Factors Related to More Severe Older Driver Traffic Crash Injuries

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Abstract: The population of the U.S. is aging, and the number of older persons licensed to drive keeps increasing. With the aging population and increase in the number of older licensed drivers, addressing safety issues related to older drivers is becoming more crucial every day. This paper reports on the analysis of 1990–1999 crash data from the State of Iowa in which an older driver (age ⩾65 years) was injured. The main focus of the study was to isolate factors that contribute to more severe injuries to older drivers involved in traffic crashes. The ordered probit modeling technique was used to investigate factors from vehicle, roadway, driver, crash, and environmental characteristics that can potentially contribute to older driver crash injury severity. Model findings were primarily as expected. New findings from this study were that older drivers who consumed alcohol were more likely to be seriously injured and older driver injuries in farm vehicles were more severe as compared with other types of vehicles. The writers discuss implications of the findings for the safety of older drivers.

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Introduction

According to the National Highway Traffic Safety Administration (NHTSA), 253,000 individuals aged 65 years or older were killed or injured in traffic crashes in 1999. Although persons aged 65 years and older represent only 13% of the total U.S. population, they constituted 17% of all traffic fatalities and 16.5% of all vehicle occupant fatalities in 1999 (NHTSA 2000). Furthermore, according to the Federal Highway Administration (FHWA), the number of older persons who are licensed to drive continues to increase (FHWA 2000).

The United States' population is undergoing a major demographic transformation that is resulting in a larger proportion of older individuals in the population. Due to major advances in medical technology, life expectancy has increased substantially, resulting in the "aging" or "graying" of the population. With the aging population and the increase in the number of older licensed drivers, addressing safety issues related to older drivers is becoming more crucial every day.

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Research Objectives

Previous research indicates that, when involved in a crash, older drivers are more vulnerable to injury and fatality as compared with other drivers. Factors that tend to contribute to injury severity in older drivers have been discussed in various research reports. This paper presents an analysis of known factors identified through previous research efforts and explores the statistical significance of additional factors related to older driver traffic crash injuries. Specifically, the objectives of this paper include:

- To conceptualize and investigate factors from driver, vehicle, environment, roadway, and crash characteristics that tend to increase injuries to older drivers involved in traffic crashes, and
- To quantify the impacts of significant factors on different severity levels of older driver injuries.

This research utilized crashes involving injured older drivers that were reported in Iowa between 1990 and 1999. By taking into account data spanning ten years, the writers were able not only to isolate important contributory factors to severity of older driver injuries but also to assess changes in injury severity of older Iowa drivers over time.

The next section provides a review of literature on crashes involving older drivers and the severity of their injuries. After that, the characteristics of dataset analyzed in this study are described and data analysis methodology presented. Finally, the research conclusions and a brief discussion on implications of the findings for transportation agencies are presented.

Background

As people age, they become more susceptible to injury of all types, including traffic accidents. Injury propensity increases with the aging process and is due to age-related changes in the human body, such as deterioration of sight and hearing, the onset of muscle, joint, and skeletal disorders, and deterioration of mental

