Ordinal Discrete-Choice Analyses of Wisconsin Cross-Median Crashes

By

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ABSTRACT:

Cross-median crashes (CMCs), in which a vehicle crosses the highway median, are one of the most severe crashes due to high speeds and risk of collision with an opposing vehicle. This paper describes the ordinal discrete-choice modeling efforts for investigating the nexus between the severity propensity and miscellaneous variables pertinent to roadway safety for single- and multi-vehicle CMCs which occurred between 2001 and 2007 in Wisconsin. Ordinal Logit (ORL) and Probit (ORP) regression models were employed for severity analyses. For multi-vehicle CMCs, both models revealed road surface condition has a significant effect on the severity. Adverse road surfaces enhance the likelihood of being involved in a more severe multi-vehicle CMC if one occurs. Winter snow or ice impacts the CMC severity, and logically Wisconsin's geographical location plays a significant role. Although both models found the speed limit significant, they revealed different severity propensities, implying this factor should be treated cautiously and the necessity of applying different discrete-choice models to severity analyses if more comprehensive understanding is pursued. Final ORP model for single-vehicle CMCs shows alcohol/drug use, lane curvature, and unfriendly roadway visibility exacerbate the severity if a single-vehicle CMC occurs. Interestingly, dry road surface is found to significantly incur more severe consequences, which implies more severe single-vehicle CMCs are closely related to maintaining high speeds. ORL modeling results were found statistically invalid for single-vehicle CMC severity analyses. The median width and average daily traffic were found insignificant factors for both multi-vehicle and single-vehicle CMCs.

Key words:
Cross-median crash, severity analysis, ordered discrete-choice, statistical regression

INTRODUCTION

From 2001 to 2007, a total of 298,198 people lost their lives in traffic crashes on roadways in the United States. In 2007 alone, 41,059 people were killed on roadways in this country (*1*). Roadway departure crashes (RDCs) are frequently severe and account for the majority of highway fatalities. In 2008, there were 17,818 fatal RDCs resulting in 19,794 fatalities, which was 52 percent of fatal crashes in that year in the United States. A RDC is defined as a *non-intersection* crash which occurs after a vehicle crosses an edge line or a centerline, or otherwise leaves the traveled way (*2*). Often times, this crash type involves collisions with one (or more) objects including opposing vehicles, bridge rails, utility poles, embankments, guardrails, parked vehicles, or trees (*3*). Over the same seven-year period, 5,439 people were killed on roadways in Wisconsin, representing approximately 1.82 percent of the national total. Wisconsin experienced 737 fatal crashes in 2007 (*4*), being without exception to the high number of RDCs experienced nationally. A recent report shows that roughly 54 percent of all non-intersection crashes on undivided roadways in Wisconsin were RDC-type crashes (*5*). This proportion is likely larger on the median-divided roadway system. Separation of opposing traffic streams can be important and effective in the attempt to prevent head-on collisions, one of the most potentially serious types of crashes resulting from roadway departures. Median areas which separate opposing traffic flows have long been an important safety design consideration. The American Association of State Highway Transportation Officials (AASHTO) defines a median as "the portion of a highway separating directions of the traveled way". AASHTO's "A Policy on Geometric Design of Highways and Streets" states "medians are highly desirable on arterials carrying four or more lanes" of traffic (*6*). Even with the implementation of AASHTO's policy and median widths of 60 feet or more, the frequency of crashes which involve vehicles crossing over the median area and then entering the opposing traffic are increasing nationally.

The definition of cross-median crash (CMC) varies amongst state transportation agencies (STAs). This makes the application and comparison of CMC rate warrants impracticable. Most STAs exclude in their definition the single-vehicle CMC in which the crossing vehicle only partially enters the opposing lane, or stops in (or passes through) the opposing lane(s) without striking a vehicle. These variations may have a significant impact upon the number and length of highway segments identified for safety analysis. To overcome this problem, Wisconsin Department of Transportation (WisDOT) adopts a definition originally developed by Caltrans: all crashes in which vehicles "traversed the median area, entered or went beyond the opposing lanes of traffic, involved *multiple* vehicles in head-on or sideswipe collisions, and there was property damage, injury, or fatality associated with the accident". However, single-vehicle CMCs, in which a vehicle crossed the median and entered opposing lanes without hitting an opposing vehicle or a roadside barrier, composed 80 percent of the cross-median incidents in this study. Although the severities of single-vehicle CMCs are lower, they are still relatively severe as they often involve rollovers or roadside objects, but not head-on collisions. Single-vehicle CMCs had the potential to become the more severe multi-vehicle CMCs, but simply found a gap in the opposing stream. Additionally, the single-vehicle CMC severity is an important factor in predicting the safety performance of divided highways and in taking median-related safety measures. Therefore, single-vehicle CMCs were included in this study but modeled and analyzed separately.

Although CMCs have been investigated in other states, their attributes in Wisconsin are not well understood. A recent study using Texas data concluded that no roadway, vehicle, or driver factors affected the CMC severity significantly (*7*). This study considered a small number of roadway factors and separated single-vehicle crashes from multi-vehicle ones, grouping them with non-cross median crashes. This distinction reduced the sample size and contributed to insignificant regression results for severity. A similar study in Pennsylvania, based on 138 CMCs which occurred across the entire state Interstate network between 1994 and 1998, indicated that only curves and drug use were significant factors in severity prediction (*8*). A detailed analysis of CMCs' severity in Wisconsin will contribute to more understanding of nationwide CMCs and enhancing countrywide highway safety. This paper describes the discrete-choice modeling efforts for exploring the nexus between the severity propensity and miscellaneous explanatory factors closely pertinent to roadway safety, with an intention to facilitate the decision-making process for identifying significant factors influencing CMCs' severities and taking correspondent median-related safety enhancement schemes.

HISTORICAL RESEARCH

In North America, research has been conducted for more than 50 years on relevant policies and practices for highway geometry design, especially median width and cross section, to address the median-related safety issue. In one of the earliest studies, Hutchinson and Kennedy (*9*) studied Illinois's Interstates and concluded rural highway medians should have a minimum width (30 feet) and a mild and obstacle-free cross-slope. The "clear-zone" concept contributed to the standard median design for high-order highways. Garner and Deen (*10*) examined median-related crashes and the practices regarding median width and cross-slope in Kentucky. They found a wider median facilitated the crossover prevention and a refuge for vehicles seeking to avoid in-lane collisions. The crash rate and severity were lower on highways with wide medians. Traffic volumes were found limitedly influential on the crash occurrence. This study supported the need for a clear and traversable median. Deeply depressed and raised medians were discouraged to prevent roll-overs. Later, Foody and Culp (*11*) studied mounded and depressed median types. The former had slightly higher crash rates than the latter, but there was no significant difference in injury-related crashes, the number of encroachments, and the roll-over frequency.

