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Driver aging and its effect on male and female single-vehicle accident injuries: Some additional evidence

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Abstract

Introduction: This study explores the differences in injury severity between male and female drivers, and across the different age groups, in single-vehicle accidents involving passenger cars. *Method:* Given the occurrence of an accident, separate male and female multinomial logit models of injury severity (with possible outcomes of no injury, injury, and fatality) were estimated for young (ages 16 to 24), middle-aged (ages 25 to 64), and older (ages 65 and older) drivers. *Results:* The estimation results show statistically significant differences in the factors that determine injury-severity levels between male and female drivers and among the different driver age groups. *Conclusions:* We discuss a number of plausible explanations for the observed age/gender differences and provide suggestions for future work on the subject. *Impact on Industry:* A better understanding of age and gender differences can lead to improvements in vehicle and highway design to minimize driver injury severity. This paper provides some new evidence to help unravel this complex problem.

Keywords: Accident injury severity; Gender differences; Age differences

1. Introduction

By 2030, it is estimated that the number of Americans aged 65 years and older will double to 70 million and constitute 20% of the population (U.S. Department of Transportation, 2003). Today, this population cohort (65 years old and older) constitutes roughly 13% of the population but represents 16% of the total highway fatalities (National Highway Traffic Safety Administration [NHTSA], 2004). There are also disturbing trends with regard to older drivers. From 1981 to 2000, fatality rates (traffic deaths per 100,000 drivers) for drivers aged 16 to 24 declined roughly 23%, and for those aged 25 to 64 these rates declined about 17%. However, during this same period, fatality rates for drivers aged 65 to 74 held steady while the rates for drivers aged 75 and older rose by 7% (U.S. Department of Transportation, 2003). These numbers suggest that the significant advances in highway safety (with various design improvements in signalization, signage, and crash attenuation), vehicle safety (with introduction of airbags and active safety systems such as antilock brakes), and safety countermeasures (safety belt laws, impaired driving enforcement) that have occurred over this time period have, for some reason, not been nearly as effective for older drivers as they have been for other age groups.

There are many physiological, psychological, and behavioral reasons to expect fundamental differences in the driving behavior and the resulting accident injuries of different age groups. For example, accumulated driving experience and levels of acceptable risk are two factors that are known to change with age. At the same time, there are also the physical/reflex degradation issues that result in longer reaction/perception times, quicker onset of fatigue, reductions in the

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ability to process information, reductions in strength and mobility, and degradation in vision and hearing as drivers age (Smith, Meshkati, & Robertson, 1993). However, as individual drivers age, there is clearly a complex interaction among behavioral and physical elements. For example, as drivers gain experience, potentially making them safer drivers, they are also confronted with these general age-related degradations. At some point, the age-related degradations exceed the benefits accrued from increasing experience and drivers become more likely to become involved in severe accidents as they age. There could also be vehicle and highway design issues that contribute to this phenomenon. For example, there is a body of literature that suggests that vehicles are not ergonomically designed for older drivers (with their potential limited movement) and that this may be a contributing factor to older-driver accident frequency and severity (Herriotts, 2005).

Another previously-researched but still not well understood matter relates to how risk perception and risk-taking behavior change as drivers age and how age affects the response of drivers to improvements in vehicle safety characteristics (airbags, antilock brakes, traction control systems), and highway safety (improvements in highway design and traffic control). As one recent example of possible risk compensation and offset behavior resulting from improvements in safety, Winston, Maheshri, and Mannering (2006) provide empirical evidence suggesting that improvements in vehicle safety (the mass introduction of airbags and antilock brakes) have been largely negated by individuals who drive more aggressively because of the perceived reduction in accident risk that such safety features provide.

Complicating matters relating to driver aging are the prevailing differences between male and female drivers. Several studies have found significant differences in vehicle accident rates between males and females (Laberge-Nadeau, Maag, & Bourbeau, 1992; Mannering, 1993; Massie, Campbell, & Williams, 1995), and others have found significant differences in male and female accident injury severities (Evans, 1988; Abdel-Aty & Abdelwahab, 2001; Evans, 2001; Ulfarsson & Mannering, 2004; Dellinger 2005). The results of these research efforts suggest there are significant behavioral and physiological differences between male and female drivers that influence the severity of vehicle accidents and that these differences may change as drivers age.

