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Contributing factors to right-turn crash severity at signalized intersections: An application of econometric modeling

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ABSTRACT

Motorists are required to interact with both roadway infrastructure and various users. The complexity of the driving task in certain scenarios can influence the frequency and severity of crashes. Turning vehicles at intersections, for example, pose a collision risk for both motorized and non-motorized road users. The primary goal of this paper is to investigate the underlying factors which contribute to right-turn crashes at signalized intersections. Five years of crash data across Oregon were collected. A random parameters binary logit model was developed to predict the likelihood of whether a crash resulted in an injury or fatality. It was found that 14 variables were statistically significant in contributing to crash severity. The results obtained show that dry conditions and a posted speed limit of 30 mi/hr or 35 mi/hr contributed to a higher percentage of severe crashes, while fixed-object crashes and snowy weather had a higher likelihood of resulting in no injury crashes. Time-of-day (9:00 p.m. to 6:00 a.m.), lighting conditions (dusk), gender (male driver), crash type (vehicle–pedestrian and rear-end), and driver-level crash cause (driver sped too fast for conditions, driver did not yield right-of-way, and driver disregarded the traffic control device) all led to an increase in probability of a fatal or injury crash. The vehicle–pedestrian conflict variable had the highest impact on increasing the probability of such a crash while turning right at a signalized intersection. This observation is important because right turns are often permitted during the pedestrian walk and clearance indications, and often drivers do not give right-of-way to pedestrians.

1. Introduction

Crash fatalities in the U.S. have slightly decreased (less than 1.0%) in recent years; however, this decline is only marginal (National Highway Traffic Safety Admininistration, 2018). Crash propensity remains a substantive issue within the United States, and society primarily experiences the impacts of crashes through economic costs. In 2010, the United States spent

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nearly $242 billion dollars on crashes (Blincoe et al., 2015) which includes various aspects, such as medical costs, congestion, property damage, and legal expenses. Crashes represent an enormous expense to society, and to understand how to reduce these costs one must investigate the factors that influence the occurrence of crashes. Often, population and congestion are suggested as contributing factors to these serious crashes; however, the complexity of the built environment can also greatly influence the frequency of crashes resulting in serious injuries.

Specifically, signalized intersections play a significant role in serious crashes as they require drivers to come into conflict with multiple roadway users (i.e., pedestrians, bicyclists, and vehicles); variations in geometry (i.e., lane configuration); and signal phasing (i.e., permitted movements). Furthermore, these factors and a motorist's ability to navigate them become more problematic when performing turning movements. Motorists who make turns at signalized intersections are responsible for maintaining situational awareness while interacting with signal phasing, ensuring correct usage of the right-of-way for the impending movement (i.e., when the right turn is permitted), and yielding to movements of conflicting pedestrians and bicyclists. On average, each year more than 24% of roadway fatalities occur at signalized intersections, with about 2% as a result of right-turn crashes (Hurwitz et al., 2018; Jashami et al., 2020). This trend is growing and is recognized as a significant influence on the overall frequency of serious crashes, particularly for vulnerable road users such as pedestrians and bicyclists.

In light of these trends, this work seeks to better understand the factors that lead to the severity of right-turn crashes at signalized intersections. Although the work on left-turn contributing factors is vast, the application of a crash severity analysis in the context of right turns is limited. The current study aims to fill this gap in literature by identifying significant contributory crash severity factors in right-turn crashes at signalized intersections.

2. Literature review

Currently there is limited research that directly supports factors that play into right-turn crashes; however, some researchers and practitioners have investigated crash data and driver behavior within on-road environments to determine how vehicle speeds, roadway conditions, demographics, and human factors contribute to the risks that could lead to roadway crashes.

Speed has consistently been a significant factor that influences presence and severity of crashes within the roadway paradigm. In 2017, speeding accounted for approximately 26% of all traffic fatalities (National Highway Traffic Safety Administration, 2019). While this percentage accounts for many roadway-linked fatal crashes, some can be attributed to intersections. Specifically, with intersections serving as a connection point for many roadway users, speed plays a significant role to the propensity of crash likelihood involving vehicles and vulnerable road users. For example, vehicles making turns, either right or left, are more susceptible to conflicts with vulnerable road users and with increased speed or distraction, are likely to intensify the crash likelihood (Jashami et al., 2017; Abadi et al., 2017).

In 2015, the Federal Highway Administration (FHWA) published pedestrian safety countermeasures and indicated that within right-turn lanes, higher speeds of right-turning vehicles increased the risk to pedestrians who were crossing (Federal Highway Administration, 2015). Keller et al. (2006) conducted a study of crash data in four different locations in Florida to determine the factors that relate to different types of crashes at signalized intersections based on their relative importance. Based on the data sets reviewed, right-turn crashes were significantly influenced by the traffic volume and number of lanes on the mainline. Additionally, the presence of exclusive left-turn lanes on the major roadway were statistically significant, which could indicate the potential conflict between the left-turn movement from the opposite direction and the right-turn movement from the main movement. On-road experimental studies have also been used to determine how various factors influence risk-taking behavior by drivers that could lead to right-turn crashes. Summala et al. (1996) evaluated driver visual scanning behavior at T-intersections when making right turns. The study found that drivers turning right were less inclined to visually observe aspects of the intersection in comparison to left-turning vehicles, which could indicate a higher crash potential. Wu and Xu (2017) used SHRP 2 Naturalistic Driving Study (NDS) data to evaluate influencing factors for right-turn drivers. Using 300 NDS trips at six signalized intersections, Wu and Xu (2017) found that higher conflicting traffic movements resulted in sharper deceleration closer to the intersection and that with a higher presence of pedestrians crossing, drivers' attention was more prominent. Additionally, the study found that drivers generally had lower observations and higher accelerations under permitted right-turn conditions, which is behavior that could lead to right-turn crashes and put pedestrians at higher risk. Furthermore, the data showed that only 50% of drivers yielded to pedestrians when conflicting with them on the right-turn movement. Haran et al. (2013) evaluated 10 years of right-turn crash data to determine what factors play a role and found that the higher prevalence of crashes occurred at T-junctions and in rural conditions. This coincides with the understanding that drivers may be less likely to be focused at intersections with reduced conflict points (i.e., T-intersection only has three legs) or locations where there is minimal traffic (i.e., rural conditions). More, right-turn crashes were shown to have a higher presence during PM peak hour conditions, indicating that fatigue could be contributing to the crashes. Choi (2010) analyzed crash causalities using data collected at crash scenes from 2005–2007. Among crashes at intersections, 52.5 percent occurred at intersections with at least one traffic signal, and 1.8% of vehicles at these signalized intersections were turning right before the crash. NHTSA did not find any variables that were statistically significant or critical reasons of driver error associated with the right-turn crashes. Additionally, no other analysis of statewide signalized intersection data by turning movement was found in the literature.

While there has been some research regarding the various factors that influence right-turn crashes, there is still a lack of substantial support that indicates direct factors, especially when conflicts with vulnerable road users are present. Therefore, the primary goal of this paper is to fill this gap in literature by investigating the underlying factors which contribute to right-turn crash severity at signalized intersections.

3. Data

Data used for the study consisted of police- and self-reported crash data in the state of Oregon. With recent concerns of temporal instability in parameter estimates across years of crash data (Behnood and Mannering, 2015; Mannering, 2018), this work utilizes five years of crash data (2012 to 2016). This study does not focus on temporal instability of parameter estimates, as this was beyond the scope.

To focus specifically on right-turn crashes at signalized intersections, the crash data was disaggregated based on two distinct aspects: (1) the crash occurred at a signalized intersection and (2) movement of the vehicle was turning right. Upon disaggregation, the resulting data set contained 5,381 right-turn crashes at signalized intersections. Next, the distribution of maximum crash severities was determined. The selection of crash severity is based on determining significant factors leading to the maximum injury severity sustained in the crash (i.e., crash severity) regardless of the participant. For example, due to the nature of these crashes, it may not always be the driver that sustains the most severe injury (e.g., vehicle–pedestrian crashes). Fig. 1 shows the distribution of maximum crash severity.

