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Abstract

The study analyzed injury severity of teenage and older drivers using 2015-2016 crash data from New Mexico. The fitness of the random-parameter ordered probit models developed for each age group was tested using likelihood ratio, comparing them to a unified model that combines both age groups, as well as comparing the random-parameter to fixed-parameter ordered probit for each age group. In both cases separate random-parameter ordered probit provided better results. It was found that vehicle type and age, lighting condition, alcohol or drugs use, speeding, and seatbelt use were significant both for the teenage and older driver injury severity. The weather condition and gender were significant only in the teenage driver model, while driver inattention was significant for older drivers. The impacts of crash factors on injury severity was analyzed using marginal effects. The results indicate notable differences in the effects of contributing factors on driver injury severity between teenage and older drivers, including the sensitivity to changes in the mutual predictor parameter values.

Keywords: Injury severity, Older drivers, Teenage drivers, Ordered probit model, Random parameter model.

1. Introduction

It is estimated that the United States will experience a remarkable increase in its senior population (65-years of age and older) in the coming decades, projected to grow from 46 million in 2015 to about 98 million in 2060 (Mark Mather 2015). The share of this age group in the total population is also predicted to grow from 15% to 24% within the same period. It can be expected that this increase in the number and share of the senior population will translate to their participation in the driver population. The projected increase in number and share of senior

drivers in the overall driver population draws attention to the driving performance of this age group as it relates to traffic safety.

According to the USA Life Expectancy report for 2015, road traffic accidents stood among the top five causes of death, with 35,092 people killed each year – a 7.2% increase from the previous year. About one fifth of the fatalities in these crashes were 65 years of age or older. The motor vehicle crashes also have a disproportionately high impact on teenage population in the U.S. (Insurance Institute for Highway Safety 2017). According to the National Center for Health Statistics, motor vehicle crashes were a leading cause of death for 15- to 20-year olds (Centers for Disease Control and Prevention 2015). In 2015, there were 1,886 vehicle crash fatalities among the drivers in this age group, an increase of 9 percent over the previous year (National Center for Statistics and Analysis 2017a). In fact, this increase is slightly higher than that found with drivers 65-years of age or older (National Center for Statistics and Analysis 2017b). Additionally, an estimated 195,000 young drivers were injured in motor vehicle crashes in 2015, an increase of 14 percent over the number of injured drivers in this age group in 2014. These rates are relatively high as compared to the overall percentage increase in crash-related fatalities (7.2%) for the same period (National Highway Traffic Safety Administration 2016). Therefore, in order to develop and evaluate the effectiveness of countermeasures and policies to improve system-wide traffic safety performance, specifically related to teenage and older drivers, it is important to better understand the significant factors of crash risks and injury severity for the drivers in these two age groups.

There are many physiological, psychological, and behavioral factors affecting individuals' driving behavior and crash risk (Ulfarsson and Mannering, 2004; Fountas and Anastasopoulos, 2018). For older drivers (65 years and older), the accumulated driving experience should make them more cautious and safer drivers in general (Islam and Mannering 2006). However, they also suffer from weakening cognitive functions that accompany aging, which is an important

factor in crashes for this age group (Lundberg et al. 1998). Cognitive functions refer to recognition, concentration, memory retention, judgment, and logical reasoning, which all influence daily activities, including driving. Stamina, vision, hearing, and reaction time are examples of other important factors that decline with aging. Fragility, which is defined as the risk of fatality per unit of travel when involved in a crash, is also an important factor that deteriorates with age and is used to explain the effect of aging among older drivers (Li et al. 2003).

Despite the fact that teenage drivers are clearly in better physical condition than older drivers, the disproportionate increase in both crash risk and frequency among them have been mainly attributed to driving skills and overconfidence, risk-taking behavior, and the tendency to engage in distracting actions, such as texting and talking on the phone (Jonah et al. 2001; Laapotti and Keskinen 1998; McCartt et al. 2003)

Among the abovementioned contributing factors, distraction is a similar issue for both older and young drivers. The results obtained from several studies imply that driver distraction, which is defined as performing a secondary activity that diverts the drivers' attention from the primary task of driving (Donmez et al. 2006), is an important factor for the injury severity analysis of drivers from different age groups (Bowman and Robertson 2016; Lam 2002). This becomes even more significant in the light of recent studies that have indicated a considerable increased risk of being distracted while driving as more technologies and devices are implemented in new vehicle (Olsen et al. 2005; Sarkar and Andreas 2004).

