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Investigation of Trends and Predictive Effectiveness of Crash Severity Models

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Models

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Investigation of Trends and Predictive Effectiveness of Crash Severity

Models

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1. INTRODUCTION

Analyzing, interpreting, and improving crash severity prediction for vehicular traffic is a critical step in reducing fatal and severe injury crashes and promoting traffic safety. By accurately predicting the factors and scenarios that lead to increased crash severities, lawmakers, planners, and engineers can save lives and reduce the social and economic costs of severe crashes. To this extent, traffic safety professionals must examine growing demographics within the driver population to account for the potential implications that come with different driver behavior and physical driving capability. In order to do this, traffic safety personnel must also ensure that the stochastic processes underlying crash severity are accounted for and accurately modeled.

Objectives

The goal of this thesis is to identify trends in injury severity between the senior and non-senior demographics and to determine where the greatest risks for severe crashes in seniors occur. Specifically, this research looks at overall differences, seasonal trends, and long-term time-dependant trends between the two demographics, controlling for roadway, crash, and individual characteristics known to be related to severity.

Additionally, this thesis endeavors to improve the process of crash severity modeling. The partial proportional odds modeling technique introduced in this research more closely follows the underlying processes involved in crash severity and allows for improvements in prediction accuracy and covariate significance.

Chapter 2 of this thesis "Temporal Modeling of Highway Crash Severity for Seniors and other Involved Persons", investigates the trends present in crash severity between

seniors and non-seniors and describes the measures taken in order to account for special cases in the data distribution resulting from the demographic split. Chapter 3 of this thesis, "Analysis of Driver and Passenger Crash Severity Using Partial Proportional Odds," explains the importance of using the partial proportional odds model over an ordinal (proportional odds) model or the multinomial (generalized logits) model, describes the necessary adjustments to the ordered response framework, and evaluates the effectiveness of the model alongside the ordinal and multinomial alternatives.

2. TEMPORAL MODELING OF HIGHWAY CRASH SEVERITY FOR SENIORS AND OTHER INVOLVED PERSONS

This section describes analysis using ordinal logistic regression to uncover temporal patterns in the severity level (fatal, serious injury, minor injury, slight injury or no injury) for persons involved in highway crashes in Connecticut. Existing state sources provide data describing the time and weather conditions for each crash and the vehicles and persons involved over the time period from 1995 to 2008 as well as the traffic volumes and the characteristics of the roads on which these crashes occurred. Controlling for characteristics known to be related to severity, e.g., age, crash type, and road characteristics, statistical modeling enables us to predict the probability of an individual to have a specific severity outcome if he/she is involved in a crash. Specifically, this section investigates overall, long-term, time dependant and seasonal trends in senior drivers and travelers (65 years and over). This study also accounts for special conditions in data distribution and modeling in order to point to significant impacts on public health and safety as seniors become a larger portion of the population. Findings indicate an overall increase in increased crash severity probability for seniors, as well as a distinct seasonal trend. Other time-dependant trends in the data were visible, but not significant.

Introduction

With the aging of the US population, in many areas of the nation the demographics of the driver population are changing dramatically, with senior drivers (65 years of age or older) making up an increasing proportion. For example, according to the 2001 National Household Travel Survey (Bureau of Transportation Statistics, 2001), "the fastest

growing segment of the driving population, seniors make up 9 percent (about 19 million) of the nation's drivers. This figure is expected to jump to more than 30 million drivers by 2020." Seniors make up an increasing proportion of the population at large as well; the Census Bureau projects a rise from 13 percent in 2010 to 19 percent in 2030 (Yedinak, 2010).

This increase in the senior driver and traveler population has potentially significant impacts on road safety. Seniors exhibit different driver behavior and physical abilities than younger drivers, including requiring longer gaps to make left turns, as well as having longer perception reaction times and less visual acuity (Zhou et al., 2010; Dissanayake et al., 2002). As well, in the same crash scenario, a senior traveler is more likely to be killed or experience a more serious injury than a younger traveler, due to physiological issues (Zajac and Ivan, 2003; Zeeger et al., 1993; Jensen, 1999). On the contrary, while seniors make fewer work trips than younger drivers due to most commonly being retired, many travel just as often in retirement as they did when working, replacing work trips with social/recreational trips as they remain active long into retirement. As a consequence, the observed and expected increases in the senior driving and traveling population could result in increases in crash experience, especially in more severe and fatal crashes.

An Insurance Institute for Highway Safety (IIHS) report found that older drivers have lower rates of fatalities and injuries (all levels) per licensed driver than other drivers (Cheung and McCartt, 2010). This result is somewhat misleading however, as it does not account for miles or time spent driving. On the other hand, Eberhard (2008) found that older drivers have much higher rates of crash involvement and fatality per mile driven

than other drivers, but these higher rates tend to be experienced by those who drive least frequently, possibly because they drive most in complex traffic situations and contend with reduced physical and mental abilities. Keall and Frith (2010) accounted for these factors by considering the type of road (freeway or non-freeway) along with temporal variables such as time of day, day of week and season of year for predicting severity of crashes involving older drivers in New Zealand. They found that older driver risks were comparable to those of drivers in other age groups in each time group, suggesting that their higher risks are due more to the concentration of their trips at times of day at which traveling is more risky for all drivers.

Khattak et al (2010). examined factors related to the motor vehicle driver crash severity, and found that older drivers, males, drivers not using occupant restraint systems and those using alcohol all had greater severity levels than other drivers. Crashes on curves in level terrain and crashes resulting in overturned vehicles or fixed objects and crashes in dry weather were more injurious to older drivers (over 70 years old). Eluru et al. (2008) used a mixed ordered response model to examine pedestrian and bicycle injury severity levels. They found the usual factors of higher speed limit and higher age of the pedestrian or bicyclist to be associated with higher severity levels. Classen et al. (2008) investigated interactions among factors describing the individual, vehicle and the environment for explaining the crash severity of older drivers, in order to better identify which interventions can be most effective for reducing fatalities and serious injuries and where and how to implement them. They also considered time of day, finding the highest severity risk was in late afternoon and with fixed object crashes and when the involved person was not wearing a seatbelt.

None of these studies account for any trends over time that may be important for predicting crash severity distributions in the future, especially as the population ages. However, the exact outcomes are not obvious for several reasons. First, senior drivers and travelers may use different roads than younger drivers, e.g., avoiding limited access highways and high speed roads. Second, senior drivers and travelers travel at different times of day than younger drivers, and crashes at night tend to be more severe, though it is riskier to drive during the day (Ivan et al., 1999); Ivan et al., 2000). Third, motor vehicle crashes are more likely to result in fatalities in rural areas than in urban areas, both due to the higher vehicle speeds and the distance from emergency medical services. Fourth, over time there have been improvements in vehicle active and passive safety features and programs and legislation have been passed that are aimed at improving senior driver safety (as noted above). Finally, weather and daylight conditions vary through the year, both of which exacerbate safety in conjunction with reduced perception reaction time and visual acuity.

The objective of this section is to statistically analyze trends in motor vehicle and pedestrian crash occurrence by severity level and age over the time period from 1995 to 2009 in the State of Connecticut. These trends also consider the month of the year and the type of road and location (limited access or surface roads, and urban or rural). We estimate models to predict the injury severity for any individual involved in a crash as a function of the year and month, weather conditions, whether the individual is senior or non-senior, the type of involvement (driver, passenger, or pedestrian), type of road and location and type of collision (e.g., head-on, angle, sideswipe). Specifically, we study variants of logistic regression models, which will yield valuable knowledge about the

spatial and temporal scenarios when older drivers are most at risk for serious or fatal crashes and how that compares to other drivers, giving road safety professionals better information about where to expect increases in fatal and severe injury crashes to help decide what kinds of initiatives could help to reduce these risks.

Description of Data

The central data source in this study was the Connecticut Department of Transportation (ConnDOT) crash database. This source contained crash records from 1995 to 2009. We focus on crashes that occurred on State maintained roads, as the crash reporting threshold was consistent on these roads through this entire time period.

The raw crash data from the ConnDOT database were compiled by agency personnel from written and electronic reports completed by police officers investigating the crashes. Connecticut statute 14-108a states that a police report (and, in this case, a data entry) must be filed when a police officer reports either an injury or fatality, or a minimum of one thousand dollars of property damage resulting from a motor vehicle crash (16). Consequently, some crashes occurring on Connecticut state roads may go unrecorded, and reported injury severity is limited to the knowledge available to the investigating officer on the scene. ConnDOT personnel check the reported crash data for inaccuracies and remove unnecessary or private information before releasing it to analysts for use. This data is assumed to be complete and accurate for the purposes of our investigation.

