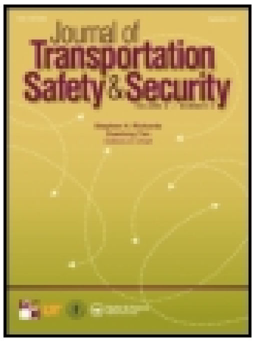

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Effects of heavy rainfall in different light conditions on crash severity during Arizona's monsoon season

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ABSTRACT

Environmental factors, including adverse weather and light conditions, have been widely recognized as contributing factors to crash severity and frequency. Heavy downpours occur during the monsoon season in Arizona and surrounding areas during the summer. Considering the effects of light conditions on driver perception of adverse weather, and thus on crash risk, this study investigates the effects of weather and light conditions on crash severity by estimating four separate multinomial logit models for specific weather (heavy rainfall or clear) and light conditions (daytime or nighttime). Marked differences were found between these conditions in terms of the significant factors affecting crash severity. Drivers likely behave differently in different environmental conditions. Findings indicated that addressing factors such as age groups, speed limits, roadway types, slow driving in heavy rain, and excessive speeding with safety strategies and educational efforts may improve traffic safety during heavy rainfall as well as in clear weather. Various other significant factors are discussed and compared based on the weather and light conditions models.

KEYWORDS

adverse weather; monsoon season; light condition; crash severity; multinomial logit model; heavy rainfall

1. Introduction

Environmental factors, including adverse weather and light conditions, have long been known to affect the severity and frequency of traffic crashes. Driving at night, in rain, snow, or other types of adverse conditions is more complicated and challenging than driving in clear daylight conditions due to reduced visibility and slippery roads. Also, vehicle maneuverability and stability decrease due to lower friction between tires and the road surface in adverse weather. Jones, Janssen, and Mannering (1991) stated that adverse weather conditions increase the risk of crashes. Koetse and Rietveld (2009) suggested that precipitation generally increases crash frequencies while decreasing their severity. To explain this relationship, Khattak, Kantor, and Council (1998) postulated that drivers may reduce their speed, maintain larger headway, and drive more carefully in adverse weather to

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compensate for reduced visibility and slippery roads. Researchers have found conflicting results on the effect of wet roadway surfaces on the severity of crashes. Lee and Mannering (2002) found wet surfaces to be a positive increasing factor in crash severity whereas Donnell and Manson (2004) found this to be a negative relationship.

According to motor vehicle crash facts (Arizona Department of Transportation [ADOT], 2015), 3,152 crashes occurred during rainy weather in the State of Arizona. These crashes resulted in 1,339 injuries and 23 fatalities. Out of all the categories of adverse weather, rainy weather had the greatest number of fatal and injury crashes. In Arizona, a significant proportion of annual precipitation falls during the North American Monsoon. According to the U.S. National Weather Service, the North American Monsoon affects Arizona during the summer between 15 June 15 and 30 September (U.S. Department of Commerce, NOAA, 2015). During this period, thunderstorms, lightning, wind, dust storms, and torrential downpours can occur, often in a short duration. In contrast, rainfall during the rest of the year is usually lighter but of longer duration. These monsoon conditions reduce driving visibility and vehicle stability, potentially increasing exposure to crash risk. Our analysis of crash data in Tucson, Arizona, revealed that between 2008 and 2012, 3.49% of traffic crashes occurred during rainy weather. Of these crashes, 40% occurred during the monsoon season, even though it represents only a small portion of annual rainfall duration. Jung, Qin, and Noyce (2010) used microscopic weather data for crashes in Wisconsin and found that severe crashes were 1.878 times more likely to occur during increased rainfall intensity (defined as rainfall amount over 15-minute intervals). They speculated that drivers may not perceive the risk of driving in intense rainfall. Furthermore, Abdel-Aty and Pemmanaboina (2006) found that the rain index (a measure of rainfall intensity) is associated with a higher probability of crashes due to visibility problems.

Torrential monsoon downpours in Tucson challenge drivers more than light winter rains and worsen visibility. The ability of drivers to adjust for this type of weather varies depending on light conditions. Various researchers have found that the crash risk increases at night (Johansson, Wanvik, & Elvik, 2009; Sullivan & Flannagan, 2002). Johansson et al. (2009 stated that the risk of injury crashes at night increases in urban, rural, and urban and rural areas combined by 30%, 50%, and 40%, respectively. Abdel-Aty (2003) demonstrated that crashes occurring in adverse weather and dark light conditions were significantly associated with higher severity. Many researchers have also found that crash severity at night is higher than crash severity during the day (Gray, Quddus, & Evans, 2008; Rifaat & Tay, 2009).