In general, the ability to perform multiple tasks simultaneously declines with drivers' age (McKnight and McKnight 1993). Lam (2002) found that the cognitive ability versus age is a U-shaped curve, which suggests that the risk of distraction-related crash injuries is high for 16-20-year-old drivers. This rate decreases as drivers become cognitively mature and then increases

98 for drivers older than 65 with deteriorating cognitive functioning. The types of distractions
99 affecting teenage and older drivers also seem to differ. For example, Neyens and Boyle (2008)
100 found that older drivers are more prone to cognitive distractions, while younger drivers are more
101 likely to be distracted by cell phones or other passengers. These complex differences in the
102 physical attributes and their interactions with behavioral characteristics among older and
103 teenage drivers raise the question of which factors are more critical and to what extent they
104 influence the severity of crashes for each age group.

105 Noticeably, only a few studies have been dedicated to comparing the risk factors among drivers
106 from different age groups. Weiss et al. (2014) examined the factors involved in the crash injury
107 severity for 15–24-year-old drivers in New Zealand. The analysis concluded that alcohol, failure
108 to use a seatbelt, and a lack of driving experience are the most important factors in single-
109 vehicle crashes, while risky actions, not wearing a seatbelt, and fatigue were found to be the
110 deadliest contributing factors in crashes involving two or more vehicles. Morgan and
111 Mannering (2011) investigated the role of road-surface condition, age, and gender on the crash
112 severity. The results showed that for older males driving on wet, snow-covered, or icy surfaces
113 increases the probability of sustaining more severe injuries in vehicle crashes. The effect of the
114 same parameters was found to be opposite for male drivers under 45 years of age. The findings
115 of this study also suggest that the reaction of drivers to roadway surface conditions is highly
116 correlated to the age and gender of the drivers. Islam and Mannering (2006) explored how age
117 and gender correlate to injury severity of drivers by applying six different multinomial logit
118 models. Klauer et al. (2014) reported that performing a secondary task, such as dialing a phone,
119 eating, or drinking, is associated with a significant increase in the number of crashes involving
120 younger drivers. Braver and Trempe (2004) suggested that older drivers put other vehicles,
121 themselves, and their passengers at high risk. Li et al. (2003) asserted that significant effort
122 should be made to identify countermeasures that reduce the vulnerability of older drivers to

crash injury. They expressed that fragility is more critical for older drivers than increased involvement in crashes when it comes to fatality rate per vehicle-mile of travel. Another study by Kim et al. (2013) suggested that male drivers, drunk drivers, unsafe speed, old vehicles, darkness without street lights, and driver's age of 65 years or older considerably increase the probability of fatalities in motor vehicle crashes.

However, while separate studies have been done on teenage and older drivers, it is still ambiguous how much fragility, driving experience, and other physical and behavioral factors related to these two age groups contribute to the incidence of vehicle crashes. This becomes even more important considering that there is no specific parameter to determine the fragility, experience, and even physical condition of a driver at the time of collision.

This paper suggests that a comparison between crash injury severity for teenage drivers and older drivers (65 years of age or older), considering different contributing factors such as driving experience and physical condition, may provide insight into the relative importance of each factor. The presented analysis controls for many of the driver, vehicle, roadway, weather, and crash characteristics to address this issue.

2. Methodology

2.1 Data Description

The proposed methodology was demonstrated using motor vehicle crash data obtained from the New Mexico Department of Transportation (NMDOT) for a two-year period, 2015-2016. The data set provided a wide variety of crash attributes (equivalent to crash explanatory variables), but only those most relevant to the differences between the older and teenage drivers were used in this study. These variables included driver characteristics, vehicle characteristics, environmental characteristics, and roadway factors.

Because the analysis focused on teenage and older drivers, only the injuries of drivers of the vehicles involved in crashes were considered in the analysis (i.e., passengers, pedestrians, bicyclists, and other participants were not included in the analysis). The study considered both single-vehicle and multi-vehicle crashes. As the parameters related to motorcycle crashes differ in nature from those for other motor vehicles, the crashes involving motorcycles were excluded from this study. All crashes that did not involve motor vehicles were also omitted for the same reason. Finally, the crash records with “unknown” values for the crash factors selected as explanatory variables were excluded from the analysis as well.

Driver injury severities in the NMDOT crash database are classified into five discrete ordinal classes based on the KABCO scale provided by the National Safety Council as follows: no injury, possible injury, non-incapacitating injury, incapacitating injury, and fatal injury. To overcome the problem of low frequency of fatal injuries in some classes, this study consolidated the KABCO codes into three-level injury severity outcome classes as follows: (1) no/possible injury (combining no injury and possible injury classes in the KABCO classification), (2) minor injury (equivalent to non-incapacitating injury in the KABCO classification), and (3) severe injury (combining incapacitating and fatal injury classes in the KABCO classification).