In addition to injury severity data, we also have covariate information at the person level, such as age, gender and position in the vehicle, as well as segment-based information from the Connecticut Highway Log. These data, also produced by

ConnDOT, relate roadway characteristics, including area type (urban or rural) and

functional classification, to the rest of the dataset. The variables we are using for senior

severity models are described in detail in Table 1.

Table 2.1. Frequency and Statistical Comparison of Full and Stepwise models

Variable	Stepwise Selection Model			Full Model		
	Sig. Months	Mean	STD	Sig. Months	Mean	STD
Limited Access Road Indicator	76	-0.21739	0.097567	71	-0.10178	0.131708
Possible Injury Intercept	180	-1.72578	0.712598	180	-1.56759	1.828295
Minor Injury Intercept	180	-3.10923	0.710453	180	-2.95362	1.831629
Severe Injury Intercept	180	-4.73279	0.766851	180	-4.57907	1.844325
Fatal Intercept	180	-7.06661	0.786337	180	-6.91325	1.863131
Urban Land Use Indicator	33	-0.17203	0.26521	34	-0.09444	0.313548
Wet/Icy Road Surface Indicator	27	0.026303	0.210963	46	0.023795	0.14432
(W_C) Inclement Weather Indicator	44	-0.12343	0.212879	68	-0.05533	0.17142
Senior-Access Control Interaction	21	-0.15253	0.602214	30	-0.054	0.274523
Senior Indicator	48	0.090617	0.346943	38	0.073137	0.446089
Senior-At-Fault Interaction	49	0.457608	0.086966	66	0.215604	0.192798
Senior-Land Use Interaction	26	-0.49153	0.736616	35	-0.09656	0.447576
At-Fault Indicator	180	-0.63919	0.07807	180	-0.65151	0.072847
Exponential Transform VMT	22	-0.23307	1.331401	34	-0.42924	2.378899
Normalized VMT	25	-0.15708	1.863041	32	0.621546	3.746211
Same Direction Crash Type	106	-0.44889	0.86666	75	-0.39512	1.827785
Turning Opposite Direction/Angle Crash	153	0.874328	0.697859	44	0.606488	1.805107
Rear-End Crash Indicator	143	0.498575	0.746306	35	0.260475	1.813475
Head On/ Object Crash	167	1.357087	0.642987	85	1.12802	1.787188
Backing/Parking Crash	109	-1.54878	0.590795	118	-1.15293	1.913061
Crash Involving Pedestrians	48	-1.97694	0.810618	88	-1.43643	2.433284
Jackknife Crash Type	49	2.664198	0.930952	41	-1.94365	5.088773
Pedestrian Indicator	180	4.30688	0.808538	173	5.054706	2.084929
Passenger (Front Seat) Indicator	138	0.195664	0.048402	150	0.164959	0.065559
Passenger (Back Seat) Indicator	108	-0.26698	0.081168	125	-0.19472	0.113537
Passenger, Not In Seat Indicator	108	-0.61667	0.821571	126	-0.4326	0.708252
2-Wheeled Motorized Vehicle Indicator	167	3.013851	0.499108	169	2.809149	1.11915
Single Body Truck/Bus Indicator	177	-0.39534	0.106261	178	-0.39476	0.105319
Tractor-Trailer Indicator	176	-1.44111	0.42948	176	-1.50428	1.043854
Bicycle Indicator	175	3.089246	0.456986	176	3.039792	0.528636
Pedestrian/Non-Conflict Indicator	10	-0.26716	1.30527	22	-1.28223	3.051923

Study Methodology

Crash Severity Model

We used a logistic regression modeling framework in our study to determine injury severity prediction for each person involved in a crash. The logistic regression model, using multiple categorical variables to define all of the possible levels of injury severity in a crash, can be most easily represented by either the Multinomial or Ordinal Logit framework. While the Multinomial Logit model does not assume an ordering in the levels of the categorical response variable, the Ordinal Model assumes such an ordering, and further, it also accommodates a proportional odds (PO) assumption, which states that the effect of a particular predictor variable will have the same proportional effect on all levels of the response variable (Hedeker, 2008). The response variable, severity, has five distinct possible values, 1, 2, 3, 4, and 5 corresponding to the five ordered categories of injury, as follows:

$$Sev = \begin{cases} 5: Fatal\ Injury\ (K) \\ 4: Severe\ Injury\ (A) \\ 3: Minor\ Injury\ (B) \\ 2: Nonevident\ Possible\ Injury\ (C) \\ 1: Property\ Damage\ Only\ (PDO, O) \end{cases}$$

It is important to understand that severity levels are, in practice, related to one another. Severe injuries, for instance, are the result of a higher level of damage than minor injuries, minor injuries are the result of severe crashes than possible injuries or property-damage only crashes, and so on. For this reason, we select the ordinal response model as the most appropriate framework for crash severity modeling.

Note that the ordinal logistic model does not assume equi-spaced distances between any two levels. For example, the model assumes that the difference between a level 1 and a level 2 severity may be different from a level 4 and a level 5 severity. This remains consistent with previous studies modeling crash severity on an individual level (Greene, 2000). The general form of the link function for this model is

$$\eta_{ji} = logit(p_{ji}) = log\left(\frac{Prob(S_i \geq j)}{1 - Prob(S_i \geq j)}\right) \text{ for } j = 1, 2, .., J - 1$$

where η is the logit transformation of the probability of individual i having an accident severity of j or greater. The expected regression surface is defined by the linear model

$$\eta_{ji} = \beta_{0ji} + \beta_{1i}X_{1i} + \cdots + \beta_{Pi}X_{Pi}; \text{ for } j = 1, 2, .., J - 1$$

where $X_{1i} \ldots X_{Pi}$ are relevant predictor variables. With J=5, the proportional odds assumption implicit in the ordinal model leads to a regression equation with four different intercepts and a common slope corresponding to each of the P predictors.

Senior Trend Analysis

This section analyzes the association between a person being a senior and his/her crash severity in three ways: an overall analysis of significance, analysis of a time-dependant trend, and an investigation of seasonal patterns.

The setup for analyzing the overall significance is very similar to that for analyzing time-dependant trends. Both investigations segment the full ConnDOT database by month, from m=1 (January 1995) to m=180 (December 2009). The monthly breakdown and analyses provide sufficient information for carrying out a subsequent temporal analysis and allows us to account for monthly variation in vehicle miles travelled (VMT) and driving conditions, as well as long-term changes in road safety.

Separate ordinal logistic regression models are then fit to the data in each month. Predicted probabilities for each severity level are obtained for each person in the data set. For the overall trend analysis, the cases in each month are further separated by the senior indicator, and the predicted probabilities by severity level are compared between the senior and the non-senior groups. Because we cannot be sure of the distribution of these probability levels for seniors and non-seniors, the non-parametric two-sample Wilcoxon-Mann-Whitney test is appropriate for comparing the mean of the monthly averages of these predicted probabilities. The hypotheses for the two-sample Wilcoxon test are as follows:

$$H_0: \mu_a = \mu_b;\ H_a: \mu_a \neq \mu_b$$

where μ_a denotes the mean of the senior population and μ_b denotes the mean of the non-senior population. In addition, empirical QQ plots for senior versus non-senior average monthly predicted probabilities for each severity level allow us to compare whether the entire empirical distributions of seniors and non-seniors are similar.

We test for time-dependant trends in the data by obtaining predicted probabilities by severity level for all seniors and non-seniors for each month, as well. We then separate this data by senior and non-senior individuals, and the mean predicted probabilities and variance are obtained for each severity level. In order to isolate all of the effects of the senior indicator while accounting for irrelevant time-dependant accident trends, we take the difference between the predicted probability for senior and non-senior individuals. The probability difference Δp_j for severity j over all months follows a normal distribution

$$\Delta p_j \sim N(\bar{p}, \sigma_{Senior}^2 + \sigma_{Non\ Senior}^2)$$

for a sufficiently large data size. Linear and exponential smoothing models are then fit to these points in order to determine the existence and significance of temporal trends in the data.

For investigating seasonal trends in the senior variable, we grouped the dataset by month of the year and fit separate ordinal logistic regression models to each. Similar to the overall temporal trend analysis, we find the predicted probabilities for every case in each month, for the difference between senior and non-senior individuals. We then investigate the difference between the senior and non-senior predicted probabilities by month. To determine whether a particular month is significantly different from others, we verify whether the 95% confidence interval for the mean predicted probability includes zero, and whether the interval changes significantly from month to month.