Knuiman et al. (*12*) examined the relationship between median width and crash rates in Illinois and Utah. With medians widened, head-on, sideswipe, and single-vehicle crashes decreased. A 30-feet width was believed necessary to influence crash rates and further narrowed widths would compromise roadway safety. The largest improvements by widening medians were the reduction in overall crash rate, due to drivers using the median as an anti-collision refuge. This reduction continued until a width (60 to 80 feet) where the safety improvement was maximized. Donnell et al. (*13*) found CMCs rare in Pennsylvania; however, nearly 15 percent involve fatalities and 72 percent involve injuries. Crash rates at earth-divided highways decreased as medians become wider. Crossover crashes appeared more likely to occur downstream of interchange entrance ramps and involve adverse road conditions than other crashes. Richl and Sayed (*14*) determined the safety of using narrow medians due to mountainous terrain in British Columbia. Their analysis revealed that narrow medians combined with tight horizontal curves made the sight distance insufficient. Based on 140 single-vehicle "median-side" and "right-side" encroachments, Sanderson (*15*) investigated vehicle encroachments on Canadian highways and found average roadway departure angle for both encroachments was 14 degrees and "median-side" types were twice as many as "right-side" ones. No significant correlation was found between traffic volumes and the encroachment rate.

Noyce and McKendry (*16*) developed a cost analysis using information in the Wisconsin Crash Outcome Data Evaluation System database and the National Highway Traffic Safety Administration model. They found that CMCs, in medical cost, exceed median-barrier crashes by approximately $19 million per year. Although the cost of installing median barriers could not be quantified, they concluded the potential medical and societal cost savings of installing median barriers at locations with high CMC frequency is significant. The safety and cost-effectiveness analyses by Donnell and Mason (*17*) found installing median barriers along Pennsylvania highways with median width up to 70 ft can produce safety and economic benefits which vary with traffic volumes. In 1988, the AASHTO established guidelines to evaluate the need for median barrier under specific combinations of median width and ADT (*18*). Current AASHTO median barrier warrant criteria are intended for use on *high-speed, fully controlled access* facilities with traversable medians. A nationwide survey of median design and safety practices revealed that 43 of 50 STAs use the AASHTO criteria as state standard (*17*). Importantly, the AASHTO guidelines suggest considering the roadway accident history in median-related safety design and practice, which motivated this CMC severity analysis.

OBJECTIVE AND ACCIDENT DATA

Based on CMC data in Wisconsin, the study objective was to explore the association of the severity propensity with median width, ADT, and other factors. As the first step, traffic crash reports were assembled and analyzed to assess the magnitude of CMC occurrences in Wisconsin. Roadway segments constructed with divided medians were selected as examination sites from Wisconsin's roadway database. Roadway segments installed with median barriers were excluded given the study scope was limited to segments classified as "non-barrier" type. Crash reports between 2001 and 2007 were collected; this seven-year period was chosen to get comprehensive results of recent years of data available. Wisconsin Motor Vehicle Accident Report (WMVAR) system contains extensive data (e.g., time, drivers/vehicles information, weather/road conditions, alcohol/drugs presence, collision manner, etc.) for each crash and supporting narratives and drawings from law enforcement personnel. However, WMVAR procedure has no entry which explicitly identifies a CMC, so all RDCs on median-divided roadways were identified as *potential* CMCs. Totally 37,277 reports were gathered from the WisDOT crash data archives, and each one was reviewed to determine whether the crash involved a vehicle that crossed the median and met the WisDOT-defined criteria. Identification of CMCs was made by studying narratives and pictorial representations on reports. Median widths and ADTs were supplemented to the data: width values were obtained from the "Wisconsin State Trunk Highway Log" and ADTs from the "Wisconsin Highway Traffic Volume Data Book" annually published by the WisDOT (*21*). Each selected crash was geo-located either through its WisDOT Reference Point number or crossroads reference. Several roadways and crash locations were verified through field investigations.

CMCs were identified on all highway classes (Interstates, US Highways, and State Highways)(Table 1). After completing the screening procedure, 1,899 *potential* CMCs were initially identified. Each selected crash was scrutinized to ascertain the prior action which could be viewed as the potential cause. A total of 243 crashes were disqualified from the pool during this process. Crossover crashes involving objects (e.g., tire, animal, crash debris, or person) were removed as it was determined that standard median safety improvements may not have prevented these objects from traveling airborne across the median. Tire crossovers compromised 108 of the 139 total object crossover crashes; the remaining 31 crashes were made up of various objects. Since only crashes that occurred at a location without a barrier were concerned, this criterion disqualified 88 crashes that involved a vehicle crossing the median despite an existing barrier; most of these vehicles vaulted or flipped over the barrier. Additional 16 crashes were discarded due to drivers' purposeful intention to cross medians, while 97 trailer-crossover crashes identified were excluded. Using the WisDOT definition which only includes crashes in which a vehicle crosses the median and strikes or is struck by an opposite vehicle, 1,250 single-vehicle crossover crashes were treated separately. To reduce the noises in data, some more CMCs were excluded due to low speed limits and records with missing information. To this end, 263 multi-vehicle CMCs and 1,019 single-vehicle ones were finally identified for analysis (Table 1).

A majority of multi-vehicle CMCs involved a vehicle going straight in lanes before the collision. The next most common actions include changing lanes or slowing/stopping maneuvers. A WMVAR report review was performed to determine the most likely initial event leading to each multi-vehicle CMC. Even though various factors may have been contributory, what was sought was the primary or initial event that causes all ensuing consequences. A majority of multi-vehicle CMCs resulted from "a vehicle control loss on dry pavement" or "a vehicle control loss due to weather". The former pertained to CMCs in which the initial loss of control event happened on dry pavements. This loss of control came from avoidance maneuvers, distractions, blackouts, or inattentiveness. The latter pertained to CMCs where weather issues were cited in the report as a contributor. Weather-related crashes could be broken down into wet roads resultant from rain, snow, and ice. Since all WisDOT-defined CMCs involved a collision, the crossover extent was a function of the final resting position of the crossing vehicles. "Partial" extent means finally some portion of the vehicle encroached into the opposing shoulder. "Into" extent means vehicles finally rested within opposing lanes. "Beyond" extent means vehicles finally rested beyond the outside shoulder of the opposing roadway. It was found that "Into" accounted for most of total and "Partial" is the fewest.