Because of the effects of environmental factors on the frequency and severity of traffic crashes mentioned above, the safety effects of environmental factors require detailed investigation. The majority of researchers have used either indicator variables to account for the effects of weather and light conditions on crash severity or aggregated crashes to analyze the effects of these factors. However, as Morgan and Mannering (2011) suggested, using indicator variables could explain only the general effects of these factors on crash injury severity. These variables may not be able to capture the changes in driving patterns and behaviors in adverse conditions. Also, they cannot quantify driver perception of conditions other than daylight clear weather. Thus, investigating the contributing factors to crash severity in different data subsets could offer an effective alternative to using indicator variables (Morgan & Mannering, 2011; Ulfarsson & Mannering, 2004).

In this study, the crashes that occurred during the monsoon season from 2008 to 2012 were separated from the main data set due to the unique nature of monsoon rainfall. Then, four separate models were estimated for specific weather (rainy or clear) and light conditions (daytime or nighttime) instead of simple indicator variables for these conditions. This allowed the significant variables to vary between subsets and thus show the difference in contributing factors to crash severity under different environmental conditions. Statistical tests showed that estimating four separate models for different weather and light conditions was statistically justifiable, and many differences in contributing factors to crash severity were present under these conditions. The results of this study could provide a better understanding of the complex effects of adverse environmental conditions on crash severity and how drivers perceive and react to these changes.

2. Data description

Crash information in Arizona is obtained through crash report forms. The full set of factors related to each crash (including crash-specific, driver, environmental, and roadway characteristics) are recorded at the scene and forwarded to the ADOT traffic record division for further analysis. In this study, only crashes that occurred in Pima County from 2008 to 2012 were used for severity analysis. This data was provided by the Pima Association of Governments (PAG) in three Microsoft Access tables:

1) Crash: This table contained a total of 69,808 crashes reported by law enforcement agencies during the study period. Incident characteristics included the time of accident, day of week, seasonal, light and weather conditions, collision type, crash location, and road type.
2) Person: This table contained information on the 195,637 persons involved in the traffic crashes including drivers, pedestrians, bicyclists, and passengers. Individual characteristics such as gender, age, safety device usage, physical condition, and violation were included in this table.
3) Unit: This table contained 136,422 mode units involved in these crashes including vehicles, pedestrians, and cyclists. So, the information provided in this table is more general without any details about the persons in crashes. Individual incident features were included in this table, including the unit's action before the crash, unusual environmental factors, unusual road factors, traffic control devices, road alignment, speed limit, and road grade.

The information in these three tables was combined based on incident ID, persons involved, and mode unit. For the purpose of this research, the 19,384 crashes that occurred during the monsoon season from mid-June to the end of September were separated from the total data set for further analysis. The crashes that occurred in clear and cloudy weather were categorized as clear weather crashes as opposed to rainy weather crashes. Rainfall in Tucson during monsoon season is usually monsoon or heavy rainfall, and thus it is unique by nature and different from rainfall in other seasons. Therefore, all rainy crashes including in monsoon or heavy rainfall are noted as “heavy rainfall crashes” hereafter.

Crashes were separated based on time of day into either daytime or nighttime categories (dark without light and dark with light). Note that the number of crashes reported during severe crosswinds, blowing dust, and dusk/dawn light conditions was very small. Therefore, these conditions were not considered in this study. Also, crashes were removed from the data set if the weather or light condition was unknown or not reported. A total of 36,813 drivers remained in the final data set. Crashes were divided into five severity levels including property damage only (PDO), possible injury, nonincapacitating injury, incapacitating injury, and fatal. Due to the small number of fatalities, incapacitating injury and fatal crashes were combined and categorized as severe crashes. Table 1 shows the frequency and percentage distribution of clear and rainy weather crashes with the subsamples of daytime and nighttime crashes. As shown in the table, sample size of severe crashes during daytime and nighttime heavy rainfall is small. Larger number of observations in the data set could definitely help to better fit the models. However, the small number of data samples for severe crashes does not affect the significance of those variables that are found by the models. A small sample size of severe crashes has also utilized in some previous studies (Jung, Qin, & Noyce, 2012; Morgan & Mannering, 2011; Shankar & Mannering, 1996). To conserve space, only the significant variables for the four models will be presented and discussed.

