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Differences in male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car accidents

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Abstract

This research explores differences in injury severity between male and female drivers in single and two-vehicle accidents involving passenger cars, pickups, sport-utility vehicles (SUVs), and minivans. Separate multivariate multinomial logit models of injury severity are estimated for male and female drivers. The models predict the probability of four injury severity outcomes: no injury (property damage only), possible injury, evident injury, and fatal/disabling injury. The models are conditioned on driver gender and the number and type of vehicles involved in the accident. The conditional structure avoids bias caused by men and women's different reporting rates, choices of vehicle type, and their different rates of participation as drivers, which would affect a joint model of all crashes. We found variables that have opposite effects for the genders, such as striking a barrier or a guardrail, and crashing while starting a vehicle. The results suggest there are important behavioral and physiological differences between male and female drivers that must be explored further and addressed in vehicle and roadway design.

Keywords: Gender differences; Injury severity; Sport-utility vehicles; Multinomial logit; Transferability; Elasticity

1. Introduction

Consumers are increasingly purchasing larger vehicles, including sport-utility vehicles (SUVs), pickup trucks, and minivans. These light trucks and vans (LTVs) comprised over 34% of the US vehicle fleet and between 40 and 50% of new vehicle sales in 1996 (NHTSA, 1998). The changing composition of the vehicle fleet is having a considerable effect on accident types and injury severity. Studies have shown that the accident characteristics of LTVs are different from those of passenger cars (Malliaris et al., 1996; NHTSA, 1997). LTVs have been shown to have a higher rate of rollovers than passenger cars, particularly SUVs. In fact, the rollover rate of SUVs is the highest of all vehicle types, with 36% of fatal accidents in SUVs involving a rollover compared to just 15% of fatal accidents in passenger cars involving a rollover (NHTSA, 1997).

Consumer Reports (1998) point out that occupants in LTVs may be safer in accidents involving smaller vehicles but are less safe in single-vehicle accidents with fixed objects because of the LTVs' greater rigidity. This is corroborated by an Insurance Institute of Highway Safety study (Consumers' Research, 1998), which found that for comparable weights, the fatality rate of SUVs and pickups in single-vehicle accidents is more than twice that of passenger cars. This study also reported that in two-vehicle accidents involving an LTV and a passenger car, the passenger car occupants are much more likely to be fatally injured than the LTV occupants, and that this probability increases as the passenger car weight goes down relative to the LTV weight. Adding to this, NHTSA (1998) reports that the weight difference between LTVs and passenger cars has increased steadily in the 1990s.

Although vehicle size and weight have an effect on occupant safety (Evans and Frick, 1993; Gattis et al., 1996; Chang and Mannering, 1999), it can be problematic to isolate the significance of this effect due to a number of confounding factors. For example, Mateja (1995) points out that, of the previous studies that have concluded that larger passenger cars were safer, many ignored that such passenger cars tended to be driven by older and safer drivers. The inability to untangle the effect of vehicle size from the effect of driver attributes can shed doubt on a study's fundamental findings. This underscores the need to perform multivariate statistical analyses that include variables accounting for

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the characteristics of the driver, roadway design, and environmental conditions, as well as the type and size of the vehicle.

One key element in such multivariate analyses is the gender of the driver and the effect that behavioral and average physiological differences between males and females may have on accident-injury severity. Physiological differences can arise from average differences in male/female size and weight and their interaction with vehicle safety design (location of and operation of airbag, crash zones and even safety belt design), as well as differences in the body to withstand impacts. Behavioral differences may arise from different responses to driving conditions, particularly when operating LTVs. This could include male/female differences in risk compensation such as driving more aggressively to compensate for the perceived increased safety provided by LTVs because of their size, weight and higher driving position.

Numerous studies have found differences in accident rates between males and females (Laberge-Nadeau et al., 1992; Mannering, 1993; Massie et al., 1995). Few have explored male/female differences in accident severities. Among those that have, Evans (1988, 2001) found that females have a higher probability of dying relative to males in similarly severe accidents in the same vehicle type. Also, Abdel-Aty and Abdelwahab (2001) found that female drivers were more likely to suffer severe injury than males.

The objective of this research is to estimate statistical models to examine the differences between male and female driver-injury severity in passenger cars, pickup trucks, sport-utility vehicles and minivans. To do this, single-vehicle accidents and two-vehicle accidents involving an LTV and a passenger car are examined separately. For single-vehicle accidents, separate models for drivers of passenger cars, pickup trucks, and SUVs/minivans are estimated. For two-vehicle accidents, driver-injury severity for the passenger car and the LTV driver are examined separately. In all cases, separate models are estimated for male and female drivers and these gender-specific models are then compared.

2. Methodology

The methodological framework is formed by first identifying variables that can be expected to be explanatory when predicting injury severity, and variables that are likely to capture any remaining unobserved effects. Statistical models predicting the probability of injury severity outcomes for males and females by number of vehicles in the accident (single-vehicle, car versus pickup, car versus SUV/minivan) and vehicle type are then developed, estimated, and analyzed. The following subsections describe the statistical approach, the calculation of elasticity, the model design, limitations and strengths, the statistical testing, the data and its limitations.

2.1. Statistical approach

Statistical models are developed to estimate the probability of discrete driver-injury severity outcomes conditioned on an accident having occurred and having been reported to police. The data provide four injury severity outcomes: no injury, possible injury, evident injury, and fatal/disabling injury. To derive an estimable model of discrete outcomes, we follow the work of Shankar et al. (1996), Chang and Mannering (1999), and Lee and Mannering (2002). Let P_{ni}, the probability of driver n being injured with severity outcome i, where $i = 1, \dots, I$, be determined by injury-severity function S_{ni}. Let S_{ni} be separable into a systematic component, s_{ni}, determined by exogenous variables influencing injury outcomes, and a random component, ε_{ni}, that represents unobservable influences on injury outcomes. The systematic component is fixed for each n and can be represented as the linear-in-parameters function,

$$s_{ni} = \beta_i' x_n, \tag{1}$$

where x_n is a vector of exogenous explanatory variables influencing injury severity and β_i is a vector of injury-specific estimable coefficients. Note, x_n depends here only on the individual because all variables in this research are accident-specific and do not vary across injury outcomes. The probability of driver n experiencing injury outcome i now becomes

$$P_{ni} = P(\max_{i' \neq i} s_{ni'} + \varepsilon_{ni'} \leq s_{ni} + \varepsilon_{ni}). \tag{2}$$

P_{ni} is the probability that the propensity of driver n towards injury outcome i is greater than or equal to the propensity of driver n towards all other injury-severity outcomes. If ε_{ni} are assumed to be generalized extreme value (GEV) distributed, a multinomial logit (MNL) model can be derived, such that (McFadden, 1981),

$$P_{ni} = \frac{e^{\beta_i' x_n}}{\sum_{i'=1}^{I} e^{\beta_{i'}' x_n}}. \tag{3}$$

The coefficients are estimated simultaneously using maximum likelihood. Note, the multinomial logit models are related to logistic regression models in form but the assumptions leading to the models differ, along with the estimation technique and the associated results.

