Final Report

Emerging Econometric and Data Collection Methods for Capturing Attitudinal and Social Factors in Activity, Travel Behavior and Safety Modeling

Prepared for **Teaching Old Models New Tricks (TOMNET) Transportation Center**

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16. Abstract The intent of this project is to explore unobserved heterogeneity and its interpretation by undertaking a series of empirical applications that use some of the most advanced heterogeneity models available. The project report begins by studying effect of information on changing opinions toward autonomous vehicle adoption (Chapter 2). The report then moves to Chapter 3 with an analysis of bikesharing use and its potential as an auto-trip substitute. Chapter 4 addresses the emerging issue of temporal instability in travel and safety models by assessing the temporal instability of the factors determining motorcyclist injury severities. Continuing along this temporal theme, Chapter 5 looks at time-of-day variations and temporal instability of the factors affecting injury severities in large-truck crashes. Chapter 6 goes on to address some technical issues associated with a heterogeneity model used commonly in advanced travel behavior and safety studies. Lastly, the project report concludes with Chapter 7, which gives an application of Lin's conception of social capital as resources embedded in social networks as a basis for describing leisure activity outcomes.			
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Chapter 1

1.1 Introduction

In recent years, a number of new econometric methods have been introduced that have the potential to introduce attitudinal effects and other elements into travel-behavior and safety models. Many of these methods have, at their core, an approach to address unobserved heterogeneity (factors affecting outcomes but unobserved to the analyst). Numerous studies in travel behavior and safety analysis have found unobserved heterogeneity to be statistically significant and important in forecasting outcomes. However, this presents a problem for the interpretation if the source of the unobserved heterogeneity is not known or fully understood. One could argue, however, that unobserved heterogeneity is really capturing the effects of attitudes and social interaction as well as other potentially measurable factors. But applied work in travel behavior and safety analysis has been limited in its guidance in this regard. The intent of this study is to explore unobserved heterogeneity and its interpretation by undertaking a series of empirical applications that use some of the most advanced heterogeneity models available.

The project report begins by studying effect of information on changing opinions toward autonomous vehicle adoption (Chapter 2). There is extensive theoretical literature that looks at factors that make people more or less likely to change their opinions as additional information is gathered. People whose opinions are less likely to change in response to information may have strong anchoring effects (commitments to initial opinions) or may support their initial opinion by selectively processing information to confirm their initial opinion (confirmation bias). Selectively processing information can also result in opinion polarization where opinions become more extreme as additional information is provided. While theoretical literature has been relatively abundant on this topic, there has been limited empirical evidence with transportation-related opinions as to how anchoring effects and confirmation bias may affect changing opinions and possible opinion polarization. The intent of Chapter 2 is to provide some initial evidence of changing opinions and possible polarization as it relates to the potential adoption of autonomous vehicles, which will likely be a key element in future sustainable transportation strategies. Specifically, the chapter studies how people's initial autonomous-vehicle adoption likelihoods change after being asked a common set of questions that leads them through an assessment of factors involved in adoption. A series of discrete outcome models were estimated to determine the factors that influence the likelihood of people changing their initial opinions. Although the empirical models identified many variables associated with opinion change, it is argued that traditional transportation surveys may not be gathering the type of data needed to truly understand how people's transportation-related decisions evolve in response to new information.

The report then moves to an analysis of bikesharing use and its potential as an auto-trip substitute. Bikesharing has become increasingly popular in urban areas as an alternative transportation mode that can help relieve congestion, protect the environment, and improve public health through increased physical activity. Given this, it is important to identify the factors that may influence how often registered users use bikesharing, and whether their bikesharing use is displacing an auto trip. For this purpose, a survey of individuals was conducted, and random parameters logit models were estimated to study bikesharing usage rates and modal substitution. In addition to standard socio-demographic and travel behavior characteristics of the survey respondents, health-related indicators were considered as explanatory variables in the estimated models. It was found that gender, age, income, household size, commute type and length, and vehicle ownership all played significant roles in bikesharing usage and modal substitution decisions. Regarding health measures, respondents' body mass index (BMI) was also a significant

predictor of bikesharing usage. Model estimation findings provide some initial insights into the bikesharing decision-making process that can help in the development of policies to improve the performance of bikesharing systems and making them a more viable transportation option.

Chapter 4 addresses the emerging issue of temporal instability in travel and safety models by assessing the temporal instability of the factors determining motorcyclist injury severities. Two data sources are used; one covers the 2012 to 2016 crash histories of Florida motorcyclists who were newly licensed in 2012, and the second covers motorcycle crashes that occur on horizontal curves in Florida from 2005 to 2015. In the first dataset (2012 new riders), temporal changes may result from riders gaining experience as well as general temporal shifts. In the second dataset, rider experience is unknown (thus becoming a source of potential unobserved heterogeneity) but the temporal changes will be largely from general temporal shifts. With three possible motorcyclist injury severity outcomes (no visible injury, minor injury, and severe injury), random parameters multinomial logit models, that allow for heterogeneity in means and variances, were estimated for all possible annual time periods in each dataset. Likelihood ratio tests were conducted to examine the overall stability of model estimates across time periods, and marginal effects of each explanatory variable were also considered to investigate the temporal instability of the effect of individual parameter estimates on motorcyclist injury-severity probabilities. A wide range of variables was considered including motorcyclists' attributes (such as ethnicity and age), roadway and environmental conditions (such as light and road surface conditions), motorcycle characteristics (such as motorcycle make and type of motorcycle), rider actions (such as speeding and improper driving actions), and roadway conditions (such as obstacles on the road and speed limits). The results show significant temporal instability in motorcyclist-injury severity models, which likely result from changes in motorcycle technology and performance, changes in macroeconomic conditions, changes induced by how riders respond to the changing behavior of other road users (whose behavior may be changing as a result of technology changes in their vehicles, evolving use of personal technologies in their vehicle, such as cell phones, etc.), and the changes in riders' behavior and skills over time.

Continuing along this temporal theme, Chapter 5 looks at time-of-day variations and temporal instability of the factors affecting injury severities in large-truck crashes. Using the data from large-truck crashes in Los Angeles over an eight-year period (January 1, 2010 to December 31, 2017), the variation in the influence of factors affecting injury severities during different time periods of the day (morning and afternoon) and from year to year is studied. To capture potential unobserved heterogeneity, random parameters logit models with heterogeneity in the means and variances of the random parameters were estimated considering three possible crash injury-severity outcomes (no injury, minor injury, and severe injury). Likelihood ratio tests were conducted to assess the transferability of model estimation results from different times of the day and from year to year. Marginal effects of the explanatory variables were also calculated to investigate the stability of individual parameter estimates on injury-severity probabilities across time-of-day/time-period combinations. A wide range of parameters were considered including drivers' characteristics, driver actions, truck's characteristics, weather and environmental conditions, and roadway attributes. The results show instability in the effect of factors that influence injury severities in large-truck vehicle crashes across daily time periods and from year to year. However, there are several variables that exhibit relatively stable effects on injury-severity probabilities including driver ethnicity, crashes occurring while backing, sideswipe crashes, hit-object crashes, parked-vehicle crashes, fixed-object crashes, and truck-driver at fault crashes. The

findings of this chapter should be useful for decision makers and trucking companies to better regulate truck operations by time of day.

Chapter 6 goes on to address some technical issues associated with a heterogeneity model used commonly in advanced travel behavior and safety studies. Specifically, the Mixed Generalized Ordered Response (MGOR) model, that allow random heterogeneity in thresholds, is considered. A potential limitation of these models is addressed (as applied in most empirical research) in that the variances of the random thresholds are implicitly assumed to be in a non-decreasing order. This restriction is unnecessary and can lead to difficulty in estimation of random parameters in higher order thresholds. In this chapter the use of negative correlations between random parameters as a variance reduction technique to relax the property of non-decreasing variances of thresholds in MGOR models is investigated. To this end, a simulation-based approach was used (where multiple datasets were simulated assuming a known negative correlation structure between the true parameters), and two models were estimated on each dataset; one allowing correlations between random parameters, and the other not allowing such correlations. Allowing negative correlations is shown to relax the non-decreasing variance property of MGOR models. However, maximum simulated likelihood estimation of parameters on data with correlations occasionally encountered model convergence and parameter identification issues. Comparison of the models that did converge suggests that ignoring correlations leads to an estimation of fewer random parameters in the higher order thresholds and results in bias and/or loss of precision for a few parameter estimates. Importantly, ignoring correlations leads to an adjustment of other parameter estimates such that overall likelihood values, predicted percentage shares, and the marginal effects are similar to those from the models with correlations.

Lastly, the project report concludes with Chapter 7, which gives an application of Lin's conception of social capital as resources embedded in social networks as a basis for describing leisure activity outcomes. This is accomplished through using a position generator for indirect resource access, a resource generator for direct resource access, and a global name generator for social support size. The research in this chapter is the first in the transportation and activity literature to use both a position generator and resource generator to measure social capital. The validity of these measures is tested in a trial survey via self-administered web-based format across three non-probability samples of varying origin. Results indicate that care needs to be taken when using these measures (under the question and answer formats used) for mobile device users, older and less formally educated respondents, and across inattentive samples. The chapter concludes by providing evidence towards the conclusion that social capital is positively correlated with leisure activity variety.

Chapter 2: The Effect of Information on Changing Opinions Toward Autonomous Vehicle Adoption: An Exploratory Analysis

2.1. Introduction

Decision making, as it relates to transportation-related choices, has been studied for many decades. The use of random utility models, and associated econometric analyses, has enabled transportation researchers to empirically study a wide variety of transportation-related choices (McFadden, 2007). However, an implicit assumption made in almost all these decision-making studies and empirical models is that individual opinions and preferences remain temporally stable. This assumption may not be problematic when analyzing well-established transportation technologies (conventional cars and buses), travel patterns, and other transportation-related decisions. However, with decisions relating to new technologies such as autonomous vehicles, where new information is being continuously gathered by decision makers, the assumption of the temporal instability of decision making could present a serious model-estimation concern that could ultimately adversely affect policy decisions.

In a recent article, Mannering (2018) draws from a vast array of literature from psychology, neuroscience, economics, cognitive science and other fields to argue that temporal instability, due to changing preferences and behavior, is likely to play an important role in the analysis of transportation accident data. Similarly, with the introduction of a new transportation technology such as autonomous vehicles, individuals' preferences and opinions regarding the likelihood of adoption are likely to be highly unstable, at least initially, as individuals gather information and modify their opinions based on this information.

The intent of the current chapter is to provide some initial evidence as to how opinions with regard to individuals' likelihood of adopting an autonomous vehicle may change when additional information is provided. To undertake this analysis, a survey that first asks respondents their likelihood of adopting an autonomous vehicle was developed. Then, after having respondents go through a series of questions that had them think about various detailed aspects of autonomous vehicle characteristics and likely their performance, the same adoption-likelihood question was asked again to see how their adoption opinions may have changed. A series of decision-change models were then estimated to understand various respondent characteristics that made them more or less likely to change their opinion.

The chapter begins with an overview of considerations associated with autonomous vehicles followed by a description of the experimental approach. Model estimation results of peoples' initial likelihood of autonomous vehicle adoption are then presented, and this is followed with a series of models that estimate people's likelihood of changing their initial opinions after being provided additional information. The chapter concludes with a discussion of the implications of the chapter's empirical findings and suggestions for future work.

2.2 The Adoption of Autonomous Vehicles

Automotive companies are committed to the development of autonomous vehicles because they anticipate that the technology will be highly profitable for them and beneficial to transportation-system users. Safety is often touted as a primary benefit with autonomous-vehicle technology by potentially eliminating crashes involving human errors such as speeding, tailgating, distraction, drowsiness, and so on. However, the transition to autonomous technology has benefits beyond safety, including the movement toward a more sustainable transportation environment with reductions in traffic congestion, increased fuel efficiency, lower emissions, and other system-wide benefits (Bansal and Kockelman, 2017; Haboucha et al., 2017).

Still, there is considerable skepticism relating to the potential benefits of autonomous vehicle technology (Bansal and Kockelman, 2017). People continue to express strong concerns about software hacking/misuse, safety, potential litigation, and possible data transmission issues relating to automated vehicles (Haboucha et al., 2017; Bansal and Kockelman, 2017; Barbour et al., 2018). Additionally, recent highly-publicized crashes involving autonomous vehicles have raised more safety-related concerns and demonstrate that opinions and attitudes can be highly volatile in the early stages of this new and potentially disruptive technology (Edison and Geissler, 2003; Heffner et al., 2007; Moore, 2009; Bansal and Kockelman, 2017).

2.3. The Importance of Initial Opinions, Anchoring Effects, and Confirmation Bias

As previously discussed, a critical concern in autonomous vehicle adoption is understanding how people's autonomous vehicle adoption opinions change over time in response to new information. In determining the likelihood of changes in autonomous vehicle adoption opinions, initial opinion formation, potential anchoring effects, and confirmation bias may all play a role. There is an abundance of literature that shows that individual opinions and judgements are strongly influenced by the initial information provided, and the opinions formed based on this information. Early work in this area by Tversky and Kahneman (1974) refer to this as an anchoring effect, where opinions are biased towards initially gathered values. In our case (the likelihood of adopting an autonomous vehicle), people's initial adoption-likelihood opinions capture a wide variety of initial information they may have gathered regarding autonomous vehicles. The question then becomes, how will their opinions evolve, given possible anchoring effects, after being directed through a group of questions that has them think more deeply about the potential characteristics and issues associated with autonomous vehicles? Given possible anchoring effects, people's initial autonomous vehicle adoption likelihoods served as the starting point for our empirical analysis.