3. Method

Contributing factors to crash severity under different weather and light conditions were investigated in this study. As severity levels for crashes are discrete outcomes, a discrete choice model could be utilized to address this type of data. Researchers have used various discrete choice models to estimate the

Table 1. Frequency and percentage of crash severity levels by weather and light conditions.

	Severe		Nonincapacitating injury		possible injury		PDO		
Weather and light condition group	Freq.	%	Freq.	%	Freq.	%	Freq.	%	Total
Heavy rainfall crashes	35	3.61	152	15.68	159	16.41	623	64.29	969
Daytime	12	2.32	84	16.28	84	16.27	336	65.11	516
Nighttime	20	5.36	58	15.54	58	15.54	237	63.54	373
Clear weather crashes	902	4.92	2739	14.96	3037	16.59	11621	63.50	18,299
Daytime	615	4.38	2026	14.44	2423	17.27	8965	63.90	14,029
Nighttime	255	7.37	590	17.05	488	14.11	2126	61.46	3459

Note. PDO = Property Damage Only.

severity of crashes. Four levels of severity were used in this study including PDO, possible injury, nonincapacitating injury, and severe. As crash severity levels are ordinal by nature, many researchers have used ordinal probability models for crash severity analysis (Abdel-Aty, 2003; Ariannezhad, Razi-Ardakani, & Kermanshah, 2014; Kockelman & Kweon, 2002; Prato & Kaplan, 2013; Razi-Ardakani, Ariannezhad, & Vaziri, 2014). However, as suggested by previous studies, ordered response models place a restriction on the impact of variables and are also more likely to underreport the minor non-injury crashes (Islam & Mannering, 2006; Ulfarsson & Mannering, 2004). One of the most common approaches that has been widely used to analyze the crash data is multinomial logit model (Islam & Mannering, 2006; Ulfarsson & Mannering, 2004; Ye & Lord, 2011). The focus of this study is separating the data set to four different subsets based on weather and light conditions to show the differences in contributing factors to severity of crashes in different subsets. Multinomial logit model has shown reasonable results in previous studies and is still used in crash injury severity modeling (Wu et al. 2016). Therefore, this model was selected for estimating the models in this study. To introduce this model, following the study by Islam and Mannering (2006) crash severity function is defined as:

$$S_{in} = \beta_i \, X_{in} + \varepsilon_{in} \tag{1}$$

Where, S_{in} is the severity function related to crash severity level of i in crash n (in this study severity levels are severe injury, nonincapacitating injury, possible injury, and PDO); Xin is the vector of explanatory variables (in this study different crash, driver, roadway and environmental characteristics) for crash severity level of i in crash n; $\boldsymbol{\beta i}$ is the estimable coefficient vector for crash severity level of i; and ε_{in} is the random error term assuming to have extreme value distribution (Islam & Mannering, 2006). The probability function for the standard multinomial logit model could be defined as (Train, 2003):

$$P_n\ (i) = \frac{EXP[\beta_i X_{in}]}{\sum_{\forall I} EXP(\beta_I X_{In})} \tag{2}$$

Where, $P_n(i)$ is the probability that crash n results in severity outcome i and I is the set of severity levels.

A likelihood ratio test was used to indicate whether estimating four separate models for different weather and light condition is statistically justifiable. The test statistic is presented in Equation (3) (Washington, Karlaftis, & Mannering, 2010). This test is based on the null hypothesis in which it is assumed that parameters in the model with total data are similar to those in separate models.

$$X^2 = -2\left[LL(\beta_T) - \sum_{k=1}^{K} LL(\beta_k)\right] \tag{3}$$

Where, $LL(\beta_T)$ is the log-likelihood at convergence for the total data model; $LL(\beta_k)$ is the log-likelihood at convergence for the models with subset k data (weather and light conditions); and K is the total number of subsets used for modeling ($K = 4$ in this study). The resulting χ^2 test statistic is chi squared distributed with degrees of freedom equal to the difference in the summation of estimated coefficients in all subset k models and the number of estimated coefficients in the model with total data. Comparing the values for test statistic and the critical chi-squared indicates the confidence level that the null hypothesis can be rejected.