To be sure, many studies have explicitly addressed the effects of driver aging and gender. The majority of these have focused on the likelihood of accident involvement (Abdel-Aty, Chen, & Radwan, 1999; Abdel-Aty & Radwan 2000; Kim, Li, Richardson, & Nitz, 1998; Lourens, Vissers, & Jessurun, 1999; McGwin & Brown 1999; Richardson, Kim, Li, & Nitz, 1996; Ryan, Legge, & Rosman, 1998; Stamatiadis & Deacon 1995). However, others have focused on differences in accident injury severity given the occurrence of an accident (Kim, Nitz, Richardson, & Li, 1995; Ulmer, Williams, & Preusser, 1997).

In this paper, we seek to provide some additional evidence to the growing body of literature on the effects of aging and gender on driver-injury severity. We do so by conducting a disaggregate-level (individual accident) statistical analysis of driver injuries in single-vehicle accidents in the state of Indiana (United States). Our analysis will control for many of the highway characteristics (e.g., pavement type, pavement condition, traffic control, speed limit, and roadside features), vehicle attributes (e.g., vehicle age and tire condition), environmental factors (e.g., fog, snow, and rain), and driver behavior (e.g., safety belt usage, avoidance maneuvers, and vehicle occupancy). We will statistically test the differences between age and gender with regard to driver-injury severity. Our results will provide some additional insights into this important problem and begin to suggest some ways to address age/gender differences to improve highway safety.

2. Methods

To analyze the effect of gender and age on driver-injury severity, we will limit our analysis to police-reported, single-vehicle passenger-car accidents occurring in the state of Indiana in 1999. This allows us to define a manageable problem by eliminating the confounding effects of accidents involving multiple vehicles (2 or more) and the associated driver age/gender combinations. In 1999, in Indiana, single-vehicle passenger-car accidents accounted for nearly half of all fatal accidents, a third of the injury accidents, and a quarter of the no-injury accidents. The dynamics that determine driver-injury severity in multi-vehicle accidents can be significantly different than those in the single-vehicle accident case (e.g., Ulfarsson & Mannering, 2004), thus our findings cannot be generalized to the multi-vehicle case.

In the current study, three driver-injury severity outcomes are considered: no injury (property damage only), injury, and fatality. Because possible driver-injury outcomes are discrete and have an order from lower severity to higher severity, an ordered probability model, such as an ordered probit or ordered logit, would seem appropriate. In fact, there are a number of research studies that have used ordered probability models for injury severity analysis. For example, Abdel-Aty (2003), Duncan, Khattak, and Council (1998), Khattak (2001), Khattak, Pawlovich, Souleyrette, and Hallmark (2002), Kockelman and Kweon (2002), Kweon and Kockelman (2003), O'Donnell and Connor (1996), Renski, Khattak, and Council (1999), Yamamoto and Shankar (2004) all have used this technique. However, while typical accident-injury-severity data are indeed ordered, many studies have used unordered multinomial discrete-outcome models because ordered probability models place a restriction on the impact of variables (see Carson & Mannering, 2001; Chang & Mannering, 1999; Khorashadi, Niemeier, Shankar, & Mannering, 2005; Lee & Mannering, 2002; Shankar, Mannering, & Barfield, 1996; Ulfarsson & Mannering, 2004). To see the restriction implied on variables when using the ordered probability approach, consider our three driver-injury outcomes (no injury, injury, and fatality). Suppose that one of the key factors in determining the level of injury is whether or not an airbag was deployed. The airbag-deployment indicator variable in an ordered model is constrained (due to the model structure) to either increase the probability of a fatality (and subsequently decrease the probability of property damage only) or decrease the probability of fatality (and subsequently increase the probability of property damage only). But the reality may be that the deployment of an airbag increases the probability of an injury by reducing fatalities but increasing minor injuries (from airbag deployment). In an unordered discrete-modeling framework, this would result in the statistically estimated coefficient for the air bag deployment variable having a negative value in the severity function for the fatality outcome and also a negative value for the no-injury outcome (with the injury outcome having an increased probability in the presence of an air-bag deployment). If this situation exists, an ordered probability model may be less appropriate because it does not have the flexibility to explicitly control interior severity-category probabilities.

Another potential problem with using an ordered probability approach is the likely presence of under-reporting of accidents, particularly minor non-injury accidents. In the presence of such under-reporting, it can readily be shown that all estimated coefficients of an unordered multinomial logit, discrete-outcome model are consistent except for the constant term (see McFadden, 1981; Washington, Karlaftis, & Mannering, 2003). However, the presence of underreporting in an ordered probability model can result in biased and inconsistent coefficient estimates.

Thus, one must be cautious in the selection of ordered and unordered discrete-outcome models. A tradeoff is inherently being made between recognizing the ordering of responses, potential biases in coefficient estimations, and losing the flexibility in specification offered by unordered probability models. In this study, as in many others, we chose the unordered discrete outcome models as the model for injury severity.