With regard to how people's opinions may change (overcoming anchoring effects) after being directed through informational questions, the extant literature provides some guidance. For example, Van Exel et al. (2006) argue that people with lower familiarity with a topic can be greatly influenced by an authoritative source resulting in stronger anchoring effects. For our autonomous vehicle case, this implies that individuals with little familiarity with autonomous-vehicle technology may have strong anchoring effects if what little information they have is from what they consider to be an authoritative source. However, Galinsky and Mussweiler (2000) and LeBoeuf and Shafir (2009) argue that this authoritative-source effect can be mitigated if specific types of confirmatory information is provided, but empirical work has found considerable uncertainty with regard to the types of information that can actually mitigate this effect.[1]

How people adjust based on their initial opinions (anchoring effects) has been a topic of considerable debate among psychologists. Some have argued that anchoring values serve merely as a reference point from which people start to adjust when given additional information (Strack and Mussweiler, 1997). However, the concept of confirmatory hypothesis testing has become a widely accepted behavioral response with regard to anchoring effects (Strack and Mussweiler, 1997; Chapman and Johnson, 1999; Mussweiler and Strack, 2001; Wegener et al., 2010; Furnham and Boo, 2011). In this case, individuals consider their anchoring values to be plausible and

[1] As will be shown, the experimental design that is used in this paper cannot directly account for authoritative-source effects. However, it is important to keep in mind that one of the determinants of a strong anchoring effect is an authoritative-source effect, and that people with certain measurable characteristics may be more or less susceptible to such an effect.

continually test the hypothesis that the anchor value is correct. In doing so, individuals may tend to search for ways to reinforce their anchor value by selectively considering information that is consistent with their initial estimate, which leads to a confirmation bias (Nickerson, 1998). This confirmation bias can support polarization of opinions (with confirmatory information leading to more extreme positions as initial opinions are reinforced). Polarization is thus a process by which people with opposing opinions observe the same data and somehow strengthen their opposing beliefs (Lord et al., 1979; Jern et al., 2014; Benoit and Dubra, 2017). The manner in which individuals are affected by their initial opinions (anchors) and thus adjust to new information has also been found to be influenced by individual differences (Brandstatter, 1993) and information processing styles (Wegener et al., 2001).

In the forthcoming empirical analysis, individuals were segmented based on their initial responses to their likely adoption of autonomous vehicles in an attempt to account for the anchoring effect. After classifying individuals on initial adoption opinions, the probability that additional information will change these initial opinions was studied. In essence, this research seeks to identify explanatory variables that capture the strength of individuals' anchoring effects, tendency toward confirmation bias, and even individual informational processing styles, all of which may affect the likelihood that their opinions will change in response to new information.

2.4. Experimental Approach

To obtain insight into how additional information might affect peoples' likelihood of adopting autonomous vehicles, a survey was developed to track the stated likelihood of autonomous-vehicle adoption before and after detailed information relating to key elements of autonomous vehicles were presented.[2] The approach used was to first have individuals initially indicate their likelihood of autonomous vehicle adoption with responses provided on a 5-point scale ranging from *extremely unlikely*, *unlikely*, *uncertain*, *likely*, to *extremely likely*. After this initial likelihood assessment, individuals were led through a series of questions that had them think more carefully about the various aspects that might affect autonomous vehicle adoption (many of which they may not have fully considered in their initial assessment). In this series of questions individuals were asked to rate their opinions on various potential benefits and concerns related to autonomous vehicle adoption. Benefit-related questions had them consider autonomous-vehicle aspects such as fewer vehicle crashes and increased roadway safety, less traffic congestion, potentially less stressful driving experiences, and lower vehicle emissions. Concern-related questions had them consider autonomous vehicle related elements such as system/equipment failure, autonomous vehicle system hacking, performance in unexpected traffic situations and extreme weather conditions, giving up of control of the steering wheel to the vehicle, loss in human driving skill over time, safety of the vehicle occupants and other road users such as pedestrians and bicyclists, and liability in the event of a crash. After recording individuals' initial opinions and having them go through the questions shown in Appendix 2.A, their likelihood of adopting an autonomous vehicle was

[2] An alternative to this experimental approach would be to gather longitudinal data and track changing opinions. However, in addition to the high cost associated with the acquisition of such longitudinal data, there would be significant challenges in survey design to capture the effects of people's information gathering from media, social networks, and other sources. While the experimental approach adopted herein allows for a much tighter control on information availability, exploring this opinion-change issue with a detailed longitudinal survey is a promising direction for future research.

asked again with the same response options; *extremely unlikely*, *unlikely*, *uncertain*, *likely*, to *extremely likely*.[3,4,5]

Data for this chapter were collected from a sample of American Automobile Association members across the southeastern United States in June 2015. Data from a total of 2,338 survey respondents, all of whom commuted to work or school, were obtained. The sample includes participants from 12 states, and roughly 1 in 4 households in the United States are members of the American Automobile Association. In comparison to the United States population as a whole, members of the American Automobile Association tend to come from wealthier households with higher vehicle ownership levels, a group that would be a natural target for autonomous vehicle adoption. For example, the sample used herein had 42% of respondents coming from households with annual household incomes greater than $100,000 (compared to 24.7% nationally). Household vehicle ownership in the American Automobile Association sample was 3.18 compared to 2.28 nationally, and 59% of the respondents were male (compared to 49.2% nationally). It is important to note the source of the data used herein when projecting this chapter's findings to other populations (for further details and additional applications of these data please see Menon et al., 2016, 2018; Barbour et al., 2018).

In addition to autonomous-vehicle-specific questions, the survey collected extensive data on respondents' transportation-related decisions, commute experiences (all respondents were either worker or students and thus all had commutes), travel history, modal use, and extensively detailed socioeconomic data.

2.5. Methodological Approach – Initial Opinion

Initial opinions with regard to the likely adoption of autonomous vehicles were studied first. This is important because this initial opinion will establish a baseline for potential anchoring effects that will affect final opinions on the likelihood of adoption. Respondents had autonomous vehicle adoption choices of *extremely unlikely*, *unlikely*, *uncertain*, *likely*, and *extremely likely*. Given the ordered nature of the available responses to this question an ordered probability modeling approach was appropriate (Washington et al., 2011). Traditional ordered probability models are specified by defining an unobserved variable, *z*, for each respondent *i* as the linear function,

$$z_i = \boldsymbol{\beta}\mathbf{X}_i + \varepsilon_i, \tag{2.1}$$

where $\mathbf{X}_i$ is a vector of explanatory variables determining the discrete responses for respondent *i*, $\boldsymbol{\beta}$ is a vector of estimable parameters, and ε_i is a disturbance term. Using this equation, observed

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[3] Consideration must also be given to the primacy/recency effect with regard to the questions in the appendix. That is, the fact that questions presented at the beginning (primacy) and the end (recency) are likely to be given more weight than questions in the middle. A potentially fruitful direction for future research would be to randomize these questions, or present respondents with a finite group of alternate orderings of these questions, to study the possible extent of the primacy/recency effect in this context.

[4] It should be pointed out here that the approach of asking questions as a means of having people think about elements of autonomous vehicle adoption is fundamentally different than providing them with specific information or have them gather information themselves through various media and social networks. Thus, some caution should be exercised in extending the findings to these other forms of information gathering.

[5] Please note that the experimental approach used is potentially susceptible to hypothetical bias. That is, in unfamiliar contexts (such as autonomous vehicle adoption) individuals may not fully understand or perceive how the hypothetical decision they are making will differ from an actual decision (Rakotonarivo et al., 2016). This point should be kept in mind in assessing the forthcoming empirical findings of this paper.

ordinal responses, y_i, are defined as (with 1 = *extremely unlikely*, 2 = *unlikely*, 3 = *unsure*, 4 = *likely*, and 5 = *extremely likely*),

$$\begin{aligned} y_i &= 1 \text{ if } z_i \le \mu_0 \\ &= 2 \text{ if } \mu_0 < z_i \le \mu_1 \\ &= 3 \text{ if } \mu_1 < z_i \le \mu_2 \\ &= 4 \text{ if } \mu_2 < z_i \le \mu_3 \\ &= 5 \text{ if } z_i \ge \mu_3, \end{aligned} \tag{2.2}$$

where μ's are estimable parameters (thresholds) that define y_i and are estimated jointly with the model parameters $\boldsymbol{\beta}$. With this, as shown in Washington et al. (2011) and other sources, if ε_i is assumed to be normally distributed across respondents an ordered probit model results with ordered categorical selection probabilities (removing subscripting *i* for notational convenience and noting that without loss of generality, μ_0 can be set equal to zero thus requiring the estimation of only three thresholds, μ_1, μ_2, and μ_3 to define all 5 selection probabilities),

$$\begin{aligned} P(y = 1) &= \Phi(-\boldsymbol{\beta}\mathbf{X}) \\ P(y = 2) &= \Phi(\mu_1-\boldsymbol{\beta}\mathbf{X}) - \Phi(-\boldsymbol{\beta}\mathbf{X}) \\ P(y = 3) &= \Phi(\mu_2-\boldsymbol{\beta}\mathbf{X}) - \Phi(\mu_1-\boldsymbol{\beta}\mathbf{X}) \\ P(y = 4) &= \Phi(\mu_3-\boldsymbol{\beta}\mathbf{X}) - \Phi(\mu_2-\boldsymbol{\beta}\mathbf{X}) \\ P(y = 5) &= 1 - \Phi(\mu_3-\boldsymbol{\beta}\mathbf{X}), \end{aligned} \tag{2.3}$$

where $\Phi(.)$ is the cumulative normal distribution.

For model interpretation, a positive value of $\boldsymbol{\beta}$ implies that an increase in $\mathbf{X}_i$ will increase the probability of getting the highest response (*extremely likely*) and will decrease the probability of getting the lowest response (*extremely unlikely*), but to interpret the intermediate categories (to estimate the direction of the effects of the interior categories of *unlikely*, *uncertain* and *likely*) and the probability effect of the any variable in the vector $\mathbf{X}_i$ on each outcome category, average marginal effects are computed as (Washington et al., 2011),

$$\frac{P_i(y = n)}{\partial \mathbf{X}_i} = \left[\phi\left(\mu_{n-1} - \boldsymbol{\beta}\mathbf{X}_i\right) - \phi\left(\mu_n - \boldsymbol{\beta}\mathbf{X}_i\right)\right]\boldsymbol{\beta}, \tag{2.4}$$

where $P_i(y = n)$ is the probability of ordered discrete outcome *n* for respondent *i*, $\phi(.)$ is the normal density, and all other variables are as previously defined. The computed marginal effects quantify the effect that a one-unit change of an explanatory variable will have on outcome category *n*'s selection probability, and these marginal effects are averaged over all respondents to arrive at an average marginal effect for the population.

Finally, the possibility of unobserved heterogeneity in the data was accounted for by allowing parameters to vary across respondents. A standard random parameters approach was used with (please see Mannering et al., 2016, for a full description of alternate heterogeneity modeling approaches),

$$\beta_{ki} = \beta_k + \varphi_{ki}\ , \tag{2.5}$$

where β_{ki} is the parameter estimate for explanatory variable *k* (one of the elements in the parameter vector $\boldsymbol{\beta}$) for respondent *i*, β_k is the mean parameter estimate for explanatory variable *k*, and φ_i is a randomly distributed term (for example, normally distributed term with mean zero and variance σ^2). Estimation of the random parameters ordered probit was undertaken by simulated maximum

likelihood approaches (Washington et al., 2011). Previous studies have shown that Halton draws provide a more efficient distribution of simulation draws than purely random draws (Bhat, 2003). In the forthcoming model estimations 1,000 Halton draws were used in the simulated likelihood functions, a number that has been shown to be more than sufficient to provide accurate parameter estimates (Halton, 1960; Bhat, 2003; Anastasopoulos and Mannering, 2009).

2.6. Initial-Opinion Estimation Results

Random parameters ordered probit model estimates of the stated initial likelihood of adopting an autonomous vehicle are presented in Table 2.1, and corresponding marginal effects are presented in Table 2.2. Table 2.1 shows that eight variables were found to significantly influence initial autonomous vehicle adoption opinions, and the model has a reasonably good overall statistical fit with a McFadden ρ^2 of 0.404.

Table 2.1. Random parameter ordered probit model of the stated initial likelihood of adopting an autonomous vehicle [dependent variable responses are integers between 1 (*extremely unlikely*) to 5 (*extremely likely*)]. All random parameters are normally distributed.

Variable	**Estimated Parameter**	***t* Statistic**
Constant	0.608	4.55
Younger adult indicator (1 if age less than 40 years, 0 otherwise) (Standard deviation of parameter distribution)	0.352 (0.592)	3.49 (6.13)
Male indicator (1 if respondent is male, 0 otherwise) (Standard deviation of parameter distribution)	0.174 (0.460)	2.61 (10.89)
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	-0.184	-1.73
No injury indicator (1 if the respondent has not encountered any injury in a crash, 0 otherwise)	-0.108	-1.69
Higher education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	0.220	3.16
High income indicator (1 if the household has income greater than $100,000/year, 0 otherwise)	0.239	3.40
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	0.115	1.76
Worker indicator (1 if the respondent is a worker, 0 otherwise)	0.128	1.83
Threshold μ_1	0.535	15.10
Threshold μ_2	1.23	25.70
Threshold μ_3	2.08	33.75
Log-likelihood at zero [$LL(0)$]	-2938.55	
Log-likelihood at convergence [$LL(\boldsymbol{\beta})$]	-1751.98	

McFadden ρ^2 [1-$LL(0)/LL(\boldsymbol{\beta})$]	0.404
Number of observations	1490

Table 2.2. Average marginal effects for the initial adoption opinion model shown in Table 2.