Table 1 shows the definition of the explanatory variables used in the analysis, and their corresponding frequency (denoted as n) and percentages (%) for the older and teenage drivers. The final dataset included 29,347 records among which 16,239 were drivers of the age between 16 and 20 (teenage drivers), and 13,108 were drivers of the age 65 years or older (older drivers).

2.2 Driver Injury Severity Modeling

Previous studies applied a variety of different discrete statistical models to analyze crash severity, among which the multinomial logit and ordered probit models were the most commonly used (Savolainen et al. 2011).

Yan et al. (2011) developed two separate multinomial logit models to analyze the motor vehicle-bicycle crashes in Beijing. Kaplan and Prato (2012) estimated a generalized ordered logit model to investigate the contributing factors of bus crash severity in the United States. Lemp et al. (2011) applied an ordered probit model to analyze the effects of various truck, person, and environmental characteristics on injury severity outcomes. Kockelman and Kweon (2002) applied an ordered probit model, which suggested that the manner of collision, number of vehicles involved, driver gender, vehicle type, and driver alcohol consumption considerably influence the severity of the drivers' injury.

Despite the extensive use of traditional fixed effect models, they all suffer from the problem of inability to account for the factors that can vary across observations. To overcome this problem, different random effect approaches have been presented in recent studies (Behnood and Mannering 2016; Behnood and Mannering 2017a, 2017b; Islam and Hernandez 2013; Jalayer et al. 2018; Malyshkina and Mannering 2009).

Considering that the injury severity outcomes can be treated as both nominal and ordinal, choosing the best model fit was one of the most important steps in this study. Ordered response models account for the ordering nature of the outcomes; they are easier to interpret (Zhu and Srinivasan 2011) and the results of a recent comparison also showed that ordered probit model gives a relatively better goodness-of-fit for medium and large sample sizes (Ye and Lord 2014).

Considering the underlying assumption of normality of the ordered probit models, they are usually chosen over the ordered logit models (Washington et al. 2011). To this end, two random-parameter ordered probit model were selected in this study for the analysis of factors related to injury severity of teenage and older drivers. Likelihood ratio test was also conducted to assess the need for implementing models for the two groups of drivers.

193 2.3 Injury Severity Random-Parameter Ordered Probit Model

194 In the ordered probit model, a latent variable Y_n^* , as shown in Equation (1), is used to estimate
 195 the injury severity for driver n involved in a collision:

$$196 \quad Y_n^* = \beta X_n' + \varepsilon_n \quad (1)$$

197 where X_n' denotes the column vector of independent explanatory variables; β is the row vector
 198 of regression coefficients to be estimated; and ε_n represents the random disturbance term with
 199 a standard normal distribution (Greene 2017).

200 The observed discrete crash injury severity Y_n is defined as follows:

$$201 \quad Y_n = \begin{cases} 0 & \text{if } -\infty \leq Y_n^* \leq \mu_1 & (\text{No/possible injury}) \\ 1 & \text{if } \mu_1 \leq Y_n^* \leq \mu_2 & (\text{Minor injury}) \\ 2 & \text{if } \mu_2 \leq Y_n^* \leq +\infty & (\text{Severe injury}) \end{cases} \quad (2)$$

202 where μ_i denotes unknown thresholds for injury severity levels, which are to be estimated along
 203 with the coefficient β .

204 To express how changes in the explanatory variables translate into the probability of driver n
 205 sustaining a specific level of injury, the probability functions are considered as follows:

$$206 \quad P_n(0) = \Pr(Y_n = 0) = \Pr(Y_n^* \leq \mu_1) = \Pr(\beta X_n + \varepsilon_n \leq \mu_1)$$

$$207 \quad = \Pr(\varepsilon_n \leq \mu_1 - \beta X_n) = \Phi(\mu_1 - \beta X_n),$$

$$208 \quad P_n(1) = \Pr(Y_n = 1) = \Pr(\mu_1 - \beta X_n < \varepsilon_n \leq \mu_2 - \beta X_n) \quad (3)$$

$$209 \quad = \Pr(\varepsilon_n \leq \mu_2 - \beta X_n) - \Pr(\varepsilon_n \leq \mu_1 - \beta X_n)$$

$$210 \quad = \Phi(\mu_2 - \beta X_n) - \Phi(\mu_1 - \beta X_n),$$

$$P_n(2) = \Pr(Y_n = 2) = \Pr(\varepsilon_n \leq \mu_3 - \beta X_n) - \Pr(\varepsilon_n \leq \mu_2 - \beta X_n)$$

$$= \Phi(\mu_3 - \beta X_n) - \Phi(\mu_2 - \beta X_n),$$

where Φ indicates the cumulative distribution function for standard normal distribution.