Methodological Considerations

In order to ensure the validity and power of these trend analyses, we need to account for anomalies and inconsistencies in the data structure, the models, and the analyses. The main concerns in finding significant trends in senior severity prediction for our research project deal with the consistency of variables in multiple models, the assumption of ordinal versus non-ordinal response levels, and possible correlation issues with analyzing multiple persons involved in the same crash. While these issues would not necessarily disprove the existence of significant trends and effects in our data analysis, the existence of these problems would indicate that a choice between different methodologies needs to be considered in modeling senior crash severity distribution for this application.

Variable Selection

A stepwise model selection procedure was considered to produce reduced-variable best-fit models for crash severity. Summary statistics for each of the predictor variables, including the frequency of use in the model, can be found in Table 1. On a month-to-month basis, the stepwise variable selection allows variables to be significant more frequently than with a full model with similar selection criteria (stepwise selection in this case used a p-value of 0.1 for entry and a p-value of 0.05 for removal; the full model needed $\alpha=0.1$ to obtain comparable frequency figures). However, since we are obtaining several separate seasonal and monthly models as opposed to a single model for crash severity modeling, one of our main concerns is to keep consistency in the model. While certain predictor variables may not be significant at $\alpha=0.1$ or $\alpha=0.05$ in every monthly model, they may still alter the overall severity probability prediction. The stepwise model does have similar overall partial predictor values to the full model and may be suitable for the dataset. When accounting for interaction terms between the senior variable and other predictors, though, the full model is still the most suitable approach to our study.

Response Value Distribution

The use of an ordinal response model is logical for this analysis because it correctly assumes the probability of one severity level to be related to the probability of other severity levels. However, the major drawback of using an ordinal logistic regression model is the assumption of proportional odds, under which, a predictor affects each of the J response values in the same manner.

An alternative model is the Multinomial Logit model which assumes the response variable is nominally scaled, and assumes non-proportional odds. The non-proportional odds assumption can allow each predictor variable to affect each level of severity differently in the model, although it does not account for dependence among severity levels.
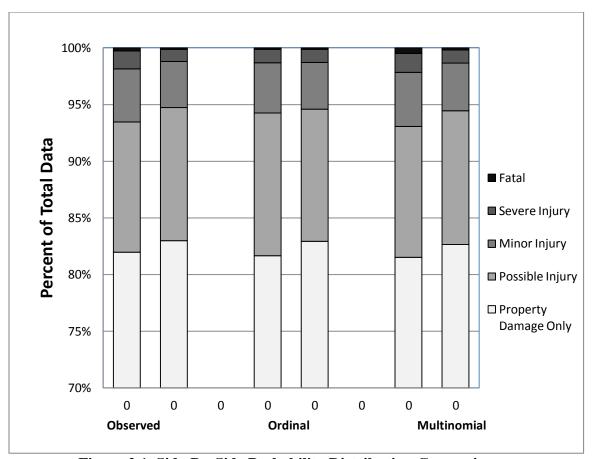
Figure 2.1. Side-By-Side Probability Distribution Comparisons.

Figure 1 shows the cumulative severity predicted probabilities for the entire data set, separated by the senior indicator for the multinomial and ordinal logistic regression models, plotted against the observed severity distribution. The two models have very similar severity probability distributions for both senior and non-senior individuals. The

similarities between the distributions indicate that the ordinal response model is justified as a practical model for crash severity prediction.

Another possible alternative is the Partial Proportional Odds model, which allows selected predictors to have varying effects on each level of severity, while others are forced to have the same proportional effect on all response levels. Having certain variables affect levels of crash severity differently may improve prediction accuracy, as some variables understandably might have very different effects on the probability fatal injuries, for example, than minor or possible injuries. The benefit of the Partial Proportional Odds model, though, is that it still recognizes the response variable as having correlated levels, which allows us to represent the data in a more practical manner.

A comparison of the ordinal response model and the partial proportional odds model can be found in Figure 2. The partial proportional odds model has a very similar structure to the ordinal model. However, due to instability in the estimation methods, the partial proportional odds model code provided by a SAS macro is unable to handle the large number of variables that we used in the ordinal model. As a result, we ran a partial proportional odds model and an ordinal model with the same set of fewer variables in order to compare the two in a similar context. The partial proportional odds model has the potential to improve on the ordinal logistic regression model, but will need further research to properly model crash severity in the presence of a large number of predictors.
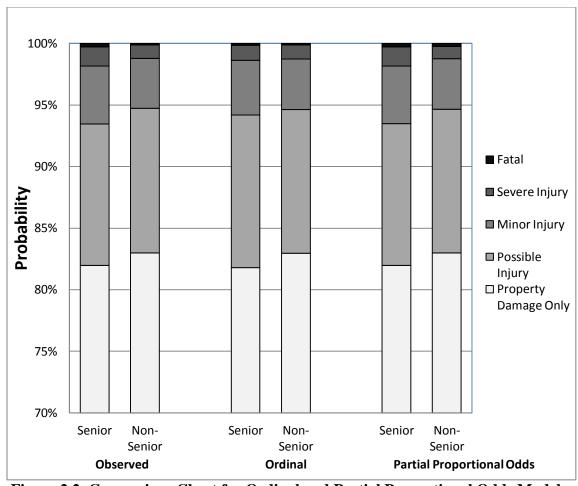
Figure 2.2. Comparison Chart for Ordinal and Partial Proportional Odds Models.

Cluster Effect

Because our model predicts severity for every person involved in a crash, a concern about our model's validity comes from the possible correlation among individuals in the same crash. Normally, a three-level model built assuming correlation for persons within each crash and crashes within each month would solve this possible clustering effect. However because of the instability of multi-level models with the large number of variables and cases in our data, we instead look at this correlation using a variation of the Multinomial Logit model that adjusts for correlation within crashes.

To test whether clustering individual persons within crashes changes the model significantly, we construct our dataset as a clustered model, finding the severity probability distribution. We then compare the probability distribution from the clustered model to a standard ordinal model by creating empirical QQ plots for each severity level (Figure 3).
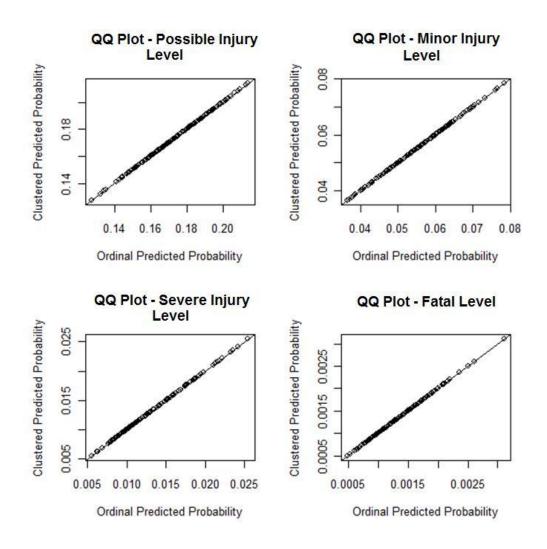
Figure 2.3. Empirical QQ Plots of Ordinal Response Model VS Clustered Model.

The empirical QQ plots provide a 45 degree line as a reference for perfect similarity of empirical distributions between predicted probabilities from the two models. The plotted points fit the line with no discernable deviance for any point at any severity level. We can thus conclude that correlation within crashes does not have any significant bearing on the results of the crash severity models.

Results

We performed separate two-sample Wilcoxon tests on each severity level for every month between senior and non-senior predicted severity probabilities for the entire population, as well as a monthly mean model. The population data set did not show any differences between severity levels, with the test yielding a p-value of 0.07 for all severity levels. The results of the Wilcoxon test for the monthly mean model yielded a p-value of 0.0000014 for PDO and possible injury levels, and a value of 0.0051 for minor injuries. However, p-values of 0.65 and 0.87 were obtained for severe injuries and fatalities, respectively.