	Marginal Effects				
Variable	**Extremely Unlikely**	**Unlikely**	**Uncertain**	**Likely**	**Extremely Likely**
Younger adult indicator (1 if age less than 40years, 0 otherwise)	-0.0875	-0.0397	-0.0082	0.0593	0.0590
Male indicator (1 if respondent is male, 0 otherwise)	-0.0497	-0.0171	0.0028	0.0325	0.0314
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	0.0483	0.0199	0.0016	-0.0373	-0.0326
No injury indicator (1 if the respondent has not experienced an injury in a vehicle crash, 0 otherwise)	0.0300	0.0109	-0.0090	-0.1990	-0.0201
Higher education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	-0.0601	-0.0229	0.0005	0.0400	0.0424
High income indicator (1 if the household has income greater than $100,000/year, 0 otherwise)	-0.0659	-0.0244	0.0014	0.0437	0.0452
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	-0.0323	-0.0116	0.0012	0.0213	0.0213
Worker indicator (1 if the respondent is a worker, 0 otherwise)	-0.0360	-0.0128	0.0016	0.2374	0.0234

Turning to the estimation results shown in Table 2.1, two of the eight variables were found to produce normally distributed random parameters with statistically significant standard deviations indicating significant unobserved heterogeneity in the data.[6] Individuals less than 40 years of age (an age cut-off that produced the most statistically significant findings) had a mean parameter estimate of 0.352 and standard deviation of 0.592 indicating that the effect of this variable increased the likelihood of being *extremely likely* to adopt for roughly 72 percent of respondents and decreased it for 28 percent. This reflects considerable variation in the preferences among this age group. Similarly, for male respondents, a statistically significant random parameter was found with a mean of 0.174 and a standard deviation of 0.460 indicating that the effect of this variable increased the likelihood of being *extremely likely* to adopt for roughly 65 percent of respondents and decreased it for 35 percent. The estimation results suggest that both younger respondents and male respondents had considerable unobserved heterogeneity in their initial opinions toward their likely adoption of autonomous vehicles.

With regard to other statistically significant variables, respondents identifying themselves as white and those who had not experienced an injury in a vehicle crash were found to have had a lower probability of being *likely* or *extremely likely* to adopt an autonomous vehicle (see Table 2.2). The reluctance among whites to adopt was likely reflecting some socio-demographic elements associated with this group that were not being captured by other questions in the survey. The finding that individuals not involved in injury crashes had lower probabilities of being *likely* or *extremely likely* to adopt suggests that these individuals may feel less of a need for the potential safety benefits that autonomous vehicles may provide relative to those who had experienced an injury crash.

Tables 2.1 and 2.2 show that more highly educated individuals (holding a bachelor's degree or above), those having household incomes greater than $100,000 per year, and those individuals whose most recent vehicle purchase was a new vehicle had higher probabilities of being *likely* or *extremely likely* to adopt autonomous vehicles. This highly educated, wealthy, and new-vehicle-centric group of individuals seem a natural demographic target for autonomous vehicle adoption. Finally, workers were found to have higher probabilities of being *likely* or *extremely likely* to adopt an autonomous vehicle (Table 2.2). This likely reflects the potential these individuals see in autonomous vehicles to mitigate adverse commute-related conditions they may face.

2.7. Methodological Approach – Opinion Change

As the previous discussion on anchoring effects suggests, initial opinions are likely to be critical determinants of final opinions and serve as a guide to any change in these opinions. To establish that respondents' opinions were not stable between their initial assessment of autonomous vehicle adoption likelihoods and their final assessment (after being provided additional information based on a series of questions as previously discussed), estimation results from three ordered probit models were used; an initial model (opinions before being led through the informational questions, previously estimated as shown in Table 2.1), a final model (opinions after being led through the informational questions), and an overall model that includes adoption likelihood responses before and after the questions.[7] With these model estimates, a likelihood ratio test was conducted as $\chi^2 =$

[6] In addition to the normal distribution, models were estimated with several other distributions, but no other distribution produced estimation results that were significantly better than the normal distribution.

[7] There is also the possibility that people may not remember their initial opinion selection and just select a new opinion by chance even though their core opinion has not changed. However, this possibility is believed to be

-2[$LL(\boldsymbol{\beta})_{combined}$ - $LL(\boldsymbol{\beta})_{initial}$ - $LL(\boldsymbol{\beta})_{final}$], where $LL(\boldsymbol{\beta})_{combined}$ is the log-likelihood at convergence of a model using the data from both before and after, $LL(\boldsymbol{\beta})_{initial}$ is the log-likelihood at convergence of a model estimated before providing the information, and $LL(\boldsymbol{\beta})_{final}$ is the log-likelihood at convergence of a model after providing the information. The resulting χ^2 statistic (with the degrees of freedom equal to the summation of the number of parameters in the before and after models minus the number of estimated parameters in the combined model) was found to be 24.00 and, with 10 degrees, this χ^2 value suggests that there is more than 99% confidence that the before and after parameter values were not the same, suggesting that the informational questions were significantly affecting individual preferences.

Given this result, a series of models were estimated to understand what factors determine the likelihood of respondents shifting from their initial opinions about autonomous vehicle adoption. With the previous ordered probit estimation results providing some insight into the factors that may determine initial opinions, attention was directed toward studying opinion change by segmenting respondents into four groups, those initially indicating *likely*, *unlikely*, *extremely likely*, and *extremely unlikely* to adopt an autonomous vehicle,[8] and then developing a statistical model that determined their new probability of being *extremely unlikely*, *unlikely*, *uncertain*, *likely* and *extremely likely* (a discrete outcome that was conditional on their initial choice because of this population-segmentation approach) after being provided additional information by being given a series of questions that has them think more carefully about various aspects of autonomous-vehicle adoption.

To develop an estimable model, for each of the four initial opinions considered (*likely*, *unlikely*, *extremely likely*, and *extremely unlikely*), a function that determines respondents' new probability of being *extremely unlikely*, *unlikely*, *uncertain*, *likely* and *extremely likely* to adopt an autonomous vehicle conditioned on their initial adoption opinion is defined as (Washington et al., 2011),[9]

$$PLR_{in|g} = \boldsymbol{\beta}_{i|g}\mathbf{X}_{in|g} + \varepsilon_{in|g}\ , \tag{2.6}$$

where $PLR_{in|g}$ is a function that determines the probability of respondent n selecting response i (*extremely unlikely*, *unlikely*, *uncertain*, *likely* and *extremely likely*) conditioned on their initial response g (either *extremely unlikely*, *unlikely*, *likely* and *extremely likely*), $\boldsymbol{\beta}_{i|g}$ is a vector of estimable parameters for corresponding to outcome response i, $\mathbf{X}_{in|g}$ is a vector of explanatory variables that affect the probability of outcome response i for respondent n, and $\varepsilon_{in|g}$ is a disturbance term. If the disturbance terms are assumed to be generalized extreme-valued distributed, a standard multinomial logit model results as (McFadden, 1981),

$$P_n(i \mid g) = \frac{EXP\left[\boldsymbol{\beta}_{i|g}\mathbf{X}_{in|g}\right]}{\sum_{\forall I} EXP\left(\boldsymbol{\beta}_{I|g}\mathbf{X}_{In|g}\right)}, \tag{2.7}$$

highly unlikely since the survey's focus was on autonomous vehicle adoption which implies this question would have been given careful thought before and after the informational questions.

[8] Respondents without an initial opinion (those who are initially *uncertain*) are not considered because the study focuses on anchoring effects and polarization. Those without an initial opinion will not have an anchoring effect, will not engage in confirmatory hypothesis testing, and thus will not technically polarize.

[9] Although the outcome data are still technically ordered (extremely unlikely, unlikely, etc.), conditioning on the initial adoption likelihood reduces the ranges of responses considerably. Given this, and the additional flexibility inherent in traditional non-ordered outcome models such as the multinomial logit, an unordered outcome modeling approach is chosen. Please see Mannering and Bhat (2014) for an extensive discussion of this point.

where $P_n(i \mid g)$ is the probability of respondent *n* giving response *i* given that their initial response places them in group g (either *extremely unlikely*, *unlikely*, *likely* and *extremely likely*).

In model estimation, the possibility of unobserved heterogeneity across respondents (the possibility that individual respondents will be affected by explanatory variables differently due to unobserved reasons) was also considered. To account for the possibility of having one or more parameter estimates in the vector $\boldsymbol{\beta}_{i|g}$ vary across respondents, a distribution of these parameters was assumed, and Equation 2.2 is rewritten as (Washington et al., 2011),

$$P_n(i \mid g) = \int_{\mathbf{x}} P_n(i \mid g)\ f\left(\boldsymbol{\beta}_{i|g} \mid \boldsymbol{\varphi}_{i|g}\right) d\boldsymbol{\beta}_{i|g}\,, \tag{2.8}$$

where $f(\boldsymbol{\beta}_{i|g}|\boldsymbol{\varphi}_{i|g})$ is the density function of $\boldsymbol{\beta}_{i|g}$, $\boldsymbol{\varphi}_{i|g}$ is a vector of parameters describing the density function (mean and variance), and all other terms are as previously defined. This gives the random parameters logit model, the estimation of which was undertaken by simulated maximum likelihood approaches as was the case for the previously estimated random parameters ordered probit model (again, 1,000 Halton draws are used).

As with the previous ordered probit model estimation results, to determine the effect that individual explanatory variables will have on response probabilities, marginal effects were computed for each explanatory variable. As before, the marginal effect of an explanatory variable gives the effect that a one-unit increase in an explanatory variable has on the outcome probabilities and the average marginal effect over all respondents is reported.

2.8. Opinion Change Estimation and Results

Table 2.3 presents summary statistics of variables included in one or more of the four sub-group models; those initially *likely*, *unlikely*, *extremely likely* and *extremely unlikely*.[10] Model

Table 2.3. Mean values for variables found to be statistically significant in one or more models.

	Initial Autonomous-Vehicle Adoption Opinion			
Variable	**Likely**	**Unlikely**	**Extremely Likely**	**Extremely Unlikely**
Younger adult indicator (1 if age less than 40 years, 0 otherwise)	0.13	0.10*	0.19*	0.10
Middle age indicator (1 if age greater than 40 years and less than 60 years,0 otherwise)	0.48	0.43	0.53	0.48*
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	0.90*	0.90	0.84*	0.89*
Single status (1 if the respondent is single, 0 otherwise)	0.22*	0.22	0.16	0.21

[10] Because the focus of the paper was on anchoring effects and polarization, recall that the statistical analysis did not address the changing opinions of the 248 people who initially indicated that they were uncertain. After going through the informational questions, 55% of these respondents remained uncertain, 26% became likely, 17% became unlikely, 2% became extremely likely, and 0% became extremely unlikely. These rather substantial shifts suggest that additional information definitely affects the likelihood of remaining uncertain. A study focusing on the effects that information has on uncertainty in the context of autonomous vehicle adoption would be a fruitful area for future research.

Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)	0.27*	0.21*	0.36*	0.27
Lower income indicator (1 if the household has an income less than $50,000/year, 0 otherwise)	0.11*	0.21	0.15	0.21
Higher income indicator (1 if the household has an income greater than $100,000/year, 0 otherwise)	0.50*	0.38*	0.48*	0.35
Higher education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	0.71*	0.64	0.37	0.63
Worker indicator (1 if the respondent is a worker, 0 otherwise)	0.48	0.48	0.62	0.46*
Retirement indicator (1 if the respondent has retired, 0 otherwise)	0.41	0.48	0.34	0.48*
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	0.52	0.51*	0.52*	0.48*
Recent vehicle acquisition indicator (1 if the most recently acquired vehicle was in the last two years; 0 otherwise)	0.59*	0.51	0.60	0.58*
Recent vehicle lease indicator (1 if the most recent vehicle acquisition was a lease; 0 otherwise)	0.16*	0.10	0.14	0.16
Lower commute distance indicator (1 if one-way distance for the commute trip is less than 3 miles; 0 otherwise)	0.11	0.14*	0.14*	0.12
Lower parking time indicator (1 if respondent spends 5 minutes or less on average in order to park their vehicle, 0 otherwise)	0.92	0.95*	0.88	0.94*
Higher daily travel time indicator (1 if respondent travels more than 60 minutes every day for all their trips, 0 otherwise)	0.32	0.25*	0.31	0.26
Vehicle crash indicator (1 if the respondent has ever been involved in a vehicle crash, 0 otherwise)	0.78	0.72	0.768	0.72*
No injury indicator (1 if the respondent has not experienced an injury in a vehicle crash, 0 otherwise)	0.58	0.61	0.50*	0.56
Number of observations	368	279	159	436

* Indicates statistically significant in initial-opinion model

estimation results of likeliness to adopt autonomous vehicles (conditioned on respondent's' initial opinions) are presented in Tables 2.4 to 2.11. Interestingly, for all model estimations no statistically significant random parameters were found. This suggests that unobserved heterogeneity is not playing a significant role in the model estimation results.[11,12] Detailed model results are discussed in the sections below.