The most widely applied discrete-outcome modeling approach has been the multinomial logit model. For accident-severity outcomes, this model defines a function that determines driver injury severity as,

$$S_{in} = \beta_i \mathbf{X}_{in} + \varepsilon_{in} \tag{1}$$

Where S_{in} is the function that determines the probability of discrete outcome i for accident observation n, $\mathbf{X}_{in}$ is a vector of measurable characteristics (highway geometric variables, environmental conditions, driver characteristics, etc.) that determine the injury severity for accident n, β_i is a vector of estimable coefficients, and ε_{in} is an error term accounting for unobserved effects influencing the injury severity of accident n.

It can be shown that if ε_{in} are assumed to be extreme value distributed (see McFadden, 1981), then a standard multinomial logit model results (estimated by maximum likelihood),

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

where P_n (i) is the probability that accident n will result in driver injury outcome i and I is the set of possible accident-severity outcomes.

To assess the vector of estimated coefficients (β_i), we calculate elasticities that measure the magnitude of the impact of specific variables on the outcome probabilities. The elasticity is computed for each accident n (n subscripting omitted) as

$$\mathrm{E}_{x_{\mathrm{ki}}}^{\mathrm{P(i)}} = \frac{\partial P(i)}{\partial x_{ki}} \times \frac{x_{ki}}{P(i)} \tag{3}$$

where $P(i)$ is the probability of driver injury severity outcome i and x_{ki} is the value of variable k for outcome i. Using Eqs. (2), (3) gives

$$E_{x_{ki}}^{P(i)} = [1-P(i)]\beta_{ki}x_{ki}. \tag{4}$$

where β_{ki} is the estimated coefficient associated with variable x_{ki}. Elasticity values can be roughly interpreted as the percent effect that a 1% change in x_{ki} has on the severity-outcome probability $P(i)$.

Note that elasticities are not applicable to indicator variables (those variables taking on values of 0 or 1). In these cases, a pseudo-elasticity can be calculated as

$$E_{x_{ki}}^{P(i)} = \frac{EXP[\Delta(\beta_i \mathbf{X}_i)] \sum_{\forall I} EXP(\beta_{kI} x_{kI})}{EXP[\Delta(\beta_i \mathbf{X}_i)] \sum_{\forall I_n} EXP(\beta_{kI} x_{kI}) + \sum_{\forall I \neq I_n} EXP(\beta_{kI} x_{kI})} - 1, \tag{5}$$

where I_n is the set of alternate injury-severity outcomes with x_k in the function determining the outcome, and I is the set of all possible injury-severity outcomes. The pseudo-elasticity of a variable with respect to a driver injury severity category represents the percent change in the probability of that severity category when the variable is changed from zero to one. Thus, a pseudo-elasticity of 0.95 for a variable in the no-injury category means that when the value of the variable in the sub-set of observations where $x_k = 0$ are changed from 0 to 1, the probabilities of the no-injury outcome for these observations increased, on average, by 95%. See Washington et al. (2003) for a complete explanation of elasticities.

A critical element of our statistical analysis will be to evaluate differences among different age groups and gender while controlling for the multivariate influences that impact driver-injury severity such as highway geometric variables, environmental conditions, driver characteristics. To accomplish this within the multinomial logit modeling framework that we have chosen, we will split our sample by male and female and further split by drivers' age groups. Following a vast body of literature (U.S. Department of Transportation, 2003), we classify drivers into three age groups: younger drivers (16–24 year old drivers), middle-aged drivers (25–64 year old drivers), and older drivers (drivers 65 years of age and older). For each age group within each gender, separate multinomial logit models are estimated. Thus a total of six multinomial logit models are estimated (three age groupings for females and three age groupings for males).

To test if the accident injury-severity models are significantly different between genders and age groups, two versions of the likelihood ratio test can be applied (Washington et al., 2003). The first estimates a model on all data (all of the age and gender groups being tested) and then estimates separate models on each individual age/gender group. The test statistic is:

$$X^2 = -2\left[LL(\beta_T) - \sum_G LL(\beta_g)\right] \tag{6}$$

where $LL(\beta_T)$ is the model's log-likelihood at convergence of the model estimated on all age and gender groups being tested, $LL\ (\beta_g)$ is the log-likelihood at convergence of the model estimated on subset data from age/gender group g, and G is the set of all age/gender groups. This statistic (X^2) is χ^2 distributed with degrees of freedom equal to the summation of coefficients estimated in the subset-data models minus the number of coefficients estimated in the total-data model.