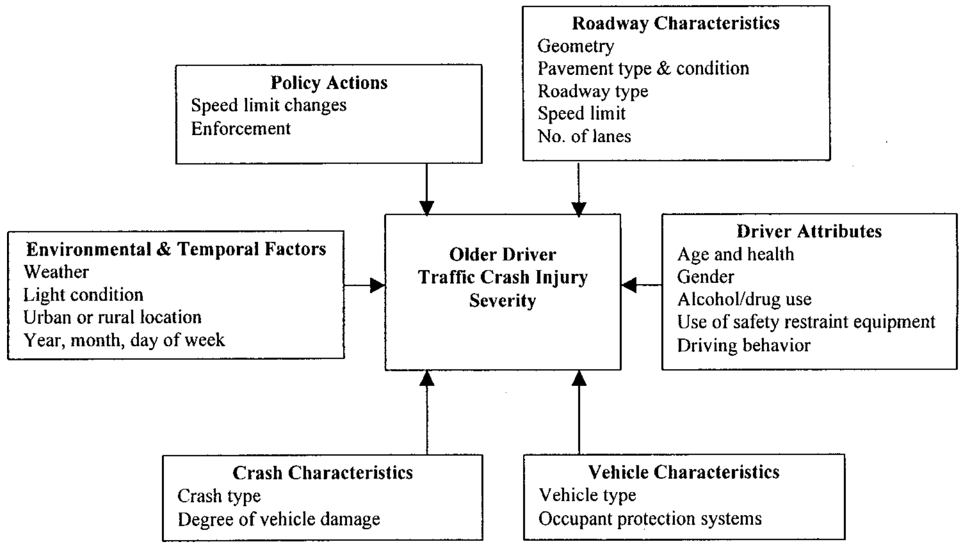

Fig. 1. Conceptualization of injury severity

and physical response times. Mercier et al. (1997) reported that driver age was an important factor in predicting injury severity in head-on collisions and the use of lap and shoulder restraints appeared more beneficial to men than to women in such crashes. They also reported that deployed air bags seemed more beneficial to women than to men. Evans (1991) found that the fatality risk for a given impact at age 70 was three times higher than the same impact for a driver at 20. Many of the same factors that increase injury propensity in older drivers also lead to an increased likelihood of crash involvement (McKelvey and Stamatiadis 1989; Zegeer et al. 1993; Richardson et al. 1996; Rogers 1997; Kim et al. 1998).

Staplin et al. (1998) suggested that older drivers were more likely to commit certain types of driving violations that lead to crash involvement. Their study indicated that drivers aged 65 and older demonstrated a significantly higher proportion of "failure-to-yield" violations and were more likely to be charged with "driver inattention," "disregarding a signal control," and "disregarding a stop/yield sign" than drivers aged 50–64. A study by the U.S. Dept. of Transportation (1993) reported that, 18% of the time, the primary error made by older drivers that resulted in a crash was a right-of-way violation. Fourteen percent of primary error attributed to older drivers resulting in crashes was making errors at signed or signalized intersections, excessive speed was the primary error for 5%, and another 5% was attributed to driver inattention (including falling asleep at the wheel). In only 2% of the crashes, blood alcohol concentrations (BAC) were above 0.1% for drivers aged 65 and older. However, this BAC level was observed in 6% of fatalities involving drivers aged 65 and older.

Previous research has identified factors that are related to automobile crashes for older drivers. Stamatiadis et al. (1991) indicated that, in terms of involvement to exposure ratio, drivers in the age group from 70+ were overrepresented in accidents involving any turning movement, head-on accidents while turning left, accidents in rural areas at night, and in snowy weather. An earlier study by Stamatiadis et al. (1990) identified overrepresentation of crashes by older drivers at nonsignalized intersections. Another study found that 47% of older driver fatalities occurred as a result of right-angle collisions and 20% as a result of head-on/left-turn collisions. The same study indicated that injuries most frequently resulted from rear-end collisions (38%); 25% were right-angle collisions, and 15% of injuries resulted from head-on/left-turn crashes at signalized intersections. At nonsignalized intersections, rear-end crashes were the most frequent (35%) cause of injury, followed by right-angle crashes (18%), other-angle crashes (10%), and head-on/left-turn crashes (Staplin et al. 1998). Garber and Srinivasan (1991) found that older driver involvement at intersections was higher outside cities, likely due to driving behavior. They also reported that, if older drivers were in an accident, they were more likely to have committed a traffic violation and that older drivers were more likely to commit traffic violations at stop-controlled intersections. Preusser et al. (1998) indicated that older drivers were most likely to have a crash involving multiple-vehicles at an intersection with a particularly high crash risk at uncontrolled and stop sign-controlled intersections.

Conceptualization and Data Compilation

A number of factors can potentially affect injury severity in a crash. These can be grouped by categories including policy actions, roadway characteristics, driver attributes, vehicle characteristics, crash characteristics, and environmental and temporal factors (Fig. 1). Each category consists of multiple factors that could potentially contribute to the severity of injuries in a crash. Ideally, each factor would be analyzed for relevance; however, availability of data limited the actual number of factors that could be investigated to those contained on the police accident report.