3.1. Variable selection

Using the Oregon crash data, various indicator variables were created to be tested for statistical significance in the crash severity model. Variables related to various crash characteristics were included. Table 1 shows the crash-, vehicle-, and driver-related variables present in the Oregon crash data. Of the right-turn crashes at signalized intersections, the majority occurred during midday (41.3%) and evening (28.6%) time periods. In regards to roadway classification, 49.5% of crashes happened on urban principal arterials, 33.4% took place on urban minor arterials, and 7.1% occurred on urban major collectors. As for posted speed limits, 27.2% of crashes happened at intersections where the associted posted speed limit is 30 mi/hr or 35 mi/hr. Of the intersection types where these crashes happened, 75.2% occurred at cross (4-legged) intersections and 19.2% occurred at 3-legged intersections. Considering weather condition, the majority of crashes happened during clear weather (68.4%), while 15.3% happened during rainy conditions and 3.0% happened during snowy conditions. 72.0% of crashes occurred on dry surface conditions, 21.5% happened on wet surface conditions, and 2.8% took place on icy surface conditions. Most crashes happened during daylight (72.2%), while 19.2% happened at dark where street lights were present and 4.6% happened at dusk. Lastly, just over 3.0% of crashes involved the use of alcohol.

Regarding vehicle-related variables, the first variable is related to the number of vehicle involved in the crash. In addition to considering the variable as continuous, indicators were created for single-vehicle crashes (22.3%) and multi-vehicle crashes (77.7%). The other vehicle-related variable was type of vehicle, in which 90.5% were passenger vehicles and 4.6% were truck tractor trailers.

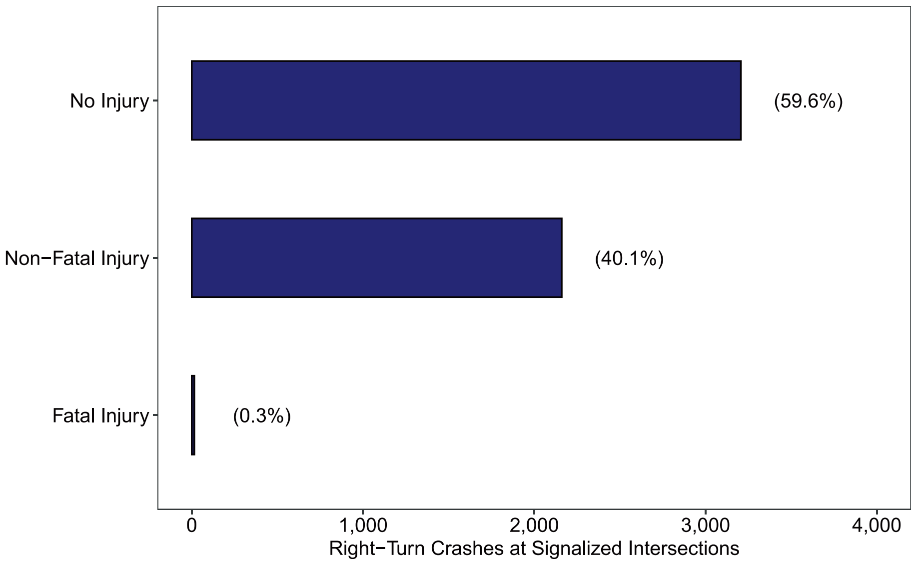


Fig. 1. Crash severity proportions of right-turn crashes at signalized intersections.

Table 1
Crash data variables for model development.

Variable	Frequency (%)	Fatal or Injury (%)	No Injury (%)
Crash-Related Variables			
Time-of-Day			
1 if 6:00 a.m. to 10:00 a.m.	818 (15.2%)	321 (14.8%)	497 (15.5%)
1 if 10:00 a.m. to 4:00 p.m.	2,222 (41.3%)	859 (39.5%)	1,363 (42.5%)
1 if 4:00 p.m. to 8:00 p.m.	1,538 (28.6%)	640 (29.4%)	898 (28.0%)
1 if 8:00 p.m. to 6:00 a.m.	770 (14.3%)	346 (15.9%)	424 (13.2%)
Unknown	33 (0.6%)	9 (0.4%)	24 (0.7%)
Roadway Classification			
1 if Urban Principal Arterial	2,662 (49.5%)	1,085 (49.9%)	1,577 (49.2%)
1 if Urban Minor Arterial	1,799 (33.4%)	711 (32.7%)	1,088 (33.9%)
1 if Urban Major Collector	381 (7.1%)	148 (6.8%)	233 (7.3%)
1 if Rural Major Collector	9 (0.2%)	4 (0.2%)	5 (0.2%)
1 if Rural Minor Arterial	23 (0.4%)	6 (0.3%)	17 (0.5%)
1 if Rural Minor Collector	1 (0.0%)	1 (0.0%)	0 (0.0%)
1 if Grade-Separated Ramp (Rural Interstate)	4 (0.1%)	1 (0.0%)	3 (0.1%)
1 if Rural Principal Arterial	46 (0.9%)	16 (0.7%)	30 (0.9%)
1 if Urban Local Road	80 (1.5%)	33 (1.5%)	47 (1.5%)
1 if Urban Minor Collector	1 (0.0%)	1 (0.0%)	0 (0.0%)
1 if Grade-Separated Ramp (Urban Interstate)	186 (3.5%)	95 (4.4%)	91 (2.8%)
1 if Grade-Separated Ramp (Urban Freeway/Expressway)	188 (3.5%)	74 (3.4%)	114 (3.6%)
Unknown or Not Reported	1 (0.0%)	0 (0.0%)	1 (0.0%)
Posted Speed Limit			
1 if 5 mi/hr to 15 mi/hr	3 (0.1%)	2 (0.1%)	1 (0.0%)
1 if 20 mi/hr or 25 mi/hr	340 (6.3%)	160 (7.4%)	180 (5.6%)
1 if 30 mi/hr or 35 mi/hr	1,463 (27.2%)	656 (30.2%)	807 (25.2%)
1 if 40 mi/hr or 45 mi/hr	268 (5.0%)	123 (5.7%)	145 (4.5%)
1 if 50 mi/hr or 55 mi/hr	212 (3.9%)	106 (4.9%)	106 (3.3%)
1 if 60 mi/hr or 65 mi/hr	12 (0.2%)	5 (0.2%)	7 (0.2%)
No Statutory Speed Limit	130 (2.4%)	55 (2.5%)	75 (2.3%)
Unknown or Not Reported	2,953 (54.9%)	1,083 (49.0%)	1,870 (58.9%)
Intersection Type			
1 if 2-Legged Intersection	4 (0.1%)	2 (0.1%)	2 (0.1%)
1 if 3-Legged Intersection	1,034 (19.2%)	420 (19.3%)	614 (19.2%)
1 if 4-Legged Intersection	74 (1.4%)	37 (1.7%)	37 (1.2%)
1 if 5-Legged Intersection	186 (3.5%)	61 (2.8%)	125 (3.9%)
1 if 6-Legged Intersection	20 (0.4%)	10 (0.5%)	10 (0.3%)
1 if Cross Intersection	4,048 (75.2%)	1,642 (75.5%)	2,406 (75.0%)
1 if Unknown or Not Reported	15 (0.3%)	3 (0.1%)	12 (0.4%)
Crash Type			
1 if Angle	67 (1.2%)	35 (1.6%)	32 (1.0%)
1 if Backing	1 (0.0%)	1 (0.0%)	0 (0.0%)
1 if Fixed-Object	286 (5.3%)	81 (3.7%)	205 (6.4%)
1 if Head-On	2 (0.0%)	1 (0.0%)	1 (0.0%)
1 if Miscellaneous	7 (0.1%)	6 (0.3%)	1 (0.0%)
1 if Non-Collision	16 (0.3%)	13 (0.6%)	3 (0.1%)
1 if Parking Maneuver	15 (0.3%)	3 (0.1%)	12 (0.4%)
1 if Vehicle–Pedestrian	379 (7.0%)	374 (17.2%)	5 (0.2%)
1 if Rear-End	444 (8.3%)	180 (8.3%)	264 (8.2%)
1 if Sideswipe (Opposing Direction)	4 (0.1%)	3 (0.1%)	1 (0.0%)
1 if Sideswipe (Same Direction)	43 (0.8%)	6 (0.3%)	37 (1.2%)
1 if Turning Movement	4,117 (76.5%)	1,472 (67.7%)	2,645 (82.5%)
Weather Condition			
1 if Clear	3,679 (68.4%)	1,468 (67.5%)	2,211 (69.0%)
1 if Cloudy	525 (9.8%)	273 (12.6%)	252 (7.9%)
1 if Fog	38 (0.7%)	15 (0.7%)	23 (0.7%)
1 if Rain	823 (15.3%)	348 (16.0%)	475 (14.8%)
1 if Sleet	5 (0.1%)	3 (0.1%)	2 (0.1%)
1 if Snow	160 (3.0%)	32 (1.5%)	128 (4.0%)
Unknown or Not Reported	151 (2.8%)	36 (1.7%)	115 (3.6%)
Road Surface Condition			
1 if Dry	3,877 (72.0%)	1,619 (74.4%)	2,258 (70.4%)
1 if Ice	148 (2.8%)	31 (1.4%)	117 (3.6%)
1 if Snow	63 (1.2%)	12 (0.6%)	51 (1.6%)
1 if Wet	1,159 (21.5%)	484 (22.3%)	675 (21.1%)
Unknown or Not Reported	134 (2.5%)	29 (1.3%)	105 (3.3%)
Lighting Condition			
1 if Daylight	3,883 (72.2%)	1,531 (70.4%)	2,352 (73.4%)
1 if Dark With Street Lights	1,035 (19.2%)	445 (20.5%)	590 (18.4%)
1 if Dark Without Street Lights	90 (1.7%)	30 (1.4%)	60 (1.9%)