The second version of the test is used to compare two individual age/gender groups. The test statistic is:

$$X^2 = -2[LL(\beta_{AB}) - LL(\beta_B)] \tag{7}$$

where $LL(\beta_{AB})$ is the model log-likelihood produced using Group B's data using group A's estimated coefficients (the coefficients at convergence of a model estimated on group A's data) and $LL(\beta_B)$ is the log-likelihood at convergence using group B's data (coefficients are no longer restricted to group A's converged coefficients as is the case for $LL(\beta_{AB})$). This will also be reversed such that Group A's data is used with group B's estimated coefficients. For this test, the statistic is again χ^2 distributed with degrees of freedom equal to the number of estimated coefficients.

The combination of these two test statistics will allow us to make definitive statistical statements with regard to the differences between age/gender groups while controlling for a broad range of factors known to impact driver-injury severity in a multivariate analysis.

3. Data and results

The data used in this research were obtained from the Accident Information System for the state of Indiana. The system contains information on reported accidents and includes the circumstances, location, surrounding conditions of the accident and a description of the driver, including license, injury, and alcohol/drug test information. We consider only single-vehicle accidents involving passenger cars with driver injury characterized as fatality, injury, and no injury (property damage only). Fatalities are classified as an injured driver that dies within 30 days of the collision due to injuries sustained during the collision. Property damage only accidents do not result in any type of injury.

Table 1
Multinomial logit model for young (ages 16–24 years) male driver injury in single-vehicle passenger car accidents

Variable	Estimated coefficient	t-ratio
Constant [F]	−5.420	−6.80
Constant [I]	−0.576	−2.88
Driver had been drinking [F]	1.061	3.48
Driver had been drinking [I]	0.549	6.50
Driver used no restraints [F]	1.946	7.44
Driver used no restraints [I]	1.056	9.51
Driver fell asleep [F]	1.424	1.87
Driver fell asleep[I]	0.629	2.94
Driver fatigued [I]	0.558	2.20
Driver illness [I]	0.947	1.62
Operating a defective equipment [I]	−0.503	−2.84
Tire defect [I]	−1.002	−3.26
Making a turn [NI]	0.665	6.95
Merging or changing lanes [I]	0.530	2.09
Rural area [I]	−0.664	−3.91
Urban interstate [I]	−0.487	−2.30
Residential area [I]	−0.639	−3.68
Commercial/industrial/public space [NI]	−0.569	−3.15
Intersection related [I]	0.844	6.85
Posted speed limit >55 mi/h [I]	−0.157	−1.67
Driver had no restraints and posted speed limit >40 mi/h [F]	0.288	2.15
Blacktop road [I]	0.162	2.14
Wet road [F]	−0.947	−2.17
Fog/smoke/smog [I]	−0.778	−2.85
Snow/sleet/hail/freezing rain [F]	−1.786	−1.76
Snow/sleet/hail/freezing rain [I]	−0.632	−5.40
Rainy weather [I]	−0.345	−4.12
After dark[I]	−0.170	−3.02
Overturned/Rollover [F]	0.942	3.27
Overturned/Rollover and driver had no restraints [I]	0.306	1.72
Struck a pole or tree [F]	0.517	1.94
Struck a pole or tree [I]	0.470	7.86
Driver ejected [F]	4.225	6.60
Driver ejected [I]	2.830	5.24
Driver trapped [I]	1.750	4.41
Vehicle less than 5 years old [F]	0.544	2.16
Driver carrying one or more passengers [F]	1.190	4.71
Driver carrying one or more passengers [I]	0.444	8.20
Winter [I]	−0.276	−4.06
Spring [NI]	0.113	1.72
After midnight [F]	0.622	2.21
Vehicle use-personal [F]	−1.442	−2.18
Animal(s) present on the roadway [F]	−2.673	−2.63
Animal(s) present on the roadway [I]	−1.493	−14.28
Avoidance maneuver [I]	0.392	1.93
Traffic control: signal [I]	0.324	1.74
Traffic control: yield sign [I]	−0.914	−1.55
Sideswipe, same direction [I]	−0.427	−3.21
Driver age: Number of years less than 25 [F]	0.150	2.61
Driver age: Number of years less than 25 [I]	0.018	1.54
Log-likelihood at zero:		−9162.4
Log-likelihood at convergence:		−4662.8
Number of observations:		8340

Variables are defined for outcomes: [NI] no-injury, [I] injury, [F] Fatality.