Data from the Iowa crash records include information about various roadway, driver, vehicle, crash, and weather characteristics. The crash records also contain information on injury severity of the persons involved in the crash. Crash injuries in Iowa are rated by the crash investigating police officer on the KABCO scale of severity: Killed (fatality), A-type (incapacitating), B-type (visible or evident), C-type (complaint of pain), and PDO (property damage only/other). This scale of injuries is fairly common across the U.S. and widely utilized during previous research studies (O'Donnell and Connor 1996; Council et al. 1997; Duncan et al. 1998; Renski et al. 1999). The writers had 113,522 records available representing crashes reported during 1990–1999 in Iowa involving older drivers.

To discern meaningful relationships among older driver injury severity and the influencing factors, a subset of the original crash database that related specifically to older driver injuries was extracted. The reported crash data were limited to crashes involving older drivers (age $\geqslant 65$ years) in which an injury was reported. The data were limited to the categories represented by KABC; i.e., property damage crashes were taken out of the data, since they do not indicate injury to the driver. Other reasons for excluding property damage crashes were the likelihood of greater nonreporting bias compared to injury crashes, data handling consideration (most computer spreadsheets can handle a limited number of records), computer storage and memory requirements, and time and efficiency considerations in the model estimation process. The resulting analysis file contained 17,045 observations representing crashes that involved older drivers who sustained an injury. A description of the salient features of the dataset analyzed in this study follows.

Data Characteristics

Table 1 presents some of the salient features of the older driver crash dataset. Injury statistics show about 3% of the drivers were killed, whereas 11 percent sustained incapacitating injuries. About 38% of the crashes involved evident injuries to the older driver and 47% of the crash victims complained of pain. Slightly more males were injured than females, probably because there are more older male drivers than female in Iowa. The average older driver in the dataset was 74 years, and the crash victim age distribution indicates many more older drivers in the 65–75 year category than the 76–85 and 85-plus year categories. Again, this trend in age distribution is most likely due to driver population. Slightly more than 1% of the recorded crashes involved older drivers under the influence of alcohol.

A majority of the crashes involved a collision with another vehicle. The second most numerous crash type was vehicles striking fixed objects. Crashes involving animals were relatively few as compared with other types of crashes. A majority of the crashes occurred during daylight, perhaps because of older drivers electing to drive mostly during daylight hours. Different types of vehicles were involved in the crashes, with passenger cars accounting for about 83%. Passenger cars were followed by pickup trucks and sports utility vehicles. Because of the farm industry in Iowa, the relative proportion of pickup trucks to other vehicles may be somewhat high as compared with other states. Further, farm vehicle traffic is significant during the fall and spring season, even though its percentage involvement is low. A majority of crashes were reported on highways with 88 kmph (55 mph) speed limit. Most crashes occurred in the rural environment, as expected, given the rural setting of Iowa, and most of the reported crashes were on U.S./state highways.

Data Quality and Possible Biases

Iowa crash records are compiled by police agencies and processed at the Iowa Dept. of Transportation (DOT) by utilizing the Accident Processing System (APS). The APS extensively validates crash data and resolves inconsistencies to ensure good quality. Exclusion of noninjury crashes reduced nonreporting bias in the analysis; however, it is possible that the remaining data still include some bias from nonreporting. Another source of bias in the data may be from relying on police officers, who may not have adequate medical training, to consistently rate injuries. Non-