Figure 4 shows empirical QQ plots for seniors versus non-seniors for all severity levels and table 2 lists summary statistics for the differences in probabilities for seniors and non-seniors across severity levels. While predicted probabilities become similar between seniors and non-seniors for higher severity levels, the QQ plots reveal that seniors have nearly ubiquitously higher severity predictions when predicted probabilities differ.
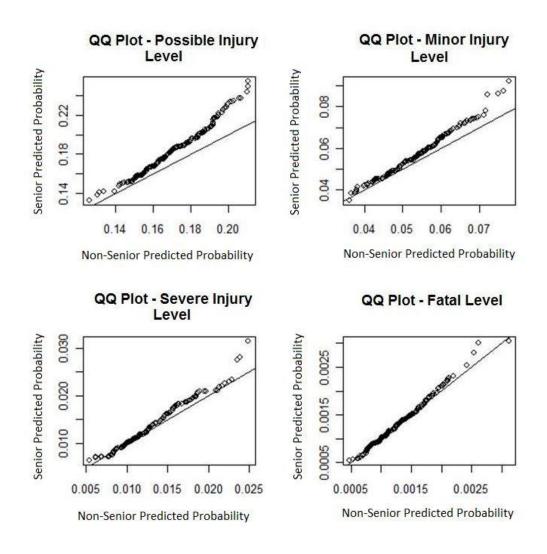
Figure 2.4. Empirical QQ Plots of Elderly VS Non-Elderly Predicted Probability.

Table 2.2. Severity Probability Statistics, Difference between Seniors and Non-Seniors

Statistic	Prob(j, Senior) - Prob (j, Non-Senior)				
	PDO	Possible Injury	Minor Injury	Severe Injury	Fatal
Mean	-0.01281	0.012814	0.003304	0.000467	1.81E-05
Variance	0.000223	0.000223	3.4E-05	3.38E-06	5.58E-08
Range	0.080319	0.080319	0.03093	0.011134	0.001886
HCI (95%)	0.01062	0.015008	0.004161	0.000738	5.29E-05
LCI (95%)	-0.01501	0.010619	0.002446	0.000197	-1.7E-05
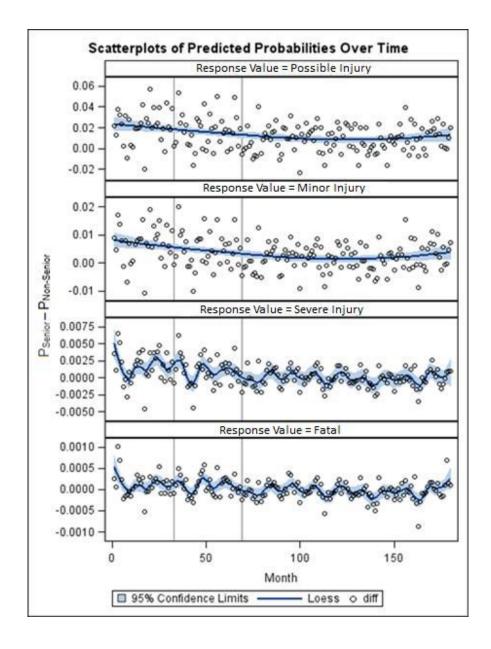
Figure 2.5. Linear Smoothing Model for Mean Monthly Predicted Probabilities.

The probability difference between senior and non-senior individuals, $P_{jim, senior} - P_{jim, non-senior}$ was calculated for each data level on a monthly basis to isolate potential temporal trends in the senior predictor (Figure 5). We then fit these monthly probability predictions with a second degree linear smoothing model. Finally, we demarcated two dates corresponding to significant changes in vehicle safety regulations on the plots (September 1997 and September 2000, denoting stricter regulation standards for airbags and brakes, respectively). While no extreme trends emerge in the data, the smoothing lines show a slight decrease in severity probability at all levels until 2003. After this, the models remain level for a few years, showing a slight increase from 2007 until the end of 2009. The two marked dates, however, do not seem to correspond to any trend in the data.
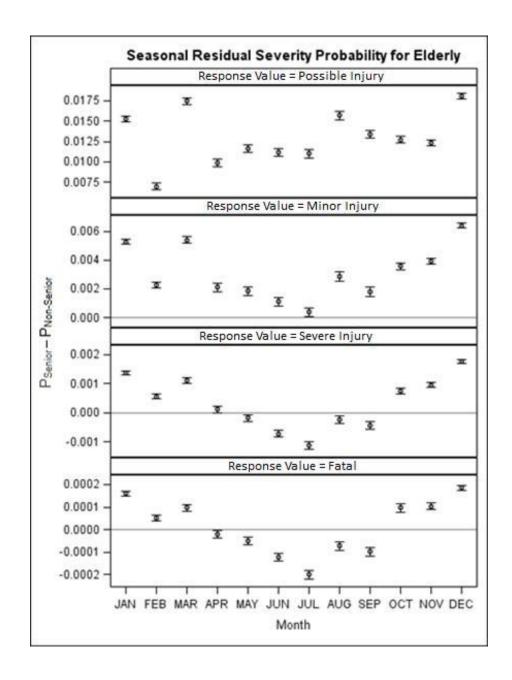
Figure 2.6 Confidence Intervals for Seasonal Senior Predicted Effects.

The residual crash severity probability for senior individuals in seasonal

groupings is shown on Figure 6. For more severe injuries, senior individuals go between

being more at risk and less at risk than non-senior individuals. However, a clear trend

emerges on a seasonal level, with a high risk of greater injury in the winter months and a

lower risk of injury and fatalities in the summer months. Low crash severities do not

show this trend as well, with possible evident injuries losing an easily distinguishable seasonal trend.

Discussion

These results show that significant trends do exist for predicted probabilities from the ordinal model for severity for senior individuals. As evidenced by QQ plots and the results of the Wilcoxon-Mann-Whitney tests, seniors show an overall increase in the probability of suffering higher levels of injury severity compared with non senior persons. Under our model, differences are much more significant at lower severity levels, with severe and fatal injuries not showing statistical significance for the test of the monthly predicted probability means. None of the predicted probabilities are significantly lower for seniors than non-seniors.

The time-based trend for senior crash severity is even more difficult to accurately predict. Our initial approach for analysis of senior crash severity was to observe the trends in the partial predictor variable for seniors. However, this data set, both due to its size and the number of predictor variables, has an extremely high probability of correlation between predictor variables. With the potential for an impractically high number of interaction terms within the data, we observed that the most effective method for determining the significance of a trend in the effect of a single predictor is to completely isolate the variable's effect. By observing the difference in the model with and without the senior indicator term added, we found a gradual temporal trend in the data distribution for each severity level.

The linear smoothing model additionally helped to identify a time-dependant trend in the data, largely because of its flexibility in modeling a locally constant trend

rather than a globally constant trend implied by a traditional regression model. The seasonal trend analysis provided the most definitive results in the study. The level of significance of the seasonal trends are due in part to the large number of cases associated with each month, narrowing the confidence interval for the analysis enough that the range of values for residual severity probability rarely overlapped from month to month. A strong seasonal effect must be prevalent to affect senior travel safety so greatly between summer and winter months.

Conclusions

While overall road safety has been improving over time, any decrease in traffic safety is an important concern. With the anticipated growth of the senior population in the United States, senior safety has the potential to become a notable issue facing road safety. This study focused on identifying the scope and development of where senior driving safety falls short. Interestingly, while our model identified an overall trend in increased severity probability for low-severity injuries with no significance in severe and fatal injuries, we found high severity injuries to exhibit the most visible seasonal trends. Similarly, the modeling for time-dependant trends shows that the linear smoothing models produce much smoother trends for low injury severities, where seniors almost exclusively have higher predicted probabilities than non-seniors. Higher severity levels, on the other hand, produce much more varied – almost sinusoidal – smoothing trends. This may indicate a stronger than expected correlation between seasonal effects and injury severity. In addition, the stark difference between possible and minor injuries and severe and fatal injuries could serve as a useful break point for simpler severity models.

The smoothing models themselves indicate potential time-dependant trends that show decreasing severity probability for seniors over the late 1990s, with a rise in probability in the late 2000s. This may indicate that recent safety features are less effective for senior drivers, or that the continued increase in the senior demographic is causing a relative increase in severity probability in recent years. However, these trends are very subtle and not statistically significant. In addition, the upward trend in relative severity probability for seniors only spans two years and may be a result of random variation in data that could be explained by regression to the mean. Thus, the trends displayed through the smoothing models are inconclusive with our current data.

These trends presented in senior crash severity from our study, while not fully reliable in terms of statistical significance, depict the potential start of long-term patterns. Additional research into the correlation between severity levels and seasonal or temporal trends for senior safety may yield more significant results. Additionally, with further investigation into more refined models for predicting crash severity probability for seniors and non-seniors, as well as the inclusion of additional years of data into future studies, we may be able to more accurately identify future trends in crash severity for seniors and non-seniors. This will allow resources to be more efficiently allocated in promoting continued improvements in road safety.