Because the explanatory variables do not vary across injuries and are not injury-specific, the $I - 1$ log-odds ratios of the model outcomes become,

$$\ln\left(\frac{P_{ni}}{P_{nI}}\right) = \beta_i' x_n - \beta_I' x_n = (\beta_i' - \beta_I') x_n, \quad \text{for } i = 1, \dots, I - 1. \tag{4}$$

Only the difference in coefficients is identifiable and the coefficients are therefore identifiable only up to an additive constant. To resolve this indeterminacy, the coefficients of one outcome (the base case) are set to zero (Greene, 1997).

For our analysis, the fatal/disabling outcome is used as the base case with $\beta_I = 0$.

We use categorical analysis rather than ordinal analysis (such as ordered logit or probit) because ordered models restrict the effect of the variables across outcomes. That is, variables are constrained to increase or decrease the outcome probabilities across the range, from low to high, of severity categories. There is no option for a variable to only increase the probabilities of the mid-level severity categories. We believe such a restriction is inappropriate because there is no compelling theoretical evidence that indicates that variables cannot increase the probability of mid-level severities and reduce the probability of no injury and fatal/disabling injury. An example might be an airbag deployment, which may cause minor abrasions (elevating some severities from no injury to possible or evident injury) while simultaneously reducing the likelihood of disabling/fatal injuries. Ordinal analysis simply cannot account for such effects.

A problem with MNL models occurs when some, but not all, of the outcomes share unobserved effects (resulting in correlated ε). This is referred to as an independence of irrelevant alternatives (IIA) violation. Various nested logit (NL) models can be derived from the assumed GEV distribution of the ε_{ni}, leading to a range of models that circumvent the IIA specification problem (see McFadden, 1981). Nested models group the outcomes with shared unobserved effects into separate model nests (which are referred to as lower nests) and then estimate the probabilities of outcomes entering these nests of outcomes (Washington et al., 2003). Previous research on injury severities suggests a nested logit structure may be more appropriate than MNL (Shankar et al., 1996; Lee and Mannering, 2002), but not always (Chang and Mannering, 1999). Saccomanno et al. (1996) tested the reliability of different nesting structures for injury severity models and found little difference in predictive power. Using the four injury-severity categories in this study, a variety of nested structures were tested, including a structure that groups no injury and possible injury together in a lower nest. Other nesting alternatives were not statistically warranted with the data used in this research (see McFadden, 1981, for a description of the criteria a nested structure must fulfill to be statistically valid). A formal test was conducted to ensure the MNL specification was appropriate. The Small and Hsiao (1985) IIA specification test did not indicate significant problems with the chosen MNL structure, which is shown in Fig. 1 and expressed in Eq. (3). This structure is used for all presented models.

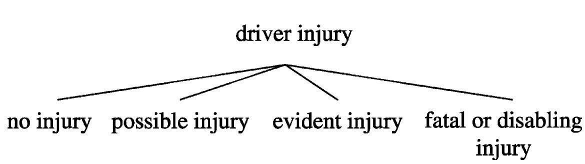

Fig. 1. The multinomial logit structure of the injury severity models.

2.2. Elasticity

In addition to the estimated coefficients, we calculate average direct pseudo-elasticities that give the average percentage change in probability when a variable is changed from zero to one. The elasticity is necessary to correctly judge the relative impact of an explanatory variable. Note that the sign of a coefficient does not always equal the sign on the change in probability (Greene, 1997). The elasticity, however, shows the change in probability when an explanatory variable changes.

The direct pseudo-elasticity, $E^{P_{ni}}_{x_{nk}}$, of the kth variable from the vector x_n, denoted x_{nk}, with respect to the probability, P_{ni}, of person n experiencing outcome i is computed as

$$E^{P_{ni}}_{x_{nk}} = \left[e^{\beta_{ik}} \frac{\sum_{i'=1}^{I} e^{\beta'_i x_n}}{\sum_{i'=1}^{I} e^{\Delta(\beta'_i x_n)}} - 1 \right] \times 100, \qquad (5)$$

where I is the number of possible outcomes, $\Delta(\beta'_i x_n)$ is the value of the function determining the outcome, s_{ni}, after x_{nk} has been changed from zero to one whereas $\beta'_i x_n$ is the value when $x_{nk} = 0$, x_n is a vector of K explanatory variables shared by all outcomes, β_i is a vector of estimated coefficients on the K variables for outcome i, and β_{ik} is the coefficient on x_{nk} in outcome i. Note, Eq. (5) is valid only for pseudo-elasticities of observation-specific binary indicator variables. This formula has been applied in other contexts by Shankar and Mannering (1996) and Chang and Mannering (1999).

2.3. Model design

The objective of this research is to determine whether there are differences between men and women's driver-injury severities in different vehicle-accident combinations. To do this, separate models are estimated for male and female drivers in each of the following seven vehicle-accident categories, yielding a total of 14 models: (1) passenger car drivers in single-vehicle accidents, (2) pickup drivers in single-vehicle accidents, (3) SUV/minivan drivers in single-vehicle accidents, (4) passenger car drivers in passenger car-pickup accidents, (5) pickup drivers in passenger car-pickup accidents, (6) passenger car drivers in passenger car-SUV/minivan accidents, and (7) SUV/minivan drivers in passenger car-SUV/minivan accidents. SUVs and minivans are in the same group because the police records, from which the data are obtained, use the same code for these vehicle types. Please note that significant differences were observed in injury severity levels among these seven vehicle accident categories. This has been observed elsewhere in the literature (e.g. Chang and Mannering, 1999). With the focus of this paper on male and female differences, results on differences in vehicle accident categories are not reported.