Table 1. Characteristics of Iowa Older Driver Crash Data, 1990–1999

Description	Value
Number of crashes involving an older driver	17,045
Reported number of injuries (%)	
K-type (fatality)	531 (3.1)
A-type (incapacitating injury)	1,925 (11.3)
B-type (evident or visible injury)	6,545 (38.4)
C-type (complaint of pain, possible injury)	8,044 (47.2)
Crash victim gender (%)	
Male	9,107 (53.4)
Female	7,930 (46.5)
Crash victim age (%)	
Between 65 and 75 years	10,578 (62.1)
Between 76 and 85 years	5,509 (32.3)
Above 85 years	958 (5.6)
Crashes involving older drivers under alcohol influence (%)	190 (1.1)
Major types of crashes (%)	
Vehicle overturned	286 (1.7)
Collision with vehicle in traffic	13,754 (80.7)
Collision with parked vehicle	360 (2.1)
Collision with animal	175 (1.0)
Struck fixed object	1,732 (10.2)
Other	738 (4.3)
Lighting condition at time of crash (%)	
Daylight	14,970 (87.8)
Dawn or dusk	371 (2.1)
Dark	840 (4.9)
Lighted	816 (4.8)
Involved vehicle types (%)	
Passenger car	14,118 (82.8)
Pickup trucks	1,638 (9.6)
Other trucks	302 (1.7)
Sports utility	557 (3.3)
Motorcycles	87 (0.5)
Farm vehicles	80 (0.5)
Other	263 (1.5)
Crash distribution across different highway speed limits (%)	
105 kmph (65 mph)	487 (2.9)
88 kmph (55 mph)	4,335 (25.4)
80 kmph (50 mph)	437 (2.6)
72 kmph (45 mph)	1,083 (6.4)
65 kmph (40 mph)	325 (1.9)
56 kmph (35 mph)	2,619 (15.3)
40 kmph (25 mph)	3,597 (21.1)
Other/unknown	4,162 (24.4)
Urban/rural split of crashes (%)	9,542 (56.0)/7,502 (44.0)
Crash road classification (%)	
Interstate	893 (5.2)
U.S. or state highway	7,724 (45.3)
County road	2,038 (12.0)
City street	6,352 (37.3)
Other	38 (0.2)

Note: Categories not adding to 100% have missing values.

reporting biases are expected to be minimal, because the study focused on injury crashes, but reliance on police officers to rate injuries probably introduces some bias. While K-type crashes (fatalities) and A-type (incapacitating) injuries are fairly obvious, the categories B-type (visible or evident) and C-type (complaint of pain) are more difficult to evaluate consistently. As with most state crash files consisting of police officer recorded data, more detailed injury data are not readily available in Iowa.

Modeling Injury Severity

The dependent variable in this study was the severity of injury sustained by older drivers involved in traffic crashes. The crash severity scale is ordinal (K-type representing most severe and C-type representing minimal injuries). The appropriate models to use for ordinal data are ordered probit and ordered logit models. Although the results from the two models are fairly similar, several researchers (O'Donnell and Connor 1996; Duncan et al. 1998; Renski et al. 1999) have used the ordered probit model in safety-related studies.

According to Long (1997), the ordered probit model can be derived from a measurement model in which a latent, unobservable, continuous variable y^* ranging from $-\infty$ to $+\infty$ is mapped to an observed ordinal variable, say, injury severity with four levels (KABC), denoted by y. Variable y^* provides injury propensity and variable y is thought of as providing incomplete information about the underlying y^* according to the measurement equation:

$$y_i = m \quad \text{if } \tau_{m-1} \leq y_i^* < \tau_m \tag{1}$$

where the τ's are thresholds or cut points between the intervals. The extreme categories, 1 and J, are defined by open-ended intervals with $\tau_0 = -\infty$ and $\tau_J = \infty$. The observed y is related to y^* according to the measurement model:

$$y_i = \begin{cases} 1 \Rightarrow \text{C-type injury} & \text{if } \tau_0 = -\infty \leq y_i^* < \tau_1 \\ 2 \Rightarrow \text{B-type injury} & \text{if } \tau_1 \leq y_i^* < \tau_2 \\ 3 \Rightarrow \text{A-type injury} & \text{if } \tau_2 \leq y_i^* < \tau_3 \\ 4 \Rightarrow \text{K-type injury} & \text{if } \tau_3 \leq y_i^* < \tau_4 = \infty \end{cases} \tag{2}$$

The ordered probit model has the structural form

$$y_i^* = \mathbf{x}_i \boldsymbol{\beta} + \varepsilon_i \tag{3}$$

where $\mathbf{x}_i$ is a row vector (with 1 in the first column for the intercept); β is a column vector of structural coefficients (with the first element being the intercept β_0); and ε is an error term.