2.8.1 Respondents with an initial opinion of likely

Of the 368 respondents who initially indicated that they were *likely* to adopt an autonomous vehicle, roughly 80% made the same *likely* choice after the informational questions, 9% polarized to *extremely likely*, and 11% depolarized (8% to *uncertain*, 2% to *unlikely*, 1% to *extremely unlikely*). Given this distribution of outcomes, for model estimation, three possible outcomes were considered; *extremely likely* (polarize), *likely* (no change), and *other* (which includes *uncertain*,

Table 2.4. Opinion model for respondents with an initial autonomous vehicle adoption likelihood opinion of *likely*.

			Marginal Effect		
Variable	**Estimated parameter**	**t-statistic**	**Other**	**Likely**	**Extremely Likely**
Other (*Uncertain, Unlikely and Extremely Unlikely*) – Base set to zero					
Likely – no change					
Constant	0.765	1.67	-	-	-
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	0.740	1.69	-0.0659	0.1147	-0.0488
Higher education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	0.761	2.65	-0.0679	0.1181	-0.0502
Lower income indicator (1 if the household has an income less than $50,000/year, 0 otherwise)	0.842	1.59	-0.0751	0.1307	-0.0556
Recent vehicle lease indicator (1 if the most recent vehicle acquisition was a lease; 0 otherwise)	1.36	2.44	-0.1221	0.2124	-0.0904
Extremely likely – polarize					
Constant	-0.839	-1.75	-	-	-

[11] The possibility of heterogeneity in means and variances was also considered (Behnood and Mannering, 2017a, 2017b; Seraneeprakarn et al., 2017). However, likelihood ratio tests showed that these formulations did not significantly improve the model estimation results.

[12] Latent-class logit models were also estimated but these did not result in statistically different classes. This adds additional support indicating that unobserved heterogeneity was not playing a significant role in the model estimations (Mannering et al., 2016).

Higher income indicator (1 if the household has an income greater than $100,000/year, 0 otherwise)	0.856	2.00	-0.0099	-0.0565	0.0664
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)	0.682	1.52	-0.0079	-0.0450	0.0529
Single status indicator (1 if the respondent is single; 0 otherwise)	0.992	1.99	-0.0115	-0.0655	0.0769
Recent vehicle acquisition indicator (1 if the most recently acquired vehicle was in the last two years; 0 otherwise)	-0.734	-1.87	0.0085	0.0484	-0.0569
Log-likelihood at zero [$LL(0)$]			-404.28		
Log-likelihood at convergence [$LL(\boldsymbol{\beta})$]			-225.40		
McFadden ρ^2 [$1-LL(0)/LL(\boldsymbol{\beta})$]			0.442		
Number of observations			368		

Table 2.5. Factors increasing/decreasing the likelihood of opinion change with an initial autonomous vehicle adoption likelihood opinion of *likely*.

Factors decreasing the likelihood of an opinion change
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)
Higher education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)
Lower income indicator (1 if the household has an income less than $50,000/year, 0 otherwise)
Recent vehicle lease indicator (1 if the most recent vehicle acquisition was a lease; 0 otherwise)
Recent vehicle acquisition indicator (1 if the most recently acquired vehicle was in the last two years; 0 otherwise)
Factors increasing the likelihood of an opinion change
Higher income indicator (1 if the household has an income greater than $100,000/year, 0 otherwise)
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)
Single status indicator (1 if the respondent is single; 0 otherwise)

Table 2.6. Opinion model for respondents with an initial autonomous vehicle adoption likelihood opinion of *unlikely*.

Variable	Estimated Parameter	t-statistic	Marginal effect		
			Other	Unlikely	Extremely Unlikely
Other (*Uncertain, Likely and Extremely likely*) – Base set to zero					
Unlikely – no change					
Constant	0.955	5.49	-	-	-
Younger adult indicator (1 if age less than 40 years, 0 otherwise)	1.317	2.40	-0.0771	0.2483	-0.1713
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)	0.757	1.87	-0.0804	0.1691	-0.0888
Extremely Unlikely - polarize					
Constant	1.590	2.35	-	-	-
Higher income indicator (1 if household has an income greater than $100,000/year, 0 otherwise)	-0.650	-1.94	0.0250	0.0748	-0.0999
Lower commute distance indicator (1 if one-way distance for the commute trip is less than 3 miles; 0 otherwise)	-0.826	-1.57	0.0314	0.0950	-0.1263
Lower parking time indicator (1 if respondent spends 5 minutes or less on average in order to park their vehicle, 0 otherwise)	-1.037	-1.57	0.0401	0.1216	-0.1618
Higher daily travel time indicator (1 if respondent travels more than 60 minutes every day for all their trips, 0 otherwise)	0.789	2.41	-0.0305	-0.0925	0.1230
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	-0.860	-2.73	0.0333	0.1009	-0.1342
Log-likelihood at zero [$LL(0)$]			-306.51		
Log-likelihood at convergence [$LL(\boldsymbol{\beta})$]			-247.40		
McFadden ρ^2 [$1-LL(0)/LL(\boldsymbol{\beta})$]			0.193		
Number of observations			279		

Table 2.7. Factors increasing/decreasing the likelihood of opinion change with an initial autonomous vehicle adoption likelihood opinion of *unlikely*.

Factors decreasing the likelihood of an opinion change
Younger adult indicator (1 if age less than 40 years, 0 otherwise)
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)
Higher income indicator (1 if household has an income greater than $100,000/year, 0 otherwise)
Lower commute distance indicator (1 if one-way distance for the commute trip is less than 3 miles; 0 otherwise)
Lower parking time indicator (1 if respondent spends 5 minutes or less on average in order to park their vehicle, 0 otherwise)
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)
Factors increasing the likelihood of an opinion change
Higher daily travel time indicator (1 if respondent travels more than 60 minutes every day for all their trips, 0 otherwise)

Table 2.8. Opinion model for respondents with an initial autonomous vehicle adoption likelihood opinion of *extremely likely*.

Variable	Estimated Parameter	t-statistic	Marginal Effect	
			Likely/ Uncertain	Extremely Likely
Likely/Uncertain – Base set to zero				
Extremely likely – no change				
Constant	0.64	1.20	-	-
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	-1.45	-2.75	0.2952	-0.2952
Higher income indicator (1 if household has an income greater than $100,000/year, 0 otherwise)	-0.99	-2.23	0.2035	-0.2035
No injury indicator (1 if the respondent has not experienced an injury in a vehicle crash, 0 otherwise)	0.908	2.53	-0.1849	0.1849
Younger adult indicator (1 if age less than 40 years, 0 otherwise)	-0.76	-1.45	0.1294	-0.1294
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)	0.72	1.87	-0.1423	0.1423
Lower commute distance indicator (1 if one-way distance for the commute trip is less than 3 miles; 0 otherwise)	0.78	1.57	-0.1594	0.1594
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	0.59	1.62	-0.1540	0.1540
Log-likelihood at zero [$LL(0)$]		-110.21		
Log-likelihood at convergence [$LL(\boldsymbol{\beta})$]		-93.99		
McFadden ρ^2 [$1-LL(0)/LL(\boldsymbol{\beta})$]		0.147		
Number of observations		159		

Table 2.9. Factors affecting a change in an initial autonomous vehicle adoption likelihood opinion from *extremely likely*.

Factors decreasing the likelihood of an opinion change
No injury indicator (1 if the respondent has not experienced an injury in a vehicle crash, 0 otherwise)
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)
Lower commute distance indicator (1 if one-way distance for the commute trip is less than 3 miles; 0 otherwise)
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)
Factors increasing the likelihood of an opinion change
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)
Higher income indicator (1 if household has an income greater than $100,000/year, 0 otherwise)
Younger adult indicator (1 if age less than 40 years, 0 otherwise)

Table 2.10. Opinion model for respondents with an initial autonomous vehicle adoption likelihood opinion of *extremely unlikely*.

			Marginal Effect	
Variable	**Estimated Parameter**	**t-statistic**	**Unlikely/ Uncertain**	**Extremely Unlikely**
Unlikely/Uncertain – Base set to zero				
Extremely Unlikely – no change				
Constant	0.284	1.74	-	-
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	-0.615	-1.84	0.1447	-0.1447
Retirement indicator (1 if the respondent has retired, 0 otherwise)	0.359	1.50	-0.0845	0.0845
Vehicle crash indicator (1 if the respondent has ever been involved in a vehicle crash, 0 otherwise)	0.313	1.45	-0.0767	0.0767
Lower parking time indicator (1 if respondent spends 5 minutes or less on average in order to park their vehicle, 0 otherwise)	-0.769	-1.77	0.1810	-0.1810
Middle age indicator (1 if age greater than 40 years and less than 60 years,0 otherwise)	-0.457	-2.16	0.1171	-0.1171
Worker indicator (1 if the respondent is a worker, 0 otherwise)	0.703	2.68	-0.1652	0.1152
Recent vehicle acquisition indicator (1 if the most recently acquired vehicle was in the last two years; 0 otherwise)	-0.367	-1.80	0.0888	-0.0888
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	-0.744	-1.96	0.1666	-0.1666
Log-likelihood at zero [$LL(0)$]			-302.21	
Log-likelihood at convergence [$LL(\boldsymbol{\beta})$]			-288.85	
McFadden ρ^2 [$1-LL(0)/LL(\boldsymbol{\beta})$]			0.046	
Number of observations			436	

Table 2.11. Factors affecting a change in an initial autonomous vehicle adoption likelihood opinion from *extremely unlikely*.

Factors decreasing the likelihood of an opinion change
Retirement indicator (1 if the respondent has retired, 0 otherwise)
Vehicle crash indicator (1 if the respondent has ever been involved in a vehicle crash, 0 otherwise)
Worker indicator (1 if the respondent is a worker, 0 otherwise)
Factors increasing the likelihood of an opinion change
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)
Lower parking time indicator (1 if respondent spends 5 minutes or less on average in order to park their vehicle, 0 otherwise)
Recent vehicle acquisition indicator (1 if the most recently acquired vehicle was in the last two years; 0 otherwise)
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)
Middle age indicator (1 if age greater than 40 years and less than 60 years,0 otherwise)

unlikely and *extremely unlikely* and was the base choice and was set to zero in the model estimation). In this case, individuals that changed their opinion from *likely* to *extremely likely* may have had weaker anchoring effects and/or may have been undertaking confirmatory hypothesis testing to solidify their opinion and thus polarize. Those that moved to *uncertain*, *unlikely* and *extremely unlikely* would appear to have had relatively weak anchoring effects.

Table 2.4 presents the results of model estimates and corresponding marginal effects. The overall statistical fit of the model was quite reasonable with a McFadden ρ^2 of 0.442. Table 2.5 summarizes the overall influence of explanatory variables based on their marginal effects. In looking at the summarized results in Table 2.5, it was found that respondents with white ethnicity, higher education levels, lower incomes, those recently leasing a vehicle, and those recently purchasing a vehicle were less likely to change their initial opinion after being presented the additional informational questions. In contrast, it was found that respondents with higher incomes, those living in larger households, and those identifying themselves as single were more likely to shift their opinion from *likely* to *extremely likely*. It is interesting that the factors found to be significant in this model mostly related to socio-demographic variables (education, ethnicity, household size, marital status and income) and not to commute-related characteristics (which will be shown to play a role in forthcoming model estimations). The notable exception to this was the vehicle acquisition variables (leasing and recent purchases) both of which were associated with respondents being less likely to change their opinion. These findings underscore the relationship between current vehicle ownership patterns and opinions regarding autonomous vehicle adoption, as previously found by Menon et al. (2018).

The finding that respondents that leased vehicles were less likely to change their opinion relates to a whole body of literature that shows the characteristics of lessees differ significantly from those who finance or purchase vehicles with cash. For example, Mannering et al. (2002)

found that individuals who leased had significantly higher credit ratings and were more prone to vehicle-upgrading behavior (continually improving the quality and status-value of vehicles they acquire in successive acquisitions) relative to individuals who financed or paid cash. This variable is likely capturing fundamental vehicle acquisition and behavioral characteristics of lessees that spill over into their opinions of autonomous vehicle adoption. And, it is noteworthy that the marginal effect of this variable is quite large indicating the lessees have a 0.2124 higher probability of remaining *likely* relative to their non-lessee counterparts, an indication of strong anchoring effects.

2.8.2 Respondents with an initial opinion of unlikely

Of the 279 respondents who have initially indicated they were unlikely to adopt an autonomous vehicle, roughly 60% made the same *unlikely* choice after the informational questions, 22% polarized to *extremely unlikely*, and 19% depolarized (11% to *uncertain*, 8% to *likely*, 0% to *extremely likely*). Interestingly, while only 9% of respondents went from *likely* to *extremely likely* in our previous model estimate, a full 22% went from *unlikely* to *extremely unlikely*. This would seem to suggest that respondents in the *unlikely* category had inherently weaker anchoring effects and that the body of questions provided between initial and final opinions seem to result in more confirmatory bias in this group (which would tend to move them to more extreme positions as they reinforce their initial opinions), which results in a polarization to *extremely unlikely*. Table 2.6 presents the results of model estimates and corresponding marginal effects (the McFadden ρ^2 of 0.193 suggesting less of an overall fit than for the *likely* case), and Table 2.7 summarizes the overall influence of explanatory variables based on their marginal effects.