To capture the influences of unobserved heterogeneity across observations, Greene (2016) developed an estimation method based on the simulated maximum likelihood to incorporate random parameters in the ordered probit model. To this end, the new model is formulated by considering an error term, that is correlated with the unobserved factors in ε_n . The observation heterogeneity will then be translated into parameter heterogeneity as formulated in Eq. 4:

$$\beta_i = \beta + \gamma_i \quad (4)$$

where γ_i is the randomly distributed term (e.g., a normally distributed term with mean 0 and variance σ^2). The random parameters can be estimated using Halton draws to maximize the simulated log-likelihood function (Halton 1960; Milton et al. 2008). Two hundred Halton draws was decided to be used for this study as the previous research (Anastasopoulos and Mannering 2009; Bhat 2003) has shown that this number is usually sufficient for parameter estimation with a good level of accuracy. The random parameter density functions can follow one of the forms of normal, log-normal, triangular, or uniform distribution (Gkritza and Mannering 2008). Except for the lognormal distribution, which is suitable when dealing with parameters with strictly positive or negative signs (Train 2009), the other three distributions were examined in the initial analysis. As the log-likelihood was very similar for all three distributions, normal distribution was selected as it provides for easier interpretation of the estimation results.

2.4 Marginal Effects

The model coefficients should be interpreted by their signs only, not the magnitude. A positive sign implies more severe injury levels as the value of the corresponding explanatory variable increases, while a negative sign conversely implies a decrease in the driver's injury severity as the value of the related factor increases.

Despite all the information that ordinal regression analysis provides, to better ascertain the influence of each explanatory variable on the probability of each injury severity level, the need for a further analysis seems inevitable. Hence, marginal effects are employed to quantify the effect of contributing factors on the probability of each injury severity level when the corresponding explanatory variable changes the value from 0 to 1.

For binary variables, which is the case in our study, marginal effects determine the change in the probability of the severity outcome $P_n(j)$ for driver n as follows (Washington et al. 2011):

$$\Delta(j/X_{nk}) = P_n(j)[\text{given } X_{nk} = 1] - P_n(j)[\text{given } X_{nk} = 0] \quad (5)$$

where j denotes the severity level and X_{nk} is the k th independent variable for driver n .

2.4 Likelihood ratio tests

The likelihood ratio test was conducted to examine the need for having two separate models for teenage and older drivers rather than one aggregated model. With the null hypothesis of parameters being the same across the studied groups, the likelihood ratio test is formulated as follows (Washington et al. 2011):

$$\chi^2 = -2[L(\beta_A) - (L(\beta_T) + L(\beta_O))] \quad (6)$$

where $L(\beta_A)$ denotes the log-likelihood at convergence for a single model using the data for both teenage and older drivers, and $L(\beta_T)$ and $L(\beta_O)$ are the log-likelihood at convergence for teenage and older driver's models, respectively. The chi-square statistic, χ^2 , is distributed with the degree of freedom equal to the difference between the summation of coefficients estimated on the subset data models minus the number of coefficients estimated in the single data model. For the random-parameter ordered probit models, the χ^2 obtained was 35.872 with 6 degrees of freedom, which makes it larger than the critical value of 16.812 at 99% confidence level. In addition, the χ^2 obtained from the fixed-parameter models was 28.195 with 6 degrees of freedom, meaning that the null hypothesis that the parameters are the same across the studied age group is rejected, for both random-parameter and fixed-parameter models. This will later be confirmed by the model outputs.

3. Results and Discussion

3.1 Model Estimation

Based on the result of the likelihood ratio test, separate fixed-parameter and random-parameter ordered probit models were estimated for teenage drivers (age 16-20) and older drivers (65 years or older) using maximum likelihood estimation. The estimation is accomplished using the econometric software NLOGIT 6.0.

Two similar likelihood ratio tests (Eq. 7) were performed to decide between the fixed-parameter and random-parameter models for each age group:

$$\chi^2 = -2[L(\beta_{FIXED}) - L(\beta_{RANDOM})] \quad (7)$$

where $L(\beta_{FIXED})$ denotes the log-likelihood at convergence for the fixed-parameter ordered probit, and $L(\beta_{RANDOM})$ denotes the log-likelihood at convergence for the random-parameter

ordered probit model. The chi-square statistic is distributed with the degree of freedom equal to the difference between the number of coefficients estimated in fixed parameter and random-parameter models

For teenage driver models, the chi-square statistic with one degree of freedom had a value of $\chi^2 = 8.28$, which is greater than the critical value of 6.635 at 99% confidence level. Similarly, for the older driver model, the chi-square statistic with two degrees of freedom had a value of $\chi^2 = 18.88$, which was greater than the critical value of 9.210 at 99% confidence level. Therefore, it was concluded that the random-parameter models outperformed the fix-parameter models for both teenage and older driver groups.