Table 1 (*continued*)

Variable	Frequency (%)	Fatal or Injury (%)	No Injury (%)
1 if Dusk	249 (4.6%)	115 (5.3%)	134 (4.2%)
1 if Dawn	114 (2.1%)	49 (2.3%)	65 (2.0%)
Unknown or Not Reported	10 (0.2%)	5 (0.2%)	5 (0.2%)
Alcohol Involved			
1 if Yes	179 (3.3%)	84 (3.9%)	95 (3.0%)
Vehicle-Related Variables			
Number of Vehicles			
Number of Vehicles (Continuous)	NA	NA	NA
1 if Single-Vehicle Crash	1,199 (22.3%)	983 (54.8%)	216 (6.7%)
1 if Multi-Vehicle Crash	4,182 (77.7%)	1,192 (54.8%)	2,990 (93.3%)
Vehicle Type			
1 if Moped, Minibike, Motor Scooter, or Motor Bicycle	4 (0.1%)	3 (0.1%)	1 (0.0%)
1 if Motorcycle	35 (0.7%)	29 (1.3%)	6 (0.2%)
1 if Motorcycle (Dirt Bike)	9 (0.2%)	8 (0.4%)	1 (0.0%)
1 if Motorhome	6 (0.1%)	4 (0.2%)	2 (0.1%)
1 if Bus (Other)	41 (0.8%)	11 (0.5%)	30 (0.9%)
1 if Forklift or Backhoe	1 (0.0%)	1 (0.0%)	0 (0.0%)
1 if Passenger Vehicle	4,869 (90.5%)	2,018 (92.8%)	2,851 (88.9%)
1 if School Bus (Includes Van)	14 (0.3%)	8 (0.4%)	6 (0.2%)
1 if Truck Tractor	249 (4.6%)	53 (2.4%)	196 (6.1%)
1 if Truck with Non-Detachable Bed or Panel	64 (1.2%)	17 (0.8%)	47 (1.5%)
Unknown Vehicle Type	89 (1.7%)	23 (1.1%)	66 (2.1%)
Driver-Related Variables			
Driver Resident Status			
1 if Not an Oregon Resident	353 (6.6%)	132 (6.1%)	221 (6.9%)
1 if Oregon Resident and Unknown Distance from Home	26 (0.5%)	2 (0.1%)	24 (0.7%)
1 if Oregon Resident Within 25 Miles of Home	3,636 (67.6%)	1,837 (84.5%)	1,799 (56.1%)
1 if Oregon Resident More Than 25 Miles from Home	294 (5.5%)	134 (6.2%)	160 (5.0%)
Unknown if Oregon Resident	1,072 (19.9%)	70 (3.2%)	1,002 (31.3%)
Driver Gender			
1 if Male	2,522 (46.9%)	1,182 (54.3%)	1,340 (41.8%)
Driver Age			
Age (Continuous)	NA	NA	NA
1 if 16 Years to 20 Years	320 (5.9%)	166 (7.6%)	154 (4.8%)
1 if 21 Years to 24 Years	348 (6.5%)	186 (8.6%)	162 (5.1%)
1 if 25 Years to 34 Years	745 (13.8%)	400 (18.4%)	345 (10.8%)
1 if 35 Years to 44 Years	644 (12.0%)	354 (16.3%)	290 (9.0%)
1 if 45 Years to 54 Years	645 (12.0%)	339 (15.6%)	306 (9.5%)
1 if 55 Years to 64 Years	680 (12.6%)	331 (15.2%)	349 (10.9%)
1 if Greater Than or Equal to 65 Years	670 (12.5%)	307 (14.1%)	363 (11.3%)
Unknown Age or Not Reported	1,329 (24.7%)	92 (4.2%)	1,237 (38.6%)
Reported Driver-Level Crash Cause			
1 if Careless Driving	58 (1.1%)	37 (1.7%)	21 (0.7%)
1 if Driver Did Not Yield Right-of-Way	1,309 (24.3%)	890 (40.9%)	419 (13.1%)
1 if Driver Disregarded Other Traffic Control Device	24 (0.4%)	5 (0.2%)	19 (0.6%)
1 if Driver Disregarded Traffic Control Device (Signal)	142 (2.6%)	64 (2.9%)	78 (2.4%)
1 if Driver Sped Too Fast For Conditions	226 (4.2%)	80 (3.7%)	146 (4.6%)
1 if Driver Drowsy/Fatigued/Sleepy	3 (0.1%)	2 (0.1%)	1 (0.0%)
1 if Driver Exceeding Posted Speed Limit	5 (0.1%)	4 (0.2%)	1 (0.0%)
1 if Driver Left of Center on Two-Way Road	4 (0.1%)	1 (0.0%)	3 (0.1%)
1 if Driver Failed to Avoid Vehicle Ahead	19 (0.4%)	19 (0.9%)	0 (0.0%)
1 if Followed Too Close	130 (2.4%)	54 (2.5%)	76 (2.4%)
1 if Driver Improperly Changed Lanes	20 (0.4%)	4 (0.2%)	16 (0.5%)
1 if Driver Improperly Overtook	63 (1.2%)	8 (0.4%)	55 (1.7%)
1 if Driver was Inattentive	29 (0.5%)	15 (0.7%)	14 (0.4%)
1 if Driver Made Improper Turn	1,026 (19.1%)	295 (13.6%)	731 (22.8%)
1 if No Cause Associated	2,160 (40.1%)	621 (28.6%)	1,539 (48.0%)
1 if Other (Not Improper Driving)	5 (0.1%)	4 (0.2%)	1 (0.0%)
1 if Other (Improper Driving)	51 (0.9%)	15 (0.7%)	36 (1.1%)
1 if Phantom/Non-Contact Vehicle	3 (0.1%)	1 (0.0%)	2 (0.1%)
1 if Physical Illness	2 (0.0%)	2 (0.1%)	(0.0%)
1 if Reckless Driving	56 1.0%	31 (1.4%)	25 (0.8%)
1 if Driver View Obscured	1 0.0%	1 (0.0%)	0 (0.0%)
1 if Wrong Way on One-Way Roadway	4 0.1%	2 (0.1%)	2 (0.1%)
Driver-Level Crash Cause Unknown or Not Reported	41 (0.8%)	20 (0.9%)	21 (0.7%)