The maximum likelihood (ML) estimation is used to estimate the regression of y^* on $\mathbf{x}$. However, to use ML estimation, distribution of the error term, ε, must be assumed. For the ordered probit model, ε is assumed distributed normal with mean 0 and variance 1. The probability density function (pdf) and the cumulative distribution function (cdf), respectively, are

$$\phi(\varepsilon) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{e^2}{2}\right) \tag{4}$$

$$\Phi(\varepsilon) = \int_{-\infty}^{\varepsilon} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{t^2}{2}\right) dt \tag{5}$$

After specification of the error term, the probabilities of observing values of y given $\mathbf{x}$ can be computed. The probability of any observed outcome $y = m$ given $\mathbf{x}$ is

$$\Pr(y_i = m | \mathbf{x}_i) = \Phi(\boldsymbol{\tau}_m - \mathbf{x}_i \boldsymbol{\beta}) - \Phi(\boldsymbol{\tau}_{m-1} - \mathbf{x}_i \boldsymbol{\beta}) \tag{6}$$

To estimate the model, let $\boldsymbol{\beta}$ be the vector with parameters from the structural model, with the intercept $\boldsymbol{\beta}_0$ in the first row, and let $\boldsymbol{\tau}$ be the vector containing the threshold parameters. Either $\boldsymbol{\beta}_0$ or $\boldsymbol{\tau}_1$ is constrained to 0 to identify the model (the software used in this study assumes $\boldsymbol{\tau}_1 = 0$). From Eq. (6):

$$\Pr(y_i = m | \mathbf{x}_i, \boldsymbol{\beta}, \boldsymbol{\tau}) = F(\boldsymbol{\tau}_m - \mathbf{x}_i \boldsymbol{\beta}) - \Phi(\boldsymbol{\tau}_{m-1} - \mathbf{x}_i \beta) \tag{7}$$

where F represents Φ; and the probability of observing whatever value of y was actually observed for the ith observation is

$$p_i = \begin{cases} \Pr(y_i = 1 | \mathbf{x}_i, \boldsymbol{\beta}, \boldsymbol{\tau}) & \text{if } y = 1 \\ \vdots & \\ \Pr(y_i = m | \mathbf{x}_i, \boldsymbol{\beta}, \boldsymbol{\tau}) & \text{if } y = m \\ \vdots & \\ \Pr(y_i = J | \mathbf{x}_i, \boldsymbol{\beta}, \boldsymbol{\tau}) & \text{if } y = J \end{cases} \tag{8}$$

If the observations are independent, the likelihood equation is

$$L(\boldsymbol{\beta}, \boldsymbol{\tau} | y, X) = \prod_{i=1}^{N} p_i \tag{9}$$

Combining Eqs. (7)–(9):

$$L(\boldsymbol{\beta}, \boldsymbol{\tau}, | y, X) = \prod_{j=1}^{J} \prod_{y_i = j} \Pr(y_i = j | \mathbf{x}_i, \boldsymbol{\beta}, \boldsymbol{\tau}) = \prod_{j=1}^{J} \prod_{y_i = j} [F(\boldsymbol{\tau}_j - \mathbf{x}_i \boldsymbol{\beta}) - F(\boldsymbol{\tau}_{j-1} - \mathbf{x}_i \boldsymbol{\beta})] \tag{10}$$

$\Pi_{y_i = j}$ indicates multiplying over all cases where y is observed to equal j. Taking logs, the log likelihood is

$$\ln L(\boldsymbol{\beta}, \boldsymbol{\tau} | \mathbf{y}, X) = \sum_{j=1}^{J} \sum_{y_i = j} \ln[F(\boldsymbol{\tau}_j - \mathbf{x}_i \boldsymbol{\beta}) - F(\boldsymbol{\tau}_{j-1} - \mathbf{x}_i \boldsymbol{\beta})] \tag{11}$$