In looking at the summarized results in Table 2.7, it was found that, in contrast to the earlier findings in Tables 2.4 and 2.5, many commute-related variables were statistically significant with lower commute distance, lower parking times making people less likely to polarize to *extremely unlikely*, and daily travel times exceeding one hour making respondents more likely to polarize to a final opinion of *extremely unlikely*. Having lower commute distances and parking times likely reflects more satisfaction with present conditions and thus perhaps more stability in opinions relating to possible autonomous vehicle adoption.

Table 2.6 also shows that younger adults (less than 40 years old) and those from larger households were much less likely than others to change their initial *unlikely* position. The marginal effects of these variables show a 0.2483 higher probability of staying in the *unlikely* category for respondents less than 40 and a 0.1691 higher probability of staying in the *unlikely* category for larger households. It would seem that individuals with these characteristics, and an initial *unlikely* opinion, had stronger anchoring effects and thus were less influenced by the additional information provided.

Two variables (incomes exceeding $100,000 and households with 3 or more people) were common to models in both Tables 2.4 and 2.6. For respondents with an initial opinion of *likely*, these two variables made them more likely to move to *extremely likely* suggesting perhaps a combination of weaker anchoring effects and confirmation bias which would tend to move them to a more extreme position. For respondents with an initial opinion of *unlikely*, these two variables made them less likely to change their opinion, suggesting strong anchoring effects among this group. Thus, it is safe to say that these two variables consistently moved respondents to more favorable opinions with regard autonomous vehicle adoption.

As with the initial *likely* opinion model shown in Table 2.4, it was also found that recent vehicle purchases were influential in final opinion formulation. In the *unlikely* model case, if the

most recently purchased vehicle was new (as opposed to pre-owned), individuals were less likely to polarize their decision.

2.8.3 Respondents with an initial opinion extremely likely and extremely unlikely

Of the 159 respondents who initially indicated that they were *extremely likely* to adopt an autonomous vehicle, roughly 75% made the same choice after the informational questions (21% moved to *likely*, 2% to *uncertain*, 2% to *unlikely*, and 0% to *extremely unlikely*). Table 2.8 presents the estimation results and Table 2.9 provides a summary of variable effects.

Table 2.9 shows that respondents that were never injured in a vehicle crash, in households with 3 or more family members, having commute distances less than 3 miles, and whose most recent vehicle acquisition was new, were more likely to not change their opinion from *extremely likely*, indicating strong anchoring effects. Those respondents who identified as being white, had incomes greater than $100,000/year and were less than 40 years old were more likely to become less enthusiastic with regard to autonomous vehicle adoption suggesting weaker anchoring effects.

At the other extreme, of the 436 respondents who initially indicated that they were *extremely unlikely* to adopt an autonomous vehicle, roughly 80% made the same choice after the informational questions (14% moved to *unlikely*, 4% to *uncertain*, 2% to *likely*, and 0% to *extremely unlikely*). Table 2.10 presents the estimation results and Table 2.11 provides a summary.

Table 2.11 shows that respondents who were retired, had never been involved in a vehicle crash, and those who were currently working had strong anchoring effects and were less likely to change their opinion. Those respondents who identified as being white, spent less than 5 minutes parking their vehicle on average, had a vehicle acquisition within the last two years, whose most recently acquired vehicle was new, and were 41 to 59 years of age (an age grouping that produced the most statistically significant findings) had weaker anchoring effects and were more likely to become more enthusiastic with regard to autonomous vehicle adoption.

Interestingly, for both *extremely likely* and *extremely unlikely* models the overall model fit, as reflected by the McFadden ρ^2's of 0.146 and 0.046, respectively, were notably less than those for the *likely* and *unlikely* models. This suggests that variables commonly collected in transportation surveys are less likely to explain how individuals with these extreme initial opinions respond to information relative to those individuals with less extreme opinions.

2.9. Discussion of Findings

Table 2.12 presents a summary of all variables found to be significant in at least one of the four previously discussed models. This table classifies variables by model into those variables making respondents more likely to change their opinion (+), less likely to change their opinion (–) or having no statistically significant effect on their opinion-changing probability (ns).

Table 2.12 shows that there are few if any consistent results in terms of variables that increase or decrease the likelihood of changing opinion. Only the lower commute-distance variable made change less likely across two or more initial-opinion models. Many other variables were significant in only one of the initial-opinion models. Still others (respondents less than 40 years old, respondents in household with more than 3 people, respondents whose most recent vehicle purchase was new, and respondents facing average parking times of 5 minutes or less) actually had opposite effects, increasing the likelihood of opinion changes in some models and decreasing it in others.

The inconsistency of these results is itself an important finding. It suggests that the anchoring effects, possible confirmation bias, and the resulting polarization from such bias cannot

be consistently explained by traditionally collected variables. In fact, this chapter's model estimates are likely picking up correlations with some underlying psychological variables that truly explain the behavioral and psychological processes by which people process information to inform solidification or changes in their opinions. This has important implications for transportation survey design, particularly when studying topics that are likely to be associated with temporally unstable preferences, such as new vehicle technologies.

Table 2.12: Summary of changing-opinion model findings.

	Initial Autonomous-Vehicle Adoption Opinion*			
Variable	**Likely**	**Unlikely**	**Extremely Likely**	**Extremely Unlikely**
Younger adult indicator (1 if age less than 40 years, 0 otherwise)	ns	–	+	ns
Middle age indicator (1 if age greater than 40 years and less than 60 years,0 otherwise)	ns	ns	ns	+
White ethnicity indicator (1 if the respondent identifies as being white, 0 otherwise)	–	ns	+	+
Single status (1 if the respondent is single, 0 otherwise)	+	ns	ns	ns
Larger household indicator (1 if respondent with household with 3 or more people; 0 otherwise)	+	-	–	ns
Lower income indicator (1 if the household has an income less than $50,000/year, 0 otherwise)	–	ns	ns	ns
Higher income indicator (1 if the household has an income greater than $100,000/year, 0 otherwise)	+	–	+	ns
Higher education indicator (1 if respondent holds a bachelor's degree or above, 0 otherwise)	–	ns	ns	ns
Worker indicator (1 if the respondent is a worker, 0 otherwise)	ns	ns	ns	–
Retirement indicator (1 if the respondent has retired, 0 otherwise)	ns	ns	ns	–
Recent new-vehicle purchase indicator (1 if the most recently acquired vehicle was a new vehicle; 0 otherwise)	ns	–	–	+
Recent vehicle acquisition indicator (1 if the most recently acquired vehicle was in the last two years; 0 otherwise)	–	ns	ns	+
Recent vehicle lease indicator (1 if the most recent vehicle acquisition was a lease; 0 otherwise)	–	ns	ns	ns

Lower commute distance indicator (1 if one-way distance for the commute trip is less than 3 miles; 0 otherwise)	ns	–	–	ns
Lower parking time indicator (1 if respondent spends 5 minutes or less on average in order to park their vehicle, 0 otherwise)	ns	–	ns	+
Higher daily travel time indicator (1 if respondent travels more than 60 minutes every day for all their trips, 0 otherwise)	ns	+	ns	ns
Vehicle crash indicator (1 if the respondent has ever been involved in a vehicle crash, 0 otherwise)	ns	ns	ns	–
No injury indicator (1 if the respondent has not experienced an injury in a vehicle crash, 0 otherwise)	ns	ns	–	ns

* "+" is more likely to change opinion, "-" less likely to change opinion, "ns" not a statistically significant effect

respondents whose most recent vehicle purchase was new, and respondents facing average parking times of 5 minutes or less) actually had opposite effects, increasing the likelihood of opinion changes in some models and decreasing it in others.

The inconsistency of these results is itself an important finding. It suggests that the anchoring effects, possible confirmation bias, and the resulting polarization from such bias cannot be consistently explained by traditionally collected variables. In fact, this chapter's model estimates are likely picking up correlations with some underlying psychological variables that truly explain the behavioral and psychological processes by which people process information to inform solidification or changes in their opinions. This has important implications for transportation survey design, particularly when studying topics that are likely to be associated with temporally unstable preferences, such as new vehicle technologies.

So, what questions should be asked to understand how people's opinions may evolve? Although the answer to this question is not readily apparent, it seems that a series of questions could be developed to get a better sense of how the effects of factors such as anchoring effects, confirmatory bias, and other opinion formation/changing factors may generally vary from one individual to the next. Developing questions that gather information on how people's attitudes and perceptions of previously disruptive technologies (such as smart phones for example) evolved could potentially provide explanatory variables that are far better predictors of changing opinions than the standard socioeconomic information currently gathered in transportation surveys. Also, it may be possible to set up a series of questions that have survey respondents go through an experiment within the survey that can be then used to form variables (through cluster analysis or latent-variable approaches) that would better capture the process and likelihood of opinion change.

2.10. Summary and Conclusions

Autonomous vehicles arguably represent the most disruptive transportation technology since the motorized vehicle itself. Understanding factors that affect potential autonomous-vehicle adoption among consumers will be extremely important in forecasting the market penetration of the technology and the overall effect that it will have on the transportation system over time.

The current chapter uses an extensive survey to estimate a statistical model of individuals' initial likelihood of autonomous vehicle adoption, and then estimates a series of statistical models to assess how additional information may change this initial opinion. While the estimation findings identified explanatory variables that significantly affected opinion-change probabilities, the effect of explanatory variables on opinion change was found to vary greatly based on individuals' initial opinions. As discussed in detail previously in this chapter, it is argued that this finding suggests that traditional transportation surveys may not be collecting the types of data necessary to fully understand how preferences toward new transportation technologies will evolve over time.

However, it is important to note that the issues discussed in this chapter are really the same concerns that the introduction of any new disruptive technology would face. And, past experience has shown that forecasting the impact of disruptive technologies, in general, has proven to be a challenging task on many levels, with conventional data sources often proving inadequate. Autonomous vehicle adoption is not going to be an exception to this, and careful attention needs to be given to data collection with a particular emphasis on the opinion-formation concepts explored in this chapter.

Appendix 2.A. Questions between initial and final autonomous-vehicle adoption opinions

1. How likely do you think the following benefits will occur when using autonomous vehicles?
   [response options: *extremely unlikely*, *unlikely*, *uncertain*, *likely*, *extremely likely*]
   - ☐ Fewer traffic crashes and increased roadway safety
   - ☐ Less traffic congestion
   - ☐ Less stressful driving experience
   - ☐ More productive (than driving) use of travel time
   - ☐ Lower car insurance rates
   - ☐ Increased fuel efficiency
   - ☐ Lower vehicle emissions
2. How concerned are you about the following issues when using autonomous vehicles?
   [response options: *not at all concerned*, *somewhat concerned*, *extremely concerned*]
   - ☐ Safety of the vehicle occupants and other road users such as pedestrians, bicyclists.
   - ☐ System/equipment failure or autonomous vehicle system hacking
   - ☐ Performance in (or response to) unexpected traffic situations, poor weather conditions (like snowstorms) and low visibility/ dark environments
   - ☐ Motion sickness
   - ☐ Giving up my control of the steering wheel to the vehicle
   - ☐ Loss in human driving skill over time
   - ☐ Privacy risks from data tracking on my travel locations and speed
   - ☐ Difficulty in determining who is liable in the event of a crash
3. How much do you agree with the following statements regarding Autonomous Vehicles?
   [response options: *strongly disagree*, *disagree*, *uncertain*, *agree*, *strongly agree*]
   - ☐ Autonomous vehicles would be as safe operating in normal traffic as they would be in dedicated autonomous vehicle lanes
   - ☐ Autonomous vehicles should be programmed so that they always follow the posted speed limit.
   - ☐ With the possibility of sharing autonomous vehicles and other innovative transportation services coming up with autonomous vehicles, I may not have to own a car
   - ☐ In future, when autonomous vehicles become a common mode of transportation, I would trust an autonomous vehicle to safely take my kids to school
   - ☐ I believe that a human driver should be able to take over the driving control of the vehicle as needed
4. Consider a situation where you are driving in mixed traffic (traffic with both human-driven vehicles and autonomous vehicles) and answer the following questions.
   [response options: *strongly disagree*, *disagree*, *uncertain*, *agree*, *strongly agree*]
   - ☐ An autonomous vehicle is in front of my vehicle. I would be comfortable maintaining a shorter separation distance between my vehicle and the autonomous vehicle than the distance I would typically maintain between my vehicle and a human-driven vehicle.
   - ☐ An autonomous vehicle is in front of my vehicle and I want to execute an overtaking maneuver. I would be more confident executing the overtaking maneuver than I would be if I was overtaking a human-driven vehicle.
   - ☐ An autonomous vehicle is next to my vehicle (in the next lane) and I want to execute a lane change. I would be more confident executing the lane change than I would be if it was a human driven vehicle.
   - ☐ An autonomous vehicle is behind my vehicle. I would be less concerned about braking suddenly, as I feel that the autonomous vehicle would be capable of stopping in time under that situation.
   - ☐ Under heavy traffic situation, I would be more confident cutting in the front of an autonomous vehicle than I would be to a human-driven vehicle.