The final set of variables considered during model development were driver-related. Of the drivers involved a crash, 67.6% were Oregon residents within 25 miles of home, 66% were not an Oregon resident, and 46.9% were male. Ages of drivers remained fairly consistent across age groups, where substantially smaller proportions of younger drivers were observed; specifically, 5.9% between 16 years and 20 years, and 6.5% between 21 years and 24 years. The final driver-related variable considered was driver-level crash cause. This information is unique to Oregon crash data, in which crash causes are recorded at the driver-level. The most occurring driver-level crash cause was not yielding the right-of-way (24.3%), followed by improper turns (19.1%) and speeding too fast for conditions (4.2%).

Using a forward stepwise procedure which considers variables presented in Table 1, 14 variables were found to be significant contributing factors to crash severity. Summary statistics of variables found to be significant are presented in Table 2, while Table 3 shows the descriptive statistics of significant variables by severity.

Table 2
Summary statistics of significant variables.

Variable	Mean	Standard Deviation	Max	Min
Dependent Variable				
Crash Severity	0.404	0.491	–	–
Time-of-Day				
1 if 9:00 p.m. to 6:00 a.m., 0 Otherwise	0.143	0.350	–	–
Lighting Condition				
1 if Dusk, 0 Otherwise	0.046	0.210	–	–
Weather Condition				
1 if Snowy, 0 Otherwise	0.030	0.170	–	–
Road Surface Condition				
1 if Dry Surface, 0 Otherwise	0.720	0.449	–	–
Posted Speed Limit				
1 if 30 mi/hr or 35 mi/hr	0.272	0.445	–	–
1 if 40 mi/hr or 45 mi/hr	0.050	0.218	–	–
Crash Type				
1 if Fixed-Object Crash, 0 Otherwise	0.053	0.224	–	–
1 if Vehicle–Pedestrian Crash, 0 Otherwise	0.070	0.256	–	–
1 if Rear-End Crash, 0 Otherwise	0.083	0.275	–	–
Driver Characteristics				
1 if Male, 0 Otherwise	0.469	0.499	–	–
Age	45.057	18.476	16	97
Reported Driver-Level Crash Cause				
1 if Driver Sped Too Fast For Conditions, 0 Otherwise	0.042	0.201	–	–
1 if Driver Did Not Yield Right-of-Way	0.243	0.429	–	–
1 if Driver Disregarded Traffic Control Device	0.026	0.160	–	–

Table 3
Summary statistics of significant variables by severity.

Variable	Mean		Standard Deviation		Min		Max	
	Fatal or Injury	No Injury	Fatal or Injury	No Injury	Fatal or Injury	No Injury	Fatal or Injury	No Injury
Time-of-Day								
1 if 9:00 p.m. to 6:00 a.m., 0 Otherwise	0.159	0.132	0.366	0.339	–	–	–	–
Lighting Condition								
1 if Dusk, 0 Otherwise	0.053	0.042	0.224	0.200	–	–	–	–
Weather Condition								
1 if Snowy, 0 Otherwise	0.015	0.040	0.120	0.196	–	–	–	–
Road Surface Condition								
1 if Dry Surface, 0 Otherwise	0.744	0.704	0.436	0.456	–	–	–	–
Posted Speed Limit								
1 if 30 mi/hr or 35 mi/hr	0.302	0.252	0.459	0.434	–	–	–	–
1 if 40 mi/hr or 45 mi/hr	0.059	0.043	0.236	0.204	–	–	–	–
Crash Type								
1 if Fixed-Object Crash, 0 Otherwise	0.037	0.064	0.189	0.245	–	–	–	–
1 if Vehicle–Pedestrian Crash, 0 Otherwise	0.172	0.002	0.377	0.040	–	–	–	–
1 if Rear-End Crash, 0 Otherwise	0.083	0.082	0.276	0.275	–	–	–	–
Driver Characteristics								
1 if Male, 0 Otherwise	0.543	0.418	0.498	0.493	–	–	–	–
Age	44.071	46.010	17.986	18.923	16	16	96	97
Reported Driver-Level Crash Cause								
1 if Driver Sped Too Fast For Conditions, 0 Otherwise	0.037	0.046	0.188	0.209	–	–	–	–
1 if Driver Did Not Yield Right-of-Way	0.409	0.131	0.492	0.337	–	–	–	–
1 if Driver Disregarded Traffic Control Device	0.029	0.024	0.169	0.154	–	–	–	–

4. Methodology

For the current study, crash severity is being analyzed through an econometric modeling approach. The choice of crash severity, as opposed to driver injury severity, stems from two aspects. First, the current study is interested in determining significant factors leading to the maximum injury severity sustained in the crash regardless of the participant. Second, there is not an adequate number of observations for the higher severity levels, as illustrated in Fig. 1. The aforementioned also holds true for crash severity, in which the majority of crashes that occurred resulted in no injury. With this in mind and considering that crash severity is being analyzed (not injury severity), the current work dichotomizes crash severity into two distinct outcomes: 1 if the crash resulted in any form of injury (including fatalities), and 0 if the crash resulted in no injury.

Being that crash severity has been dichotomized into binary format, a binary modeling framework is considered. Of the potential methods to model crash severity, the present study applies a binary logit model, as previous work has shown that the use of a binary logit model on data with a large number of observations is preferred (Young and Liesman, 2007; Haleem and Gan, 2013; Perez-Fuster et al., 2013; Sarwar et al., 2016). It should be noted, the premise behind the current study is to identify significant factors, as this is limited in the literature, where the binary logit model is most appropriate in this context.

Logit models are based on the following logit probability (McFadden, 1981; Train, 2009):

$$P_n(i) = \frac{e^{\left(\beta_i X_{i,n}\right)}}{\sum_{\forall i} e^{\left(\beta_i X_{i,n}\right)}} \tag{1}$$

where $P_n(i)$ is the probability of crash n resulting in crash severity i, β_i is a vector of parameters to be estimated, and $X_{i,n}$ is a vector of explanatory variables (e.g., crash characteristics, vehicle characteristics, driver characteristics). Normalizing one of the outcomes to zero to satisfy the alternative-specific–constant rule, Eq. (1) can be expressed as:

$$P_n(i) = \frac{e^{\hat{\beta}}}{1 + e^{\hat{\beta}}} \tag{2}$$

and:

$$\hat{\beta} = \beta_0 + \beta_i X_{1,n} + \cdots + \beta_i X_{i,n} + \varepsilon_{i,n} \tag{3}$$

where $\varepsilon_{i,n}$ is a Type I Extreme Value distributed error term and all other terms have been defined previously. The purpose of $\varepsilon_{i,n}$ is to capture unobservables in the data, or factors that are unobserved to the analyst (i.e., factors or variables that are not present in the data). However, most often, $\varepsilon_{i,n}$ is unable to capture all of these unobservables which, in turn, results in unobserved heterogeneity. This stems, in crash data, from two aspects. The first of these aspects pertains to information (i.e., variables) not being present. For crash data, this is typically attributed to data collection forms, in which each and every factor that contributes to the severity of a crash is not collected by police or on self-report forms. The second aspect refers to variation within existing, or observable, variables. For example, it is known if the crash was a fixed-object crash, but other contributing factors are often unknown. That is, speed at the time of impact, the type of fixed-object (e.g., telephone pole, jersey barrier, tire barrier, etc.), or specific information about the driver (e.g., perception reaction time, visual acuity, etc.) are unknown. Although unobservable, these factors are likely to contribute to the severity of a crash. Due to unobserved heterogeneity, parameter estimates can be biased and result in incorrect inferences made on the entire population (Mannering et al., 2016). Therefore, this data limitation must be considered during model estimation.