Table 1 Specifics of CMC Data for Severity Analysis

Section I: WI highways reviewed for crossover crashes	
Interstates	I-39, I-43, I-90, I-94
U.S. Highways (USH)	10, 12, 14, 18, 41, 45, 51, 53, 141, 151
WI State Highways (STH)	23, 29, 30, 35, 54, 57, 172

Section II: Summary of crossover crash total calculations	
Initial selected crossover crashes	1,899
Object crossover crashes	-139
[tire crossover crashes]	[-108]
[other object crossover crashes]	[-31]
Median barrier crossover crashes (vehicle rollover or penetrated existing barrier)	-88
Intentional crossover crashes (median U-turns or police evasion)	-16
Initially selected single-vehicle CMCs	-1,250
Trailer crossover crashes	-97
Multi-vehicle crashes at locations with low speed limit (<45mph)	-8
Multi-vehicle crashes with missing information	-38
Finally selected multi-vehicle (and single-vehicle) CMCs for severity analysis	263 (1,019)

Section III: Multi-vehicle CMCs and single-vehicle CMCs by year

Year	Frequency distribution of crashes			
	Multi-vehicle CMCs		Single-vehicle CMCs	
	Frequency	Percent (%)	Frequency	Percent (%)
2001	28	10.65	146	14.33
2002	35	13.31	160	15.70
2003	40	15.21	129	12.66
2004	41	15.59	164	16.09
2005	55	20.91	165	16.19
2006	40	15.21	130	12.76
2007	24	9.13	125	12.27
Total	263	100.0	1,019	100.0

Section IV: Subject CMCs by severity

CMC Severity	Frequency distribution of crashes			
	Multi-vehicle CMCs		Single-vehicle CMCs	
	Frequency	Percent (%)	Frequency	Percent (%)
PDO	44	16.73	442	43.38
Injury	161	61.22	542	53.19
Fatal	58	22.05	35	3.43
Total	263	100.0	1,019	100.0

Section V: Subject CMCs and related median width

Median Width Level (ft)	Frequency distribution of crashes			
	Multi-vehicle CMCs		Single-vehicle CMCs	
	Frequency	Percent (%)	Frequency	Percent (%)
< 30	13	4.94	38	3.73
30 – 39	24	9.13	84	8.24
40 – 49	10	3.80	44	4.32
50 – 59	54	20.53	217	21.30
60 – 69	137	52.09	536	52.60
70 – 79	3	1.14	24	2.36
80 +	22	8.37	76	7.46
Total	263	100.0	1,019	100.0

STUDY METHODOLOGY

Road safety analysis often applies a statistical regression model to historical data of historical accidents and roadway, driver, weather and miscellaneous factors. The hope is that the fitted model can estimate the safety effect of factors of interest (*22*). Traffic crash study addresses the probability of a crash occurrence or the severity resultant from a crash involvement. Through statistically analyzing previous crash data, the severity study explores the influence of variables of interest on the injury levels if a crash occurs.

Severity Modeling

Crash severity is ordinal in nature and the nexus between the response and independent variables involved is nonlinear, so linear regression is inappropriate for severity modeling. Ordinal discrete-choice models, which use factors selected to predict the probability that the severity is of an ordinal scale given a crash involvement, are appropriate (*23*). Logistic model is in common use: Kim et al. used it to explain the likelihood of an impaired motorcycle crash as a function of rider characteristics and some factors (*24*); Krull et al. employed it to study how some factors impact the probability of fatality and injuries (*25*). In contrast, multinomial Logit (MNL) and Probit (MNP) models neglect the ordinality in severity and require more parameter estimates since each discrete choice is connected to a separate set of parameters. The MNL model has an undesirable property known as the “independence of irrelevant alternatives (IIA)”, which states that the ratio of the probabilities of two alternatives is independent from any other alternatives present (*26*). Contrary to the MNL model, the MNP model is more flexible because it relaxes the IIA assumption, thus allowing for correlations among alternative-based error terms. However, the integrations in MNP regression are computationally burdensome, especially when there are many alternatives (*26*). Yet the most frequently chosen model is ordinal Logit (ORL) or Probit (ORP) model based on continuous and/or discrete variables (*27*). The former converges more quickly, whereas the latter is more commonly employed perhaps due to an appealing theoretical rationale: if the disturbance term represents the mixed impact of various factors not mathematically expressed in model, Central Limit Theorem can be invited to justify the normality assumption. Previously, Duncan et al. used the ORP model to identify factors influencing rear-end crash severities (*28*). Renski et al. employed it for speed limits (*29*). Kockelman and Kweon looked at injury risk sustained under all crash types (*30*). Abdel-Aty calibrated ORP models for varied infrastructure elements (*31*). Deng et al. employed it to analyze the association between head-on crashes and causal factors (*32*). The ORL model was also widely used for severity analyses. As two examples, Lu et al. (*33*) employed it for three-year median-crossover crashes in Wisconsin, while Donnell and Mason (*17*) conducted similar research in Pennsylvania.

Model Structures

An ordinal discrete-choice model can be derived from a measurement model in which a latent, unobservable, continuous variable y_i^* is mapped to an observed ordinal $\dot{y}$. Ranging from -∞ to +∞, y_i^* provides the injury propensity and $\dot{y}$ is observed to unveil incomplete information about underlying y_i^* based on the measurement equation:

$$y_i = j \quad \text{if} \quad \gamma_{j-1} \le y_i^* \le \gamma_j \qquad \text{(Equation-1)}$$

Where $\boldsymbol{\Gamma}=\left\{\gamma_0,\gamma_1,\ldots,\gamma_j,\ldots,\gamma_J\right\}$ denotes cut points: $\gamma_0 < \gamma_1 < \cdots \gamma_j \ldots < \gamma_J$, $\gamma_0 = -\infty$, $\gamma_J = +\infty$, and $J = 3$. The observable $\dot{y}$ is related to y_i^* through y_i in Equation-1, and the ordinal model has generic form:

$$y_i^* = \boldsymbol{X_i^T}\boldsymbol{\beta} + \varepsilon_i \qquad \text{(Equation-2)}$$

Where: $\boldsymbol{X_i} = \{1, x_{i1}, \ldots, x_{ik}, \ldots, x_{iK}\}^T$ – Vector of the ith observation ($i = 1, \ldots, N$; $k = 1, \ldots, K$);
$\boldsymbol{\beta} = \{\beta_0, \beta_1, \ldots, \beta_k, \ldots, \beta_K\}^T$ – Vector of variable coefficients;
x_{ik} – The kth variable for the ith observation;
N – Total number of independent observations;
K – Total number of variables;
ε_i – Error term.

It is assumed ε_i has the probability density and cumulative distribution functions $(f(\varepsilon_i), F(\varepsilon_i))$ with $E(\varepsilon_i) = 0$. Based on Equation-2, the probability that the ith observation has severity j is:

$$Pr(y_i = j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma}) = Pr(\gamma_{j-1} - \boldsymbol{X_i^T\beta} < \varepsilon_i \le \gamma_j - \boldsymbol{X_i^T\beta}) = F(\gamma_j - \boldsymbol{X_i^T\beta}) - F(\gamma_{j-1} - \boldsymbol{X_i^T\beta}) \quad \text{(Equation-3)}$$

Logit Model – When ε_i has a Logistic distribution $f(\varepsilon_i) = e^x(1+e^x)^{-2}$, the odds that the severity is j or higher versus lower than j are:

$$\Omega_j = \frac{Pr(y_i \ge j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma})}{1-Pr(y_i \ge j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma})} = \frac{Pr(y_i \ge j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma})}{Pr(y_i < j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma})} = e^{(\gamma_{j-1} - \boldsymbol{X_i^T\beta})} \quad \text{(Equation-4)}$$

Equation-4 shows the effect of a unit change in $x_{.k}$ on severity propensity can be quantified by odds ratio $e^{-\beta_k}$.