The 14 gender-specific models are estimated separately, rather than estimating one large model in which gender and vehicle type are variables. Models are separated into single-vehicle and two-vehicle accidents because these accidents have different characteristics (roadside object crashes versus multi-vehicle crashes) and these differences can not be expected to be accurately captured by one model. The separation is also done to alleviate and minimize biases inherent in such a joint model. For example, the different reporting rates of single and two-vehicle accidents to police. Men and women are also represented unequally as vehicle drivers and vehicle types are represented unequally because men and women tend to drive different types of vehicles. A further complication is that men and women have been found to report accidents to the police at different rates (Massie et al., 1995) as will be discussed later. These frequency differences will cause bias in gender-specific and vehicle-specific variables in the joint model, merely because of exposure differences. A lack of significance of a gender indicator variable would not necessarily indicate lack of significant differences between the genders, but could well be caused by fewer numbers of women than men in the data. In a joint model of genders and vehicle types, the differences caused by men and women driving different types of vehicles would be impossible to untangle from gender differences.

Conditional models alleviate these problems. Similarly-sized data samples are drawn for each model and similar models are estimated for men and women in the same type of vehicle (car, pickup, SUV or minivan), and for the same type of crash (single-vehicle, car-pickup, car-SUV/minivan). A joint model of all crashes is more appropriate to judge societal significance of injury differences between men and women. If a female indicator is insignificant in such a model because women rarely drive pickups, it indicates it may not be significant to society if women pickup drivers' injury severity is different from men's. The models presented here are at the disaggregate level. This allows us to explore if there is a significant difference in injury severity between men and women on the whole, and in which explanatory variables the most important differences lie.

The models are designed initially with the same set of variables that are, by theory, thought to be likely to affect injury severity or to capture important unobserved effects that would otherwise bias other variables. To set a conceptual framework for the analysis, variables in eight main groups were chosen to be in the models: (1) driver characteristics (driver age, familiarity with area through close residence with accident location, restraint usage, intoxication, inattention, driver asleep), (2) driver violations (such as speeding, operating defective equipment, did not grant right of way, following to closely, etc.), (3) driver action preceding collision (such as going straight, turning, slowing, merging, etc.), (4) vehicle characteristics (such as vehicle age, manufacturer and specific defects), (5) road and operating characteristics (such as interstate, major arterial, two-way road, intersection related, speed limit, traffic controls, curved road, grade, wet, snowy, icy road, blacktop asphalt road), (6) collision characteristics (such as rollovers, struck barrier, guardrail, tree, pole, drove off the road, driver ejected, head-on, sideswipe, rear-end), (7) environmental characteristics (rain, fog, snow, twilight, darkness), and (8) temporal characteristics (rush hour, weekend, season, year).

Some of the variables are merely there to capture unobserved effects that would cause estimation bias. Examples are the year-specific variables, vehicle manufacturer indicators, vehicle age, and season indicators. For example, accidents occurring in the same year may share unobserved effects (correlated with each other) and the year-specific variables capture that correlation. The same holds for seasons, which have different speeds and conditions, such as varying weather conditions. Those effects are mostly captured by particular variables for the conditions and speed limit, but there may still be omitted effects that the seasonal variables capture. Vehicle age and vehicle manufacturer variables share the same purpose.

Fully-specified models are then estimated with maximum likelihood (see, for example, Greene, 1997, for a description of maximum likelihood estimation). Coefficients that are not found to be significantly different from zero at the $P = 10\%$ level (t-statistic $= 1.282$) are restricted to be zero and not presented. It is important to restrict those coefficients to zero to improve the efficiency of the estimates of the significant coefficients. Note that the models are not built up by adding variables by the significance of their coefficients. Such a scheme is likely to lead to spurious correlations and is dependent on the order of inserted variables. A multivariate model must be designed carefully first and then estimated with all variables so as not to suffer from omitted variables bias. Then, upon significance testing, the insignificant coefficients are restricted to zero. Initial model design, significance tests of individual coefficients, significance tests of differences in coefficients across outcomes, and the model tests of differences between males and females as groups, help reduce the likelihood of spurious relationships.

2.4. Statistical testing

Within each of the seven accident categories, the significance of male/female group differences is evaluated using likelihood ratio tests. As recommended by Cox (1961, 1962), the union of the variables in the gender-specific models is used to estimate a joint model for both genders (accounting for the different ratios of men and women in the data, but not the different reporting rates as they are largely unknown). The likelihood ratio statistic is,

$$\mathrm{LR} = -2(L_{\mathrm{j}} - L_{\mathrm{f}} - L_{\mathrm{m}}), \tag{6}$$

which is χ^2 distributed with J degrees of freedom, where $J = K_{\mathrm{f}} + K_{\mathrm{m}} - K_{\mathrm{j}}$ (K_{j}, K_{f}, and K_{m} are the number of coefficients in the joint model for males and females, females alone, and males alone, respectively) and L_{j}, L_{f}, and L_{m} are the log-likelihoods at convergence for the models of all-drivers, female, and male drivers, respectively.

We also test the transferability of coefficients for one gender to the other's data. Such a test is powerful in detecting significant differences between two groups. For example, a model is estimated for females. The resulting model is applied to data for males with all coefficients restricted to the values estimated for the females, yielding the restricted log-likelihood L_R. Then the exact same model specification is set free and coefficients estimated on the data for males, yielding the unrestricted log-likelihood L_U. The likelihood ratio statistic is then

$$\mathrm{LR} = -2(L_R - L_U), \tag{7}$$

which is χ^2 distributed with J degrees of freedom, where J is the number of restrictions.

The null hypothesis for Eq. (6) is that the restricted model (joint model of males and females) does not have a significantly lower log-likelihood than the unrestricted models (separate male and female models) together, indicating a lack of significant difference between the gender-specific models and the joint model. The null hypothesis for Eq. (7) is that the coefficients are equal for males and females. A likelihood ratio test statistic larger than the χ^2 value with J degrees of freedom at a predetermined confidence level would allow one to reject the null hypothesis.