Chapter 3: A Statistical Analysis of Bikesharing Use and Its Potential as an Auto-Trip Substitute

3.1. Introduction

The concept of bikesharing has been around since 1960's, but only recently has it begun to receive large-scale acceptance as a viable transportation option (Fishman, 2016; Nikitas, 2018). However, the success of bikesharing systems can be highly variable because bikesharing is inherently tied to a geographical location that is defined by factors such as weather, urban density, local culture, or design, and thus each bikesharing system has a set of unique characteristics. Depending on location, bikesharing system could exhibit variable popularity, level of interest, and operational features. The level of utilization is generally estimated by trips per day per bike, in order to determine the number of bikes required in each system (Fishman, 2016). Smaller networks are at an inherent disadvantage relative to their larger counterparts because lower bicycle densities imply less convenient for potential users to find bikes. It has been shown that each location and bikesharing network attract different types of users, including commuters, students, local residents, or tourists (O'Brien et al., 2014). Depending on the trip purpose and type of user, the trip duration can vary. However, it has been found that, with the data from Melbourne, Brisbane, Washington, D.C., Minnesota and London, the average bikesharing trip lasts between 16 and 22 minutes (Fishman et al., 2014). Interestingly, many bikesharing users do not seem to be regular users but rather use these networks as a complement to their primary mode of transportation (Fishman, 2016). Also, the factors determining whether individuals decide to participate in bikesharing can vary significantly. If bikesharing is available, different individuals will have different sets of constraints that may prevent them from utilizing the system. Because of the wide number of factors (environmental or personal) influencing whether someone decides to use bikesharing, and the complexities of human decision making, understanding bikesharing use has been challenging.

In addition, in recent years the impacts of transportation on public health has been the subject of multiple research efforts. However, how the health conditions (or perceived health conditions) of travelers affect their decisions of travel and mode choice, especially regarding active transportation, is not yet fully understood. Past studies targeting cycling behavior indicated that physical capability is an implicit constraint in the choice of bicycle use (Stinson and Bhat, 2004; Smith and Kauermann, 2011; Ehrgott et al., 2012; Garcıa-Palomares et al., 2012; Larsen et al., 2013; Habib et al., 2014; Wadud, 2014), although this has often not been considered explicitly (Philips et al., 2018). In recognition of the potential issues associated with not explicitly considering physical capability, Menghini et al. (2010) suggested the need to investigate the heterogeneity of cyclists in more detail. Further, McArdle (2010) pointed out that age, gender, body mass index, and levels of physical activity are all known to be key determinants of fitness and thus the capability to cycle, and Shaheen (2016) indicated that understanding the physical and behavioral casual factors associated bikesharing usage remains a key challenge. Thus, in this research, the typical set of socio-demographic variables was expanded with health-related variables such as height, weight and self-reported health status. This data expansion was an attempt to minimize unobserved heterogeneity and potential omitted-variables bias in statistical-model estimation. It was hypothesized that body mass index (BMI) and overall wellbeing will be significant factors determining one's willingness to use an active transportation mode (such as bikesharing) on more regular basis, and that these factors will affect their likelihood of using bikesharing as a substitute for auto trips.

This chapter uses survey data gathered with help of CycleHop Bike Share Company as well the University of South Florida. The survey was disseminated through multiple channels

such as CycleHop registered users list, University of South Florida mailing list, as well as social media. The questionnaires (distributed between February and April of 2018) incorporated a number of detailed questions relating to bikesharing, health, and socio-demographics. These collected data were then used to estimate two mixed logit models (random parameters logit models) addressing the frequency of bikesharing use and mode substitution while incorporating health-related factors.

The remainder of this chapter begins with a literature review that focuses on various elements of bikesharing usage and modal substitution, followed by a detailed description of the survey, research design, methodological approach, and model estimation results. Finally, the chapter concludes with a summary and discussion of key findings.

3.2. Bikesharing as a Sustainable Mode of Transportation

Because biking does not involve harmful emissions while offering flexibility and convenience, it has become a valuable and environmentally friendly alternative to short auto trips in urban areas. The National Association of City Transportation Officials (2017) estimated that 25 percent more bikesharing trips were taken in 2016 than in 2015, and they also indicated that bikesharing growth is likely to continue to increase in future years as more people recognize it as a low cost and health-inducing transportation option. Other research has found bikesharing to increase mobility, save cost, reduce traffic congestion and fuel use, increase use of public transit, environmental awareness and economic development as well as improve health (Shaheen et al., 2016). Fishman et al. (2014) estimated that there was a significant reduction in motor vehicle use due to the presence of bikesharing systems. Their analysis was performed in the cities located in the United States, Great Britain, and Australia, and in every one of these cities a decrease in auto usage was found. Lu et al. (2018) reported benefits of bikesharing to include reductions in greenhouse gas emissions and fuel consumption, increased public transport use, improved accessibility, decreased traffic congestion and noise, lower travel cost, and increased physical activity and thus improved health and physical fitness. Such results have also been supported by other studies (Shaheen et al., 2010; Shaheen et al., 2013; Bauman et al., 2016; Pal and Zhang, 2017).

Bikesharing has also experienced significant growth in university-campus environments. This is because universities tend to have high population densities, large percentages of smart phone users, and extensive demands for shorter trips (between buildings on campus and to/from nearby student housing), all of which are potentially important ingredients for bikesharing success. Indeed, sustainability plans have become a concern in campus design and a bikesharing program is often a key element of such plans (Balsas 2003; Norton et al. 2007), because it can reduce traffic and parking congestion on and around campuses (Kaplan and Knowles, 2015).

With regard to the environmental factors, multiple studies have found that they play a significant role in willingness to use bikesharing (Nikitas, 2018). Some research revealed that proximity to the workplace or home tends to increase the usage of bikesharing systems (Shaheen et al., 2011; Molina-Garcia et al., 2015). In other work, Sun et al. (2017) studied the impact of environmental factors on bikesharing usage and found that traffic congestion did not influence the usage of bikesharing. On the other hand, bus accessibility was found to be positively associated with the usage of bikesharing, while metro accessibility was negatively associated with its usage. As expected, safety also plays a key role in bikesharing usage, and Sun et al. (2017) found that both on-street and off-street violent crimes tended to decrease the usage of bikesharing systems. Other studies found high population density, high levels of public transit accessibility, and the

presence of upgraded facility types (bicycle lanes or bicycle paths), tended to increase the usage of bikesharing systems (Faghih-Imani et al., 2014; El-Assi et al., 2017).

Although, bikesharing systems in different locations will have different designs, sizes, numbers of residents, and types of customers, they all are likely to share similarities with regard to user attitudes and perceptions. The difference between the desire to use a bikesharing program and their actual use has to do with impediments, which can be self-imposed or based on factors that cannot be changed, such as the weather (Kaplan and Knowles, 2015). It should be noted that because the data in the current chapter will be drawn from bikesharing registrants in the state of Florida (with its highly favorable weather), the possibility to explore some of these impediments (such as weather) will be limited.

3.3. Socio-Demographics of Bikesharing Users

Prior research has provided considerable insight into the relationship between socio-demographic characteristics and bikesharing usage. With regard to gender, Pucher et al. (2011) identified that about 65% to 90% of trips are done by men in countries where biking did not serve as a primary mode of transportation (US, UK, and Australia). In a study performed in London, less than 20% of bikesharing trips were made by females (Goodman and Cheshire, 2014). Akar et al. (2013) also found that women were less likely to ride a bicycle relative to men. In Netherlands, in contrast, more women than men use bicycles (Harms et al., 2014).

Where age is concerned, Buck et al. (2013) found that the users of shared-bike systems in Washington D.C. were, on average, younger than local cyclists. The average age for local cyclists was found to be 42 years old, whereas the average age for annual members of the shared-bike system and short-term users was 34 and 35 years old, respectively. In the U.S., Pucher, et al. (2011), concluded that the number of 40 to 64-year-old cyclists increased the most of all the age groups that they studied, and between 2001 and 2009, cyclists in this age group doubled their share of bike trips.

Ethnicity has also been found to be an important factor determining whether an individual uses a bikesharing system. Studies in Washington D.C. and London found that the bikesharing population is not representative of the overall population composition of these cities (Buck et al., 2013; Fishman, 2016). Caucasians were overrepresented in the samples of bikesharing users relative to other ethnicities. Similarly, Borecki et al. (2012) found that bikesharing was largely undertaken by Caucasians.

With regard to income, prior studies found that people who use bikesharing had higher average income (Woodcock et al., 2014; Fishman et al., 2015; Fishman 2016). And, Shaheen et al. (2014) found that bikesharing participants tended to be wealthier.

Another perspective on analyzing bikesharing adoption was undertaken by Gulsah et al. (2013). Their analysis was performed on the Ohio State University campus and was able to reveal some of the gender differences, as well as gender-based preferences and attitudes towards bikesharing. Although, the surveyed population stayed in similar environments, women were found to feel less safe walking and biking (Gulsah et al., 2013). In other work, traffic, lack of awareness of bike lanes, pedestrians, safety and campus design were found to be main impediments to bikesharing usage (Kaplan and Knowles, 2015). Similarly, Swiers et al. (2017) analyzed the cycling behavior of a university-student population and found that the two primary barriers to cycling were weather and safety.

Stinson and Bhat (2004) found a positive relationship between recreational cycling and cycling to commute. Moreover, Xing et al. (2010) found that 90% of those who cycled for

transportation were cycling for other purposes as well. This suggests an association in cycling behavior and possibly its connection to other modes of shared transportation systems (Wuerzer and Mason, 2015).

There is also an extensive body of literature that links transportation and public health. The fact that active transportation modes help fight obesity and improve health has been addressed by many. Also, a correlation has been found between being overweight and living in less walkable communities (Ewing et al., 2003; Frank et al., 2004; Giles- Corti et al., 2003; Saelens et al., 2003; Lopez, 2004). Furthermore, Strum and Cohen (2004) found an association between urban sprawl in metropolitan areas and the prevalence of chronic diseases. Active transportation was also shown to significantly improve population health in California, with potential decreases in chronic diseases (Maizlish et al., 2017).

Other researchers have analyzed the connection between active transportation, health, and the usage of social networking services. For example, Hong et al. (2018) found that intensive users of social networking services were more likely to be obese, and tended to spend less time walking, making this group a natural target for interventions designed to increase physical activity.

Past research has shown that expanding the set of variables could be essential for more fully understanding bikesharing behavior and developing strategies for bikesharing implementation and adoption. For example, Earl and Lewis (2018) suggested examining the role of context in health behavior and emphasized the importance of considering the environment while trying to influence health behavior.

In the current research, in addition to traditional socio-demographic characteristics, travel behavior, and travel history variables, the body mass index (BMI) will be considered as an explanatory variable. The BMI gives an estimation of excess body weight, which is not a direct estimate of body fatness. Nevertheless, some studies have confirmed direct body fat measurements do correlate with BMI. Body mass index does have its limitations because of natural variances across factors such as age, gender, ethnicity and body composition (BMI does not distinguish between excess fat, muscle, water or bone). BMI is non-invasive and easily calculated and, in spite of these limitations, it has been widely shown to be a good overall predictor of morbidity, mortality and a good assessment of individual's overall health risks.

3.4. Survey and Research Design

A web-based survey was designed to collect the data on the bikesharing usage of registered bikesharing users. The survey dissemination took place between February and April of 2018. To make sure that a wide variety of demographic groups was reached, multiple distribution channels to disseminate the survey were used. CycleHop Bike Share Company, which operates bikesharing programs in Tampa, St. Petersburg, Orlando and the University of South Florida (Tampa campus) assisted in distributing the survey to its registered users as well as posting it on social media. To increase the number of responses, the survey was also sent to the students and faculty of the University of South Florida Tampa campus (where one of the bikesharing systems is operating). Respondents were asked about their use frequency of bikesharing. To determine the characteristics of usage, they were asked how often they used the bikesharing and were provided five possible answers; less than once a month, 1 to 3 times per month, 4 to 5 times per month, 6 to 10 times per month, and more than 10 times per month. Because the literature review concluded that bikesharing users do not generally bikeshare on a regular basis, the survey did not ask about the actual number of uses but rather a usage category. Based on the number of observations in each category, the data were two groups; one group indicating that they typically use bikesharing less

than once a month, and the other group indicating that they typically use bikesharing once a month or more. Of the 301 registered bikesharing users, 165 are in the first group and 134 in the second group.

The second question in the survey focused on mode substitution. That is, which mode of transportation would the respondent use if bikesharing was not available on a trip that they chose to ride a shared bike. Because the substitution of auto trips is critical in terms of environmental impacts and relieving traffic congestion in urban areas, the focus was on identifying the characteristics of the group who would make their bikesharing trip by auto if bikesharing was not available on a trip they chose to use shared bikes. Out of 301 respondents, 140 indicated that they would use an automobile in the absence of bikesharing while the remaining 161 would use other modes including bus, personal bicycle, or walking.

The survey covered a variety of socio-demographic and household characteristics, as well as travel behavior and travel history characteristics (commute time and distance, traffic-crash history, parking time, grocery store proximity, total daily travel time, and so on). Furthermore, health-related questions such as weight, height and self-assessed health were added. Given the responses, the body mass index (BMI) was calculated using self-reported height and weight. In the sample, 175 respondents had a normal BMI (BMI equals to 25 or less), 81 people were classified as overweight (BMI between 25 and 30) and 45 respondents were classified as obese (BMI greater than 30). The respondents were asked to assess their health on the following scale: extremely bad, slightly bad, neither good nor bad, good, extremely good. In the collected sample only 1% reported their health as extremely bad, followed 3% as slightly bad, 4% as neither good nor bad, whereas 61% indicated good health and 31% extremely good. Respondents were also asked if they struggle with any illness or health condition on daily bases, and only 34 of the 301 respondents indicated such a struggle. Because of the exploratory nature of incorporating the health questions and potential issues with confidentiality regarding health information, the type of illness or health condition was not specified.