In addition to the mentioned test, a series of individual tests were conducted to test the transferability of coefficients in all four models. This likelihood ratio test is presented in Equation (4) (Washington et al., 2010).

$$X^2 = -2\left[LL\left(\beta_{k_1k_2}\right) - LL\left(\beta_{k_2}\right)\right] \tag{4}$$

In which $LL\left(\beta_{k_1k_2}\right)$ is the log-likelihood at convergence of a model using the converged parameters from data subset k_1 (using only the data of subset k_1) on data subset k_2 (using only the final estimated coefficients of k_1's model in k_2 model) and $LL\left(\beta_{k_2}\right)$ is the log-likelihood at convergence for the model with subset k_2 data. This test can also be conducted reversed using $LL\left(\beta_{k_2k_1}\right)$ and $LL\left(\beta_{k_1}\right)$. Similar to the previous test, the test statistic has chi-squared distribution with the degrees of freedom equal to the number of final significant coefficients in $\beta_{k_1k_2}$. The result of this test indicates the confidence level that the transferability of parameters could be rejected (Morgan & Mannering, 2011).

4. Results and discussion

As discussed previously, four models were estimated for crashes that occurred in daytime clear weather, nighttime clear weather, daytime rainy weather, and nighttime rainy weather. The likelihood ratio tests in Equations (3) and (4) were conducted to determine whether estimating separate models was statistically justifiable. Therefore, four separate models as well as a model with total data were estimated. After analyzing different combinations of variables, those that were statistically significant with 95% confidence interval or higher were retained in the five models. Number of final variables and log-likelihood values of these five models were used to find the value and degree of freedom for χ^2 test statistic. Based on these tests, it was determined that at the 95% confidence interval level, the four separate crash severity models provided a superior data fit compared to just the total data model. This indicated that the differences in weather and light conditions were significant contributing factors to crash severity. Detailed estimation results of the two models for crashes in daytime clear weather and nighttime clear weather are presented in Table 2. Table 3 shows the results for the crash severity models in daytime rainy weather and nighttime rainy weather. These tables show significant differences between the four models in terms of the number of factors found to be significant and also the severity levels for which each variable was significant. The cells with dashes indicate variables that were not found to be significant. As these findings show, the models had many contributing factors. The following subsections discuss and detail the results from the models.

4.1. Crash characteristics

Various factors related to crash characteristics were entered into the models. As expected, pedestrian and bicycle-related crashes tended to be more severe in all light and weather conditions except daytime rainy weather. Bicycle-related crashes that occurred in daytime clear weather were also found to increase the risk of nonincapacitating crashes. Single-vehicle, head-on, left-turn, and angle crashes in daytime clear weather were more likely to result in severe or nonincapacitating injury crashes, whereas only head-on and angle crashes increased the risk of these outcomes in nighttime clear weather. All of these collision types were insignificant in the heavy daytime rainfall model. Instead, left-turn and sideswipe collisions were found to increase and decrease the possibility of nonincapacitating injury crashes, respectively. Interestingly, for crashes in heavy nighttime rainfall conditions, rear-end collisions were found to increase the probability of severe injuries whereas they were insignificant in daytime clear conditions and increased the probability of possible injury in the two nighttime models. These findings indicated that different collision types had different effects on crash severity depending on weather and light conditions, especially in the heavy rainfall models. This may reflect differences in driving patterns for various weather and light conditions. Drivers usually reduce their speed and maintain a safer headway during heavy rainfall. However, drivers do not uniformly perceive and react to adverse weather. This could be the reason for finding different significant collision types between the models.

Out of all the variables related to road conditions, lane closures or lane shifts were most likely to increase the probability of severe crashes in nighttime clear weather, whereas the effect was insignificant in the other three models. Generally, lane closures and lane shifts occur in work zones. Arditi, Lee, and Polat (2007) investigated the effect of lighting and weather conditions on the frequency of fatal crashes in work zones and demonstrated that nighttime construction is more hazardous than daytime construction. They did not find any relationship between weather parameters and the risk of fatal crashes in work zones.

Table 2. Crash severity estimation results for daytime and nighttime clear conditions.