The test of transferability of coefficients is particularly decisive. If a large sample of observations is randomly separated into two groups with a uniform distribution, those two samples will be asymptotically equivalent. A model estimated for one group can then be transferred to the other and the test would not reject transferability. When the two groups are not formed randomly but by gender (or other variable), the groups are not necessarily equivalent. If the test of transferability rejects transferability at a high significance it is statistical evidence that the two groups are not equivalent. Such global tests for the groups do not show where the difference lies because they do not show which particular variables are different. They show there is a significant difference between the groups because the coefficients of one group do not transfer to the other group, which is itself an important result.

2.5. Data

Data were acquired from the Master Accident Record System (MARS) of the Washington State Department of Transportation. The system contains information on accidents that are in police records in Washington State. The subset of the database that is used in this research contains information for accidents that occurred between January 1, 1993 and July 31, 1996 in the northwest region of Washington State. This region includes the counties of San Juan, Island, Whatcom, Skagit, Snohomish, and King (home of the Seattle metropolitan area). Accident records of 22,068 driver-injuries and non-injuries were used in this study. This represents sub-samples from the entire database. The sub-samples were taken for each of the models. The model-specific sub-samples were chosen using exogenous, random sampling with a uniform distribution, which leaves the samples unbiased. This sampling will not significantly affect logit model coefficient estimates because the estimates remain consistent and asymptotically unbiased (Manski and McFadden, 1981).

In the two-vehicle accident cases there will be a correlation between the two observed vehicles in the same accident. However, because we employ a random sampling from a larger dataset it is unlikely that there are many cases of vehicles being from the same accident. However, we did not restrict the random choice so this can occur. The presence of such observation-pairs will cause a violation of the model assumptions, resulting in decreased efficiency, but the estimates are still consistent. This decrease in efficiency will be small because of the rarity of this pairing.

The database is formed from police records. It is widely reported that there are discrepancies between police records and hospital data. Many accidents that cause property damage only or minor injury are likely to go unreported. Shankar and Mannering (1996) explored accident severity in motorcycle accidents using a database created from police records. They point out that, because minor accidents are more likely to go unreported, the database is a stratified sample. Sample stratification does not affect the coefficients of explanatory variables in a logit model but it does shift the outcome-specific constant terms (Manski and McFadden, 1981).

As for the accuracy of police data, Barancik and Fife (1985) found that 15% of the patients in their sample of emergency room patients that reported a vehicle related injury had police reports that did not indicate injury. They also found that police records were more accurate for drivers than passengers. Cercarelli et al. (1996) found similar results, showing a difference between police records and hospital records of numbers of people admitted. It has been shown that the accuracy of police records improves as injury severity increases (Agran et al., 1990; Harris, 1990; Rosman and Knuiman, 1994; Cercarelli et al., 1996; Aptel et al., 1999). Still, there are discrepancies, even for fatal accidents. Part of this discrepancy is likely caused by the way fatalities are counted. In particular, police records do not include deaths that happen after the accident has occurred while hospital records do. It is, however, a reasonably safe assumption that such injuries are likely to be recorded as evident or disabling by the police.

3. Results

Table 1 shows the number of observations and percentage distribution across injury severities for all drivers, male drivers, and female drivers, for all accident types considered. Note, because the random sampling was conditional on model type the frequency distribution across rows in Table 1 does not represent the universe. This has no effect on the models because they are conditioned in the same way and

Table 1
Driver injury frequency and percentage distribution for the estimated models, by vehicle type, passenger cars, pickups, sport-utility vehicles (SUV) and minivans, and gender

	No injury		Possible injury		Evident injury		Fatal/disabling injury		Total
Single-vehicle accidents									
Passenger car drivers	2,848	62.8%	838	18.5%	695	15.3%	152	3.4%	4,533
Male	1,479	66.7%	318	14.3%	339	15.3%	82	3.7%	2,218
Female	1,369	59.1%	520	22.5%	356	15.4%	70	3.0%	2,315
Pickup drivers	1,075	62.2%	256	14.8%	334	19.3%	63	3.6%	1,728
Male	891	63.7%	183	13.1%	274	19.6%	51	3.6%	1,399
Female	184	55.9%	73	22.2%	60	18.2%	12	3.6%	329
SUV/minivan drivers	838	64.1%	205	15.7%	222	17.0%	43	3.3%	1,308
Male	566	66.7%	110	13.0%	148	17.5%	24	2.8%	848
Female	272	59.1%	95	20.7%	74	16.1%	19	4.1%	460
Car vs. pickup accidents									
Passenger car drivers	2,835	74.1%	658	17.2%	284	7.4%	48	1.3%	3,825
Male	1,451	78.3%	250	13.5%	129	7.0%	22	1.2%	1,852
Female	1,384	70.1%	408	20.7%	155	7.9%	26	1.3%	1,973
Pickup drivers	2,900	82.5%	490	13.9%	109	3.1%	18	0.5%	3,517
Male	1,663	85.0%	236	12.1%	48	2.5%	9	0.5%	1,956
Female	1,237	79.2%	254	16.3%	61	3.9%	9	0.6%	1,561
Car vs. SUV/minivan accidents									
Passenger car drivers	2,635	73.5%	696	19.4%	214	6.0%	38	1.1%	3,583
Male	1,422	78.8%	262	14.5%	102	5.7%	19	1.1%	1,805
Female	1,213	68.2%	434	24.4%	112	6.3%	19	1.1%	1,778
SUV/minivan drivers	2,933	82.1%	503	14.1%	115	3.2%	23	0.6%	3,574
Male	1,455	78.3%	326	17.5%	62	3.3%	15	0.8%	1,858
Female	1,478	86.1%	177	10.3%	53	3.1%	8	0.5%	1,716
Total	16,064	72.8%	3646	16.5%	1973	8.9%	385	1.7%	22,068

The male/female rows correspond to estimated models. Note, that the sampling of observations was conditioned on vehicle type and gender, as the models, so that the distribution across rows does not represent the universe whereas the distribution across columns for males and females does.

we account for this in our tests of joint male/female models. The descriptive statistics in Table 1 show general trends. In single-vehicle accidents, pickup and sport-utility vehicle/minivan drivers tend to have a larger percentage in the more severe categories than the passenger car drivers. The opposite holds in passenger car versus pickup and passenger car versus SUV/minivan accidents where passenger car drivers have a larger percentage in the more severe injury categories.