Probit Model – When ε_i has a standard Normal distribution $F(\varepsilon_i) = \Phi(\varepsilon_i)$, the marginal effect of $x_{.k}$ on severity j can be quantified by taking the partial derivative of Equation-3:

$$\partial Pr(y_i = j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma})/\partial x_{.k} = \beta_k[\phi(\gamma_{j-1} - \boldsymbol{X_i^T\beta}) - \phi(\gamma_j - \boldsymbol{X_i^T\beta})] \quad \text{(Equation-5)}$$

Note that the marginal effect on the interior category (injury) is vague because a shift in the distribution can cause the probability of the injury level to ascend or descend, depending on the position of the average response. Therefore, the extreme care must be taken in interpreting ORP modeling results.

MLE Regression – Maximum likelihood estimation (MLE) generates the regression of y_i^*'s on N observations. Equation-3 gives the log-likelihood function for either model:

$$ln[L(\boldsymbol{\beta},\boldsymbol{\Gamma}|\dot{y})] = \sum_{i=1}^{N}\sum_{j=1}^{J}\delta(y_i = j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma}) \cdot ln[F(\gamma_j - \boldsymbol{X_i^T\beta}) - F(\gamma_{j-1} - \boldsymbol{X_i^T\beta})] \quad \text{(Equation-6)}$$

Here the indicator $\delta(y_i = j|\boldsymbol{X_i},\boldsymbol{\beta},\boldsymbol{\Gamma})$=0 or 1. To maximize Equation-6 generates estimates: $\hat{\boldsymbol{\beta}} = \{\widehat{\beta_0}, \widehat{\beta_1}, \dots, \widehat{\beta_k}, \dots, \widehat{\beta_K}\}^T$, $\hat{\boldsymbol{\Gamma}} = \{\widehat{\gamma_1}, \dots, \widehat{\gamma_j}, \dots, \widehat{\gamma_{J-1}}\}$. Odds ratio and marginal effects can be estimated by $e^{-\widehat{\beta_k}}$ and $\partial Pr\{y_i = j|\bar{\boldsymbol{X}},\hat{\boldsymbol{\beta}},\hat{\boldsymbol{\Gamma}}\}/\partial x_{.k} = \widehat{\beta_k}\left[f\left(\widehat{\gamma_{j-1}} - \bar{\boldsymbol{X}}\hat{\boldsymbol{\beta}}\right) - f\left(\widehat{\gamma_j} - \bar{\boldsymbol{X}}\hat{\boldsymbol{\beta}}\right)\right]$, while $\bar{X}$ denotes averages from all observations. Marginal effects follow the constraint that the probabilities add to 1. Note that, for a dummy variable in ORP models, the derivative while treating it as a continuous variable offers an "often surprisingly accurate" approximation (*26*).

MODEL ESTIMATION

The crash-related attributes recorded in reports are critical in severity analyses. Those factors are temporal in nature and depict prevailing situations in which a crash occurred. As they vary, it is expected the driver behaviors and the vehicle performance change too; thus, when a crash happens, the severity propensity may differ. For instance, it is more difficult to control a vehicle on a wet or icy road surface than on a dry surface, and impact speeds may be larger. Some factors regarding geometry, roadway, weather, environment, driver, vehicle, and traffic flow were selected for the severity modeling, based on data availability, accuracy, and relevant information in previous studies. Some factors (e.g., gender) were excluded due to inaccurate or missing records in crash reports; while others (e.g., safety belt use) were disregarded for the sake of reasonable interpretation because the observation unit was based on all occupants in a vehicle and the severity level refers to the worst injury that all occupants experienced in a CMC. These factors, and their dummy variables, selected for single-vehicle and multi-vehicle analyses are depicted separately in Section I & II of Table 2. The circumstances under which a more severe injury was expected were defined to be 1 and otherwise 0. For example, an adverse weather was expected to contribute to a more severe CMC, so MWEATHER were defined to 1 when the weather was adverse and 0 otherwise.

Table 2 Wisconsin CMC Severity Modeling: Variables, Definition, and Statistics

Section I: Multiple-vehicle WisDOT-defined CMCs for analysis (N = 263 Observations)					
Variable Name in Analysis	Explanation of Variables	Type	WMVAR Categories, Independent Variables Defined, Data Ranges	Statistics Counts(n) Minimum Mean	Percentage Maximum Std. Dev.
MSEVRITY	Severity levels of Multiple-Vehicle (M-V) CMCs	Categorical (Response)	1: PDO 2: Injury 3: Fatality	n = 44 n = 161 n = 58	16.7% 61.2% 22.1%
MVEHS	Non-trucks (car, SUV, van) and/or trucks (large truck, semi tractor, and pickup truck) involved in a M-V CMC	Categorical (predictor)	1: Truck(s) and car(s) involved 0: Same vehicle types involved	n = 101 n = 162	38.4% 61.6%
MALCODRUG	Whether a driver was listed as drinking alcohol (or using drugs) before the recorded M-V CMC	Categorical (predictor)	1: Alcohol/drugs used 0: No alcohol/drugs used	n = 16 n = 247	6.1% 93.9%
MWETRD	Pavement surface of the roadway at the point of M-V CMC site	Categorical (predictor)	1: Adverse (wet/snowy/icy) surface 0: Dry road surface	n = 139 n = 124	52.9% 47.1%
MWEATHER	Weather condition under which the recorded M-V CMC occurred	Categorical (predictor)	1: Fog/Snow/Sleet/Rain 0: No adverse conditions	n = 115 n = 148	43.7% 56.3%
MDARK	The lighting condition at time of M-V CMC	Categorical (predictor)	1: Dark, dawn, or dusk 0: It is daylight	n = 91 n = 172	34.6% 65.4%
MXOVREXNT	Crossover extent based on stoppage position related to lanes in opposing direction	Categorical (predictor)	1: "Beyond" or "Into" extent 0: "Partial" extent	n = 251 n = 12	95.4% 4.6%
MRDCURV	The horizontal alignment at the point of impact	Categorical (predictor)	1: Curved 0: Straight	n = 143 n = 120	54.4 % 45.6%
MRDHILL	The vertical alignment at the point of impact	Categorical (predictor)	1: Hilly 0: Level/Flat	n = 50 n = 213	19.0% 81.0%
MPOSTSPD	The speed limit posted on the roadside at the point of impact	Interval (predictor)	Range: 45 – 65 mph	Min =45	Max=65
MMDNWDTH	Highway median width where the recorded M-V CMC occurred	Interval (predictor)	Range: 10-730 feet	Min = 10	Max = 730
MTOTLADT	Total ADTs on both directions at the point of M-V CMC site	Continuous (predictor)	Range: 4,700-92,600 vehicles per day	Mean = 38,008.82	S.D.= 18554.81