As discussed previously, a total of six models were estimated: young male drivers (ages 16 to 24), young female drivers (ages 16 to 24), middle-aged male drivers (ages 25 to 64), middle-aged female drivers (ages 25 to 64), older male drivers (ages 65 and older), and older female drivers (ages 65 and older). To conserve space, we present only the coefficient estimates for the young male driver model as an illustration (see Table 1). This table shows that a large number of factors were found to significantly influence driver-injury severity.

While our estimation results show that individual coefficient estimates varied significantly across age/gender groups (more on this below), likelihood ratio tests were conducted to confirm these differences (as shown in Eqs. (6) and (7)). For differences between the genders in each of the three age groups, almost all tests indicate that the hypothesis that the male and female severity models are equal can be rejected with over 99.5% confidence. This includes comparing a combined male/female model with separate male/female models (as indicated in Eq. (6)) and comparing male-converged coefficients using female data and female-converged coefficients using male data (see Eq. (7)). The one exception was the combined male/female model with separate male/female models (see Eq. (6) for the test statistic) in the older-age category, which indicated rejection of the null hypothesis of equality between the genders at the 86% confidence level. The results show generally significant differences between men and women in the three age groups.

For differences between age groups within each gender, for all likelihood ratio test combinations, the hypothesis that the age groups were the same was rejected with over 99.5% confidence. Thus, there is compelling statistical evidence to suggest that there are significantly different determinants of accident-injury severity by age for both men and women.

To provide information on individual models' estimation results, we present average elasticity comparisons across age groups and genders (individual elasticities are computed for each accident in the age/gender group data sample and then averaged over that sample). As Table 1 indicates, the models have an extensive list of explanatory variables. To keep the elasticity-comparison tables to manageable size, and to highlight the important differences among age/gender groupings, we present only variables that produced estimated coefficients that resulted in an average elasticity above 1.0 in at least one of the age/gender models, and compare their elasticities with other age/gender models. For indicator variables, an elasticity of 1.0 implies a 100% increase in the outcome probability, so these are variables that have a large impact. Please note that restricting the impact of a variable to this 1.0 elasticity standard excludes many significant variables. For example, driver intoxication had a significant impact on injury severity in all of the models but did not always cross the 1.0 average elasticity threshold.

Table 2 presents elasticity comparisons for male drivers across the three age groups. Among the six variables in the table that were significant across all age groups, there are

Table 2
Comparison of elasticities for variables in the models for male drivers of young, middle-age and older age groups (elasticities are specific to driver injury: [NI] no-injury, [I] injury, [F] Fatality)

Young male (ages 16–24)	Elasticity	Middle-aged male (ages 25–64)	Elasticity	Older male (ages 65 and greater)	Elasticity
Variables significant in all three models					
Driver used no restraints [F]	2.11	Driver used no restraints [F]	2.93	Driver used no restraints [F]	2.13
Driver used no restraints [I]	1.01	Driver used no restraints [I]	1.47	Driver used no restraints [I]	1.32
Intersection related [F]	0.73	Intersection related [F]	1.57	Intersection related [F]	0.60
Driver fell asleep [I]	0.51	Driver fell asleep [I]	1.02	Driver fell asleep [I]	1.30
Overturned/Rollover [F]	1.54	Overturned/Rollover [F]	1.16	Overturned/Rollover [F]	2.20
Overturned/Rollover [I]	0.24	Overturned/Rollover [I]	1.38	Overturned/Rollover [I]	1.33
Variables significant in two of the three models					
Driver fell asleep [F]	1.32	Driver fell asleep [F]	1.42		
Driver fatigued [I]	0.45	Driver fatigued [I]	1.33		
Driver ejected [F]	3.88	Driver ejected [F]	5.06		
Driver ejected [I]	2.86	Driver ejected [I]	3.22		
Driver trapped in [I]	1.71	Driver trapped in [I]	4.06		
Driver carrying one or more passengers [F]	1.14	Driver carrying one or more passengers [F]	0.70		
Vehicle less than 5 years old [F]	0.71			Vehicle less than 5 years old [F]	2.16
		Driver trapped [F]	5.24	Driver trapped [F]	101.58
Variables significant in only one of the three models					
		Exceeded reasonable speed or speed limit [F]	1.25		
		Friday/Saturday after midnight [F]	1.56		
		Violation of driver's license [I]	7.15		
				Spring [F]	2.58
				Struck a pole or tree [F]	2.43
				Fog/smoke/smog [F]	20.00
				Driver illness [F]	3.00
				Number of years over 65 [F]	1.38

some noteworthy differences. For example, accidents that resulted in an overturned/rollover increased the likelihood of a fatality by 220% for older males but only 116% for middle-aged males. Such accidents increased the likelihood of injury by 133% and 138% for older and middle-aged males respectively, but only 23.6% for young males.