Model estimation involves maximizing Eq. (11) using numerical methods to estimate the $\boldsymbol{\tau}$'s and the $\boldsymbol{\beta}$'s. The marginal effects of factors $\mathbf{x}$ on the underlying injury propensity can be evaluated by taking the partial derivative of Eq. (6) with respect to $\mathbf{x}_k$, resulting in

$$\frac{\partial \Pr(y = m | \mathbf{x})}{\partial \mathbf{x}_k} = \frac{\partial F(\boldsymbol{\tau}_m - \mathbf{x}\boldsymbol{\beta})}{\partial \mathbf{x}_k} - \frac{\partial F(\boldsymbol{\tau}_{m-1} - \mathbf{x}\boldsymbol{\beta})}{\partial \mathbf{x}_k}$$

or

$$\frac{\partial \Pr(y = m | \mathbf{x})}{\partial \mathbf{x}_k} = \beta_k [\phi(\boldsymbol{\tau}_{m-1} - \mathbf{x}\boldsymbol{\beta}) - \phi(\boldsymbol{\tau}_m - \mathbf{x}\boldsymbol{\beta})] \tag{12}$$

The partial change or marginal effect is the slope of the curve relating $\mathbf{x}_k$ to $\Pr(y = m | \mathbf{x})$, holding all other variables constant, and is usually computed at the mean values of all variables. For a dummy independent variable, the derivative while treating it as a continuous variable provides an approximation that, according to Greene (1997), is "often surprisingly accurate." A measure of the model goodness of fit (ρ^2) can be calculated as

$$\rho^2 = 1 - \left[\frac{\ln L_b}{\ln L_0}\right] \tag{13}$$

where $\ln L_b$ = log likelihood at convergence; and L_0 = restricted log likelihood. The ρ^2 measure is bound by zero and one. Values of ρ^2 closer to one indicate better fit of the model.

Table 2. Ordered Probit Model Results

Category	Independent variable	Estimated coefficient	z-statistic	Marginal values C-Type	B-Type	A-Type	K-Type
Driver	Age (in years)	0.018	13.441	−0.0073	0.0035	0.0029	0.0009
	Gender (male=1, female=0)	0.086	4.833	−0.0344	0.0165	0.0135	0.0044
	Absence of occupant protection systems (absence=1, presence=0)	0.525	19.668	−0.2091	0.1001	0.0821	0.0269
	Drunk (under influence=1, otherwise=0)	0.283	3.372	−0.1126	0.0539	0.0442	0.0145
Roadway	Curves in level terrain (curve in level terrain=1, otherwise=0)	0.122	2.134	−0.0489	0.0234	0.0192	0.0063
	Speed limit (in km per hour)	0.008	15.578	−0.0035	0.0017	0.0014	0.0004
	Roadway class is city street (city street=1, otherwise=0)	−0.085	−3.950	0.0340	−0.0163	−0.0134	−0.0044
Vehicle	Farm vehicle (farm vehicle=1, otherwise=0)	0.354	3.157	−0.1411	0.0675	0.0554	0.0181
Crash	Vehicle overturned (overturned=1, otherwise=0)	0.204	2.954	−0.0814	0.0390	0.0320	0.0105
	Fixed object struck (hit fixed object=1, otherwise=0)	0.211	7.010	−0.0840	0.0402	0.0330	0.0108
	Animal related crash (animal involved=1, otherwise=0)	−0.170	−1.694	0.0680	−0.0325	−0.0267	−0.0087
	Hit parked vehicle (parked vehicle=1, otherwise=0)	0.212	3.382	−0.0844	0.0404	0.0331	0.0108
	Hit train (hit train=1, otherwise=0)	0.955	6.280	−0.3801	0.1820	0.1493	0.0489
Environment	Rural environment (rural=1, urban=0)	0.274	13.320	−0.1091	0.0522	0.0428	0.0140
	Dark, unlit conditions (dark, unlit conditions=1, otherwise=0)	0.143	3.650	−0.0570	0.0273	0.0224	0.0073
	Indicator for pre-1997 crashes (pre-1997=1, post-1997=0)	−0.104	−5.481	0.0417	−0.0200	−0.0164	−0.0054
Model-specific attributes	Constant	−1.750	−16.449	0.6962	0.3333	0.2734	−0.0895
	μ_2	1.225	94.137	⋯	⋯	⋯	⋯
	μ_3	2.107	93.616	⋯	⋯	⋯	⋯

Note: Model summary statistics: Number of observations=17,036; degrees of freedom=16; log likelihood=−17,278.98; restricted log likelihood =−18,337.94; rho-squared (ρ^2)=0.057. Dependent variable injury severity details: k-type=killed/fatality, coded 3; A-type=incapacitating, coded 2; B-type=visible and evident, coded 2; C-type=complaint of pain, possible injury, coded 0.