	Daytime clear conditions		Nighttime clear conditions	
Variable	Coefficient	*t* statistic	Coefficient	*t* statistic
Property damage-only crash				
Same-direction sideswipe	0.854	16.7	0.981	6.35
Driver age group: older than 75	—	—	0.336	2.41
Male driver	0.061	2.32	—	—
Possible injury crash				
Constant	−1.241	−38.62	−2.133	−19.8
Rear end	—	—	0.409	4.63
Same-direction sideswipe	—	—	0.771	3.93
Driver age group: 25–54	0.072	2.31	—	—
No influence of driver's physical condition	—	—	0.228	2.6
Failed to yield right-of-way	0.218	3.25	—	—
Intersection: noninterchange	—	—	0.842	8.29
Intersection related: noninterchange	—	—	0.685	7.36
Traffic control signal	−0.296	−2.8	—	—
Speed limit: 40–50 mph	0.102	3.28	—	—
Nonincapacitating crash				
Constant	−1.852	−44.58	−1.924	−19.54
Single vehicle	0.521	7.44	—	—
Angle (other than left turn)	0.571	11.44	—	—
Left turn	0.872	16.36	0.534	5.21
Head on	0.928	7.47	0.95	5
Bicycle crashes	2.271	17.64	—	—
Driver age group: 55–64	0.105	1.99	—	—
Safety device not used	1.118	9.78	1.092	5.81
Exceeded lawful speed	0.593	2.18	—	—
Alcohol	0.433	3.09	0.491	4.52
Not junction related	0.122	2.95	—	
Intersection related: noninterchange	—	—	0.19	2.05
One-way traffic way	−0.234	—2.14	—	—
Two-way undivided	−0.177	−3.47	—	—
Two-way undivided with continuous left-turn lane	0.278	4.87	0.358	2.99
Two-way divided with unprotected painted 4-foot median	0.114	2.59	0.215	2.44
Speed limit: 25–35 mph	—	—	0.314	2.82
Speed limit: 40–50 mph	—	—	0.464	4.24
Weekend	0.131	2.85	—	—
Fatal or incapacitating (severe) crash				
Constant	−3.656	−46.62	−3.622	−24.85
Single vehicle	0.693	6.06	—	—
Angle (other than left turn)	0.986	11.51	0.675	4.33
Left turn	1.234	13.31	—	—
Head on	1.803	11.25	1.133	3.95
Bicycle crashes	2.571	15.06	1.813	5.46
Pedestrian crashes	2.245	12.25	1.931	7.42
Lane-shift closure	—	—	0.0001	4.58
Driver age group: 18–24	—0.246	−2.92	—	—
Driver age group: 25–54	—	—	0.391	3.13
Driver age group: 65–74	—	—	0.674	1.95
Male driver	0.159	2.44	—	—
No safety device used	1.84	13.11	2.461	12.46
Alcohol	1.302	7.88	1.025	6.74
Drugs	—	—	1.969	3.94
Exceeded lawful speed	1.02	2.85	—	—
Not junction-related	0.212	2.73	—	—

(*Continued on next page*)

Table 2. (*Continued*)

Variable	Daytime clear conditions Coefficient	Daytime clear conditions *t* statistic	Nighttime clear conditions Coefficient	Nighttime clear conditions *t* statistic
T-intersection	0.252	2.54	0.363	1.86
Two-way undivided with continuous left-turn lane	0.565	6.24	0.629	3.25
Two-way divided with unprotected painted 4-foot median	0.356	5	0.44	3.08
Speed limit: 40–50 mph	—	—	0.394	2.98
Speed limit: 55–65 mph	—	—	0.808	4.1
Speed limit: over 65 mph	1.053	5.77	—	—
Curve left	—	—	0.789	2.87
Model				
Number of observations	27806		5710	
Log-likelihood at convergence	−26786.21		−12676.73	