Overall, female drivers have a notably larger percentage in the possible injury category relative to male drivers. Females also have a higher percentage of fatal/disabling injuries in SUV/minivan single-vehicle accidents and as drivers of passenger cars that collided with a pickup. This partially fits with the results of Evans (1988, 2001) who found that females were generally more likely to die in crashes than males in similar vehicles. However, the descriptive statistics for the database in this research show that here, females generally have lower percentages in the more severe injury categories. These aggregate data suggest the possibility of differences in injury severity levels between male and female drivers. The forthcoming multivariate analysis will explore this in detail.

3.1. Interpretation of multinomial logit model results

For illustrative purposes, we present two of the 14 models estimated (complete estimation results for all models are provided in Ulfarsson, 2001). Tables 2 and 3 present single-vehicle SUV/minivan driver-injury severity models for females and males, respectively. Tables 2 and 3 contain the list of significant coefficients, along with coefficient estimates, standard errors of the estimate, and the *t*-statistic for the test of significant difference of a coefficient from zero.

After each variable name in Tables 2 and 3, we list in brackets the numbers of the outcomes to which each coefficient belongs, with (1) denoting the no injury outcome, (2) possible injury, (3) evident injury, and (4) fatal/disabling injury. As previously described, the coefficients for one outcome must be restricted to zero (base case) and the results for the other outcomes are differences from this base case. This gives meaning to insignificant coefficients on a variable in the non-base case outcomes in that the effect of the variable on those outcomes is not significantly different from the effect on the base case. The fatal/disabling injury category is taken as the base case and its number, (4), therefore omitted on the variables, with one exception. When the coefficients

Table 2
Multinomial logit model for female sport-utility vehicle/minivan driver injury in single-vehicle accidents

Variable	Coefficient	Standard error	t-Statistic
Constant (1)	4.41	0.74	5.94*
Constant (2,3)	1.99	0.68	2.93*
Driver residence within 24 km (1,2)	0.94	0.26	3.61*
One or more passengers (2,3)	0.35	0.23	1.55
Driver used no restraints (1)	−5.27	0.83	−6.33*
Driver used no restraints (2,3)	−2.86	0.62	−4.62*
Driver fell asleep (2)	−1.08	0.80	−1.35
Driver inattention (2)	−0.63	0.42	−1.48
Exceeded reasonable speed or speed limit (2)	−0.60	0.26	−2.26*
Defective equipment (except tires/wheels/lights) (1)	1.22	0.71	1.72
Vehicle is 6–10 years old (2)	0.43	0.24	1.77
Defective tires/wheels (2,3)	2.02	0.81	2.48*
Chrysler, Dodge, Plymouth, Jeep, Eagle (1,2)	0.68	0.29	2.37*
Ford, Mercury, Lincoln (4)	−2.27	1.11	−2.05*
Nissan, Infiniti (1)	0.97	0.63	1.54
Arterial (1)	0.34	0.23	1.49
Two way road, alley, two-way left, driveway (4)	1.27	0.66	1.91
Intersection related (4)	−1.98	1.23	−1.61
Wet road (2,3)	1.13	0.35	3.27*
Blacktop road (3)	0.51	0.26	1.92
Overturned/rollover (2,3)	0.67	0.27	2.45*
Run-off-roadway (1)	−2.03	0.37	−5.45*
Rainy weather (1)	1.08	0.37	2.95*
Foggy or snowy weather (2,3)	1.95	0.66	2.95*
After dark (1)	0.44	0.25	1.81
Rush hour, morning 6–9:59 a.m. (2)	0.57	0.29	1.94
Summer (1,2)	−0.66	0.30	−2.17*
Year 1993 (2)	−0.57	0.30	−1.87
Log-likelihood at zero	−637.7		
Log-likelihood at convergence	−398.04		
ρ^2	0.3758		
Number of observations	460		

Coefficients with $|t| \leq 1.28 \Leftrightarrow P \geq 0.1$ in each tail of the distribution, have been restricted to zero and omitted. Coefficients are specific to: (1) no injury, (2) possible injury, (3) evident injury, and (4) disability/fatality.

* $t \geq 1.96 \Leftrightarrow P \leq 0.025$: coefficient significant at the 95% level, P-value <2.5% in each tail of the distribution.

on a variable in the no injury, possible injury, and evident injury outcomes were not found to be significantly different at the $P = 10\%$ level, rather than write the coefficient as being specific to outcomes (1–3), it was, for convenience, written as specific to the fatal/disabling equation, (4), and its sign changed. This produces an equivalent result and is not to indicate that only these variables affect fatal/disabling injury. Indeed, all variables affect all outcomes as shown in Eq. (5).

Interpreting the coefficients in Tables 2 and 3 is difficult as explained in the elasticity section. We therefore present in Tables 4 and 5 the average direct pseudo-elasticity of all variables in Tables 2 and 3 with respect to all outcomes. Contrary to the coefficients, for which at least one outcome must be restricted to zero, pseudo-elasticities can be calculated for all outcomes. The interpretation of the pseudo-elasticity is straightforward. It is the percentage change in probability of an outcome when a variable changes from zero to one. Explanatory variables that have an average pseudo-elasticity larger than 100% are elastic and have important effects. For example, looking at Table 4, female drivers not using restraints had on average an 82.1% decrease in probability of no injury, the probability of possible and evident injuries increased on average by 99.4%, and for fatal/disabling injury, the increase was 3374%. The corresponding values for male drivers (Table 5) were a 54.2% decrease, a 128.6% increase, and a 2624% increase, respectively. This example shows the importance of considering the marginal effects, as given by the pseudo-elasticity, rather than the coefficient values. The coefficients are negative for the possible and evident injury outcomes, yet the probability of possible and evident injuries goes up. The negative coefficients are relative to fatal/disabling, so the propensities towards no injury, possible and evident injury are lower than towards fatal/disabling injury. Lack of restraint usage reduces the propensity towards no injury so much that even though the propensity towards possible and evident injury is also reduced relative to fatal/disabling, the probability of those outcomes increases.

