is more pronounced for nighttime conditions so that the probability of severe injuries during the night increases by a factor of 20.7%. To explain this finding, it should be noted that generally, the probability of WWD crashes is significantly higher during the night. For example, Pour-Rouholamin et al. (2016) found a 5.5-time increase in the probability of WWD crashes at night. Moreover, factors like sleepiness, glare, dark adaption, reduced visibility of roadway, signs and markings, and a higher proportion of drunk drivers contribute to higher injury severities at nighttime (Bella et al., 2014).

As would be expected, drivers are exposed to higher injury severities when the lighting condition is not appropriate. According to the results, darkness (whether the roadway is lit or not) increases the severity of WWD crashes significantly. The average direct pseudo-elasticities show that darkness without any lighting may cause a 35.0% increase in the probability of driver severe injuries in WWD crashes. This number is decreased to 12.7% when lighting provided during dark hours. Clarke et al. (2006) and Williams (2003) have demonstrated the disproportionality between fatality risks during nighttime and daytime conditions so that fatality risk at night is more than four times the fatality risk during daylight.

Driver injuries tend to be more severe when the WWD crash happens in rural areas compared to urban areas. The findings of this study show an increase of 26.7% and 9.2% in the likelihood of severe and minor injuries in rural WWD crashes as opposed to urban WWD crashes, respectively. Some reasons might explain this finding. For example, it is claimed that rural road users are more likely to be speeding and be DUI drivers compared to urban road users, which consequently result in higher injury severities (Boufous et al., 2008; Clark, 2001). Furthermore, emergency medical services (EMS) are more accessible and faster in urban areas, which may reduce the severity of injuries when a crash happens. This is because EMS confronts several challenges specific to rural areas, such as getting notified, locating, and transporting victims in a timely and effective manner (Minge, 2013). This delayed response becomes more significant as the studied states (Illinois and Alabama) update the injury severity level within 30 days of the crash.

A wet surface, which is a surrogate measure of inclement weather condition, is shown to significantly decrease the severity of injuries incurred by drivers in WWD crashes, compared to a dry surface condition. Specifically, a reduction of 12.3% and 35.5% is observed in minor and severe injuries, respectively, whereas no injuries increased by 23.2%. It is noteworthy that drivers seem to decrease their driving speeds while driving on wet surfaces which decreases the severity of crashes either with other vehicles or other objects (Christoforou et al., 2010). Moreover, drivers tend to be more vigilant of their surroundings during these conditions.

Regarding the effect of collision type, the obtained results show that there is a significant difference between the severity outcomes of head-on crashes compared to non-head-on crashes so that head-on crashes are found to significantly increase the probability of severe outcomes. Notably, this parameter shows various effects across different severity levels (i.e., violates the parallel line assumption). Relative to non-head-on crashes, head-on crashes are associated with a decrease of 69.4% in no injuries, an increase of 20.0% in minor injuries, and a considerable increase of 120.6% in the probability of severe injuries. This highly increased severity outcome is due mainly to the higher speed of vehicles driving on freeways, which in turn intensifies the severity of crashes. A review on the existing literature studying head-on crashes on highways shows the same result, bolstering the significant effect of this parameter among the others in terms of increasing the severity of injury (Jafari-Anarkooli and Hadji-Hosseinlou, 2016; Deng et al., 2006).

6. Conclusions and recommendations

This study analyzed at-fault drivers' injury severity in 398 WWD crashes using 10-year crash records in Illinois and 5-year crash records in Alabama. In order to account for the ordinal nature of the injury severity, three ordered-response models (i.e., PO, GOL, and PPO) were nominated to fit the data. The main difference between these models is whether they account for the parallel regression assumption and how they handle it. The data used was categorized using a three-level injury severity of no injury, minor injury, and severe injury. Based on the results of the Brant test, three variables (i.e., older drivers, deployed airbag, and head-on collision) were found to violate the parallel regression assumption, thus the PPO model was finally employed for analysis. This study is the first to identify and quantify the effect of various significant variables on the injury severity of at-fault drivers in WWD crashes. The identification of these variables can contribute to the development of appropriate safety countermeasures, and the quantification of their effects can help prioritize these possible countermeasures when the implementation of all countermeasures is not possible under financially-restricted conditions. Accordingly, the prioritization should be based on the variables with a higher expected increase in the probability of severe injuries, assuming that addressing these variables is potentially related to more effectively alleviating the severity of driver injuries.