4.2. Driver characteristics

Based on our findings, driver age groups had different effects on crash severity levels in various weather and light conditions. Young drivers ages 18 to 24 were found to decrease the probability of severe crashes in both daylight models, whereas they were insignificant in the nighttime models. Numerous studies have concluded that the crash rate has a *U*-shape relationship with age. Crash rate is high among young drivers, lower among middle-age drivers, and high again among older drivers (McGwin & Brown 1999). However, in a technical report by National Highway Traffic Safety Administration (NHTSA) (Liu, Utter, & Chen, 2007), analysis of NHTSA's National Automotive Sampling System — Crashworthiness Data System (NASS-CDS) from 1993 through 2004 indicated that the younger the drivers the lower the percentage of drivers to sustain severe injuries in motor vehicle crashes. These results also showed that young drivers involved in crashes with less severity more than other drivers. A lower risk of severe crashes for young drivers was also found by previous studies (Khattak et al., 1998; Xie, Zhao, & Huynh, 2012). Our results compliment these previous findings by showing that young drivers were more likely to decrease the probability of severe crashes only in daytime crashes and did not show any effect on nighttime crashes. Middle-age drivers (ages 25 to 54) were associated with an increased probability of PDO crashes in daylight clear conditions, nonincapacitating injury crashes in nighttime rainfall conditions, and severe crashes in nighttime clear conditions. These results show that middle-age drivers tended to be involved in more severe crashes in any type of adverse weather or light conditions compared to daytime clear conditions. Perhaps drivers in this age group were overconfident in their driving abilities due to multiple years of experience and thus did not maintain safe headways or speeds during adverse conditions. Rifaat and Tay (2009) found that middle-age drivers (ages 25 to 44) were more prone to involvement in higher severity crashes. Malyshkina and Mannering (2010) also found that middle-age drivers were associated with an increased probability of injury crashes. Crashes in nighttime clear conditions involving older drivers (ages 65 to 74) were more likely to result in severe injury. These drivers also increased the probability of nonincapacitating crashes in

Table 3. Crash severity estimation results for daytime and nighttime rainy conditions.

	Heavy daylight rainfall conditions		Heavy nighttime rainfall conditions	
Variable	Coefficient	*t* statistic	Coefficient	*t* statistic
Property damage-only crash				
Driving straight ahead	—	—	−0.482	−2.53
Not junction related	−0.755	−2.98	—	—
Possible injury crash				
Constant	−1.791	−11.22	−2.268	−9.93
Rear end	0.468	2.45	—	—
Driver age group: younger than 18	0.697	1.79	—	—
Driver age group: 55–64	—	—	0.651	1.75
Failed to yield right-of-way	0.959	2.09	—	—
Intersection: non-interchange	—	—	1.574	5.09
Intersection related: non-interchange	—	—	1.133	4.24
Traffic control signal	0.801	2.17	—	—
Nonincapacitating crash				
Constant	—1.458	—11.88	−2.399	−9.95
Left turn	0.989	2.96	—	—
Angle (other than left turn)	—	—	0.736	2.14
Same-direction sideswipe	—1.866	—3.07	—	—
Driver age group: 25–54	—	—	0.664	2.76
Driver age group: 65–74	0.676	1.93	—	—
No safety device used	2.225	3.37	1.381	2.41
Alcohol	2.184	2.12	—	—
T-intersection	—0.8522	—1.92	—	—
Two-way undivided	—1.482	—4.11	—	—
Two-way divided with unprotected painted 4-foot median	—	—	0.755	2.99
Weekend	0.805	3.38	—	—
Fatal or incapacitating (severe) crash				
Constant	—3.401	—8.94	−5.843	−5.8
Rear end	—	—	2.393	3.2
Head on	—	—	4.452	3.79
Bicycle crashes	—	—	9.154	3.62
Pedestrian crashes	—	—	2.148	5.2
Driver age group: 18–24	—1.953	—1.96	—	—
Male driver	—	—	1.446	2.12
No safety device used	2.998	2.89	3.852	3.94
Alcohol	3.211	2.33		—
Exceeded lawful speed	—	—	0.938	1.99
Slowing in traffic way	—	—	1.274	1.82
Making left turn	1.251	2.25	—	—
Not junction related	0.249	2.59	—	—
Two-way undivided	—2.297	—2.39	—	—
Two-way divided with median barrier	—0.97	0.52392	—	—
Weekend	1.355	2.74	—	—
Peak hours	0.888	1.99	—	—
Speed limit: 25–35 mph	—	—	−5.99	−1.93
Straight	—	—	−1.427	−2.47
Model				
Number of observations	930		586	
Log-likelihood at convergence	−1824.91		−1023.43	

daylight rainy conditions whereas their effects were insignificant in other models. As Islam and Mannering (2006) speculated, behavioral and psychological differences in different driver age groups could contribute to the marked differences in age related variables in different light and weather conditions.