Modeling Results

An ordered probit model with injury severity of older drivers as the dependent variable and some of the factors shown in Fig. 1 as the independent variables was estimated. Table 2 presents the modeling results. A positive estimated coefficient in the model implies increasing injury severity with increasing values of the explanatory variable. Independent variables from each category that were tried in the model specification as well as the ones that the model indicated as significantly contributing to injury levels are discussed below. The marginal values provide information on how the injury severity probabilities change with a unit change in the value of an independent variable beyond its mean value when all other variables are held at their means. Thus, the marginal effects allow us to determine the impact of each independent variable on the probability of each level of injury severity.

The model indicates a positive estimated coefficient for driver age, which is statistically significant at the 95% confidence level (a z-statistic of 1.96 or higher indicates significance at the 95% confidence level). This indicates that advancing age increases the propensity of more severe injury to older drivers, as expected. The positive sign of the estimated coefficient for gender (coded as male=1, female=0) in the model indicates that older male drivers experience more severe injuries when compared with older female drivers. The presence of occupant protection systems was investigated by including an indicator variable for cases where a protection system was not available in the vehicle in the model specification. As expected, the model indicated strong statistical evidence that unprotected older drivers incurred more severe injuries. The model also indicated evidence that older drivers under the influence of alcohol experience more severe injuries when compared with older drivers who are not under the influence.

Several roadway characteristics were examined for their influence on injury levels of older drivers. The model indicated that crashes occurring on horizontal curves in level terrain were more injurious as compared with crashes occurring at other locations. Speed limit was included in the model specification to evaluate its effect on injury severity of older drivers. As expected, injury levels were higher on higher speed limit roadways. Roadway classification was investigated for its effects on injury levels of older drivers; the model indicated that injury levels were low on city streets as compared with other classes of roadways, again as expected. Different types of vehicles (passenger car, pickup truck, etc.) were tried in the model specification. Interestingly, crashes involving farm vehicles resulted in significantly higher injury levels as compared with other types of vehicles.

Crash type was also evaluated as a contributory factor. As expected, the model indicated that overturned vehicles, vehicles striking fixed objects, vehicles hitting other parked vehicles, and those hitting trains resulted in more severe injuries to older drivers as compared with other types of crashes. Crashes involving animals were not as injurious as other types of crashes (the variable is statistically significant at the 90% confidence level).

Environmental factors, such as rural/urban setting and light condition at the time of crash, were investigated. The model indicated that injuries to older drivers tended to be more severe if the crash occurred in a rural area. Crashes in dark, unlit conditions also resulted in more severe injuries to older drivers. Finally, temporal effects were investigated for trend in injury severity levels of older drivers by using indicator variables for data reported in each year. Although there was no trend evident from year to year, the model indicated that crashes prior to 1997 were of lower severity level as compared with those reported in 1997 and after.

Other variables, such as different weather conditions and differences in injury levels across highway sections and intersections, were explored but the model did not indicate the presence of any statistical evidence. These variables were then excluded from the model specification for parsimony.

Marginal values for driver age show that for a one-year increase in a driver's age beyond the mean value (74 years), the probability of a C-type injury decreases by 0.0073, and this is captured by an increase in the probability of B-type (0.0035), A-type (0.0029), and K-type (0.0009) injuries, provided other variables in the model are kept at their means. Note that the marginal effects sum to zero; this follows from the requirement that the probabilities add to 1. Except for crashes on city streets, those involving animals, and those that occurred prior to 1997, all other independent variables in the model increase the likelihood of B-type, A-type, and K-type injuries.