The results of the estimation for the fixed-parameter and random-parameter ordered probit models are provided in Table 2 and Table 3 respectively. The results indicate a reasonable goodness of fit as the McFadden's pseudo R^2 for all models are greater than 0.1 (Ulfarsson et al. 2010). All the parameters included in the model are statistically significant considering the significance level of 0.1.

Based on the results presented in Table 3, it can be concluded that road surface condition, road surface type, and passenger presence have no significant effect on the injury severity in both age groups. Also, while driver sex and weather condition were found to have significant impact on the injury severity of the teenage drivers, the effect of these factors was not found to be significant for the older drivers group.

3.2 Vehicle Characteristics

The analysis shows that the vehicle type significantly impacts the injury severity outcomes. The vehicle type was found to be random for both age groups. For older drivers, the parameter is normally distributed, with the mean of -0.342, standard deviation of 0.85, and z-value of 0.4,

which indicates that 65% of observations have parameter values less than 0 and 35% greater than 0. This implies that for about 65% of the crashes, driving a pickup/SUV reduces the likelihood of severe injury for older drivers. Similarly, the z-value of 0.47 for teenage drivers indicates that for more than 68% of the crashes, the probability of sustaining severe injury decreases for pickup/SUV drivers. The results of the marginal effects also confirm that when considering a passenger car as the base vehicle type, driving a pickup/SUV decreases the probability of injury for both teenage and older drivers. This decrease can be mainly attributed to the weight of the vehicle: heavy vehicles are safer for the driver than light vehicles in general. This finding is confirmed by a previous study conducted by Levine et al. (1999), who claimed that every 454 kg increase in vehicle weight is equivalent to the driver's ability to withstand front impact crashes of 10 more km/h (6 mi/h) before being fatally injured.

The analysis also reveals that driving vehicles older than 10 years (i.e., ≥ 11 years) increases the possibility of drivers getting severely injured in both age groups, which is in line with the findings of Yasmin et al. (2014). For older drivers only, driving a 6-10 year old vehicle also increases the probability of injury, with marginal effects higher than those found for ≥ 11 years old vehicles. The effect of vehicle age can be explained by the more advanced safety feature applied in newer car models and various mechanical or structural deficiencies of the older ones.

3.3 Environmental Characteristics

Different lighting conditions significantly impact the severity of injury for older and teenage drivers. The results of the analysis for teenage drivers show that dark unlighted conditions, when compared to daylight, are associated with an increased probability of minor injury and severe injury by 0.0185 and 0.0013 respectively. In contrast, dawn/dusk condition is found to reduce the probability of injury outcomes for older drivers (a -0.0213 decrease for minor injury and a -0.0022 decrease for severe injury outcomes), but not for teenage drivers. The difference

between the two age groups can be mainly attributed to decreased vision and light sensitivity of older drivers. Also, the natural vision impairment and longer perception-reaction time in older drivers makes them more cautious so as to be prepared to react to unfavorable lighting conditions (Chen et al. 2015).

Our findings suggest that driving during precipitation increases the probability of minor and severe injury in crashes for teenage drivers. Rain and snow reduce drivers' perception in several ways. They filter away or even block some of the light source outputs making them less effective. Precipitation also impacts drivers' ability to see through the vehicle windshield; it impairs visibility, and increases the perception-reaction time, causing the drivers to concentrate their attention directly ahead to see the path. This reduces the ability to fully utilize peripheral vision, which could make it harder to see a car or pedestrian approaching from the side (Green 1983).

3.4 Driver Characteristics

For both groups, speeding is shown to lead to higher driver's injury severity, which is expected and in line with the findings of Chen et al. (2012), Williams (2003) and Simons-Morton et al. (2011). However, the marginal effects suggest that propensity of severe injury due to speeding is higher for older drivers (0.0157) than teenage drivers (0.0049).

The seatbelt use is found to be a significant factor with a random normally distributed parameters in both older and teenage driver models. In the model for older drivers the parameter has the mean of -0.255, standard deviation of 0.14, and z-value of 1.82. Given these estimates, 97% of observations have parameter values less than 0 and are found to be involved in less severe injuries when wearing a seatbelt. In the model for teenage drivers the mean was found to be -1.466 with standard deviation of 0.43 and z-value of 3.41, indicating that seatbelt use tends to reduce the severity of injury in teenage drivers in almost 100% of the crashes.