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3. ANALYSIS OF DRIVER AND PASSENGER CRASH SEVERITY USING PARTIAL PROPORTIONAL ODDS MODELS

The question of whether crash injury severity should be modeled using an ordinal response model or a non-ordered (multinomial) response model is persistent in traffic safety engineering. This paper proposes the use of the partial proportional odds (PPO) model as a statistical modeling technique that both bridges the gap between ordered and non-ordered response modeling, and avoids violating the key assumptions in the behavior of crash severity inherent in these two alternatives. The partial proportional odds model is a type of logistic regression that allows certain individual predictor variables to ignore the proportional odds assumption which normally forces predictor variables to affect each level of the response variable with the same magnitude, while other predictor variables retain this proportional odds assumption. This research looks at the effectiveness of this PPO technique in predicting vehicular crash severities on Connecticut state roads using data from 1995 to 2009. The PPO model is compared to ordinal and multinomial response models on the basis of adequacy of model fit, significance of covariates, and out-of-sample prediction accuracy. The results of this study show that the PPO model has adequate fit and performs best overall in terms of covariate significance and prediction accuracy. Combined with the ability to accurately represent the theoretical process of crash injury severity prediction, this makes the PPO technique a favorable approach for crash injury severity modeling.

Introduction

The improvement of traffic safety is of continual importance to US and world populations due to the high socioeconomic impacts of severe crashes. Out of the total 210 million registered drivers in the US in 2009, there were 33,808 fatalities, according the National Highway Traffic Safety Administration (NHTSA) fatality analysis reporting system (FARS) (NHTSA, 2012). While this figure was a 9.7 percent decrease from the previous year, this number of fatalities still represents a significant portion of the driving population, and will only continue to improve with continued efforts towards understanding and improving traffic safety.

One of the main steps in improving traffic safety is in distinguishing and predicting trends in crash severity. Crash severity modeling is useful for this. Crash severity modeling, as opposed to predicting the likelihood or number of crashes in a given location, determines the probability of a level of injury severity given the occurrence of a crash. Using common categories defined by US government transportation agencies, crash injury severity is classified into one of five categories: fatal injury, severe injury, minor injury, non-evident possible injury, and property damage only (PDO). With a choice-based response variable, probabilistic models are used to predict and analyze crash severity. Some of the earlier methods for crash severity analysis were adapted from econometric models (McFadden, 1981).

One of the most common approaches to predicting crash severity is the ordered logit or ordered probit models. Because the levels of crash severity are inherently related to one another, ordered probability models are often a convenient method for capturing this association between severity levels, and have been used extensively in traffic safety (Hutchinson, 1986; O'Donnel and Connor, 1996; Renksi et al., 1998; Duncan et al.,

1999; Abdel-Aty (2003); Zajac and Ivan, 2003; Yamamoto and Shankar, 2004). These models, however, must adhere to the proportional odds (PO) assumption, which forces the coefficient estimates for covariates in the model to remain constant for all response levels. For example, any given variable can only increase or decrease the probabilities of all injury levels by the same scale, rather than having different effects on each level of the response. However, we often observe that some variables may reduce the probability of one level and increase another in a way that cannot be accounted for in the ordinal model framework (Savolainen, 2007; Peterson and Harrell, 1990).

Another approach often used to predict crash severity is the multinomial probability model for unordered or nominal levels. This approach assumes that the levels of crash severity are unordered. It also allows all variables in the model to affect each response level differently, avoiding the constraints of proportional odds (Shankar and Mannering, 1996; Chang and Mannering, 1999; Carson and Mannering, 2001; Lee and Mannering, 2002; Ulfarsson and Mannering, 2004; Khorashadi et al., 2005). However, by that the injury severity levels are unordered, the multinomial approach does not account for the ordered levels inherent in crash severity. This issue has been addressed using the nested Logit model. This model uses a series of nests for the response variables to structure the data in order to apply order to the multinomial framework. This model has been effective at producing similar results to the multinomial and ordinal models. However, this method adds a great deal of complexity to the process in identifying the nested structure and does not offer a great enough increase in prediction accuracy to justify the added complication in the model (Abdel-Aty 2003). Because of this, the nested Logit model is not used as an alternative in this study.

As noted above, the multinomial and ordinal models both have inherent problems when applied to injury severity analysis. As such, neither approach fully captures all of the subtleties of crash severity probability modeling. Yet another alternative is the partial proportional odds (PPO) approach, which allows for both the ordered structure of the ordinal approach and the ability of the multinomial approach for certain variables to affect each response level differently The PPO model achieves this by allowing a combination of the two modeling frameworks, in which the model begins with an ordered response framework. From this, a subset of the predictor variables in the model can reject the PO assumption and affect each level of injury severity independently (Peterson and Harell, 1990; Hedecker et al., 2006). This alteration allows the analysis to have some of the flexibility of the multinomial approach, while adding minimal complexity to the modeling framework. Wang and Adel-Aty (2008) estimated partial proportional odds models to analyze left-turn crash severity in Florida based on conflicting patterns. Results show that the PPO model consistently performed better against the ordinal model in terms of model fit through AIC. In addition, the partial proportional odds model was able to successfully identify the increasing effect of alcohol and drug use on injury severity that was obscured by the ordinal model.

The objective of this paper is to explore the creation and refinement of PPO models for crash severity and to compare the model's performance to both the ordinal and multinomial approaches on both large-scale (200,000 crashes) and smaller-scale (20,000 crashes) sample sets. Using crash data from state roads in Connecticut, we build models using the same link function and covariates using the ordinal, PPO, and multinomial approaches. Then, we examine the three models based on three general

criteria: model fit adequacy, covariate values and significance levels, and holdout prediction accuracy. The goal of these analyses is to show that the PPO model performs better than the ordinal and multinomial models, providing predictions and covariate values that are more reliable because the PPO model is able to fully represent the underlying principles of crash severity risk.

Description of Data

The data source used for model comparison in this study was the Connecticut Department of Transportation (ConnDOT) crash database. This source contains crash records on state maintained roads from January 1995 to December 2009.

The crash data from this source come from both written and electronic reports completed by police officers that investigate the crashes. In accordance with Connecticut statute 14-108a, police officers must file a report when a crash involves an injury or fatality or a minimum of one thousand dollars of property damage resulting from the crash (CT Const. art. I § 14 cl 108a). This may result in some crashes going unrecorded. In addition, both crash occurrence reporting and injury severity recording are limited to the knowledge available to the investigating police office. These reports are then transmitted to ConnDOT, where personnel correct inconsistencies in the reported values, add linear location referencing (route and milepost) and remove any private or sensitive information before releasing it for public use. From this data, we selected several variables for use as covariates in our study. These covariates were selected based on a priori knowledge about likely association with crash severity and on completeness of information within our data source. The following variables were used: indication of at-fault vehicle, indication of senior status (65 or more years old), access control (limited

access or surface street), land use (urban or rural), weather (inclement or non-inclement), and crash type. Crash type was a categorical variable, grouped based on similarities of contributing factors to the crash (Ivan et al., 1999). Factor level proportions for the entire data set can be found in Table 1.

Table 3.1. Factor Level Proportions for Model Covariates

VARIABLE	DESCRIPTION	PROPORTION = 1
FAULT	1=in at-fault vehicle; 0=not at fault	0.5086
SENIOR	1=senior; 0=non-senior	0.075
URBAN LAND USE	1=urban; 0=rural	0.9448
LIMITED ACCESS	1=limited access; 0=surface road	0.3135
INCLEMENT WEATHER	1=inclement weather; 0=no inclement weather	0.2136
SAME DIRECTION COLLISION	1=same direction collision; 0=otherwise	0.1535
ANGLE / TURNING COLLISION	1=angle/turning collision; 0=otherwise	0.2148
REAR-END COLLISION	1=rear-end collision; 0=otherwise	0.4499
HEAD-ON, OBJECT COLLISION	1=head-on/object collision; 0=otherwise	0.1552
PACKING/PARKING COLLISION	1=backing/parking collision; 0=otherwise	0.0186
PEDESTRIAN CRASH	1=pedestrian crash; 0=otherwise	0.0053
JACKKNIFE	1=jackknife; 0=othewise	0.0006

Methodology

The general cumulative probability function for the partial proportional odds model with J response levels follows the following equation:

$$P(S_n \leq j) = F\left(\mu_j - \boldsymbol{\beta} X'_n - \boldsymbol{\gamma}_j T'_n\right), \quad j = 1, \dots, J - 1 \qquad \text{(Eq. 1)}$$

where μ_j is the threshold for level j, X_n is a p x 1 vector containing the values for observation n for all p predictor variables in the model, $\boldsymbol{\beta}$ is a p x 1 vector of regression

coefficients associated with X_n, T_n is a q x 1 vector (q ≤ p) containing the values for

observation n on the subset of p predictor variables where the proportional odds

assumption is rejected, and γ_j is a q x 1 vector of regression coefficients associated with

T_n, such that $\gamma_j T'_n$ corresponds only to the jth cumulative level of the response variable,

and $\gamma_1 = 0$ (Peterson and Harrell, 1990).