To get a sense of the respondent sample, Table 3.1 provides summary statistics for select respondent attributes.

Table 3.1. Some key survey statistics.

Respondent Characteristic	**Mean**	**Standard Deviation**
Age (in years)	37	13.9
Height (in inches)	67.4	4.37
Weight (in pounds)	164.4	42.19
Body Mass Index	25.4	5.34
Household size (persons)	2.4	1.21
Household vehicle ownership (vehicles)	1.93	1.12
Annual household income (in dollars)	82,000	61,000

3.5. Methodological Approach

In this chapter, two questions were considered; whether the survey respondent bikeshares one or more times per month (monthly usage), and whether the respondent would make an auto trip if bikesharing was not available on a trip they chose to bikeshare.

The above responses are discrete with a yes/no response indicating either monthly usage or auto trip substitution. To arrive at an estimable statistical model for both questions, a function that determines the probability of either using one or more times per month or substituting an auto trip (1 if the respondent is a monthly bikesharing user/substituting a bikesharing trip by an auto trip, 0 if not) was defined as,

$$F_n = \boldsymbol{\beta}\mathbf{X}_n + \varepsilon_n \tag{3.1}$$

where $\mathbf{X}_n$ is a vector of explanatory variables that affect the probability of observation n being a monthly bikesharing user/substituting a bikesharing trip, $\boldsymbol{\beta}$ is a vector of estimable parameters, and ε_n is a disturbance term. If the disturbance term are assumed to be generalized extreme-valued distributed, a standard binary logit model results as (McFadden, 1981)

$$P_n(1) = \frac{1}{1 + EXP - (\boldsymbol{\beta}\mathbf{X}_n)} \tag{3.2}$$

where $P_n(1)$ is the probability of the respondent being a monthly user/substituting a bikesharing trip, and other variables are as previously defined.

In model estimation, it is essential to account for the possibility of unobserved heterogeneity across respondents. That is, the possibility that different respondents will be affected by explanatory variables differently due to unobserved reasons (this is particularly likely with analyzing complex human decision-making processes). To account for the possibility of having one or more parameter estimate in the vector $\boldsymbol{\beta}$ vary across respondents, a distribution of these parameters can be assumed, and Equation 2 can be rewritten as (Washington et al., 2011)

$$P_n(1) = \int \frac{1}{1 + EXP - (\boldsymbol{\beta}\mathbf{X}_n)} f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})\, d\boldsymbol{\beta} \tag{3.3}$$

where $f(\boldsymbol{\beta}_i|\boldsymbol{\varphi}_i)$ is the density function of $\boldsymbol{\beta}$, $\boldsymbol{\varphi}$ is a vector of parameters describing the density function (mean and variance), and all other terms are as previously defined. The resulting model is referred to as random parameters or mixed logit model (see Mannering et al., 2016, for a description of alternate methods of accounting for unobserved heterogeneity).

In the model estimation the possibility for the mean and variance of individual parameters to be a function of explanatory variables is also considered giving (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017; Mannering, 2018),

$$\beta_n = \beta + \Theta\mathbf{Z}_n + \sigma_n EXP(\boldsymbol{\omega}_n \mathbf{W}_n) + \varphi_n \tag{3.4}$$

where β is the mean parameter estimate, $\mathbf{Z}_n$ is a vector of explanatory variables that influence the mean of β_n, Θ is a vector of estimable parameters, $\mathbf{W}_n$ is a vector of explanatory variables that captures heterogeneity in the standard deviation σ_n, $\boldsymbol{\omega}_n$ is the corresponding parameter vector, and φ_n is a randomly distributed term that captures unobserved heterogeneity across respondents.

Estimation of the random parameters logit model was undertaken by simulated maximum likelihood approaches because the required integration of the logit formula over the distribution of parameters is not closed form. Prior research has shown that Halton draws can deliver more efficient distribution of simulation draws than purely random draws (McFadden and Ruud, 1994; Bhat, 2003), and 1,000 Halton draws were used in the estimation process. This is a number that has been shown to be more than enough to provide accurate parameter estimates (Bhat, 2003;

Milton et al., 2008; Anastasopoulos and Mannering, 2009; Behnood and Mannering, 2016). In this chapter, the normal distribution was used for random parameters because it provided the best statistical fit for both response models (other distributions such as the log-normal, uniform, and exponential were not found to produce statistically better results than the normal distribution). It should be noted that additional approaches to address the unobserved heterogeneity have been widely applied in accident and injury-severity research (Benhood and Mannering, 2016; Osama and Sayed, 2017; Fountas and Anastasopoulos, 2018; Fountas et al., 2018; Marcoux et al., 2018; Balusu et al., 2018).

Marginal effects were calculated to determine the effect that individual explanatory variables have on response probabilities. The marginal effect of an explanatory variable gives the effect that a one-unit increase in an explanatory variable has on the response probabilities. For indicator variables (that assume values of zero or one), marginal effects will give the effect of the explanatory variable going from zero to one (Washington et al., 2011).

3.6. Model Estimation Results

Table 3.2 presents the summary statistics of variables found to be statistically significant in both models is presented. Tables 3.3 and Table 3.4 provide the random parameters logit model estimation results, including parameter estimates, t-statistics and marginal effects, for the usage of bikesharing and auto-mode substitution, respectively. The statistically significant explanatory variables in Table 3.3 and Table 3.4 were grouped into three categories; socio-demographic factors, travel behavior and history, and health indicators.

As shown in Tables 3.3 and 3.4, two variables in each model produced a statistically significant random parameter. This significance was confirmed by conducting a likelihood ratio test to compare the random parameters logit model with fixed parameters model. For both models (as shown in Tables 3.3 and 3.4) the test rejected the null hypothesis that fixed and random parameters models are the same with over 95% confidence. Thus, only the results of random parameters models are presented.

All explanatory variables are in the "Yes" response functions (use bike sharing once a month or more/substituting a bikesharing trip by an auto trip) with the "No" response functions (for both models) implicitly set to zero. Also, estimation results indicate that no variables produce an estimated parameter with statistically significant heterogeneity in the means and/or variances, so Equation 4 reduces to $\beta_n = \beta + \varphi_n$.

Table 2. Summary statistics for variables included in final model estimations.

Variable Description	Mean	Standard Deviation
Male indicator (1 if respondent is a male, 0 otherwise)	0.46	0.50
Caucasian indicator (1 if respondent is Caucasian, 0 otherwise)	0.76	0.43
Younger millennial indicator (1 if respondent is less than 30 years old, 0 otherwise)	0.53	0.50
Low annual household income indicator (1 if annual household income is less than $50k, 0 otherwise)	0.35	0.48
One-person household indicator (1 if respondent lives alone, 0 otherwise)	0.24	0.43

High annual household income indicator (1 if annual household income is more than $200k, 0 otherwise)	0.12	0.33
Drive-alone commute indicator (1 if respondent most often commutes to work by driving alone, 0 otherwise)	0.72	0.45
Lack of commute indicator (1 if respondent does not commute, 0 otherwise)	0.06	0.24
Daily travel time indicator (1 if respondent spends 90 minutes or more on total daily travel, 0 otherwise)	0.08	0.28
Higher vehicle ownership (1 if household owns or leases three or more vehicles, 0 otherwise)	0.21	0.41
Low average parking time indicator (1 if respondent spends less than 5 minutes total on finding a spot and walking to their destination, 0 otherwise)	0.66	0.47
Low parking time indicator (1 if respondent spends less than 3 minutes on finding a parking spot during a normal trip, 0 otherwise)	0.79	0.41
High BMI (body mass index) indicator (1 if respondent has BMI above 25, 0 otherwise)	0.42	0.49
Obese BMI (body mass index) indicator (1 if respondent has BMI above 30, 0 otherwise)	0.15	0.35

Table 3. Random parameters logit model estimation results for the probability of using bikesharing one or more times per month (all random parameters are normally distributed).

Variable Description	Estimated Parameter	t-Statistic	Marginal Effect
Constant	1.16	2.72	
Socio-demographic factors			
Male indicator (1 if respondent is a male, 0 otherwise)	0.72	2.77	0.17
Caucasian indicator (1 if respondent is Caucasian, 0 otherwise)	0.50	1.86	0.12
Low annual household income indicator (1 if annual household income is less than $50k, 0 otherwise) (*Standard deviation of parameter distribution*)	-1.03 (*4.60*)	-3.08 (*5.79*)	-0.25
One-person household indicator (1 if respondent lives alone, 0 otherwise)	0.53	1.91	0.13
Travel behavior and history			
Drive-alone commute indicator (1 if respondent most often commutes to work by driving alone, 0 otherwise)	-1.85	-5.30	-0.45
Lack of commute indicator (1 if respondent does not commute, 0 otherwise)	-1.51	-2.86	-0.37
Daily travel time indicator (1 if respondent spends 90 minutes or more on total daily travel, 0 otherwise)	1.19	2.69	0.29
Higher vehicle ownership (1 if household owns or leases three or more vehicles, 0 otherwise)	-0.64	-2.05	-0.16
Low average parking time indicator (1 if respondent spends less than 5 minutes total on finding a spot and walking to their destination, 0 otherwise)	-0.97	-3.55	-0.24
Health indicators			
High BMI (body mass index) indicator (1 if respondent has BMI above 25, 0 otherwise) (*Standard deviation of parameter distribution*)	0.30 (*1.87*)	1.21 (*5.08*)	0.07
Number of observations	301		
Log likelihood at zero	-232.20		
Log likelihood at convergence	-174.22		

Table 4. Random parameters logit model estimation results for the probability that a bikesharing trip would be substituted by an auto trip if bikesharing was not available (all random parameters are normally distributed).

Variable Description	Estimated Parameter	t-Statistic	Marginal Effect
Constant	-0.22	-0.59	
Socio-demographic factors			
Male indicator (1 if respondent is male, 0 otherwise) (*Standard deviation of parameter distribution*)	-0.82 (*5.30*)	-2.68 (*5.97*)	-0.20
Younger millennial indicator (1 if respondent is less than 30 years old, 0 otherwise)	0.55	2.17	0.13
High annual household income indicator (1 if annual household income is more than $200k, 0 otherwise)	-0.69	-1.84	-0.17
Travel behavior and history			
Drive-alone commute indicator (1 if respondent most often commutes to work by driving alone, 0 otherwise)	1.31	4.63	0.32
Low parking time indicator (1 if respondent spends less than 3 minutes on finding a parking spot during a normal trip, 0 otherwise)	-1.14	-3.59	-0.28
Higher vehicle ownership (1 if household owns or leases three or more vehicles, 0 otherwise)	-0.53	-1.86	-0.13
Health indicators			
Obese BMI (body mass index) indicator (1 if respondent has BMI above 30, 0 otherwise) (*Standard deviation of parameter distribution*)	1.40 (*2.32*)	3.18 (*3.29*)	0.34
Number of observations	301		
Log likelihood at zero	-208.6		
Log likelihood at convergence	-181.6		

3.6.1 Model Estimation Results: Regular Use of Bikesharing

With regard to the socio-demographic factors affecting the probability of registered bikesharing users using shared bikes one or more times per month (see Table 3), it was found that male respondents were more likely to be regular bikesharers (use it once a month or more). This finding aligns with prior research stating that males are more likely to use bikesharing in general (Pucher and Buehler, 2012; Goodman and Cheshire, 2014; Akar et al., 2013). The average marginal effect indicates that males have a 0.17 higher probability of using shared bikes one or more times per month relative to females.

Respondents who identified themselves as Caucasian were found to be more likely to use bikesharing regularly. This result also aligns with prior studies that found Caucasians to be overrepresented in samples of bikesharing users relative to other ethnicities (Buck et al., 2013; Fishman, 2016; Borecki et al., 2012). Households with an annual income below $50,000 produced a normally distributed parameter with a mean of -1.03 and a standard deviation of 4.60. This results

in 58.9% of respondents from these households being less likely to use bikesharing one time a month or more, and 41.1% respondents being more likely to do so (relative to respondents from households making $50,000 or more per year). This finding is important because it shows considerable variation among lower-income households. While previous studies found that bikesharing membership and usage is usually associated with higher incomes (Fishman et al., 2015; Fishman 2016; Woodcock et al., 2014; Shaheen, et al., 2014), the variance that was found in this effect shows that some respondents in lower-income households have higher bikesharing usage than their higher-income counterparts. Thus, bikesharing in lower socioeconomic areas could be viable and help improve equality and mobility of the most vulnerable members of the society. The variation in this effect across low-income respondents also suggests that there are factors relating to low-income respondents that are not captured by income alone (reflected by the significant unobserved heterogeneity).

Respondents from single-person households were found to be more likely to be regular users compared to respondents from households with multiple occupants. This finding could be related to the presence of children in the household. Intuitively, the presence of children makes it harder for an individual to use a bicycle in general. Lack of the appropriate bike seats for small children coupled with the vehicle-dominant facilities do not encourage but rather discourage bikesharing use among individuals with small children. It is important to stress the fact that most environments and bikesharing systems do not cater to the caregivers of small children, especially in a context of equality and equity in transportation.