When interpreting the differences between males and females we focus mainly on variables that are significant in both models. A lack of significance off a variable in one model can simply be caused by a lack of observations of that

Table 3
Multinomial logit model for male sport-utility vehicle/minivan driver injury in single-vehicle accidents

Variable	Coefficient	Standard error	*t*-Statistic
Constant (1)	9.53	1.52	6.28*
Constant (2)	8.07	1.85	4.37*
Constant (3)	7.86	1.56	5.06*
Driver is 65 or older (1)	−0.76	0.44	−1.72
Driver residence within 24 km (4)	−1.35	0.55	−2.47*
Driver used no restraints (1)	−4.09	0.59	−6.88*
Driver used no restraints (2,3)	−2.48	0.57	−4.34*
Driver had been drinking (1)	−2.91	0.66	−4.41*
Driver had been drinking (2)	−3.12	0.69	−4.49*
Driver had been drinking (3)	−1.88	0.67	−2.83*
Driver fell asleep (1)	−1.21	0.39	−3.09*
Driver inattention (4)	2.44	0.89	2.73*
Exceeded reasonable speed or speed limit (1)	−1.87	0.65	−2.89*
Exceeded reasonable speed or speed limit (2)	−1.57	0.66	−2.37*
Exceeded reasonable speed or speed limit (3)	−1.27	0.65	−1.95
Following too closely (1)	1.82	1.08	1.68
Operating defective equipment (1)	0.83	0.42	1.98*
Going straight (2)	−1.81	0.87	−2.08*
Making a turn (2)	−2.26	1.15	−1.97*
Slowing (1,3)	2.67	1.15	2.34*
Merging or changing lanes (1,3)	1.74	0.94	1.84
Ford; Mercury; Lincoln (4)	1.74	0.54	3.25*
Nissan; Infiniti (1)	−1.56	0.51	−3.04*
German manufacturers (1)	1.14	0.64	1.77
Interstate (3)	−0.75	0.35	−2.13*
Arterial (3)	−0.88	0.36	−2.47*
Two way road; alley; two-way left; driveway (2)	0.41	0.23	1.74
Posted speed limit >65 km/h (4)	2.19	0.83	2.65*
Intersection related (1)	0.61	0.35	1.75
Curved road (3)	−0.45	0.23	−1.93
Up/down grade (2)	0.32	0.22	1.43
Wet road (4)	1.19	0.53	2.26*
Snowy or icy road (3)	−1.09	0.34	−3.18*
Overturned/rollover (1)	−0.66	0.24	−2.72*
Overturned/rollover (3)	0.63	0.34	1.88
Struck barrier or guardrail (3)	0.78	0.28	2.74*
Struck a pole or tree (3)	0.63	0.35	1.79
Run-off-roadway (2)	1.16	0.42	2.75*
Rainy weather (3)	−0.53	0.28	−1.93
Foggy or snowy weather (1,2)	−0.91	0.40	−2.25*
Twilight (dawn or dusk) (1)	−0.55	0.41	−1.33
Twilight (dawn or dusk) (2)	−1.90	0.80	−2.37*
After dark (1,3)	0.59	0.23	2.55*
Spring (4)	1.68	0.62	2.71*
Summer (4)	1.33	0.64	2.08*
Log-likelihood at zero	−1175.6		
Log-likelihood at convergence	−649.6		
ρ^2	0.4474		
Number of observations	848		

Coefficients with $|t| \le 1.28 \Leftrightarrow P \ge 0.1$ in each tail of the distribution, have been restricted to zero and omitted. Coefficients are specific to (1) no injury, (2) possible injury, (3) evident injury, and (4) disability/fatality.

* $t \ge 1.96 \Leftrightarrow P \le 0.025$: coefficient significant at the 95% level, *P*-value <2.5% in each tail of the distribution.

variable in that case. A variable's lack of significance for one gender and not the other can therefore not be taken as conclusive evidence of a significant difference between the genders. Significant differences occur when a variable is highly elastic for one gender and not the other, or when the effect goes significantly into opposite directions for the two genders.

3.2. *Statistical tests of differences between males and females as groups*

The significance of the overall difference between a combined model of males and females and the gender-specific models was tested with the likelihood ratio test shown in

Table 4
Average direct pseudo-elasticity of each variable for all outcomes in the injury severity model for female drivers in sport-utility vehicle/minivan single-vehicle accidents

Variable	Elasticity (%)			
	No injury	Possible injury	Evident injury	Fatal/disabling injury
Driver residence within 24 km	27.34	27.34	−50.41	−50.41
One or more passengers	13.55	−20.12	−20.12	13.55
Driver used no restraints	−82.12	99.34	99.34	3374.56
Driver fell asleep	17.30	−60.00	17.30	17.30
Driver inattention	11.30	−40.52	11.30	11.30
Exceeded reasonable speed or speed limit	10.79	−39.11	10.79	10.79
Operating defective equipment	52.89	−54.96	−54.96	−54.96
Vehicle is 6–10 years old	−8.64	40.85	−8.64	−8.64
Defective tires/wheels	−64.20	168.56	168.56	−64.20
Chrysler; Dodge; Plymouth; Jeep; Eagle	14.10	14.10	−42.37	−42.37
Ford; Mercury; Lincoln	7.05	7.05	7.05	−88.96
Nissan; Infiniti	40.89	−46.35	−46.35	−46.35
Arterial	15.69	−17.37	−17.37	−17.37
Two way road; alley; two-way left; driveway	−4.47	−4.47	−4.47	239.39
Intersection related	6.06	6.06	6.06	−85.35
Wet road	−37.91	91.95	91.95	−37.91
Blacktop road	−7.36	−7.36	53.83	−7.36
Overturned/rollover	−22.66	50.98	50.98	−22.66
Run-off-roadway	−42.54	336.78	336.78	336.78
Rainy weather	47.94	−49.73	−49.73	−49.73
Foggy or snowy weather	63.26	−76.80	−76.80	63.26
After dark	19.67	−23.19	−23.19	−23.19
Rush hour, morning 6–9:59 a.m.	−11.87	55.12	−11.87	−11.87
Summer	−13.74	−13.74	66.13	66.13
Year 1993	11.04	−37.02	11.04	11.04

Eq. (6). The hypothesis that gender-specific models can be equally represented with a joint model can be firmly rejected with P-values near zero in all but two cases: passenger car-driver injuries in accidents involving a pickup ($P = 0.463$), and SUV/minivan driver injuries in accidents involving a passenger car ($P = 0.404$). The tests of transferability of female model coefficients to male data and vice versa, given in Eq. (7), are even more conclusive. Two such models were not estimable, female coefficients using male data in the single-vehicle pickup case, and male coefficients using female data for SUV/minivan drivers the car versus SUV/minivan case. The likely reason for these models not being estimable are the near colinearities of variables that can arise when being forced (to allow statistical testing) to include a vector of variables that are pre-determined from a previous model estimation. In all estimable cases the transferability tests indicate that the coefficients of one gender are not transferable to the other with a P-value <0.0002. Males and females as groups, are therefore significantly different with respect to injury severity. This generalizes the results of Evans (2001) who found fundamental gender-specific differences with respect to fatality risk.