Interpretation of the coefficient values and significant tests of the coefficient

matrices β and γ_j must be done carefully within the PPO framework. A single variable

X_{in} given $i \in q$ will have a coefficient β_i that applies for all response level, as well as a

value for γ_{ij}, corresponding only to response level j. Thus, the true coefficient value for

the variable X_{in} is equal to $\beta_i + \gamma_{ij}$. Likewise, when determining covariate significance

the null hypothesis must test both $\beta = 0$ and $\gamma_j = 0$. To illustrate the similarity between

the PPO model and both the ordinal and multinomial models, we can look at both of

these alternatives as special cases within the PPO framework. If $q = 0$, $\gamma_j T'_n$ drops out

of the model and the equation becomes $F(\mu_j - \beta X'_n)$, which is the ordinal response

model. If $q = p$, $T_n = X_n$ and the equation becomes the cumulative probability function

for the multinomial model, $F(\mu_j - \beta_j X'_n)$, where β_j is the sum of β and γ_j.

Here, $F(.)$ corresponds to the logistic, normal, or extreme-value distribution

functions for the multinomial Logit, multinomial probit, and multinomial HEV response

models, respectively.

The probability distribution is as follows:

$$P(S_n = j) = \begin{cases} F(\mu_1 - \beta X'_n - \gamma_1 T'_n) & S_n = 1 \\ F(\mu_j - \beta X'_n - \gamma_j T'_n) - F(\mu_j - \beta X'_n - \gamma_j T'_n) & 1 < S_n \leq J - 1 \\ 1 - F(\mu_{J-1} - \beta X'_n - \gamma_{J-1} T'_n) & S_n = J \end{cases} \text{ (Eq. 2)}$$

Because the only significant difference between the PPO model and the ordinal/multinomial models lies inside of the function $F(.)$, all statistical tests that involve the probability function of the model remain unchanged from their original form. For our study, the Logit link was used in order to promote stability in the models and to reduce calculation time for larger sample sizes. In addition, in the following comparison study, we use a slightly altered version of this general function:

$$P(S_n \geq j) = G\left(\mu_j + \boldsymbol{b}\boldsymbol{X}'_n + \boldsymbol{c}_j\boldsymbol{T}'_n\right), \quad j = 1, \dots, J-1 \qquad \text{(Eq. 3)}$$

Here, $G(u) = 1 - F(u)$, $\boldsymbol{b} = -\boldsymbol{\beta}$, and $\boldsymbol{c}_j = -\boldsymbol{\gamma}_j$. We use this distinction for ease of interpretation in results. In this way, we allow the lowest response level, PDO, to act as the reference value. In addition, a positive value of the threshold or coefficient will indicate an increased probability of a higher severity value and a negative coefficient will indicate a decreased probability.

Selecting Predictors to Reject Proportional Odds

In order to determine which predictor variables will belong to the subset q that rejects the PO assumption, we observe each variable individually using both a statistical test and a visual test. For the statistical test, we use a Wald test of proportional odds. This test takes the multinomial response variable and dichotomizes it based on cumulative probability, using $P(S_n \geq j)$ and $P(S_n < j)$ for each j. Similar to the Independence of Irrelevant Alternatives test, this method simply determines whether the effect of a variable will remain the same across all "cuts" of j.

The visual test of the data uses a similar formulation (Figure 1a, b). The test finds the empirical logits, where

$$Emplogit = \ln\left[\frac{P(S_n \geq j)}{P(S_n < j)}\right]$$

(Eq. 4)

for each cut of $S_n \geq j$ and $S_n < j$. These empirical logits are plotted across the support of the predictor variable and examined for parallelism. If there is significant deviation from parallelism, we can conclude that the variable will likely reject the PO assumption.

(a)   (b)
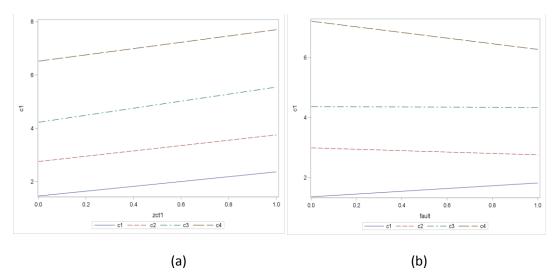
Figure 3.1. Example of (a) no PO Rejection and (b) PO Rejection

Comparative Study

Fit Adequacy

In order to compare the fit of the PPO model to the alternatives, models were run separately for each year of the data to provide an adequate sample for fit and to avoid fit problems that may come with different populations of crashes from different years. Average predicted probabilities were found for each level, which were compared to the observed percentage of injuries at each level using the mean absolute percent error

(MAPE). The boxplots of the values for each level of injury (figure #) show that all

aggregate values of MAPE fall between 0 and 1 for all three model types. Average values

for MAPE are 0.344, 0.359, and 0.099 for the ordinal, PPO, and multinomial models,

respectively. While the average value for fit for the PPO model is slightly higher than the

ordinal model, this difference is not significant, and the range of values for the PPO

model are lower than the range of the ordinal model.
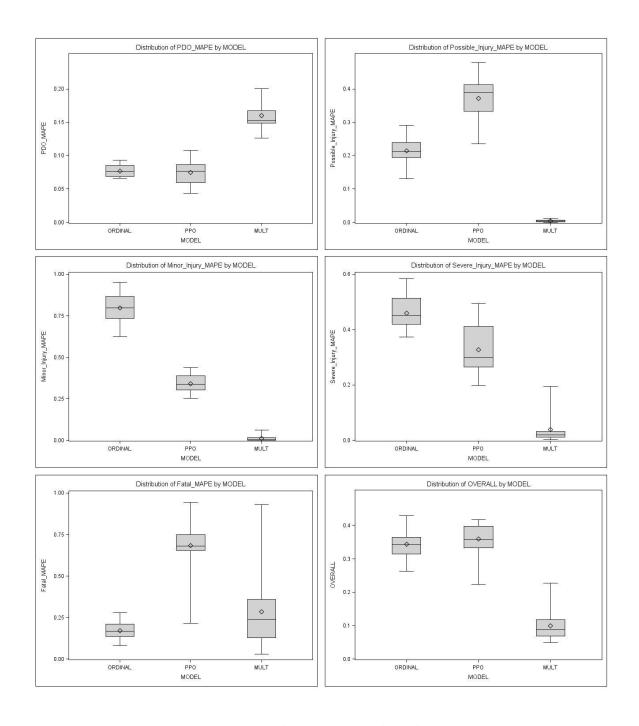
Figure 3.2. Boxplots of Aggregate MAPE for Model Fit

As an additional measure of fit comparison, the Log-Likelihoods, AIC, and BIC were computed for each of the fifteen years. Table 2 shows the averages of each measure for the ordinal, PPO, and multinomial models. Similar to the aggregate MAPE values, the

multinomial model has the best average fit, with the ordinal having the worst. As evidenced by the values for standard error, there are no significant differences between the Log-Likelihood, AIC, and BIC amongst the three models.

Table 3.2 Comparison of Log-Likelihood, AIC, and BIC.

Criterion	Ordinal		Partial Proportional Odds		Multinomial	
	Mean	Standard Error	Mean	Standard Error	Mean	Standard Error
LL	-95440.6	7920.791	-94149.621	7793.518463	-93585	7729.315
AIC	190913.3	15841.58	188355.241	15587.03693	187274	15458.63
BIC	191073.4	15842.44	188641.011	15587.03693	187794.4	15461.43

Comparison of Covariates

Table 3 shows the covariate values for every covariate at every level for each of the three models. Significant covariates are fairly similar between the models. The at-fault indicator, access control, weather, and five out of seven of the crash types were significant in the majority of the models. The covariate effects with the greatest magnitude in the model were found to be same direction and backing/parking collisions, which consistently lowered probabilities of injuries and fatalities, and pedestrian collisions, which dramatically increased the probability of injury and fatality.