Table 2 Wisconsin CMC Severity Modeling: Variables, Definition, and Statistics (*Continued*)

Section II: Single-vehicle CMCs for analysis (N = 1,019 Observations)

Variable Name in Analysis	Explanation of Variables	Type	WMVAR Categories, Indicators Defined & Data Ranges	Statistics Counts(n) Minimum Mean	Percentage Maximum Std. Dev.
SSEVRITY	Severity levels of Single-Vehicle (S-V) CMCs	Categorical (Response)	1: PDO 2: Injury 3: Fatality	n = 442 n = 542 n = 35	% = 43.4 % = 53.2 % = 3.4
SHVYTYPE	The type of the vehicle involved in a S-V CMC	Categorical (predictor)	1: Heavy vehicle types (Pickup/large trucks) 0: Non-Heavy vehicle types (Car/Van/SUV)	n = 227 n = 792	% = 22.3 % = 77.7
SALCODRUG	Whether a driver was listed as drinking alcohol (or using drugs) before the recorded S-V CMC	Categorical (predictor)	1: Alcohol/drugs used 0: No alcohol/drugs used	n = 118 n = 901	% = 11.6 % = 88.4
SWETRD	Pavement surface of the roadway at the point of S-V CMC site	Categorical (predictor)	1: Adverse (wet/snowy/icy) surface 0: Dry road surface	n = 427 n = 592	% = 41.9 % = 58.1
SWEATHER	Weather condition under which the recorded S-V CMC occurred	Categorical (predictor)	1: Fog/Snow/Sleet/Rain 0: No adverse conditions	n = 321 n = 698	% = 31.5 % = 68.5
SDARK	The lighting condition at time of S-V CMC	Categorical (predictor)	1: Dark, dawn, or dusk 0: It is daylight	n = 446 n = 573	% = 43.8 % = 56.2
SXOVREXNT	Crossover extent based on stoppage position related to lanes in opposing direction	Categorical (predictor)	1: "Beyond" or "Into" extent 0: "Partial" extent	n = 767 n = 252	% = 75.3 % = 24.7
SRDCURV	The horizontal alignment at the point of impact	Categorical (predictor)	1: Curved 0: Straight	n = 120 n = 899	% = 11.8 % = 88.2
SRDHILL	The vertical alignment at the point of impact	Categorical (predictor)	1: Hilly 0: Level/Flat	n = 152 n = 867	% = 14.9 % = 85.1
SPOSTSPD	The speed limit posted on the roadside at the point of impact	Interval (predictor)	Range: 45 – 65 mph	Min = 45	Max = 65
SAGE	The age of the driver at the time of the recorded S-V CMC, generated from birthdates	Interval (predictor)	Range: 15 - 86 years	Min = 15	Max = 86
SMDNWDTH	Highway median width where the recorded S-V CMC occurred	Interval (predictor)	Range: 10-350 feet	Min = 10	Max = 350
STOTLADT	Total ADTs on both directions at the point of S-V CMC site	Continuous (predictor)	Range: 4,500-92,600 vehicles per day	Mean = 29,822.4	S.D. = 18,121.5

WMVAR: Wisconsin Motor Vehicle Accident Report.

Model selection methods (e.g., forward, backward, etc.) are available in common tools. However, they may give incorrect estimates of the standard errors and p-values, delete critical variables, and most important, allow researchers not to think independently (*34*). It should be better to compare different models estimated from the same data based on their results, reasonableness, and goodness-of-fit, using the measures such as Akaike Information Criterion (AIC), Bayesian information criterion (BIC), etc. AIC is defined as $-2\ln\{\mathrm{L}(\hat{\boldsymbol{\beta}})\} + 2\mathrm{K}$, where $\mathrm{L}(\hat{\theta})$ is the likelihood value of the model and K is the number of free parameters (*35*). However, AIC may underperform if there are many parameters with respect to sample size (N). Sugiura derived a small-sample expression which leads to a refined criterion generally recommended for the small ratio (N/K) (<40.0): $AIC_c = AIC + 2\mathrm{K}(\mathrm{K}+1)/(\mathrm{N}-\mathrm{K}-1)$(*36*). BIC is defined as $\mathrm{AIC} + \mathrm{K}\cdot[\ln(\mathrm{N}) - 2]$, which penalizes free parameters more strongly than AIC. The advantage lies in the capability to account for the model parsimony which means, other things being equal and given any two models with equal log-likelihood values, the model with fewer parameters is evaluated as better. A model with smaller AIC, AICc, and BIC is considered "closer" to the unknown true model (*37*). Both ORP and ORL models were estimated for CMC injury status to obtain more understandings of underlying severity propensity via different ordinal discrete-choice modeling methodologies.

Multiple-Vehicle CMCs

Table 3 shows separate results for ORP and ORL analyses of multi-vehicle CMCs. The coefficients estimated are listed, and p-values (in brackets) less than 0.05 are usually considered statistically significant. Model A1 encompassed all selected variables. MWEATHER and MWETRD were strongly correlated since bad weathers lead to adverse pavement surfaces. Model A2 discarded MWEATHER and two variables (MMDNWDTH and MTOTLADT) with very high p-values. Model A2 results show MALCODRUG and MPOSTSPD are statistically significant, while MWETRD, MVEHS, and MXOVREXNT have relatively small p-values (<0.20). MRDCURV, MRDHILL, and MDARK were excluded in further modeling due to much higher p-values. Note AIC, AICc, and BIC decrease from Model A1 to A2, which means the progress in parsimony. In Model A3, MVEHS are found insignificant, while MPOSTSPD and MALCODRUG are significant at a 90% confidence level. MWETRD and MXOVREXNT have p-values little bigger than 0.10. Although MXOVEREXNT turned out to be strongly correlated with the severity, it refers to the final resting position of the vehicle after the collision and as such may have limited effect on the severity. Therefore, only three factors were retained in Model A4 in which MPOSTSPD is found significant while other two factors have p-values around 10%. Smaller AICc and BIC in A4 represent more parsimony is obtained. The marginal effects computed in Model A4 reveal that the change to alcohol/drug use decreases the probability of fatality severity by 0.079, which is entirely contradictive to the common sense. Therefore, this factor was excluded in Model A5 in which MWETRD and MPOSTSPD are significant at 90% confidence level considering the relatively small sample. BIC is reduced, and Model A5 is viewed as the final model for multi-vehicle CMCs. The score test for the equal slopes assumption has an insignificant p-value of 0.216 (degrees of freedom (d.f.)=2), which indicates that the ORP model adequately fits the data because the hypothesis that the regression lines for cumulative Probits are parallel is retained. The likelihood ratio test p-value of 0.018 (d.f.=2) indicates that the global null hypothesis is rejected, and the conclusion is that the variables given in the model affect the severity, or the model with independent variables is statistically better than the model with only the intercept.