3.3. Specific model findings

Turning to the specific findings, many instances of significant differences between male and female driver-injury severity are observed. The observed differences are mostly in the size of the pseudo-elasticity, a variable has a very large effect for one gender but not the other. Most variables cause the probability of severities to change in the same direction for both genders, but there are three notable differences, where the opposite effect was observed. The main results (with some notable exceptions as discussed later) across the 14 models are summarized in Table 6.

For both genders, drivers that did not use restraints (seatbelts) experienced an increased probability of higher severities (decreased probability of lower severities) with large pseudo-elasticities, this also holds for drivers that had been drinking. The age of the driver was not significant in all the models. It has been previously shown that when variables accounting for driver behavior are included, age can be rendered insignificant (Kim et al., 1995). However, when age was significant in the models, it generally increased the probability of greater severity for 25 or younger drivers and for 65 or older drivers.

Overtaking/passing has a large effect on male drivers of passenger cars that collided with a pickup or a SUV/minivan, increasing the average probability of evident injury by 310 and 1037%, respectively. The effect is in the same direction, toward injury, for both genders but the effect is smaller for females.

In single-vehicle accidents, making a turn increases the probability of no injury for male passenger car drivers with

Table 5
Average direct pseudo-elasticity of each variable for all outcomes in the injury severity model for male drivers in sport-utility vehicle/minivan single-vehicle accidents

Variable	Elasticity (%)			
	No injury	Possible injury	Evident injury	Fatal/disabling injury
Driver is 65 or older	−25.41	60.22	60.22	60.22
Driver residence within 24 km	5.17	5.17	5.17	−72.77
Driver used no restraints	−54.23	128.62	128.62	2624.21
Driver had been drinking	−22.43	−37.02	116.90	1326.17
Driver fell asleep	−38.96	105.06	105.06	105.06
Driver inattention	−10.97	−10.97	−10.97	920.25
Exceeded reasonable speed or speed limit	−19.82	8.25	45.83	419.08
Following too closely	53.62	−75.08	−75.08	−75.08
Operating defective equipment	27.96	−44.10	−44.10	−44.10
Going straight	9.22	−82.21	9.22	9.22
Making a turn	15.12	−87.96	15.12	15.12
Slowing	21.49	−91.62	21.49	−91.62
Merging or changing lanes	17.47	−79.28	17.47	−79.28
Ford; Mercury; Lincoln	−5.64	−5.64	−5.64	437.74
Nissan; Infiniti	−49.50	139.73	139.73	139.73
German manufacturers	35.99	−56.47	−56.47	−56.47
Interstate	10.53	10.53	−47.86	10.53
Arterial	14.08	14.08	−52.80	14.08
Two way road; alley; two-way left; driveway	−5.45	42.00	−5.45	−5.45
Posted speed limit >65 km/h	−6.29	−6.29	−6.29	735.81
Intersection related	20.64	−34.52	−34.52	−34.52
Curved road	7.31	7.31	−31.28	7.31
Up/down grade	−4.07	32.35	−4.07	−4.07
Wet road	−3.73	−3.73	−3.73	215.27
Snowy or icy road	16.40	16.40	−60.87	16.40
Overturned/rollover	−31.37	32.58	150.13	32.58
Struck barrier or guardrail	−15.33	−15.33	84.03	−15.33
Struck a pole or tree	−12.01	−12.01	64.94	−12.01
Run-off-roadway	−8.40	191.92	−8.40	−8.40
Rainy weather	8.82	8.82	−36.19	8.82
Foggy or snowy weather	−20.10	−20.10	97.70	97.70
Twilight (dawn or dusk)	−2.65	−74.77	68.02	68.02
After dark	8.86	−39.38	8.86	−39.38
Spring	−5.62	−5.62	−5.62	408.44
Summer	−4.60	−4.60	−4.60	259.59
Year 1994	−7.93	48.86	−7.93	48.86

an average elasticity of about 17%, but reduces the probability of no injury for male pickup drivers by about 160% on average and reduces the probability of possible injury for male SUV/minivan drivers by about 82%. However, making a turn was an insignificant predictor of female driver injury in the single-vehicle accidents. In two-vehicle accidents we see the opposite effect for male and female drivers of passenger cars that collided with a pickup. Male drivers have on average about 200% increased probability of possible and evident injuries, while female drivers have a reduced probability of those injury categories by about 65%. In two-vehicle accidents between passenger cars and SUV/minivans, female passenger car drivers making a turn have on average a roughly 200% increase in the probability of fatal/disabling injuries, while male passenger car drivers have on average a 490% increase in the probability of evident injury.

Avoidance maneuvers for female drivers of passenger cars that collided with an SUV/minivan, increase the probability of possible injury, while they increase the probability of evident injury in the male passenger car-driver model. The effect of this variable was insignificant in the model for drivers of SUV/minivans that collided with a passenger car.

The indicator for a sudden slowing maneuver shows a different effect for male and female drivers in passenger car versus SUV/minivan accidents. The variable increases the probability of fatal/disabling injury in the female passenger car driver model, while it increases the probability of evident injury in the male passenger car driver model. For the corresponding SUV/minivan drivers the results show an increase in the probability of no injury and evident injury for female SUV/minivan drivers while being insignificant for male drivers.