Overall, the PPO model shows similar coefficient values and significance levels to the multinomial model in variables that reject the PO assumption. When variables do not reject the PO assumption, the coefficients more closely resemble the ordinal model.

Table 3.3. Covariate comparison of model results. Grayed cells indicate no significance. Italicized cells indicate significance (α=0.05) in at least one model. Bolded cells indicate significance in all models.

MODEL TYPE	ORDINAL				PARTIAL PROPORTIONAL ODDS				MULTINOMIAL			
LEVEL	Poss. Injury	Min. Injury	Sev. Injury	Fatal	Poss. Injury	Min. Injury	Sev. Injury	Fatal	Poss. Injury	Min. Injury	Sev. Injury	Fatal
INTERCEPT	-0.974	-2.288	-3.773	-5.888	-1.030	-2.284	-3.814	-5.430	-1.492	-2.565	-4.282	-5.691
FAULT	-0.615				-0.675	-0.136	-0.341	*-0.094*	-0.873	-0.103	-0.383	0.032
SENIOR	0.088				*0.071*				-0.005	*0.072*	0.330	**0.910**
LAND USE	-0.054				-0.037	-0.165	0.057	-1.098	0.022	*-0.202*	0.621	*-1.309*
ACCESS CONTROL	-0.207				-0.200				-0.030	*-0.365*	*-1.886*	0.306
WEATHER	-0.115				-0.123				-0.030	-0.262	*-0.204*	-0.540
SAME DIRECTION COLLISION	*-1.025*				-0.973				-0.880	-0.899	-1.419	*-1.962*
ANGLE / TURNING COLLISION	0.026				0.066				0.035	0.284	0.255	*-0.110*
REAR-END COLLISION	*-0.359*				*-0.267*	-0.887	-1.115	-1.695	-0.087	*-0.068*	*-0.796*	*-1.424*
HEAD-ON, OBJECT COLLISION	*0.522*				*0.555*	*0.609*	*0.540*	1.339	0.336	*0.903*	*1.020*	1.709
PACKING/ PARKING COLLISION	-1.655				-1.540				-1.310	-1.883	-1.926	-2.465
PEDESTRIAN CRASH	1.383				1.412				*0.319*	1.608	*2.188*	4.305
JACKKNIFE	-0.098				-0.152				0.525	0.838	-0.249	0.276

Holdout Prediction

In order to determine the effectiveness of PPO models for model prediction, holdout

prediction was performed in a small (20,000 cases) and large (200,000) sample of the

data set with ten percent of the data in each sample assumed unknown in the modeling

process. The comparison of predicted probabilities to the observed outcomes within the

holdout data on an aggregate basis (Table 4) shows the predictive ability of each of the

models. The holdout prediction comparison results show that PPO has a fairly constant

error percentage, at 0.73% for the small set and 0.71% for the large set. The ordinal data

and the multinomial data change more dramatically from the small sample to the large

sample, from 3.06% to .97% error for the ordinal models and 2.32% to 0.83% error for

the multinomial model.

Table 3.4. Aggregate Holdout Prediction MAPE Values

Sample Size	Ordinal	Partial Proportional Odds	Multinomial
20,000	3.0614	0.7310	2.3188
200,000	0.9715	0.7161	0.8323

Discussion

The comparative study shows, overall, that the Partial Proportional Odds model performs more effectively than the ordinal or multinomial response models. In smaller data sets, the PPO model performed exceptionally well.

The fit adequacy comparison shows that the PPO model ranks in between the ordinal and the multinomial model in terms of how well predicted values conform to the proportions of each severity type. Upon examining the structure of the PPO model, this result is to be expected. Because the Ordinal, PPO, and Multinomial models use the same likelihood equation, the only significant difference between the three models lies in the number of degrees of freedom present in the model. While the actual variables present do not change between the models, The PPO model in this study effectively uses 28 covariates when accounting for the changing values of the PO-rejecting variables. Comparing to 16 covariates in the ordinal model and 52 in the multinomial model, we can view the ordinal model as nested within the PPO model, and the PPO model as nested within the multinomial model.

The covariate comparison additionally highlights the similarities of the PPO model to the other model types. When covariates reject the PO assumption, the values found are very similar to the multinomial model, and when covariates do not reject the PO model, the covariates are similar to the values found in the ordinal model. One key advantage of the PPO model in this case, however, is that more covariates were found significant in the PPO model than either of the other two models. By using multiple coefficients only for variables that have significant changes between levels, the PPO

model effectively accounts for PO violation without using unnecessary degrees of freedom.

The PPO model has an additional advantage over the ordinal and multinomial models in choosing predictors that violate the PO model. Similar to the multinomial model, the PPO framework allows predictors to vary when they have been shown to do so. This is the case, for instance, for the rear-end collision variable, where significantly lower negative values can be found in the higher severities. The result of this is the PPO model finding the variable significant while the ordinal model does not. The opposite is true, however for the multinomial model. Often, variables that will not normally vary significantly in the multinomial model end up doing so to better fit random error. Weather condition, for instance, was not found to vary significantly between levels, and was set constant for the PPO model. The result of this is a more representative, and thus significant value for the PPO model, while the multinomial model shows only partial significance.

Holdout prediction reveals good results for the PPO model. Holdout prediction was most accurate for the PPO model, which was significantly better than the ordinal and multinomial models for the small sample. Additionally, we see the aggregate predicted values greatly reducing from the small to the large sample size for ordinal and multinomial models, but remain fairly constant for PPO models. This may indicate that the PPO model converges towards the overall proportions of injury severity levels more quickly than the ordinal or multinomial, and may have improved aggregate prediction accuracy in smaller sample sizes.

Conclusions

This investigation shows that the Partial Proportional Odds model performs at least as well as its multinomial and ordinal counterparts in predicting the injury severity of crashes. While prediction and covariate significance levels for the PPO model were not significantly different from ordinal and Multinomial models at large sample sizes, the PPO model performed significantly better than either alternative for smaller sample sizes. This is an important distinction in our study because the smallest sample that was used contained 20,000 crashes, with our larger samples containing 200,000. Data in the latter quantity is extremely uncommon for crash severity analysis, even on a relatively large scale. Because most crash severity prediction will be performed with much smaller data sets, the PPO model will be much more useful than the ordinal or multinomial models.

The true benefit of the PPO framework, however, lies in the fact that it does not violate any key assumptions with the behavior of crash severity. When choosing between ordinal models and multinomial models, traffic safety researchers must decide whether to ignore the inherent ordered nature of injury severity levels or to ignore the ability of some covariates to affect each level of severity separately. With partial proportional odds, both of these assumptions are satisfied. Thus, the evidence that PPO models are approximately as effective as ordinal and multinomial models is sufficient to argue its use. This is especially true for model fit, as we only need to prove that the PPO model is an adequate fit for the scenario and data. Having an extremely good fit for the data, in many cases, does not translate to an extremely effective model. Over fitting with an overabundance of covariates can make lead to poor predictions with other data, especially when the predictor variables differ. This has the greatest potential in the multinomial model, which

has almost twice as many coefficients as the PPO model and over three times as many as the ordinal.

Acknowledgements

4. CONCLUSIONS

Chapter 2, Summary of Findings

The overall and seasonal-based analyses provide insights into the specific risk propensities of seniors on the road. Lower levels of injury severity show increased risks of occurrence in seniors with no specific seasonal variation. Higher levels of injury severity, on the other hand, show only non-significant increases in probability for seniors over non seniors. However, the seasonal analysis shows a distinct trend, with seniors having a higher risk of severe and fatal injuries during the winter months and non-seniors having a higher risk during the summer months.

The time dependant analysis shows that the injury propensity for seniors relative to non-seniors has remained constant over the past decade. With the growing population of seniors nationwide, this demographic is becoming much more important to consider in providing traffic safety solutions.

Chapter 3, Summary of Findings

The methodological framework of the PPO model is much more applicable crash severity prediction. PPO models do not violate the inherent ordered nature of the response variable and do not prevent individual covariates from affecting each response level independently. These attributes make the model much more representative of the process of determining the injury severity of crashes and provides more realistic results.

The statistical tests comparing partial proportional odds to ordinal and multinomial models show that the PPO models have adequate fit, as is expected of a model with the

same link function and general framework as the ordinal and multinomial models. Model performance for covariate values and significance and prediction accuracy are better overall for the PPO model. More covariates are significant in the PPO model and holdout prediction is more accurate than ordinal and multinomial models on both an aggregate and a case-by-case measure. PPO models fare significantly better than ordinal and multinomial models for smaller data sets.