Taking that into consideration, this study addresses unobserved heterogeneity through the use of random parameters. This is accomplished by introducing a mixing distribution to Eq. (2) (McFadden and Train, 2000; Train, 2009):

$$P_n(i|\theta) = \int_x \frac{e^{\hat{\beta}}}{1 + e^{\hat{\beta}}} f\left(\hat{\beta}|\theta\right)\, d\hat{\beta} \tag{4}$$

where $P_n(i|\theta)$ is the weighted probability of $P_(i)$ taking on the value 1 (i.e., the crash resulted in an injury or fatality) conditional on $f\left(\hat{\beta}|\theta\right)$. In this context, $f\left(\hat{\beta}|\theta\right)$ is the density function of $\hat{\beta}$, where θ represents the distributional parameter. The addition of this density function allows parameter estimates to vary across crash observations permitting $\hat{\beta}$ to account for crash-specific variation regarding the effects of $X_{i,n}$ on $P_n(i|\theta)$. For this work, the distribution of $f\left(\hat{\beta}|\theta\right)$ was specified to be normal.

To estimate $\hat{\beta}$, simulation techniques are applied. To accomplish this, Halton draws are used (Halton, 1960; Bhat, 2003). Through the use of Halton draws, simulated probabilities are inserted into the log-likelihood function of the logit model giving a simulated log-likelihood (Train, 2009; Washington et al., 2011):

$$SLL = \sum_{n=1}^{N}\sum_{i=1}^{I} \delta_{i,n}\ \ln\left[P_n(i|\theta)\right] \tag{5}$$

where N is the number of observations (crashes), I is the number of crash severity outcomes (fatality/non-fatal injury and no injury), and $\delta_{i,n}$ is equal to 1 if the observed crash severity for observation n is i and 0 otherwise.

To assess the effects, or impacts, of significant contributing crash severity factors, the current work utilizes marginal effects. Marginal effects are the effect of a significant contributing factor on the probability that the outcome takes on the value 1 (i.e., the probability of a fatal/non-fatal injury crash) while all other variables remain equal to their means. With both continuous and indicator variables present in final model specifications, marginal effects are computed for both. For continuous variables, marginal effects are computed as (Greene, 2018):

$$\frac{\partial P_n(i)}{\partial X_{i,n,k}} = [1 - P_n(i)]P_n(i)\beta_{n(i)} \tag{6}$$

where $\frac{\partial P_n(i)}{\partial X_{i,n,k}}$ is the partial derivative of the probability of crash n having crash severity i due to explanatory variable k. For indicator variables, marginal effects are the difference of the estimated probabilities when an indicator changes from zero to one (Greene, 2018):

$$\mathrm{ME}_{Xk} = \Pr[P_n(i) = 1|X, X_k = 1] - \Pr[P_n(i) = 1|X, X_k = 0] \tag{7}$$

where X is the mean of all other variables while X_k changes from zero to one.

5. Results and discussion

Through a forward step-wise procedure, 14 variables were found to be statistically significant contributing factors to crash severity. Variables kept in final model specifications were those that had significant parameters with at least 90% confidence and were not significantly correlated with another explanatory variable. As discussed in Section 3, summary statistics of significant variables can be viewed in Table 2. Final model specifications are shown in Table 4. As shown in Table 4, final model specifications result in a log-likelihood value of 0.18, indicating the model fits the data adequately (McFadden, 1973; McFadden, 1977; McFadden, 1981). Additionally, shown in Table 4, of the 15 estimated parameters, four are random and normally distributed, indicating the presence of unobserved heterogeneity.

Of the variables with estimated random parameters, the first is related to weather. Specifically, the indicator for snowy weather has a random and normally distributed parameter. With a mean of −1.04 and a standard deviation of 2.25, 32.2% of

Table 4
Random parameters binary logit model specifications.

Variable	Coefficient	Std. Error	*t*-statistic	Marginal Effect
Constant	−1.41	0.07	−20.08	–
Time-of-Day				
1 if 9:00 p.m. to 6:00 a.m., 0 Otherwise	0.37	0.07	5.58	0.091
Lighting Condition				
1 if Dusk, 0 Otherwise	0.18	0.11	1.70	0.045
Weather Condition				
1 if Snowy Weather, 0 Otherwise	−1.04	0.27	−3.89	−0.256
(Std. Dev. of Normally Distributed Parameter)	*(2.25)*	*(0.40)*	*(5.60)*	
Road Surface Condition				
1 if Dry, 0 Otherwise	0.13	0.05	2.40	0.032
(Std. Dev. of Normally Distributed Parameter)	*(0.48)*	*(0.04)*	*(12.21)*	
Posted Speed Limit				
1 if 30 mi/hr or 35 mi/hr, 0 Otherwise	0.14	0.05	2.66	0.034
(Std. Dev. of Normally Distributed Parameter)	*(0.23)*	*(0.06)*	*(3.67)*	
1 if 40 mi/hr or 45 mi/hr, 0 Otherwise	0.19	0.10	1.93	0.048
Crash Type				
1 if Fixed-Object, 0 Otherwise	−0.40	0.12	−3.31	−0.098
(Std. Dev. of Normally Distributed Parameter)	*(1.01)*	*(0.17)*	*(5.89)*	
1 if Vehicle–Pedestrian, 0 Otherwise	3.03	0.32	9.34	0.746
1 if Rear-End, 0 Otherwise	0.39	0.08	4.91	0.097
Driver				
1 if Male, 0 Otherwise	0.19	0.05	4.17	0.047
Age	0.01	0.01	13.18	0.003
Driver-Level Crash Cause				
1 if Sped Too Fast For Conditions, 0 Otherwise	0.50	0.12	4.14	0.124
1 if Did Not Yield Right-of-Way, 0 Otherwise	0.82	0.06	14.62	0.202
1 Disregarded Traffic Control Device, 0 Otherwise	0.31	0.13	2.39	0.075
Model Summary				
Number of Observations	5,381			
Log-Likelihood at Zero	−3,630.44			
Log-Likelihood at Convergence	−2,991.94			
McFadden Pseudo R^2	0.18			

crashes have an estimated parameter mean greater than zero and 67.8% have an estimated parameter mean less than zero. In other words, 32.2% of crashes that occurred in snowy conditions were more likely to result in an injury or fatality and 67.8% of crashes were less likely. The observed varying effects may be attributed to driver-specific behavior in crashes that occurred in snowy weather, such as a driver's experience in such conditions. Unobservables related to the vehicle, such as type of tire, brakes, etc., may also be contributing to the heterogeneous effects. The severity of the snowy weather is not indicated in the data, which can also lead to varying effects. Heterogeneous effects of snowy weather on severity were also found by Anderson and Hernandez (2017), where the majority of crashes were more likely to result in a lesser severity sustained by the driver. In addition, this finding is substantiated by various work in which snowy weather, or inclement weather, is found to increase the likelihood of no injury (Eluru and Bhat, 2007; Milton et al., 2008; Lemp et al., 2011; Eluru et al., 2012; Manepalli et al., 2012; Yasmin and Eluru, 2013; Behnood et al., 2014; Cerwick et al., 2014; Islam et al., 2014; Ye and Lord, 2014). To visualize the proportion of crashes with an estimated parameter above/below zero, refer to Fig. 2 and Fig. 3a.