In the final model, it is found that wet road surface and higher posted speed limit will strengthen the propensity of worse severity given a multi-vehicle CMC occurs. Based on Equation-5, the estimated marginal effect unveils the information on how the propensity changes with a unit change in the value of an independent variable beyond its mean provided all other variables are maintained at means. Hence, the marginal effect allows us to determine the impact of each variable on the probability of each severity level, and some cautions should be given to the "injury" severity interpretation. Marginal effects estimated for road conditions show that a unit increase beyond the mean value increases the probability of an injury and fatality-type CMC by 0.009 and 0.028 respectively given the means of other explanatory variables are maintained, and this is captured by a decrease in the probability of PDO-type (-0.037). Therefore, the severity becomes worse if there is a change from dry to adverse road surface, and it is inferred that the weather aggravates the multi-vehicle CMC severity given its strong casual association with adverse road condition which is unfriendly for driving. It is also found that the severity becomes aggravated if there is a unit increase in the speed limit posted along roadways. A unit increase beyond the mean speed limit increases the probability of an injury and fatality-type CMC by 0.003 and 0.009 respectively, and this is offset by a decrease in the probability of PDO-type CMC (-0.012). It is inferable that drivers on roadways with higher speed limits will definitely maintain a faster speed, and this increases the likelihood of being involved in a more severe consequence if a CMC happens.

Table 3 Ordinal Discrete-choice Analyses of Multi-vehicle CMCs in Wisconsin

Section I: Severity study by Ordinal Probit (ORP) regression model (N=263)

Independent Variables	Model Coefficient Estimates (p-values) A1	A2	A3	A4	A5	Marginal Effect Estimates PDO	Injury	Fatality
Driver								
MALCODRUG	-0.672(0.033)	-0.625(0.045)	0.259(0.090)	0.276(0.070)				
Roadway								
MWETRD	-0.138(0.556)	0.213(0.148)	-0.117(0.105)	-0.109(0.126)	-0.122(0.086)	-0.037	0.009	0.028
MRDCURV	-0.174(0.229)	-0.179(0.212)						
MRDHILL	-0.124(0.497)	-0.095(0.601)						
MPOSTSPD	-0.040(0.034)	-0.038(0.039)	-0.034(0.058)	-0.036(0.048)	-0.038(0.034)	-0.012	0.003	0.009
MMDNWDTH	-0.00007(0.965)							
MTOTLADT	1.02E-7(0.980)							
Crash								
MVEHS	-0.218(0.146)	-0.202(0.173)	0.097(0.188)					
MXOVREXNT	-0.573(0.099)	-0.542(0.117)	0.277(0.107)					
Environment								
MWEATHER	0.456(0.053)							
MDARK	0.166(0.286)	0.184(0.233)						
Model-specific attributes								
Intercept 1 ($-\widehat{\beta_0}$)	2.120(0.084)	1.973(0.105)	1.185(0.316)	1.036(0.375)	1.436(0.210)			
Intercept 2	3.954(0.001)	3.789(0.002)	2.987(0.012)	2.820(0.017)	3.207(0.006)			
Thresholds								
$\widehat{\gamma_1}$ ($\because \gamma_1 \equiv 0$)	0.000	0.000	0.000	0.000	0.000			
$\widehat{\gamma_2}$	1.834	1.816	1.802	1.784	1.771			
"-2 LL"	468.119	471.924	475.201	479.337	482.675			
AIC	494.119	491.924	489.201	489.337	490.675			
AICc	495.581	492.797	489.640	489.570	490.830			
BIC	540.557	527.646	514.206	507.198	504.964			
Score Test for Equal Slopes	χ^2=6.868 (d.f.=11) p=0.810	χ^2=4.310 (d.f.=8) p=0.828	χ^2= 3.247 (d.f.=5) p= 0.662	χ^2=2.945 (d.f.=3) p= 0.400	χ^2=3.064 (d.f.=2) p=0.216			
Likelihood Ratio Test	χ^2=22.601 (d.f.=11) p=0.020	χ^2=18.796 (d.f.=8) p=0.016	χ^2= 15.520 (d.f.=5) p=0.008	χ^2=11.384 (d.f.=3) p= 0.010	χ^2=8.046 (d.f.=2) p=0.018			

Table 3 Ordinal Discrete-choice Analyses of Multi-vehicle CMCs in Wisconsin (*Continued*)

Section II: Severity study by Ordinal Logit (ORL) regression model (N=263)

Independent Variables	Model Coefficient Estimates (p-values) a1	a2	a3	a4	a5	Odds Ratio	95% Wald Confidence Limits
Driver							
MALCODRUG 0	0.573(0.032)	0.539(0.041)	0.438(0.088)	0.473(0.065)			
Roadway							
MWETRD 0	0.134(0.513)	-0.196(0.132)	-0.215(0.092)	-0.197(0.117)	-0.219(0.080)	0.804	(0.396, 1.054)
MRDCURV 0	0.149(0.241)	0.161(0.202)					
MRDHILL 0	0.104(0.517)	0.088(0.582)					
MPOSTSPD	-0.069(0.036)	-0.063(0.050)	-0.058(0.069)	-0.059(0.061)	-0.063(0.045)	0.939	(0.883, 0.999)
MMDNWDTH	0.0001(0.97)						
MTOTLADT	1.72E-7(0.98)						
Crash							
MVEHS 0	0.193(0.143)	0.181(0.164)	0.172(0.183)				
MXOVREXNT 0	0.497(0.097)	0.483(0.106)	0.489(0.099)				
Environment							
MWEATHER 0	-0.415(0.045)						
MDARK 0	-0.146(0.285)	-0.169(0.214)					
Model-specific attributes							
Intercept 1 ($-\widehat{\beta_0}$)	2.566(0.219)	2.207(0.288)	1.975(0.336)	1.652(0.414)	2.333(0.239)		
Intercept 2	5.644(0.008)	5.249(0.013)	4.985(0.017)	4.621(0.024)	5.276(0.009)		
Thresholds							
$\widehat{\gamma_1}$ ($\because \gamma_1 \equiv 0$)	0.000	0.000	0.000	0.000	0.000		
$\widehat{\gamma_2}$	3.079	3.043	3.010	2.969	2.943		
"-2 LL"	468.013	471.680	475.135	479.424	482.802		
AIC	494.013	491.680	489.135	489.424	490.802		
AICc	495.475	492.553	489.574	489.657	490.957		
BIC	540.451	527.402	514.140	507.285	505.091		
χ^2 Score Test for Proportional Odds	χ^2=6.736 (d.f.=11) p=0.820	χ^2=4.291 (d.f.=8) p=0.830	χ^2=3.149 (d.f.=5) p=0.677	χ^2=2.826 (d.f.=3) p=0.419	χ^2=2.965 (d.f.=2) p=0.227		
Likelihood Ratio Test	χ^2=22.708 (d.f.=11) p=0.019	χ^2=19.040 (d.f.=8) p=0.015	χ^2=15.585 (d.f.=5) p=0.008	χ^2=11.297 (d.f.=3) p=0.010	χ^2=7.919 (d.f.=2) p=0.019		