Table 6
Notable specific estimation results that were observed generally across models, showing similarities and differences between genders, both in direction and size of effects of variables on severity probabilities

Variable	Qualitative size of effect	
	Males	Females
Greater severity for both genders		
Driver is 25 or younger	Medium to large	Large
Driver is 65 or older	Medium to large	Small to large
Driver used no restraints	Medium to very large	Medium to very large
Driver had been drinking	Small to very large	Small to large
Making a turn	Medium to large	Small to large
Head-on crash	Medium to large	Medium to large
Overturned/rollover	Medium to large	Medium
Going straight	Small to large	Small to large
Curved road	Small to medium	Medium to very large
Run-off-roadway	Large	Large to very large
Driver ejected from vehicle	Large to very large	Very large
Twilight (dawn or dusk)	Medium	Small to very large
Overtaking/passing	Large to very large	Medium to large
Lesser severity for both genders		
Operating defective equipment	Medium to large	Medium
Sideswipe	Small to medium	Small to medium
Rear end crash	Medium	Small to medium
Rainy weather	Small	Small to medium
Severities in opposite directions	Lesser severity	Greater severity
Driver did not grant right of way	Small to medium	Small to medium
Struck barrier or guardrail	Medium to large	Very large
	Greater severity	Lesser severity
Starting	Large to very large	Medium

The qualitative effect descriptions: small, medium, large, and very large, correspond to the pseudo-elasticity ranges: 0–10%, 10–100%, 100–1000%, and greater than 1000%, respectively.

Defective tires or wheels increase the probability of possible or evident injury for female SUV/minivan drivers in single-vehicle accidents by a little less than 170% on average, while the effect is insignificant in the male-driver model. For female pickup drivers in single-vehicle accidents, defective tires or wheels increase the probability of no injury but are insignificant in the male-driver model. In the single-vehicle passenger car accident models, this variable is insignificant for female drivers but increases the probability of no injury and possible injury for male drivers. In passenger car versus SUV/minivan accidents, defective tires or wheels increase the probability of all injuries for male-SUV/minivan drivers.

Curved roads increase the probability of fatal/disabling injury for female pickup drivers by about 10% in single-vehicle accidents and increase the probability of evident injury for male pickup drivers by about 27%. In the other single-vehicle accidents, curved roads are insignificant in the passenger car-driver models and for female-SUV/minivan drivers, but it decreases the probability of evident injury for male-SUV/minivan drivers by about 31%.

Wet, snowy or icy roads reduce the probability of evident injury for both male and female passenger car drivers in single-vehicle accidents. For single-vehicle pickup accidents, female drivers see a reduced probability of fatal/disabling injury on wet, snowy or icy roads. Male pickup drivers see an increase in the probability of no injury on wet roads, but a reduced probability of possible injury on snowy or icy roads. Wet roads have the worst effect on single-vehicle SUV/minivan accidents, with the probability of possible and evident injuries going up by about 92% according to the average pseudo-elasticity for female drivers and the probability of fatal/disabling injury going up by about 215% for male drivers. This is in contrast to a reduction in the probability of evident injury for passenger car drivers. For SUV/minivan drivers, snowy or icy roads were insignificant in the female-driver model but reduced the probability of evident injury for male drivers.

In head-on crashes between a passenger car and an SUV/minivan, female passenger car drivers experience a reduction in probability of no injury and an increase in the probability of fatal/disabling injury. The same is seen for male passenger car drivers, there is a reduction in their probability of no injury, which equivalently increases the probability of injuries. The effect is slightly worse for females because their fatal/disabling injury probability is directly increased above the possible and evident injury categories. The indicator for opposite direction crashes is insignificant in the female-SUV/minivan driver model but it increases the probability of evident and fatal/disabling injury for male-SUV/minivan drivers.

The indicators for the seasons are important in some of the single-vehicle models. In particular, summer is associated with a higher probability of fatal/disabling injury for female pickup drivers and for male SUV/minivan drivers. Spring is also associated with an increased probability of fatal/disabling injury for male SUV/minivan drivers. In winter, male pickup drivers in single-vehicle accidents have an average 58% increase in the probability of fatal/disabling injury.

Striking a pole or a tree is significant in the single-vehicle accident models for male drivers. The probability of fatal/disabling injury increases slightly for male passenger car drivers, the probability of evident injury declines for male pickup drivers, and the probability of evident injury increases for male SUV/minivan drivers. This variable was insignificant for females.

Striking a barrier or guardrail increases the probability of fatal/disabling injury for female drivers of passenger cars that collided with a pickup or an SUV/minivan and for the female drivers of SUV/minivans that collided with a passenger car. This variable is either insignificant in the corresponding male-driver models or it increases the probability of no injury or possible injury. Striking a barrier or guardrail therefore has the opposite effect for the genders when it is significant.

There is a contrast between male and female passenger car drivers that are starting and collide with an SUV/minivan. Female passenger car drivers have an average increase in the probability of no injury by about 19% while there is an average increase of 310% in the probability of fatal/disabling injury for the male drivers. The variable for merging or changing lanes is also important in pickup and SUV/minivan models, where it increases the probability of injury for males and decreases it for females.

4. Conclusions

The estimation results show there are significant differences between males and females with regard to how various factors affect injury severity. Differences in levels of significance, magnitude and even the direction of the effect that individual variables have on driver-injury severity are observed between male and female drivers. It is not surprising that differences in the magnitude of effects are found between the genders. We show where these differences are and their magnitude. What is more surprising is to observe variables that cause an opposite effect for the genders. For example, increasing the probability of greater severities for one gender but increasing the probability of lesser severity for the other gender. Notably, male drivers of vehicles striking a barrier or guardrail experienced an increase in probability of lesser severity while female drivers experienced an increase in probability of greater severity. Starting a vehicle and crashing with another vehicle was associated with an increased probability of greater severity for male drivers but increased probability of lesser severity for females. Such surprising results may be discarded as a statistical aberration if they appear in only one model. However, these results held across numerous models and this renders evidence that these differences are indeed real. Admittedly the data are somewhat limited geographically (Washington State only).

The observed male/female differences suggest that a combination of behavioral and physiological factors significantly affect driver-injury severity. To better understand the behavioral differences, additional research, using driving simulators and in-vehicle observations of male and female driving behavior, is needed. This research must account for, among other things, possible of differences in risk compensation—driving more aggressively to compensate for the perceived increased safety provided by LTVs because of their size, weight and higher driving position. To address the effects that are caused by the physiological differences between male and female drivers, in-vehicle safety features need to become more customizable for occupants of different sizes and shapes. It is important that such customization be based on advanced crash-test dummies that account for a variety of driver sizes and shapes and collisions with a variety of roadside features, such as barriers and guardrails.

The findings of this paper show the need for injury-mitigation research to seriously focus on male/female differences. This is critical because the need for, and effectiveness of, safety features varies significantly between male and female drivers.

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