The second random parameter, also normally distributed, is the estimated parameter for dry surface conditions. Model estimates show, with a mean of 0.13 and a standard deviation of 0.48, that 39.3% of crashes that occurred on dry surface conditions were less likely to result in an injury or fatality while 60.7% were more likely. Dry surface conditions have been found to be contributing factors to the severity of crashes for several years, and in nearly all cases, found to increase severity or decrease the likelihood of no injury (Sigthorsson and Finnsson, 1997; Duncan et al., 1998; Chang and Mannering, 1999; Lee and Mannering, 2002; Peng and Boyle, 2012; Yasmin and Eluru, 2013; Islam and Hernandez, 2013; Behnood et al., 2014; Shaheed and Gkritza, 2014; Behnood and Mannering, 2015; Anderson and Dong, 2017). Other studies, however, have found dry surface conditions to decrease the severity of crashes, with one finding dry surface conditions to be heterogeneous. In the same study, Islam et al. (2016) found dry surface conditions to decrease the likelihood of a fatal crash while also being heterogeneous for incapacitating injury crashes. Yasmin et al. (2014) found that dry surface conditions increase the likelihood of a more severe crash if the crash type is head-on. Rifaat and Tay (2009) found that dry surface conditions have a considerably lower injury risk compared to wet surfaces. In addition, Pahukula et al. (2015) found that dry surface conditions increase the likelihood of no injury for crashes that occurred in the afternoon. As observed, the effects of dry surface conditions vary, which previous work has stated to be a result of driver-specific behavior such as risk taking Shaheed et al. (2013). Other factors that may influence varying effects, and often not available in the crash data, are pavement quality and vehicle-specific information (e.g., tires, brakes, etc.). To visualize the proportion of crashes with an estimated parameter above/below zero, refer to Fig. 2 and Fig. 3d.

The third variable with a normally distributed random parameter is an indicator for posted speed limit. With a mean of 0.14 and a standard deviation of 0.23, 27.1 percent of crashes that occurred where the posted speed limit was 30 mi/hr or 35 mi/hr were less likely to result in an injury or fatality and 72.9 percent were more likely. In general, various years of research points towards higher posted speed limits leading to more severe crashes (O'Donnell and Connor, 1996; Farmer et al., 1997; Duncan et al., 1998; Chang and Mannering, 1999; Krull et al., 2000; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005; Eluru et al., 2008; Malyshkina and Mannering, 2008; Nevarez et al., 2009; Paleti et al., 2010; Lemp et al., 2011; Chiou and Fu,

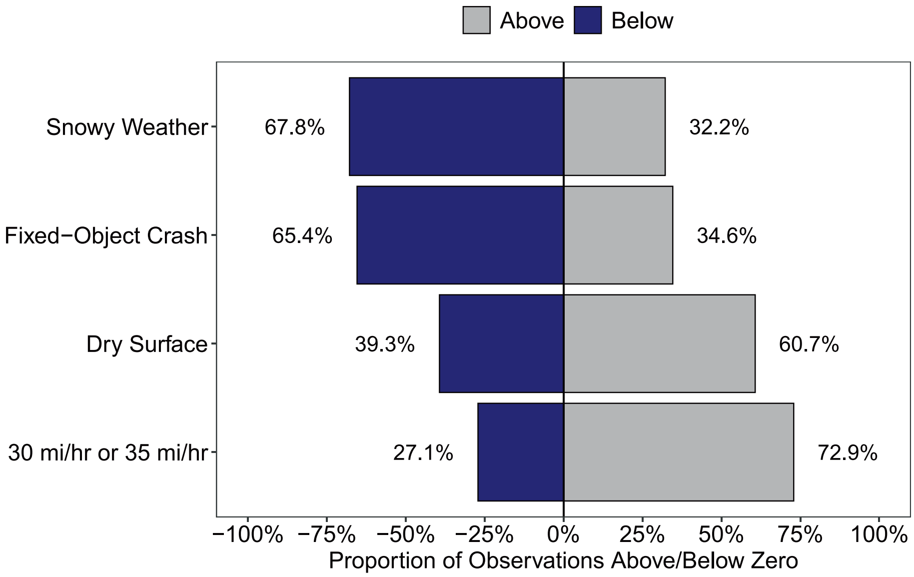


Fig. 2. Variables with random parameters and proportion of crashes with estimated parameters above/below zero (above zero indicates an increase in the likelihood of a fatal/non-fatal injury crash and below zero indicates a decrease in the likelihood of a fatal/non-fatal injury crash).

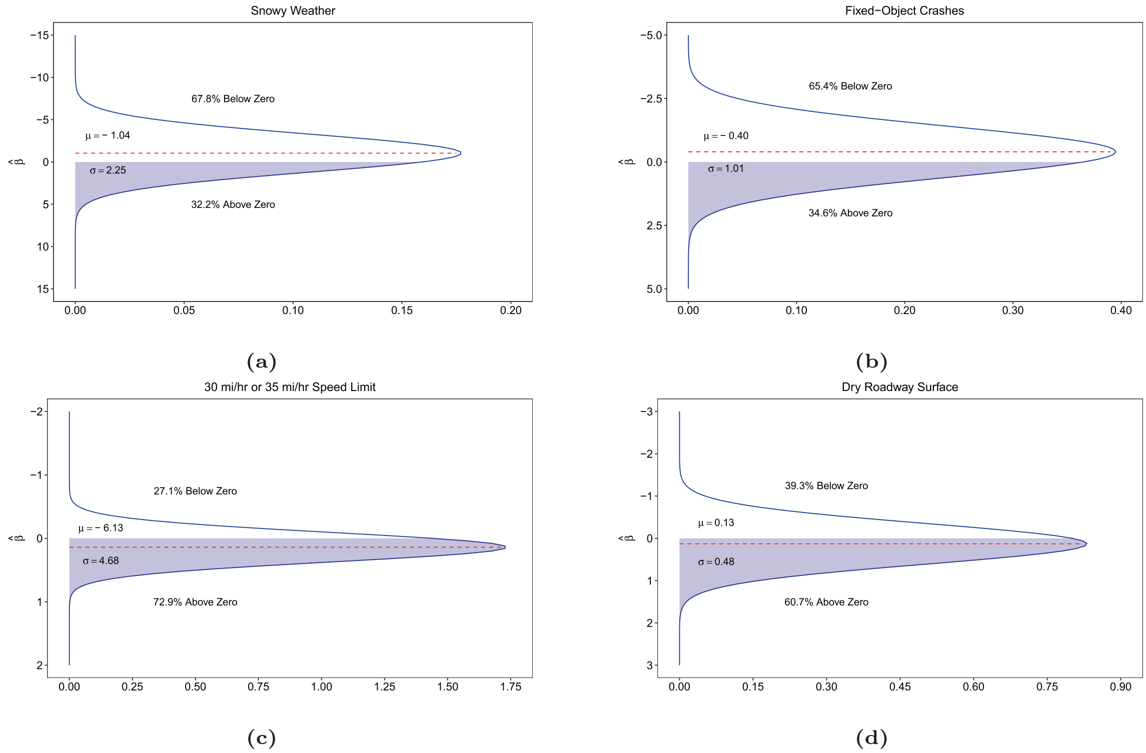
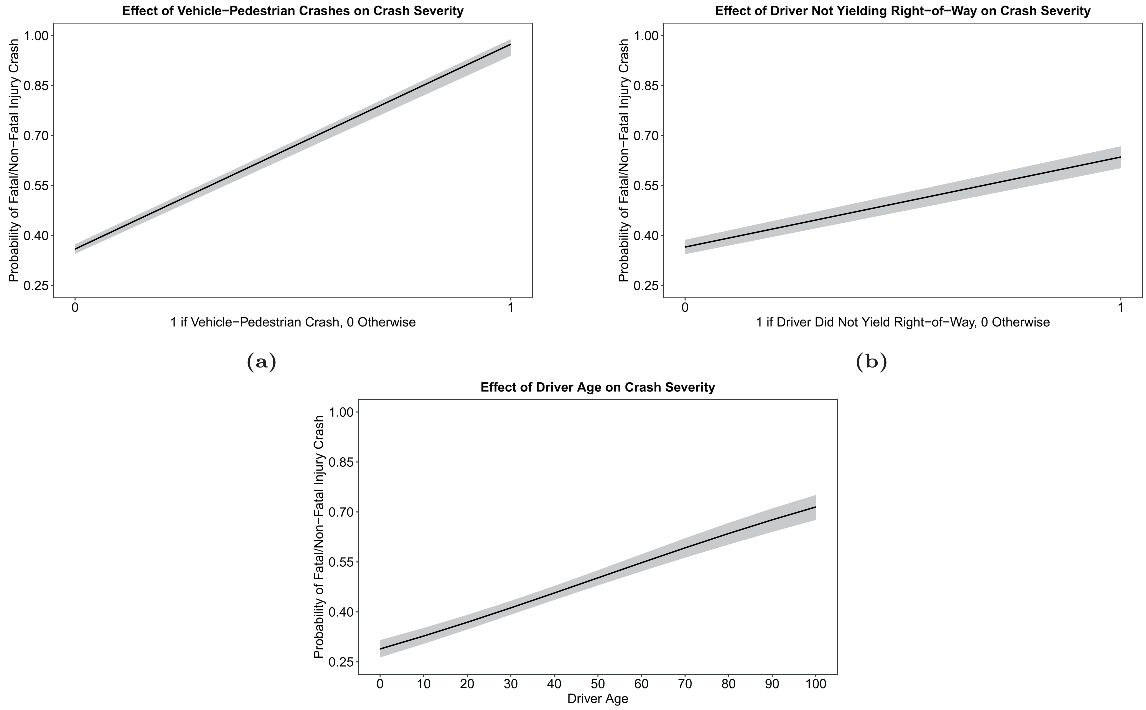