For variables significant in two of the three models, there are also some interesting findings. For example, drivers carrying one or more passengers at the time of the accident increased the likelihood of driver fatality by 114% for young males and 70% for middle-aged males, but had no significant effect on the fatality likelihood of older males.

Vehicles less than 5 years old were found to increase the likelihood of fatality for older males by 216% and for younger males by 71%, but did not have a significant effect on middle-aged male fatality likelihoods. This finding may reflect differences in driving behavior and/or vehicle purchase patterns within these age groups. For example, there is the possibility that young and older males are overcompensating for the safety features (airbags and antilock brakes) that are more likely to be present in these newer vehicles by driving more aggressively. To make a definitive statement along these lines, a thorough analysis would have to be undertaken to control for self-selectivity (the fact that riskier drivers may be more likely to be attracted certain vehicle types). Controlling for this vehicle selectivity requires highly detailed information on individual vehicle safety features, which is beyond the capabilities of our data (see Winston et al., 2006 for the type of data needed and the modeling methodologies required to address this problem).

The variables found to be significant in only one of the three models also showed interesting differences. Among these is the number of years over 65. This is a continuous variable that indicates that a 1% increase in the age over 65 results in a 1.38% increase in the likelihood of a fatality. This finding underscores the effects of aging on fatality risk as males drive over 65 years, even with the many aspects of the accident that are being controlled for in our multivariate analysis.

Table 3 presents elasticity comparisons for female drivers across the three age groups. As with the male models, this table shows interesting differences across the age groups. For example, when restraints (safety belts) were not used, the likelihood of injury increased 119% for young females, 164% for middle-aged females, and 187% for older females. Accidents occurring in rural areas increased the likelihood of fatality by 208% for young females but had no significant effect on the driver injury outcomes of the other female age groups. Also, vehicles 6 years old and older increased the likelihood of injury for middle-aged female drivers by over 200%, but had no significant effect on other female age categories. This may suggest some fundamental vehicle design issues possibly relating to the safety systems on these older vehicles (positioning of airbags, airbag acceleration rates, etc.).

Table 3
Comparison of elasticities for variables in the models for female drivers of young, middle-age and older age groups (elasticities are specific to driver injury: [NI] no-injury, [I] injury, [F] Fatality)

Young female (ages 16–24)	Elasticity	Middle-aged female (ages 25–64)	Elasticity	Older female (ages 65 and greater)	Elasticity
Variables significant in all three models					
Driver used no restraints [I]	1.19	Driver used no restraints [I]	1.64	Driver used no restraints [I]	1.87
Driver trapped [F]	3.03	Driver trapped [F]	8.00	Driver trapped [F]	70.90
Overturned/Rollover [F]	1.16	Overturned/Rollover [F]	2.02	Overturned/Rollover [F]	5.23
Overturned/Rollover [I]	1.04	Overturned/Rollover [I]	1.25	Overturned/Rollover [I]	2.41
Driver used no restraints [F]	2.13	Driver used no restraints [F]	3.01		
Driver ejected [F]	2.62	Driver ejected [F]	6.63		
Driver ejected [I]	1.61	Driver ejected [I]	3.10		
Driver trapped [I]	2.67	Driver trapped [I]	6.98		
Variables significant in two of the three models					
		Driver illness [F]	2.15	Driver illness [F]	0.88
		Struck a pole or tree [F]	1.05	Struck a pole or tree [F]	14.07
Variables significant in only one of the three models					
Rural area [F]	2.08				
Intersection related [F]	1.65				
Fog/smoke/smog [F]	3.68				
Construction site [F]	3.35				
Traffic control: flashing signal [F]	3.35				
		Curved road [I]	1.88		
		Daytime [F]	1.01		
		Driver had been drinking [F]	2.05		
		Vehicle 6–10 years old [I]	2.03		
		Vehicle more than 10 years old [I]	2.12		
				Driver fell asleep [I]	2.03
				Curve road [F]	7.77

Table 4
Comparison of elasticities for variables in the models for young male and female drivers (elasticities are specific to driver injury: [NI] no-injury, [I] injury, [F] Fatality)