Similar to many previous studies of drunk driving (Li et al. 2018; Maistros et al. 2014; Traynor 2005; Wu et al. 2016), the analysis shows that both teenage and older drivers with a blood alcohol concentration (BAC) of .08% or higher are more likely to sustain injuries. Alcohol has been found to influence vision, awareness, and perception-reaction time of the drivers, thus increasing the likelihood of getting killed or severely injured (Behnood and Mannering 2017c).

Similar are the results for driving under the influence of drugs, as it increases the probability of being injured for drivers in both age groups. This increase can be mainly attributed to the impacts of drug-impairment on driving performance, such as undertaking risky actions and reduced awareness.

The driver inattention in the NMDOT crash database refers to any activity that took the driver's eyes off the roadway at the moment before the crash. This likely includes texting or talking on the phone. As shown in Table 5, driver inattention is associated with an increased probability of older drivers sustaining injury in crashes, increasing the odds for minor injuries by 0.070, and odds for severe injuries by 0.0007. The parameter for driver inattention is random with a calculated z-value of 0.42, which implies that for 66% of older drivers, distraction resulted in an increased likelihood of sustaining injuries in crashes. The obtained result leads us to the conclusion that older drivers put themselves at greater risk by using their cellphones while driving, or by performing other activities distracting them from the task of driving. This in line with the findings of Donmez and Liu (2015) who concluded that among all types of driver distractions, dialing and texting on cell phones has the highest negative effect on the older driver's injury severity.

When it comes to teenage drivers, the analysis did not find the driver inattention alone to be a significant factor of injury severity for this age group. The potential reason might be that it is hard to ascertain from the crash records the types of distraction other than cellphone use, such

as passenger-related distractions, in-vehicle distractions (i.e., eating, drinking, playing with the entertainment systems), and distractions by out-of-the-vehicle sources (i.e., distracted by the commercial boards and other people), which are likely to be more applicable to teenage drivers. The effects of cognitive and cellphone distractions on vehicle crashes are also mentioned in the findings of Neyens and Boyle (2008).

The gender-indicator is only significant in teenage drivers. The marginal effects show a decrease in the likelihood of minor injury and severe injury if driver is a male teenager (by -0.0048, and -0.0003, respectively). This parameter is found to be random with the mean of -0.119, standard deviation of 0.14, indicating that in over 80% of crashes male teenage drivers experience a lower injury severity level. The increased possibility of higher injury risk if the driver is female may stem from the lower injury resilience of female drivers (Khattak 2001).

4. Conclusion

This study was conducted to explore the characteristics associated with the injury severity of two vulnerable groups of drivers – teenagers and older drivers – and ascertain their behavioral differences based on the examination of a wide range of crash factors and driver characteristics. The study showed that considering teenage and older drivers in separate models outperformed a unified model where age was considered as one of the estimation factors. The analysis was conducted using random-parameter ordered probit models, which were shown to outperform fixed-parameter models in studying the driver injury severity for the teenage and older drivers.

Overall, the analysis shows that older drivers are more likely to sustain severe injuries in crashes. This can be explained by the fragility of older drivers, which exacerbates their injury severity. Similar results are discovered in a study by Kim et al. (2013).

Among all the crash factors and their corresponding parameters considered in the analysis, nine factors were found to be significant for driver injury severity for each age group, with six of them being common in both models (they are listed in Table 4 and Table 5). A brief look at the effects of factors categorized as risky actions reveals that while teenage drivers are overrepresented in all cases, the sensitivity of sustaining injury (minor or severe) to the change in parameter values (from 0 to 1) is always higher for older drivers than for teenage drivers. For example, older drivers are found to be less likely to drive under the influence of alcohol or drugs, exceed the speed limit, or not wear a seatbelt. However, the analysis of the marginal effects implies that they are more injury-prone compared to their teenage counterparts. This can likely be attributed to the reduced ability of older drivers to respond to hazardous situations due to the physical condition and age-related cognitive deterioration.

In addition, our findings implicitly support the claim that older drivers tend to drive more cautiously, especially in unfavorable driving conditions. The results of the analysis show a reduced risk of injuries for older drivers in crashes occurring during dawn/dusk, while the propensity of injury increases for teenage drivers under dark unlighted conditions. Furthermore, adverse weather (i.e., precipitation), which is found to be significant for the teenage drivers, does not impact the injury severity for the older drivers. One reason for such results is that older drivers are either more likely to avoid these driving situations or drive more conservatively during adverse weather conditions compared to teenage drivers.