Fig. 3. Distribution of for the random parameter associated with (a) snowy weather, (b) fixed-object crashes, (c) 30 mi/hr or 35 mi/hr posted speed limits, and (d) dry roadway surface.

2013; Shaheed et al., 2013; Yasmin et al., 2014). However, there are some studies that have found the opposite (Morgan and Mannering, 2011; Uddin and Huynh, 2018). As it pertains to intersection-specific findings, studies have also found that higher posted speed limits lead to more severe crashes (Tay and Rifaat, 2007; Haleem and Abdel-Aty, 2010; Obeng, 2011; Tay, 2015), while Abdel-Aty and Keller (2005) found higher speed limits on minor roads reduce the likelihood of a severe crash. Considering these studies, and their difference in findings, the heterogeneous nature in the current work may be linked to heterogeneous driver behavior or be data-specific. To visualize the proportion of crashes with an estimated parameter above/below zero, refer to Fig. 2 and Fig. 3c.

The final variable to have a normally distributed random parameter is the indicator for fixed-object crashes. The estimated parameter mean of −0.40 and estimated standard deviation of 1.01 indicate that 34.6 percent of fixed-object crashes were more likely to result in an injury or fatality, and 65.4 percent of fixed-object crashes were less likely to result in an injury or fatality. The heterogeneous nature in this variable follows that of previous work, where studies have found varying impacts on severity due to a fixed object. Most notably, this includes the angle at which the vehicle hit the fixed object or the type of fixed object, both of which are not included in the utilized crash data. For instance, Bédard et al. (2002) found that the angle of impact can impact severity. Specifically, if the fixed object was struck by the left side of the vehicle, a severe injury was more likely to occur. Similarly, Yamamoto and Shankar (2004) found that the type of fixed object impacts severity. In particular, crashes into the ends of guardrails and crashes with trees were found to lead to severe injuries. On the other hand, Yamamoto and Shankar (2004) also found that crashes with sign posts, ”appurtenances” in a ditch, faces of guardrails, concrete barriers or bridges, and fences lead to less severe injuries. Morgan and Mannering (2011) also found that the type of fixed object impacts severity, as well as the age of the driver. Some studies, however, have found that fixed-object crashes have a homogeneous effect on severity (Paleti et al., 2010; Chu, 2014; Islam et al., 2014).These varying results suggest that fixed-object crashes should be further investigated, which has been documented and suggested recently (Wu et al., 2014). To visualize the proportion of crashes with an estimated parameter above/below zero, refer to Fig. 2 and Fig. 3b.

Moving to marginal effects, several variables have substantial to moderate impacts on crash severity probability. Marginal effects are shown in Table 4, and illustrated in Fig. 4 and Fig. 5. The most impactful, according to marginal effects, are vehicle–pedestrian crashes (Fig. 4a). Based on marginal effects, vehicle–pedestrian crashes have a 0.746 higher probability of resulting in an injury or fatality. Marginal effects also show that crashes which occurred as a result of a driver not yielding the right-of-way have a 0.202 higher probability of resulting in an injury or fatality (Fig. 4b). This is in line with previous



(a) (b) (c)

Fig. 4. Visualization of effects on crash severity probability due to (a) vehicle–pedestrian crashes, (b) driver not yielding right-of-way, and (c) driver age.

findings, in which crashes reported to be caused by the driver failing to yield the right-of-way were more likely to result in a severe crash or less likely to result in no injury (Cerwick et al., 2014; Behnood and Mannering, 2015; Anderson and Dong, 2017). In addition, this crash cause has also been found to increase the likelihood in severity if a driver is young (Zhang et al., 1998) or old (Zhang et al., 1998; Zhang et al., 2000).

Likewise, marginal effects indicate that crashes which occurred due to a driver speeding too fast for conditions have a 0.124 higher probability of resulting in an injury or fatality (Fig. 5g). As anticipated, this follows findings of several previous works where exceeding a "reasonable safe speed" has been shown to lead to more severe crashes (Chang and Mannering, 1999; Lee and Mannering, 2002; Savolainen and Mannering, 2007; Boufous et al., 2008; Kim et al., 2008; Kim et al., 2013; Rifaat and Tay, 2009; Islam and Hernandez, 2013; Qin et al., 2013; Shaheed and Gkritza, 2014; Chu, 2014; Islam et al., 2014; Anderson and Hernandez, 2017).

Lastly, and with the least effects, is the indicator for drivers who disregarded a traffic control device. According to marginal effects, crashes that occurred as a result of drivers disregarding a traffic control device have a 0.075 higher probability of resulting in an injury or fatality (Fig. 5a). Disregarding a traffic control device is a common driver error that leads to severe injuries, as documented in recent work (Mohamed et al., 2013; Bakhtiyari et al., 2015; Behnood and Mannering, 2015; Penmetsa and Pulugurtha, 2017). In addition, age has been found to impact this finding. Specifically, Amarasingha and Dissanayake (2013) found that crashes in which a young driver (15 to 24 years old) disregarded a traffic control device were more likely to result in a severe injury. Likewise, Sabbour and Ibrahim (2010) found that crashes in which young medical students disregarded a traffic control device were significantly associated with severe injuries. Xie et al. (2018) also found that disregarding a traffic control device leads to more severe injuries, as well as secondary crashes.

One final notable indicator is that of rear-end crashes, in which marginal effects show that rear-end crashes have a 0.097 higher probability of resulting in an injury or fatality. Previous work has identified a variety of factors related to rear-end crashes that increase severity, such as younger drivers (Abdel-Aty and Abdelwahab, 2004); older drivers (Abdel-Aty and Abdelwahab, 2004; Yan et al., 2005); distracted driving (Abdel-Aty and Abdelwahab, 2004); nighttime crashes (Duncan et al., 1998, 2001, 2004, 2005, 2014, 2015); driving under the influence (Duncan et al., 1998; Yan et al., 2005; Chen et al., 2015); and wet surface conditions (Duncan et al., 1998; Yan et al., 2005). Another potential factor that may lead to increased severity in rear-end crashes is vehicle size (i.e., passenger vehicle vs. freight-related vehicle). Based on these findings, and findings from previous work, a further investigation into rear-end crashes (as it pertains to right-turn crashes) is recommended.