Young male drivers (ages 16–24)	Elasticity	Young female drivers (ages 16–24)	Elasticity
Variables significant in both models			
Driver used no restraints [F]	2.11	Driver used no Restraints [F]	2.13
Driver used no restraints [I]	1.01	Driver used no Restraints [I]	1.19
Overturned/ Rollover [F]	1.54	Overturned/ Rollover [F]	1.16
Driver ejected [F]	3.89	Driver ejected [F]	2.62
Driver ejected [I]	2.86	Driver ejected [I]	1.61
Driver trapped [I]	1.71	Driver trapped [I]	2.67
Variables significant in only one of the two models			
Driver fell asleep [F]	1.32		
Driver carrying one or more passengers [F]	1.14		
		Rural area [F]	2.08
		Intersection related [F]	1.65
		Fog/smoke/ smog [F]	3.68
		Overturned/ Rollover [I]	1.04
		Driver trapped in [F]	3.03
		Construction [F]	3.35
		Traffic control: flashing signal [F]	1.85

Table 4 presents a comparison of findings for young male and female drivers. For the variables significant in both models, elasticities are similar with a few exceptions (male drivers that are ejected have a higher increased likelihood of injury or fatality and women drivers that are trapped have a higher likelihood of injury). For young males, falling asleep and carrying passengers increased the likelihood of fatality but these variables were insignificant in the young female model. However, young females had a number of variables (rural area, intersection-related, fog/smoke/smog, overturned/rollover for injury outcome, driver trapped in for fatality outcome, construction site, flashing signal traffic control) that increased their likelihood of fatality or injury, but these same variables did not have a significant effect on young male accident severity. This suggests some significantly different behavioral, highway engineering, and/or vehicle design issues between genders in this age group.

The comparison of middle-aged male and female drivers is presented in Table 5. Again, for variables found to be significant in both male and female models, elasticity magnitudes were generally similar. Variables that were found to be significant in only one of the two severity-outcome models were more telling. For middle-aged men, falling asleep increased the likelihood of fatality and injury; exceeding the speed limit, intersection related accidents, and accidents occurring on Friday or Saturday after midnight all increase the likelihood of fatality; and driving without a valid drivers license significantly increased the likelihood of injury. None of these variables were found to significantly influence middle-aged female driver injuries. For middle-aged females, driver drinking, driver illness, and driving in the daytime all increased the likelihood of fatality, whereas driving on curved roads and driving vehicles 6 years old and older increased the likelihood of injury. None of these variables were found to significantly influence middle-aged male driver injuries.

Finally, older male and female drivers are compared in Table 6. Unlike young drivers and middle-aged drivers, the variables that are common to older males and females tended

Table 5
Comparison of elasticities for variables in the models for middle-aged male and female drivers (elasticities are specific to driver injury: [NI] no-injury, [I] injury, [F] Fatality)

Middle-aged male drivers (ages 15–64)	Elasticity	Middle-aged female drivers (ages 15–64)	Elasticity
Variables significant in both models			
Driver used no restraints [F]	2.93	Driver used no restraints [F]	3.01
Driver used no restraints [I]	1.47	Driver used no restraints [I]	1.64
Overturned/ Rollover [F]	1.16	Overturned/ Rollover [F]	2.02
Overturned/ Rollover [I]	1.38	Overturned/ Rollover [I]	1.25
Struck a pole or tree [F]	0.73	Struck a pole or tree [F]	1.06
Driver ejected [F]	5.06	Driver ejected [F]	6.63
Driver ejected [I]	3.22	Driver ejected [I]	3.10
Driver trapped [F]	5.24	Driver trapped [F]	8.00
Driver trapped [I]	4.06	Driver trapped [I]	6.98
Driver fatigued [I]	1.33	Driver fatigued [I]	0.58
Variables significant in only one of the two models			
Driver fell asleep [F]	1.42		
Driver fell asleep[I]	1.02		
Exceeded reasonable speed or speed limit [F]	1.25		
Intersection related [F]	1.57		
Friday/Saturday after midnight [F]	1.56		
Violation of driver's license [I]	7.15		
		Driver had been drinking [F]	2.05
		Driver illness [F]	2.15
		Curve [I]	1.88
		Daytime [F]	1.01
		Vehicle 6–10 years old [I]	2.03
		Vehicle more than 10 years old [I]	2.12

Table 6
Comparison of elasticities for variables in the models for older male and female drivers (elasticities are specific to driver injury: [NI] no-injury, [I] injury, [F] Fatality)