The estimation results of this paper identified several risk factors at driver, temporal, vehicle, and crash levels that significantly change the probability of at-fault driver injury severity. Accordingly, driver age and condition, seatbelt use, time of day, airbag status, type of setting, surface condition, lighting condition, and type of crash show significant association with driver injury severity in WWD crashes. Based on these findings, several countermeasures, grouped into categories of engineering, education, and enforcement, can be recommended to help address the driver injury severity in WWD crashes.

The findings of this study demonstrate the role of drunk driving in significantly increasing the probability of more severe crashes and suggests the implementation of appropriate countermeasures for drunk driving. For example, DUI driving prevention campaigns are recommended to be established, and stricter enforcement rules seem to be necessary. Illinois has already published the "DUI Fact Book" to enhance awareness of driving while intoxicated. For repeat violators, the use of ignition interlock devices (IIDs) are suggested (Zhou and Pour-Rouholamin, 2014). Drivers, especially middle-aged drivers, should be educated to understand the risk associated with WWD and drunk driving and the potential effects on families and society. These educational programs and enforcement rules can also cover seatbelt use because not using this restraint system is found to considerably increase the fatality probability by a factor of 85.4%.

WWD crashes that occurring during the night when the roadway is dark are associated with higher injury severities for drivers. As the lighting condition at WWD entry points are shown to be of high importance (Pour-Rouholamin et al., 2014), the method developed and proposed by Zhou et al. (2012) can be used to identify entry points of WWD crashes, and a field review of these locations can be conducted to identify whether appropriate lighting is provided at entry locations. It is suggested to provide uniform lighting at the intersection of exit ramps and crossroads, especially when exit and entrance ramps are closely spaced (e.g., partial cloverleaf interchanges). In addition to adjusting the lighting level at possible entry points, the use of red retroreflective strips can be helpful, when applied to the supports of DO NOT ENTER and WRONG WAY signs, at the intersection of exit ramps and crossroads, and along the exit ramp and freeway mainline. These strips are capable of increasing the nighttime visibility of signs, reducing the frequency of WWD incidents, and helping decrease the severity of these crashes by alerting the at-fault drivers. Our investigation shows that Illinois has recently adopted the use of these strips, but their use is not a current practice in Alabama. Other innovative countermeasures, such as LED-illuminated signs might also be considered. Furthermore, signs should be inspected periodically for their visibility and legibility (Balali and Golparvar-Fard, 2015) as signs are only effective when they clearly convey the intended message in both day and nighttime conditions (Khalilikhah and Heaslip, 2016; Khalilikhah et al., 2015).

WWD crashes in rural areas were also found to have a higher probability of more severe injuries. WWD head-on crashes are clearly the most influencing factor on the severity of the injury, as this kind of crash increases the probability of fatalities by more than two times. Crashes that caused airbag deployment show decreased probability of severities, and WWD crashes on wet surfaces have also shown a lower possibility of minor and severe injuries.

In addition to finding the contributing factors to injury severity of drivers in WWD crashes, a comparison between three commonly used ordered-response models (PO, GOL, and PPO) were made using log-likelihood at convergence, AIC, and BIC. This comparison demonstrates that, given our database, the PPO model surpasses the performance of the other two models. Of course, this result is based solely on the available database with the given sample size, and, therefore, a more general conclusion needs more investigation based on data with varying sizes.

Similar to most studies, this study also has some limitations. One limitation that is specific to the crash record-based research is the inevitable role of human errors in collecting the crash data at the scene, which affects the level of detail and accuracy of the obtained results. Another limitation specific to the WWD studies is the sample size. The authors tried to bolster the sample of crashes by combining the data from two states to overcome this issue. It is also beneficial to add more years of crash data or even data from other states when the opportunity presents itself as it will strengthen the work.

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