Recommendations for Future Research

- Further research should be developed to identify specific factors that cause seasonal fluctuations in the probability for severe and fatal injuries in seniors. Changes to roadway features and driver education focused on improving roadway safety for seniors during the winter months would result in the greatest reduction of high injury crashes for this demographic.
- Additional studies on the trends in demographic proportion and accident severity propensity for seniors, especially in different regions of the United States, would provide more extensive and accurate predictions for trends in crash severity for seniors.
- The partial proportional odds model should be used for more specific applications of crash severity prediction, including expanding the preliminary PPO models from our study on trends in senior crash severity. The extent of the improvement in prediction accuracy can be further tested in varying samples and more valuable insights can be found from factors affecting crash severity.

5. REFERENCES

1. Abdel-Aty, M.A., Chen, C., Schott, J.R., 1998. An assessment of the effect of driver age on traffic accident involvement using log-linear models. Accid. Anal. Prev. 30 (6), 851–861.

2. Abdel-Aty, M.A., 2003. Analysis of driver injury severity levels at multiple locations using ordered probit models. J. Saf. Res. 34 (5), 597–603.

3. Bureau of Transportation Statistics, 2001. Highlights of the 2001 National Household Travel Survey, United States Department of Transportation. http://www.bts.gov/publications/highlights_of_the_2001_national_household_tra vel_survey/. Accessed December 10, 2010.

4. Carson, J., Mannering, F., 2001. The effect of ice warning signs on accident frequencies and severities. Accid. Anal. Prev. 33 (1), 99–109.

5. Chang, L.-Y., Mannering, F., 1999. Analysis of injury severity and vehicle occupancy in truck- and non-truck-involved accidents. Accid. Anal. Prev. 31 (5), 579–592.

6. Cheung, I., McCartt, A., 2010. Declines in Fatal Crashes of Older Drivers: Changes in Crash Risk and Survivability. Insurance Institute for Highway Safety, Arlington, VA.

7. Classen, S., Awadzi, K., Mkanta, W., 2008. Person-Vehicle-Environment Interactions Predicting Crash-Related Injury Among Older Drivers. The American Journal of Occupational Therapy, 63 (5) 580-587.

8. CT Const. art. I § 14 cl 108a.

9. Dissanayake, S., Lu, J, Yi, P., 2002. Driver Age Differences in Day and Night Gap Acceptance Capabilities. IATSS Research 20 (1) 71-79.

10. Duncan, C., Khattak, A., Council, F., 1998. Applying the ordered probit model to injury severity in truck-passenger car rear-end collisions. Transport. Res. Rec. 1635, 63–71.

11. Eberhard, J, 2008. 'Older Drivers' 'High Per-Mile Crash Involvement': The Implications for Licensing Authorities. Traffic Injury Prevention 9 (4) 284-290.

12. Eluru, N., Bhat, C., Henscher, D., 2008. A Mixed Generalied Ordered Response Model for Examining Pedestrian and Bicyclist Injury Severity in Traffic Crashes. Accid. Anal. Prev. 40 1033-1054.

13. Greene, W.H, 2000. Econometric analysis, 4th edition. Prentice Hall, Upper Saddle River, NJ.

14. Hedeker, D., Berbaum, M., Mermelstein, R, 2006. Location-Scale Models for Multilevel Ordinal Data: Between- and Within-Subjects Variance Modeling. Journal of Probability and Statistical Science 4 (1), 1-20.

15. Hedeker, D, 2008. Multilevel Models for Ordinal and Nominal Variables. In Handbook of Multilevel Analysis, Jan de Leeuw, Erik Meijer eds. Springer.

16. Hutchinson, T., 1986. Statistical Modeling of Injury Severity,With Special reference to Driver and Front Seat Passenger in Single-Vehicle Crashes. Accid. Anal. Prev. 18 (2), 157– 167.

17. Ivan, J., R. Pasupathy, and P. Ossenbruggen, 1999. Differences in Causality Factors for Single and Multi-vehicle Crashes on Two-Lane Highways. Accid. Anal. Prev. 31 (5), 695-704.

18. Ivan, J., Wang, C, Bernardo, N., 2000. Explaining Two-lane Highway Crash Rates Using Land Use and Hourly Exposure. Accid. Anal. Prev. 32 (6) 787-795.

19. Jensen, S., 1999. Pedestrian Safety in Denmark. In Transportation Research Record: Journal of the Transportation Research Board, No. 1674, Transportation Research Board of the National Academies, Washington D.C., 61-69.

20. Keall, M. Frith, M., 2010. Older Driver Crash Rates in Relation to Type and Quantity of Travel. Traffic Injury Prevention 5 (1) 26-36.

21. Khattak, A. J., Pawlovich, M., Souleyrette, R., 2010. Crash Injury Severity of Older Drivers in Iowa. Proceedings of the Mid-Continent Transportation Symposium, Ames Iowa, 235-240.

22. Khorashadi, A., Niemeier, D., Shankar, V., Mannering, F., 2005. Differences in rural and urban driver-injury severities in accidents involving large trucks: an exploratory analysis. Accid. Anal. Prev. 37 (5), 910–921.

23. Lee, J., Mannering, F., 2002. Impact of roadside features on the frequency and severity of run-off-roadway accidents: an empirical analysis. Accid. Anal. Prev. 34 (2), 149–161.

24. McFadden, D., 1981. Econometric models of probabilistic choice. In: Manski, C.F., McFadden, D. (Eds.), Structure Analysis of Discrete Data with Econometric Applications. MIT Press, Cambridge MA.

25. National Highway Traffic Safety Administration, 2012. Fatality Analysis Reporting System Encyclopedia, 2000-2009 National Statistics. http://www-fars.nhtsa.dot.gov/Main/index.aspx (Accessed April 20, 2012).

26. O'Donnell, C., & Connor, D., 1996. Predicting the Severity of Motor Vehicle Accident Injuries Using Models of Ordered Multiple Choices. Accid. Anal. Prev. 28 (6), 739– 753.

27. Peterson, B., Harrell, F., 1990. Partial Proportional Odds Models for Ordinal Response Variables. Appl. Statist. 39 (2), 205-217.

28. Renski, H., Khattak, A., & Council, F., 1998. Impact of Speed Limit Increases on Crash Injury Severity: Analysis of Single-Vehicle Crashes on North Carolina Interstate Highways. Presented at the 78th Annual Meeting of the Transportation Research Board, Washington, D.C.

29. Savolainen P., Mannering, F., 2007. Probabilistic Models of Motorcyclists' Injury Severities in Single- and Multi-Vehicle Crashes. Accid. Anal. Prev. 39, 955-963.

30. Shankar, V., Mannering, F., 1996. An exploratory multinomial logit analysis of single-vehicle motorcycle accident severity. J. Saf. Res. 27 (3), 183–194.

31. Ulfarsson, G., Mannering, F., 2004. Differences in male and female injury severities in sport-utility vehicle, minivan, pickup and passenger car accidents. Accid. Anal. Prev. 36 (2), 135–147.

32. Wang, X., Abdel-Aty, M., 2008. Analysis of left-turn crash injury severity by conflicting pattern using partial proportional odds models. Accid. Anal. Prev. 40 (8), 1674-1682.

33. Yamamoto, T., Shankar, V., 2004. Bivariate ordered-response probit model of driver's and passenger's injury severities in collisions with fixed objects. Accid. Anal. Prev. 36 (5), 869–876.

34. Yedinak, G, 2010. Census Bureau Says Aging Baby Boomers Will Increase Dependency Ratio. Senior Housing News. http://seniorhousingnews.com/2010/06/03/census-bureau-says-aging-baby-boomers-will-increase-dependency-ratio/. Accessed December 10, 2010.

35. Zajac, S., and J. Ivan, 2003. Factors Influencing Injury Severity of Motor Vehicle - Crossing Pedestrian Crashes in Rural Connecticut. Accid. Anal. Prev. 35 (3) 369-379.

36. Zeeger, C.V., Stutts, J.C., Huang, H., Zhou, M., Rodgman, E., 1993. Analysis of Elderly Pedestrian Accidents and Recommended Countermeasures. In Transportation Research Record: Journal of the Transportation Research Board, No. 1405, Transportation Research Board of the National Academies, Washington, D.C., 56-63.

37. Zhou, H., Lownes, N., Ivan, J., Gårder, P., Ravishanker, N., 2010. Gap Acceptance of Senior Drivers making Left Turns at Unsignalized Intersections. Presented at 90th Annual Meeting of the Transportation Research Board, Washington, D.C.