Discussion on Model Results

The model for older driver injuries indicated the statistical significance of various explanatory variables in predicting injury severity. Several had been reported in prior research efforts while some new factors were discovered as well. Advancing driver age and absence of occupant protection systems increase older driver injury severity. Reasons for the significance of both factors are relatively straightforward: increased age and a lack of protection in the vehicle increases vulnerability to injury. The finding that male older drivers are more prone to injury as compared with older females is somewhat unexpected and needs further investigation. The model indicates that older drivers under alcoholic influence experience more severe injuries. The role of alcohol in crash causation is well-established; however, this finding indicates an added effect of alcohol in terms of more severe injuries to the drunk older driver. Most likely, drunk older drivers do not take evasive maneuvers to prevent or reduce injury in a crash. This information can be utilized in driver educational and awareness programs.

Among roadway characteristics, crashes occurring on curves in level terrain were more injurious to older drivers. The roadway network in Iowa consists mostly of straight highway sections. It is possible that older drivers may not fully compensate in terms of vehicle speed for curves on the highways. This may result in more severe injuries at curves on level terrain when compared with other locations.

A unique and new finding of this study is that injuries to older drivers in farm vehicles are more severe as compared with other vehicles. Farm vehicle traffic in Iowa significantly increases during the spring and the fall. Although usually slow moving, farm vehicles are unique and significantly different in design than the "regular" vehicular traffic on roadways. It is possible that farm vehicles offer a different level of safety as compared with passenger cars and trucks, resulting in more severe injuries to older drivers. This issue needs further research to discern factors that lead to more severe older farm vehicle driver injuries and to assess if relatively young drivers are also affected similarly.

Crashes that resulted in overturned vehicles, vehicles hitting fixed objects or parked cars, and vehicles hitting trains were more injurious to older drivers. Animal-related crashes resulted in relatively less severe injuries to older drivers, most likely since the animals rather than the vehicles/drivers receive most of the impact.

Crashes that occurred in rural areas and those that occurred under dark, unlit conditions were more injurious to older drivers. One reason for more severe injuries in rural areas may be related to how quickly crash victims receive help. Less traffic in rural areas may delay crash notification and the relatively limited access to regular telephones and partial mobile phone coverage may further exacerbate the situation. Help to crash victims in rural areas may also be delayed due to larger travel distances as compared with urban areas. The reasons for more severe injuries in crashes occurring in dark, unlit conditions are perhaps the diminished eyesight of older drivers and longer reaction times when encountering a sudden, critical traffic situation.

The model indicates lower injury levels for pre-1997 crashes. The U.S. Congress repealed the National Maximum Speed Limits in 1995 and Iowa increased speed limits on many of its highways in 1996. It is possible that the increase in speed limits may be responsible for increased levels of injuries to older drivers, especially since the Iowa DOT has documented an overall increase in fatalities, injuries, and total crashes following the speed limit change (IDOT 1998). This issue, however, requires more in-depth analysis.

The findings from this study have several important implications for the safety of older drivers. Advancing age increases the propensity of more severe injury, and older drivers need to be aware of this when they are considering a reduction in driving. Alcohol consumption by older drivers and absence or nonusage of occupant restraint systems significantly increase injury levels. These strengthen the current policy of emphasis on reduction in alcohol-related driving and enforcement of restraint usage. Transportation agencies may consider installing curve warning signs or using rumble strips on long sections of highways that are followed by curves to alert older (and younger) drivers to oncoming curves in the road geometry. Older driver injuries in crashes involving farm vehicles need further investigation to assess causal factors behind the higher levels of injury severity. Assessment of the effects of policy actions regarding increase in speed limits needs in-depth investigation.

This study indicated that several factors found significant during previous safety-related research on older drivers are also significant in case of drivers in Iowa. It was successful in uncovering some new variables, as well. This study did not explore variations in injury severity within subgroups of older drivers and did not compare older drivers to younger drivers. Future studies may focus on investigation of subgroups of older drivers and on younger drivers to uncover differential impacts of the factors identified in this study or perhaps uncover new factors. Further, this study was focused on factors that lead to more severe injury to older drivers and crash causation was not investigated. Future studies may focus on both crash causation and injury severity.

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