Older male drivers (ages 65 and greater)	Elasticity	Older female drivers (ages 65 and greater)	Elasticity
Variables significant in both models			
Driver used no restraints [I]	1.32	Driver used no restraints [I]	1.87
Driver fell asleep [I]	1.30	Driver fell asleep [I]	2.03
Overturned/ Rollover [F]	2.20	Overturned/ Rollover [F]	5.22
Overturned/ Rollover [I]	1.33	Overturned/ Rollover [I]	2.41
Struck a pole or tree [F]	2.43	Struck a pole or tree [F]	14.07
Driver trapped [F]	101.58	Driver trapped [F]	70.90
Variables significant in only one of the two models			
Driver used no restraints [F]	2.13		
Driver illness [F]	3.08		
Fog/smoke/ smog [F]	20.00		
Spring [F]	2.58		
Vehicle less than 5 years old [F]	2.16		
Driver age: Number of years over 65 [F]	1.38		
		Curved road [F]	7.77

to vary substantially in their magnitude and almost always had a greater impact on the injury probabilities of older female drivers. For example, driving without restraints, falling asleep, and overturned/rollover all resulted in an increased likelihood of injury for older females – more so than their male counterparts. Similarly, overturned/ rollover, striking a pole, and being trapped resulted in an increased likelihood of fatality for older females – substantially more so than their male counterparts. There were many factors that only had a significant effect on older male drivers. These all increased the likelihood of fatality and included: driving without restraints, driver illness, fog/smoke/smog, driving in spring, driving a vehicle less than 5 years old, and the number of years over 65 years of age. The significance and impact of these factors again highlight the gender differences in this age group.

4. Estimation notes

There are a number of points relating to the model estimations that are worthy of note. First, with regard to the suitability of the unordered multinomial logit model used relative to ordered probability models, a large number of variables were found to be significant only for injuries, which is the middle category among the injury severity outcomes considered. As discussed earlier, in ordered models, the probability of a no-injury outcome and a fatality outcome cannot both increase or both decrease. A variable that is significant in only the injury category violates this restriction by producing no-injury and fatality probabilities that both increase or both decrease (depending on whether the estimated injury outcome coefficient is negative or positive, respectively). Thus, significant variables appearing only in the injury category are an indication that the unordered modeling approach may be warranted in this case.

Second, a potential limitation of the standard multinomial logit model is the assumption that the error terms accounting for unobserved effects associated with each severity outcome are independent from the effects in other categories. If correlation among unobserved effects is present, the standard multinomial logit model will not be appropriate. Some past accident-severity research has found correlation among unobserved effects to be present (Shankar et al., 1996) and other research has not (Shankar & Mannering, 1996). Our tests of alternate nested structures indicated that the standard multinomial logit model was the appropriate model structure (see Washington et. al. 2003 for a description of testing alternatives).

5. Summary and conclusions

The purpose of this study was to explore the differences in driver-injury severity between male and female drivers and across three different age groups for single-vehicle accidents involving passenger cars. Using 1999 accident data from Indiana, six separate multinomial logit models were estimated, one for each of the six defined gender/age groups, with three possible driver-injury outcomes considered: no-injury, injury, and fatality. Statistical tests were conducted to evaluate the differences between age/gender groups and average elasticity values were calculated and compared.

Our findings show that substantial, and statistically significant, differences exist between male and female injury severities as well as among different driver ages. There are some striking findings. These include the increased likelihood of fatality for young and middle-aged male drivers when they have passengers (which was not a significant factor for females); the increased likelihood of fatality for young and older male drivers when driving vehicles less than 5 years old (which was not a significant factor for females); the increased likelihood of injury for middle-aged female drivers when driving vehicles 6 years old or older (which was not a significant factor for males); and the increase in fatality likelihoods for older males as the age beyond 65 years (which was not a significant for females). While these differences are statistically convincing, we can only speculate as to why these differences exist. Possibilities include differences in reaction time; physical differences relating to height, weight, and body structure; vehicle design attributes that affect drivers differently; differences in safety system effectiveness that may vary by age and gender (airbags, safety belts, antilock brakes); differences in risk perceptions and resulting behavior; and the different effects that highway design (including roadside features) may have on different drivers. What is clear is that safety research and safety policy must begin to seriously address gender- and age-related matters because there are compelling differences and considerable potential to improve safety if these differences are properly addressed. For the behavioral differences, such as young males having higher fatality probabilities when driving with passengers, information and education campaigns may be appropriate. For differences that may be more likely to be vehicle related, such as middle-aged females having higher injury probabilities when driving vehicles 6 years old and older, a closer look at the design of vehicles and the design of their active and passive safety systems may be warranted.

There are several important avenues for further research. Expanding the analysis to consider accidents involving more than one vehicle and accidents in other geographical areas would potentially provide more information on the differences between specific age and gender groups. Also, detailed analyses of the effect of various vehicle safety systems on drivers of different height, weight, and body structure are definitely warranted. In general, comprehensive analyses of male/female and age-related biomechanics and behavioral response are research areas with considerable potential.

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