Along the same thought line, the final ORL model (a5) indicates the MWETRD and MPOSTSPD are also significant at 90% confidence level. The score test for the proportional odds assumption has a *p*-value of 0.227 (d.f.=2), which indicates that the proportional odds model adequately fits the data because the hypothesis that the regression lines for cumulative Logits are parallel is retained. The likelihood ratio test *p*-value of 0.019 (d.f.=2) indicates that the global null hypothesis is rejected, then the predictor variables given in the model are believed to affect the severity. The odds ratio is used to quantify the effect of significant independent variables on the response variable, which can explain the relative effects of a unit change in the variable on the severity propensity. The relative effect of a dry road surface versus an adverse surface is exp(-0.219)=0.804. This indicates that the odds of "fatality" severity versus "injury or PDO" severity (or "fatality or injury" severity versus "PDO" severity) decrease by 19.6% when the road surface changes from adverse to dry condition. Alternatively, this implies adverse road condition incurs more severe injury when a CMC occurs, which is statistically consistent with the findings from final ORP model above. However, if there is a unit increase in the speed limit posted along roadways, the odds of "fatality" severity versus "injury or PDO" severity decrease by 6.10%. This implies the probability of higher severity levels (i.e., injury or fatality) is diminished, although not substantially, when the speed limit is increased by 1 mile per hour. Alternatively, it can be interpreted that higher severities occur on roadways with lower speed limits. Although appearing to be counterintuitive, this variable could be likely capturing the safety implications of the lower design criteria of state and US Highways relative to the higher posted speed Interstate routes. On the basis of the results of the ORL analysis, the regression equations can be written:

$$\log[(\pi 3 + \pi 2)/\pi 1] = 2.333 - 0.219X_1 - 0.063X_2 \quad \text{(Equation-7)}$$
$$\log[(\pi 3)/(\pi 1 + \pi 2)] = 5.276 - 0.219X_1 - 0.063X_2 \quad \text{(Equation-8)}$$

Where

$\pi 1$ = Probability of "PDO" severity;
$\pi 2$ = Probability of "Injury" severity;
$\pi 3$ = Probability of "Fatality" severity;
X_1 = Road surface condition indicator (1 if dry road condition, 0 otherwise (adverse: wet/snowy/icy));
X_2 = Posted speed limit along roadway (Range: 45 – 65 mph);

The predicted probabilities can then be computed as follows:

$$\pi 1 = \frac{1}{1+e^{(Equation-7)}},\ 2 = \frac{e^{(Equation-7)}}{1+e^{(Equation-7)}} - \frac{e^{(Equation-8)}}{1+e^{(Equation-8)}},\ \pi 3 = \frac{e^{(Equation-8)}}{1+e^{(Equation-8)}} \quad \text{(Equation-9)}$$

Single-Vehicle CMCs

Two sections in Table 4 show separate sets of discrete-choice modeling results for single-vehicle CMCs. In section I, Model B1 represents the full model including all explanatory variables selected for single-vehicle CMCs. Following the same analytical procedure as above, Model B4 was the final model and it reveals that SALCODRUG, SWETRD, SRDCURV, and SDARK are statistically significant in influencing the severity levels at a 94% confidence level. The score test for the equal slopes assumption has an insignificant p-value of 0.099 (d.f.=4) larger than 0.05, which indicates that the ORP model adequately fits the data. The likelihood ratio test p-value of <.0001 (d.f.=4) indicates that the variables in Model B4 have significant effects.

The estimated marginal effects show the probability of a fatality-type or injury-type CMC will be increased by 0.021 and 0.103 while the probability of a PDO-type CMC will be decreased by 0.123, if alcohol/drug is used when a single-vehicle CMC occurs. Curved lanes and unfriendly (i.e., dark/dusk/dawn) roadway visibility will also increase the probability of a fatality-type CMC by 0.019 and 0.010 or the probability of an injury-type CMC by 0.093 and 0.048, while the probability of a PDO-type CMC decreases by 0.112 and 0.058. Interestingly, dry road conditions intensify the tendency to be involved in a more severe single-vehicle CMC, which is contrary to a finding in the multi-vehicle case. This could be explained by the fact that drivers on dry road conditions keep higher speeds in comparison with other adverse (i.e., wet/snowy/icy) conditions.

In section II for ORL modeling results, the score tests for the proportional odds assumption in all models (from b1 to b4) has *p*-values (i.e., 0.046, 0.030, 0.029, and 0.018) smaller than 0.05. Therefore, the hypothesis that the regression lines for cumulative Logits are parallel is rejected, which means the ORL models are statistically inappropriate for analyzing 1,019 single-vehicle CMCs.

Table 4 Ordinal Discrete-choice Analyses of Single-vehicle CMCs in Wisconsin

Section I: Severity study by Ordinal Probit (ORP) regression model (N = 1,019)							
	Model Coefficient Estimates (p-values)				Marginal Effect Estimates		
Independent Variables	B1	B2	B3	B4	PDO	Injury	Fatality
Driver							
SALCODRUG	-0.315(0.011)	-0.306(0.013)	-0.296(0.015)	-0.314(0.010)	-0.123	0.103	0.021
SAGE	-0.002(0.418)						
Roadway							
SWETRD	0.482(0.0001)	0.422(<.0001)	0.421(<.0001)	0.432(<.0001)	0.170	-0.141	-0.028
SRDCURV	-0.272(0.021)	-0.282(0.015)	-0.289(0.012)	-0.285(0.014)	-0.112	0.093	0.019
SRDHILL	-0.090(0.405)						
SPOSTSPD	-0.012(0.319)	-0.011(0.334)					
SMDNWDTH	0.0001(0.952)						
STOTLADT	2.545E-6(0.23)	2.57E-6(0.221)					
Crash							
SHVYTYPE	0.090(0.334)	0.076(0.408)					
SXOVREXNT	-0.150(0.092)	-0.145(0.104)	-0.138(0.121)				
Environment							
SWEATHER	-0.076(0.561)						
SDARK	-0.158(0.046)	-0.147(0.062)	-0.142(0.068)	-0.147(0.058)	-0.058	0.048	0.010
Model-specific attributes							
Intercept 1 ($-\widehat{\beta_0}$)	0.638(0.400)	0.521(0.487)	-0.118(0.202)	-0.221(0.0004)			
Intercept 2	2.723(0.0004)	2.603(0.0006)	1.961(<.0001)	1.853(<.0001)			
Thresholds							
$\widehat{\gamma_1}$ ($\because \gamma_1 \equiv 0$)	0.000	0.000	0.000	0.000			
$\widehat{\gamma_2}$	2.085	2.082	2.078	2.074			
"-2 LL"	1595.721	1597.470	1600.399	1602.811			
AIC	1623.721	1617.470	1614.399	1614.811			
AICc	1624.139	1617.688	1614.510	1614.894			
BIC	1692.693	1666.736	1648.885	1644.370			
Score Test for Equal Slopes	χ^2=16.107 (d.f.=12) p=0.186	χ^2=12.520 (d.f.=8) p=0.130	χ^2=8.014 (d.f.=5) p=0.156	χ^2=7.794 (d.f.=4) p=0.099			
Likelihood Ratio Test	χ^2=62.982 (d.f.=12) p=<.0001	χ^2=61.234 (d.f.=8) p=<.0001	χ^2=58.304 (d.f.=5) p=<.0001	χ^2=55.892 (d.f.=4) p=<.0001			