There were also interesting findings concerning driver gender. Daytime clear conditions involving male drivers were more likely to result in severe and PDO crashes. Ozkan and Lajunen (2006) stated that male drivers are more skillful than female drivers, whereas female drivers are generally more careful. The carelessness and skillfulness of male drivers may explain their higher involvement in PDO and severe crashes. Male drivers also increased the probability of severe crashes in heavy nighttime rainfall conditions but were insignificant in the other two models. As Laapotti, Keskinen, and Rajalin (2003) suggested, male drivers generally show a less positive attitude toward traffic safety and rules. This could put them at higher risk, especially in heavy nighttime rainfall conditions where attention to traffic rules is essential to safe driving. Conflicting results regarding the effects of male drivers on injury severity were found by previous studies. Khattak et al. (1998) and Zhang, Lindsay, Clarke, Robbins, and Mao (2000) indicated that male drivers are more likely to be involved in severe crashes, whereas Hanley and Sikka (2012) found male drivers were associated with a decreased probability of severe crashes.

As expected, drivers without safety belts and drivers under the influence of alcohol were more likely to be involved in severe crashes in all weather and light conditions. The effect of safety belt use and driving under the influence of alcohol on crash severity has been well recognized in safety studies (Hanley & Sikka, 2012; Islam & Mannering, 2006). Among precrash driver violations, exceeding the lawful speed increased the probability of severe crashes in heavy nighttime rainfall conditions and increased the probability of nonincapacitating injury in daytime clear weather crashes. Drivers who failed to yield the right of way were more likely to be involved in possible injury crashes in the daylight models. Other violation-related variables were not significant in the models. As for driver action preceding collision, when drivers made a left turn preceding the collision, severe injury crashes in heavy daylight rainfall conditions were more likely. Lower visibility in heavy rainfall, especially while making left turns, could explain this finding.

Drivers who drove slowly in the traveled way in heavy nighttime rainfall conditions were more likely to be involved in severe crashes. Drivers usually reduce their speed, especially at night, to compensate for reduced visibility in heavy rainfall. Also, maneuverability and stability decrease in heavy rain. Therefore, excessive slowing could be more dangerous than higher speeds due to the inability of other drivers to properly react to a slow vehicle in the traffic way. This result suggests that the drivers who drive slowly in the traffic way during heavy monsoon rainfall (especially at night) should pull off the traveled way and stop and wait until the rainfall stops. It is worth mentioning that monsoon or heavy rainfall in Tucson is usually short in duration and drivers would not be greatly inconvenienced by waiting it out. Other driver actions were not significant in any of the models.

4.3. Roadway characteristics and crash time

Substantial differences existed between significant variables related to crash location in different models. Daytime crashes (under all weather conditions) at any type of non-junction-related location were more likely to result in severe injuries.

On the other hand, nighttime crashes (under any weather conditions) at intersections or intersection-related areas were more likely to result in possible injuries. Researchers have found different results on the effect of intersections on crash severity. Some studies have found that crashes occurring at intersections increased crash severity (Islam & Mannering, 2006; Zhang et al., 2000), whereas others have found a negative relationship between intersections and increased crash severity (Ulfarsson & Mannering, 2004). T-intersections were the only significant intersection factor in this study. Crashes occurring at T-intersections were more likely to be severe in clear weather conditions. On the other hand, this type of intersections decreased the probability of nonincapacitating injury crashes during heavy daylight rainfall conditions.

Different results for roadway type were observed in the models. Crashes in two-way undivided roadways with continuous left-turn lanes and two-way divided roadways with unprotected painted medians increased the possibility of severe and nonincapacitating injuries in clear weather. Two-way divided roadways with unprotected painted medians also increased the probability of nonincapacitating injury crashes during nighttime rainfall conditions. These results were similar to previous studies (Rifaat & Tay, 2009; Ulfarsson & Mannering, 2004). Ulfarsson and Mannering (2004) found that two-way roadways increased the risk of possible injury and severe crashes for male drivers of sport utility vehicles. Rifaat and Tay (2009) also found that crash severity was higher on larger volume roads such as divided with barrier and divided with no barrier. As these authors postulated, the increased traffic on higher speed roadways could explain the increased crash severity. Interestingly, for crashes in heavy daytime rainfall, two-way undivided roadways and two-way divided roadways with median barriers were associated with a decreased possibility of severe crashes. Lower vehicles speed and larger headway during heavy rainfall may contribute to this lower crash risk. The results in this study may reflect differences in driving behavior under different weather and light conditions. They suggest that drivers could avoid severe crashes on more important road categories in clear weather if they maintained a similarly safe headway and speed.