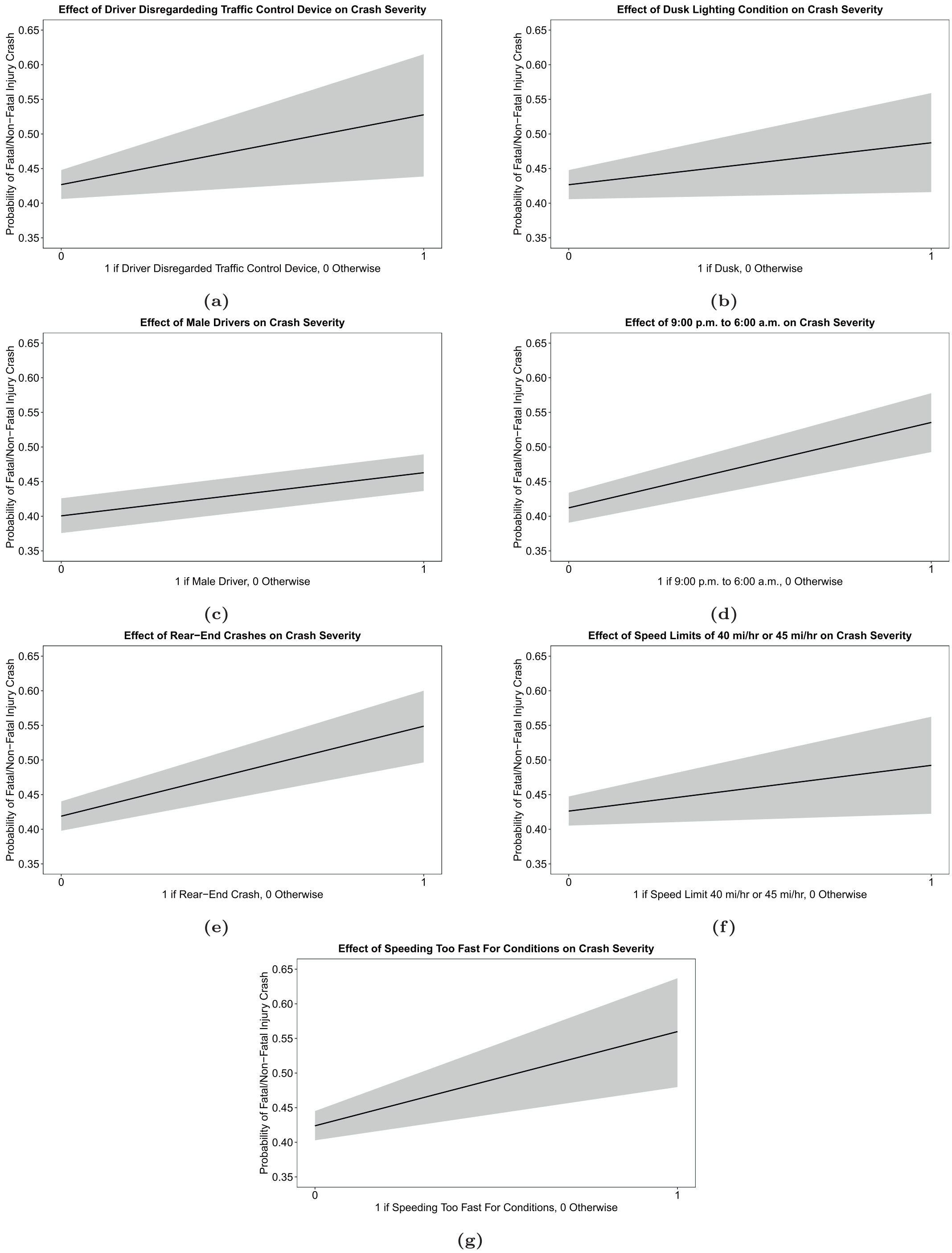


Fig. 5. Visualization of effects on crash severity probability due to (a) driver disregarding traffic control device, (b) dusk lighting, (c) male drivers, (d) nighttime crashes, (e) rear-end crashes, (f) speed limits of 40 mi/hr or 45 mi/hr, and (g) speeding too fast for conditions.

6. Conclusion

In summary, this research provided a crash severity analysis with respect to right-tun movements at signalized intersections through an econometric modeling approach. The outcome of this study can help fill the gap in current research in terms of right-turn crashes. Using five years of police- and self-reported crash data in the state of Oregon (2012 to 2016), a random parameters binary logit model was used to study the significant factors leading to the maximum injury severity sustained in the crash regardless of the participant (1 if the crash resulted in a non-fatal or fatal injury and 0 if the crash resulted in no injury). The mixed logit method attempts to capture the heterogeneity in the data (Barlow, 2019). Additionally, marginal effects were used to assess the impacts of significant factors. Using a forward step-wise procedure, 14 variables were found to be statistically significant in contributing to crash severity. The results obtained show that weather conditions, road surface conditions, fixed-object crashes, and posted speed limits (30 mi/hr or 35 mph) had heterogeneous effects. Dry road surfaces and 30 mi/hr or 35 mi/hr posted speed had higher percentages resulting in a severe crash, while fixed-object crashes and crashes in snowy weather had higher percentages resulting in a no injury crash.

On the other hand, the remaining variables were found to have homogeneous effects and assessed using marginal effects. Time-of-day (9:00 p.m. to 6:00 a.m.); lighting conditions (dusk); gender (male); crash type (vehicle–pedestrian and rear-end); and, crash cause (driver speeding too fast for conditions, driver did not yield right-of-way, driver disregarded traffic control devices) had higher probabilities of resulting in a severe crash (an injury or fatality). The results obtained show that the vehicle–pedestrian variable had the highest impact on increasing the probability of causing a severe crash. This suggests that because right turns are generally permitted during the pedestrian walk and clearance indications, it is not uncommon for right-turning drivers to make yielding errors. The design of phasing schemes at signalized intersections are complex multifaceted transportation engineering problems. Therefore, in terms of practice, this finding could help traffic engineers come up with an optimal phasing solution which could promote both the safety and efficiency of signalized intersections through decreasing vehicle–pedestrian conflicts (Hurwitz et al., 2018; Jashami et al., 2019; Kothuri et al., 2020).

This research is limited by the fact the work was done based on police- and self-reported crash data in Oregon which leaves unclear how these could be translated to real-world behavior. Oregon data does not include information on vehicle model, but only vehicle type. The data does not contain any information on the traffic signals, such as permitted right-turn-on-red, phase lengths, and so forth. This analysis was focused on driver behavior, therefore pedestrian-specific characteristics were not considered. Future work can expand on this study by including data that was not available, while other work can focus on the pedestrian aspect of these types of crashes. Additionally, crash data used for the current study does not have information related to curve radii, which work has shown to increase turning movement speeds and associated crash modification factors (Fitzpatrick et al., 2022). To address this, future work can consider a driver simulator study or SHRP2 Naturalistic Driving Study data to investigate the relationship between turning movement speed and crash frequency or severity.

There is a need for additional research to give clear guidance on the appropriate vehicle and pedestrian volume thresholds that lead to increases in safety (e.g., safety-in-numbers for pedestrians). As pedestrian volume increases, so does their visibility to drivers. This can impact driver behavior and response, such as lowering their operating speed; if a crash were to occur, it would likely be less severe. Further, questions remain about the display of signals during a crash scenario. Finally, a driving simulator study could help identify the factors contributing to such crashes. Meanwhile, drivers are not exposed to real crashes.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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