Finally, assuming that older drivers are generally more risk-averse than teenage drivers, the negative effect of driver distraction (e.g., due to cell phone use), on their injury severity can be explained by the older drivers' inexperience with new technologies and their diminishing ability of effectively performing multiple simultaneous tasks.

413 Taken in concert, the results of analysis suggest that more effort and focus should be dedicated
414 to mitigation strategies, technologies, and policies addressing the physical and cognitive
415 condition of older drivers in order to reduce the rate of crashes and their severity in this age
416 group. For teenage drivers, the focus should be on mitigation strategies, technologies, and
417 policies addressing apparent lack of driving experience and responsible driving. Providing
418 better education and supervision will be helpful in this respect. For both the teenage and older
419 drivers, results of the analysis suggest that enforcement of speed limits, DUI, and seatbelt usage,
420 as well as providing effective alerts to the drivers about adverse driving conditions, would be
421 steps towards reducing the severity of crashes, considering the significance of these factors on
422 driver injury severity.

423 The presented analysis points to improvements that can be achieved in understanding traffic
424 safety aspects related to teenage and older drivers by collecting more detailed (comprehensive)
425 data on motor vehicle crashes. This would include ascertaining more descriptive attributes of
426 driver inattention preceding the crash (as opposed to noting just a single attribute of driver
427 inattention). Availability of such details in crash records would help derive more precise and
428 perhaps more revealing analysis. Furthermore, they could also give us better insight into
429 whether more tangible and intangible factors can be identified, which may also lead to a better
430 evaluation model for assessing the relative importance of driver's physical conditions, driving
431 experience, and driving behavior as factors of driver injury severity for teenage and older
432 drivers.

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1 **Table 1. Variable definition and summary statistics**

Variable	Older Drivers		Teenage Drivers	
	<i>n</i>	%	<i>n</i>	%
<i>Dependent Variable (Injury Severity)</i>				
No/possible Injury	12371	94.38%	15291	94.16%
Minor Injury	574	4.38%	789	4.86%
Severe injury	163	1.24%	159	0.98%
<i>Number of passengers</i>				
No Passenger	9782	74.63%	10887	67.04%
Passenger exists	3326	25.42%	5352	32.96%
<i>Vehicle type</i>				
Passenger car	7349	56.06%	11214	69.06%
Pickup/SUV	5759	43.94%	5025	30.94%
<i>Vehicle age</i>				
≤ 1	1984	15.14%	1577	9.71%
2 to 5	2760	21.06%	2240	13.79%
6 to 10	3449	26.31%	4369	26.90%
≥11	4915	37.50%	8053	49.59%
<i>Road surface type</i>				
Paved	12955	98.83%	15943	98.18%
Unpaved	113	0.86%	296	1.82%
<i>Road surface condition</i>				
Dry	12170	92.84%	14510	89.35%
Wet	726	5.54%	1337	8.23%
Snow/Ice	212	1.62%	392	2.41%
<i>Lighting condition</i>				
Daylight	11353	86.61%	11823	72.81%
Dawn/Dusk	372	2.84%	702	4.32%
Dark Lighted	820	6.26%	2469	15.20%
Dark Unlighted	563	4.30%	1245	7.67%
<i>Weather condition</i>				
Clear	12387	94.49%	14985	92.28%
Precipitation	655	5.00%	98	0.60%
Fog/Dust	66	0.50%	1156	7.12%
<i>Risky actions</i>				
Speeding	120	0.92%	1058	6.52%
Not speeding	12988	99.08%	15181	93.48%
Alcohol involved	222	1.69%	444	2.73%
Alcohol not involved	12886	98.31%	15795	97.27%
Drug involved	68	0.52%	105	0.65%
Drug not involved	13040	99.48%	16134	99.35%
Not wearing seatbelt	95	0.72%	186	1.15%
Wearing seatbelt	13013	99.28%	16053	98.85%
Distracted	3533	26.95%	5839	35.96%
(includes cell phone/texting)				
Not distracted	9575	73.05%	10400	64.04%
<i>Gender</i>				
Male	7495	57.18%	8677	53.43%
Female	5613	42.82%	7562	46.57%

2

Table 2. Results of estimated fixed-parameters ordered probit models for older drivers and teenage drivers