Table 4 Ordinal Discrete-choice Analyses of Single-vehicle CMCs in Wisconsin (*Continued*)

Section II: Severity study by Ordinal Logit (ORL) regression model (N = 1,019)

Independent Variables	Model Coefficient Estimates (p-values) b1	b2	b3	b4	Odds Ratio	95% Wald Confidence Limits
Driver						
SALCODRUG 0	0.238(0.028)	0.232(0.032)	0.225(0.036)	0.239(0.025)	1.270	(1.062, 2.453)
SAGE	-0.003(0.476)					
Roadway						
SWETRD 0	-0.389(0.0002)	-0.349(<.0001)	-0.349(<.0001)	-0.357(<.0001)	0.700	(0.379, 0.633)
SRDCURV 0	0.212(0.036)	0.217(0.030)	0.224(0.025)	0.221(0.026)	1.247	(1.053, 2.297)
SRDHILL 0	0.064(0.484)					
SPOSTSPD	-0.017(0.405)	-0.015(0.434)				
SMDNWDTH	0.0007(0.838)					
STOTLADT	4.86E-6(0.175)	4.80E-6(0.175)				
Crash						
SHVYTYPE 0	-0.076(0.331)	-0.066(0.388)				
SXOVREXNT 0	0.121(0.104)	0.118(0.113)	0.110(0.136)			
Environment						
SWEATHER 0	0.051(0.636)					
SDARK 0	0.140(0.037)	0.132(0.047)	0.126(0.055)	0.131(0.0.047)	1.139	(1.004, 1.679)
Model-specific attributes						
Intercept 1 ($-\widehat{\beta_0}$)	0.432(0.733)	0.343(0.785)	-0.536(0.0001)	-0.599(<.0001)		
Intercept 2	4.161(0.001)	4.069(0.0013)	3.184(<.0001)	3.116(<.0001)		
Thresholds						
$\widehat{\gamma_1}$ ($\because \gamma_1 \equiv 0$)	0.000	0.000	0.000	0.000		
$\widehat{\gamma_2}$	3.729	3.726	3.720	3.715		
"-2 LL"	1600.503	1601.785	1604.794	1607.037		
AIC	1628.503	1621.785	1618.794	1619.037		
AICc	1628.921	1622.003	1618.905	1619.120		
BIC	1697.475	1671.051	1653.280	1648.596		
Score Test for Proportional Odds	χ^2=21.281 (d.f.=12) p=0.046	χ^2=17.063 (d.f.=8) p=0.030	χ^2=12.449 (d.f.=5) p=0.029	χ^2=11.946 (d.f.=4) p=0.018		
Likelihood Ratio Test	χ^2=58.201 (d.f.=12) p=<.0001	χ^2=56.918 (d.f.=8) p=<.0001	χ^2=53.910 (d.f.=5) p=<.0001	χ^2=51.667 (d.f.=4) p=<.0001		

CONCLUSIONS

The common definition of a CMC is where a vehicle crosses the median over and collides with a vehicle(s) in opposing lane(s). For multiple-vehicle MCCs in Wisconsin between 2001 and 2007, an investigation revealed they occurred across all highway classes. Most of multi-vehicle MCCs involved a vehicle going straight in lanes before their occurrences and resulted from “a vehicle control loss on dry pavement” or “a vehicle control loss due to weather”. Wisconsin data also show that single-vehicle CMC are more common (80% of all CMCs) than multi-vehicle CMCs. Although less severe than multi-vehicle CMCs, modeling their severity expands upon previous studies and adds to the knowledge of these severe crashes not satisfactorily studied thus far.

ORL and ORP models were estimated for CMC injury status to obtain more understandings of underlying severity propensity via different modeling methodologies. The response contained three levels: fatality, injury, or PDO. For multi-vehicle CMCs, both types of severity models developed are statistically significant, and the assumption of ordinal response was appropriate. It was found road condition has a significant effect on the severity. Adverse road surfaces enhance the likelihood of being involved in a more severe consequence if a CMC occurs. Past studies on multi-vehicle CMCs were based on data collected within geographical zones where the winter precipitation is not as adverse as Wisconsin. Weather and road condition are causally associated with each other. Snow or ice in Wisconsin impacts the severity of CMCs, and logically the geographical location plays a significant role. Although ORL and ORP models found the posted speed limit significant, they revealed different features in severity propensity of CMCs. Therefore, the interpretation of this factor should be treated in a cautionary way. This also implies it is very necessary for safety researchers to use different models in analysis when pursuing more comprehensive understandings of a study topic.

Final ORP model for single-vehicle CMCs reveals that alcohol/drug use, curved alignment, and unfriendly roadway visibility exacerbate the severity tendency if a CMC occurs. An interesting finding is a dry roadway surface incurs a more severe consequence, which implies single-vehicle CMCs are more related to high speeds besides other significant factors. However, ORL models fitted to single-vehicle data are statistically inappropriate since the proportional odds assumption was rejected; while other approaches (e.g., MNL, MNP, decision tree, etc.) can be applied in future research. In historical median-related research, no significant correlation was found between traffic volumes and the encroachment rate (*15*), while crash rate and severity were found lower with wide medians and traffic volumes limitedly influenced the crash occurrence (*10*). In this study, both the median width and the ADT were found to be insignificant factors for the severity propensity in both multi-vehicle and single-vehicle CMCs.

The severity analysis is informative for state transportation agencies to assess median design policies and take safety enhancement measures against CMCs, such as the guardrail installation at curved segments or the improved public education of drivers with regard to the potential hazard of driving in snowy weather, during times with adverse visibility, under the influence of alcohol or drugs, and maintaining a high speed given good road condition.

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