Interesting results were found for the relationship of speed limits and driving conditions. Roads with speed limits over 65 mph were found to be associated with an increased possibility of severe crashes in daytime clear conditions whereas this variable was insignificant in the other models. Crashes in nighttime clear conditions on roads with speed limits between 40 and 50 mph were more likely to result in fatal and nonincapacitating injuries. Roads with speed limits between 55 and 65 mph also increased the probability of severe crashes in these conditions. These findings suggest that in clear weather, on roadways with speed limits between 40 and 60 mph, crashes are more likely to be severe at night than during the day. An increased probability of severe crashes on roadways with higher speed limits has also been concluded in previous studies (Islam & Mannering, 2006; Lee & Mannering, 2002; Zhang et al., 2000). Roadways with speed limits between 25 and 35 mph were associated with fewer severe crashes during heavy nighttime rainfall.

Crashes during weekend and peak hours were more likely to result in severe injuries in heavy daytime rainfall conditions. Weekends also increased the probability of nonincapacitating crashes in daytime conditions. Among road alignment variables, curved roads to the left were found to increase the possibility of severe crashes in nighttime clear conditions.

5. Conclusion

Environmental factors, including adverse weather and light conditions, have long been known to affect the severity and frequency of traffic crashes. Driving behaviors and the risk of involvement in different crash severity levels vary in different weather and light conditions. Using indicator variables only explains the general effects of these factors on crash severity (Morgan & Mannering, 2011) and may not be able to capture the changes in driving patterns and behaviors in adverse weather and light conditions. In Arizona, heavy downpours occur during the monsoon season between 15 June and 30 September, often in a short duration. Due to the unique nature of monsoon rainfall, this study sought to investigate the contributing factors to crash severity in different weather and light conditions using the crashes that occurred from 2008 to 2012 in Pima County, Arizona. Four separate multinomial logit models were estimated for specific weather (rainy or clear) and light conditions (daytime or nighttime).

The likelihood ratio test indicated that estimating four separate models for different weather and light conditions was statistically justifiable. The results showed substantial differences in significant factors among the four models. Some factors such as collisions with pedestrians, bicycles, driving under the influence of alcohol, and not using safety devices increased the probability of severe crashes in all models. Crashes during heavy daytime rainfall conditions tended to be more severe for left turns preceding the collision, nonjunction areas, peak hours and weekends, and driver age between ages 65 to 75. In contrast, these crashes were less severe for drivers between ages 18 to 24, T-intersections, two-way undivided roadways, and two-way divided roadways with median barriers. Factors such as male drivers, exceeding the lawful speed, slowing in the traveled way, head on, and rear-end collisions increased the probability of severe crashes, and two-way undivided roadways with painted medians and drivers between ages 25 to 54 increased the likelihood of nonincapacitating injury crashes in heavy nighttime rainfall conditions. Crashes occurring at T-intersections, on two-way undivided roadways with continuous left-turn lanes, and on two-way divided roadways with painted medians increased the possibility of severe and nonincapacitating injuries in clear weather. Interesting results were found for the effect of speed limit on crashes in clear weather. Findings showed that speed limits over 65 mph in the daytime and speed limits between 40 to 65 mph in nighttime increased the likelihood of severe crashes. More interestingly, middle-age drivers (ages 25 to 54) were associated with increased probability of PDO crashes in daylight clear conditions, nonincapacitating injury crashes in heavy nighttime rainfall conditions, and severe crashes in nighttime clear conditions. These results show that middle-aged drivers tended to be involved in more severe crashes in adverse weather and light conditions compared with daytime clear weather.

The reason for the differences in significant variables of the four models could be due to differences of visibility, surface conditions driving behaviors, driver perception of adverse conditions, resulting reaction time, and roadway characteristics. These findings suggested that the contributing factors to crash severity levels in different weather and light conditions could be examined more carefully and addressed by safety policies. The effects of factors such as age, speed limit, roadway type, excessive speed, and excessive slowdown during monsoon or heavy rainfall could be considered by policy makers for educational efforts. Addressing these factors could improve safety during monsoon rainfall as well as other conditions.

In this study, multinomial logit model was used for the modeling process. Examining other discrete choice models such as generalized ordered logit and mixed logit models and comparing the results and performance with the current model could be an extension to this research.

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