Variable description	Coefficient		SE		t-ratio		P-value	
	Old	Teenage	Old	Teenage	Old	Teenage	Old	Teenage
Number of passengers								
Passenger Exist	0.075	-	0.043	-	1.77	8.019	0.075	-
Vehicle age								
≥11	0.108	0.112	0.036	0.032	2.98	3.46	0.002	0.000
Lighting condition								
Dark Unlighted	-	0.261	-	0.051	-	5.06	-	0.000
Risky actions								
Speeding	0.653	0.569	0.129	0.503	5.07	11.31	0.000	0.000
Alcohol involved	0.409	0.351	0.109	0.078	3.74	4.50	0.000	0.000
Drug involved	0.622	0.796	0.176	0.133	3.53	5.97	0.000	0.000
Seatbelt used	-1.331	-1.099	0.127	0.094	-10.49	-11.74	0.000	0.000
Distracted	-0.006	0.073	0.025	0.033	-0.234	2.19	0.000	0.028
Gender								
Male	-	-0.084	-	0.032	-	-2.58	-	0.009
Thresholds								
μ_1	0.685	0.836	0.028	0.300	-4.542	24.29	0.000	0.000
Log-likelihood at convergence	-3128.23	-3797.92						
Log-likelihood with constant only	-3226.67	-4041.60						
McFadden's pseudo R ²	0.24	0.21						

Table 3. Results of estimated random-parameters ordered probit models for older drivers and teenage drivers

Variable description	Coefficient		SE		t-ratio		P-value	
	Old	Teenage	Old	Teenage	Old	Teenage	Old	Teenage
Vehicle type								
Pickup/SUV	-0.342 (0.85)	-0.318 (0.68)	0.057	0.044	-5.96	-7.19	0.000	0.000
Vehicle age								
6 to 10	0.241 (0.83)	-	0.077	-	-3.11	-	0.001	-
≥11	0.182 (0.38)	0.141	0.060	0.038	3.02	3.71	0.002	0.000
Lighting condition								
Dawn/Dusk	-3.512 (0.48)	-	0.655	-	-5.36	-	0.000	-
Dark Unlighted	-	0.343	-	0.059	-	5.82	-	0.000
Weather condition								
Precipitation	-	0.310	-	0.093	-	-3.31	-	0.000
Risky actions								
Speeding	1.279	0.701 (0.37)	0.169	0.059	7.53	11.87	0.000	0.000
Alcohol involved	0.409 (0.97)	0.439	0.179	0.089	2.28	4.93	0.022	0.000
Drug involved	1.252	1.050	0.232	0.151	5.38	6.95	0.000	0.000
Seatbelt used	-2.552 (0.14)	-1.466 (0.43)	0.162	0.100	-15.71	-14.58	0.000	0.000
Distracted	0.122 (0.29)	-	0.056	-	2.16	-	0.030	-
Gender								
Male	-	-0.119 (0.14)	-	0.039	-	-3.06	-	0.002
Thresholds								
μ_1	1.322	1.084	0.052	0.038	25.14	28.20	0.000	0.000
Log-likelihood at convergence	-3118.79	-3793.78						
Log-likelihood with constant only	-3458.33	-4011.57						
McFadden's pseudo R^2	0.26	0.22						

10 **Table 4. Marginal effects of the older driver model**

Variable	No/Possible injury	Marginal Effects	
		Minor Injury	Severe Injury
Vehicle Type			
Pickup/SUV	0.0141	-0.0124	-0.0017
Vehicle Age			
6 to 10	-0.0095	0.0084	0.0011
≥11	-0.0077	0.0068	0.0009
Lighting Condition			
Dawn/Dusk	0.0235	-0.0213	-0.0022
Risky Actions			
Speeding	-0.0857	0.0700	0.0157
Alcohol involved	-0.0214	0.0184	0.0030
Drug involved	-0.0855	0.0698	0.0157
Seatbelt used	0.3166	-0.2183	-0.0984
Distracted	-0.0056	0.0700	0.0007

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12 **Table 5. Marginal effects of the teenage driver model**

Variable	No/Possible injury	Marginal Effects	
		Minor injury	Severe injury
Vehicle Type			
Pickup/SUV	0.0156	-0.0146	-0.0009
Vehicle Age			
≥11	-0.0060	0.0057	0.0003
Lighting Condition			
Dark Unlighted	-0.0199	0.0185	0.0013
Weather Condition			
Precipitation	-0.0100	0.0095	0.0005
Risky Actions			
Speeding	-0.0568	0.0519	0.0049
Alcohol involved	-0.0290	0.0269	0.0021
Drug involved	-0.1248	0.1099	0.0148
Seatbelt used	0.2360	-0.1967	-0.0393
Gender			
Male	0.0051	-0.0048	-0.0003

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