With regard to travel behavior and history, the indicator variable for commuters who mostly commute by driving alone and those who do not commute at all were found to be less likely to bikeshare regularly. For drive-alone commuters, the average marginal effect is quite large (in absolute terms) at -0.45 indicting that drive-alone commuters have a 0.45 lower probability of bikesharing one or more times per month than non-drive-alone commuters. Additionally, respondents who spent more than 90 minutes on total daily travel were found to be more likely to use bikesharing once a month or more, again with a relatively large average marginal effect of 0.29. As might be expected (reflecting the ease of vehicle access and usage), respondents from households with higher vehicle ownership (owning or leasing three or more vehicles) as well as those whose average parking time for their most regular trip that is less than 5 minutes (including finding a spot and walking to the destination) were less likely to use bikesharing one or more times a month.

Finally, respondents with BMI scores over 25 produced a normally distributed parameter with a mean 0.30 and a standard deviation of 1.87. This results in 56.4% respondents more likely to be a regular bikesharing user and 43.6% of respondents with high BMI being less likely, relative to their lower BMI counterparts. The fact that higher BMI respondents have higher usage probabilities than some of their lower BMI counterparts shows that bikesharing has some significant potential for improving public health. The fact that BMI was found to be significant factors in the model again underscores the importance of health-related factors in considering active-transportation modes such as bikesharing.

To assure that the model with inclusion of the high BMI indicator provides statistically better fit for the data, a model without this variable was estimated. A likelihood ratio test comparing models with and without the BMI variable indicates that the null hypothesis that the models are the same can be rejected with 93% confidence. Also, for bikesharing usage there is the possibility that BMI could be an endogenous variable. That is, respondents who have high bikesharing usage rates may lower their BMI. However, in this case it is unlikely that the

bikesharing usage rates are high enough to directly affect BMI, although some caution should still be exercised when interpreting our results in this regard.

3.6.2 Model Estimation Results: Auto-Trip Substitution

With regard to the socio-demographic variables influencing the probability that a bikesharing trip would be substituted by an auto trip if bikesharing was not available (see Table 4), it was found that people who identified themselves as male produced a normally distributed parameter with a mean -0.82 and a standard deviation equal to 5.30. This suggests considerable heterogeneity among male respondents. The estimation results imply that 56.1% of males who use bikesharing were less likely to make the trip by auto if bikesharing was not available and 43.9% being more likely to do so. Once again, gender was found to play a key role in bikesharing-related behavior. The findings are generally consistent with prior studies that found males to be more likely to use bikesharing in general (Pucher and Buehler, 2012; Goodman and Cheshire, 2014; Akar et al., 2013), but the considerable heterogeneity among male bikesharing users with regard to their substituting a bikesharing trip with an auto trip is an interesting finding. With regard to age, it was found that bikesharing respondents who are less than 30 years old were more likely to make an auto trip in the absence of bikesharing. It is noteworthy that other researchers have also found age to be a significant variable in bikesharing (Pucher, et al., 2011; Buck et al., 2013). Respondents with annual household income above $200,000 were found to be less likely to substitute their bikesharing trip by an auto trip in the absence of bikesharing. This finding suggests that high-income households are less likely to increase their auto usage and they are more likely switch to another mode of active transportation in the absence of bikesharing. Prior studies also found income to be a significant variable while analyzing bikesharing. People who used bikesharing were found have higher average income (Woodcock et al., 2014; Fishman et al., 2015; Fishman 2016).

With regard to travel behavior, respondents who commute by driving alone were found to be more likely to substitute their bikesharing trip by an auto trip in the absence of bikesharing. The high average marginal effect of this variable indicates that respondents that most often drive alone have a 0.32 higher probability of substituting their trip by auto relative to respondents that regularly commute by other means. This finding is like that found in the previous bikesharing usage model (see Table 3) and reflects the substantial residual effect of the auto culture among bikesharing registrants. Respondents who indicated a very low time (less than 3 minutes) to find a parking spot during their most regular trip and those whose households owned or leased three more vehicles, were found to be less likely to use an auto trip in the absence of bikesharing.

Regarding the health indicators, respondents who had body mass index in the obese range (BMI above 30) produced a normally distributed parameter with a mean 1.40 and a standard deviation 2.32. This shows considerable variation across the population with regard to the effect of BMI, with 72.7% of people with the obese BMI being more likely to substitute their bikesharing trip with an auto trip if bikesharing was not available and 27.3% being less likely.

Like the previous model on the usage of bikesharing, a separate model without the BMI indicator was estimated to underscore the statistical importance of the BMI indicator. A likelihood ratio test comparing the models with and without the BMI variable indicated that the hypothesis that the two models were equal could be rejected with over 99% confidence.

3.7. Summary and Conclusions

This research focuses on exploring the determinants of bikesharing use, and its potential as an auto-trip substitute, by including self-reported health factors. Both estimated statistical models

provide insights into how various survey respondents behave with regard to bikesharing decisions. For the frequency-of-use model it was found that Caucasian males, respondents from one-person households, and those with high total daily travel times (for all trips) were more likely to be a regular user of bikesharing (use it at least once a month). In contrast, respondents who drove alone for their commute trip and those who do not commute at all were less likely to bikeshare regularly. Also, respondents from households with higher auto ownership (leased or owned at least three vehicles) and low average parking time during their most regular trip were less likely to use bikesharing at least once a month. Variables that were found to vary across respondents included low annual household income (below $50,000) and the high body mass index (BMI) indicators.

With regard to the auto-mode substitution model (asking if a respondent would make an auto trip if bikesharing was not available), younger respondents (under 30 years old) were found more likely to make an auto trip in the absence of bikesharing. In contrast, those from households with annual household income more than $200,000 were found to be less likely to make an auto trip in the absence of bikesharing. Respondents who identified themselves as male were less likely to exhibit homogenous behavior and this parameter varied across population. With regard to travel behavior, it was found that respondents who commuted by driving alone were more likely to make an auto trip if bikesharing was not available. In contrast, those who spent less than 3 minutes to find parking for their most regular trip and those whose households owned or leased three or more vehicles were less likely to make an auto trip. Obese BMI indicator (BMI above 30) was found to vary across population, which reflected the willingness of a percentage of this group being less likely to make an auto trip in the absence of bikesharing. This is important because it suggests that some people with obese BMI are willing to improve their health through participating in active transportation.

The results of this chapter can potentially help guide and develop our understanding of how bikesharing decisions are made. Household composition and vehicle ownership were found to be some of the key factors in decisions related to bikesharing behavior. It was also found that the lingering effects of auto reliance (reflected by respondents who indicated that most often commuted by driving alone) adversely affected the likelihood of a registered bikesharing user using bikesharing frequently or substituting their bikesharing trip with a non-auto mode. Finally, the model estimations did not show that self-reported health-related factors other than BMI played a significant role in bikesharing use and behavior. While the self-reported health question was unable to produce statistically significant results, variables derived from actual detailed health data may still prove valuable in future research on bikesharing behavior.

Chapter 4: A Statistical Assessment of Temporal Instability in the Factors Determining Motorcyclist Injury Severities

4.1. Introduction

The number of fatalities from motorcycle crashes has increased considerably in recent years, reaching 5286 fatalities in 2016 in the U.S. (National Highway Traffic Safety Administration, 2018). Reasons for this increase can potentially be attributed to a wide variety of factors ranging from standard possibilities such as increases in motorcycle registrations and usage, to less well understood factors such as changes in macroeconomic conditions that could affect motorcycle risk-taking behavior (Behnood and Mannering, 2016; Abay and Mannering, 2016), the effect of distracted riding, and a variety of behavioral and psychological factors that may affect risk-taking behavior among motorcyclists over time (Mannering, 2018).

The possibility that behavior may be changing fundamentally over time, thus resulting in temporal shifts in the factors that determine injury severity, is an issue that has not yet been adequately explored in the motorcycle injury-severity context, even though this topic has been a focus of considerable attention in recent research on automobile/truck drivers and their resulting crash-induced injuries. Because vehicle crashes are relatively rare events, gathering enough observations to statistically analyze factors affecting resulting injury severity requires that crash observations be gathered over some period of time. However, because driver behavior, risk perceptions, and other factors may vary overtime, the time-separation of crashes potentially problematic for model estimation. In fact, past studies have shown that there is ample evidence to suggest temporal instability in the effect that explanatory variables have on crash-injury probabilities for car/truck drivers even over small periods of time. For example, Malyshkina and Mannering (2009) estimated a Markov switching model that showed that injury-severity model parameters shifted between two states over time (from week to week). In subsequent work, Xiong et al. (2014) also found temporal shifting crash-injury determinants again using a random parameters Markov switching approach. Using more traditional statistical approaches that capture temporal variations over longer periods of time, Behnood and Mannering (2015) found that the factors that determined driver injury severities in single-vehicle automobile/truck crashes in Chicago, Illinois varied significantly from year to year using data from 2004 to 2012 inclusive. In subsequent work, again using data from Chicago, Behnood and Mannering (2016) found that the factors influencing pedestrian injury severities resulting from crashes with automobiles and trucks also varied significantly over time, and that these variations corresponded to changes in macroeconomic conditions induced by the great recession of 2007 to 2009. In fact, Mannering (2018) argues that there are compelling reasons to believe vehicle-driver behavior will shift over time and that these changes will result in fundamental shifts in the factors that determine crash injury severities. The reason for these shifts could potentially include temporal changes in driver decision-making, in cognitive biases and information gathering, in the effect of macroeconomics risk taking, and in the dissonance between driver attitudes and behavior (Mannering, 2018).

In comparison automobile/truck drivers, one would expect motorcyclists' behavior to exhibit similar temporal instability with regard to factors influencing injury severity. However, motorcycling is different in several ways. First, motorcyclists have far less physical protection in a crash relative to their automobile/truck counterparts. Thus, even small changes in behavior and/or risk taking are more likely to show up in resulting injury severities since protective features that may dissipate crash forces before reaching body are far less than those in automobile/trucks. Second, motorcycle operation is a much more complex task relative to driving an automobile or truck. Motorcycle operation typically requires excellent motor skills and physical coordination

because, in addition to steering and acceleration/braking, motorcyclists must allocate braking forces between front and rear brakes, manually shift gears (automatic transmissions are far less common than in automobile/truck counterparts), and must perform what can be counter-intuitive steering tasks[13] all while maintaining balance (Rothe and Cooper, 1987). This additional complexity will make the effect of behavioral changes over time much more pronounced. Third, because of the complexity of the motorcycling task, the effect of experience on reducing crash probabilities and resulting injuries is likely to be much more pronounced than it is for automobile/truck driving. This implies that the passage of time and subsequent experience gain will alter injury-severity probabilities.

This third point has long been recognized as a serious problem in motorcycle safety. In the U.S., to deal with the fact that the complexities of motorcycle operation mean that most riders will start off at a very low skill level and with a high risk for serious injury, the Motorcycle Safety Foundation offers a Basic Rider Course where the basic skills required to successfully operate motorcycle are demonstrated and experienced through classroom and field exercises. Several U.S. states require motorcyclist to pass the Basic Rider Course before being licensed to operate a motorcycle. For example, in Florida all motorcyclists licensed since July 1, 2008 have been required to pass the Motorcycle Safety Foundation' s 15-hour Basic Rider Course. Over the years, the effectiveness of the course has generally been difficult to assess for at least two reasons. First, in states where the course is not required to obtain a license, individuals choosing to take the course may tend to be less skilled riders. Thus, although the course likely improves their riding abilities, it may not improve them to the level of the riders who did not take the course. As a result, the crash rates of those taking the course may still be higher than those who did not, making assessment of course effectiveness difficult. Savolainen and Mannering (2007a) found this to be the case in their study of Indiana motorcyclists. Second, even courses that are mandatory for licensing may tend to attract less skilled riders to motorcycling and thus diminish the average skill set of licensed motorcyclists overall. In this case, riders who would not normally seek a license may be tempted into motorcycling by passing the course which will enable them to achieve some minimum competency. But such riders may be inherently more accident prone relative to motorcyclists who would have self-selected to become licensed even if a course was not required.

The intent of the current chapter is to provide some empirical insight into the potential temporal instability in the factors affecting motorcycle crash-injury severities. To do this, only single-vehicle motorcycle crashes will be considered, thus simplifying the crash to be one of mostly rider error.[14] For these single-vehicle crashes, possible temporal effects will be considered from two perspectives. One is to consider the crash experiences, over time, of riders that passed the Basic Rider Course in a single year. For these individuals, their crash risk and resulting severities will be affected by their rapid initial accumulation of experience, which will tend to make them particularly susceptible to temporal instability in their early years of riding. The second perspective is to consider crash experiences of a more general motorcyclist population by looking at crashes occurring on roadway curves (referred to as horizontal curves in highway engineering), and how the determinants of these crashes will change over time. Roadway curves are a common

[13] Single track vehicles such as motorcycles and bicycles require riders to initiate a turn toward a given direction by momentarily steering counter to the desired direction. Failure of motorcycles to counter steer when a crash is imminent has been shown to be a major factor in crash causality (Hurt et al., 1981).

[14] Single-vehicle crashes are quite common and accounted for nearly 50% of the total motorcycle fatalities in the U.S. from 2007 to 2016 (National Highway Traffic Safety Administration, 2018).

location for single-vehicle motorcycle crashes since riding on a curve involves steering inputs, friction assessments, and the stability of the motorcycle in a curve can easily be disrupted by improper front/rear brake applications and inappropriate throttle use.

The chapter begins with a review of relevant literature on motorcycle injury severities and the temporal instability of crash-injury severities. This is followed by a description of the methodological approach and the data. Finally, estimation results are presented and discussed, and a summary of findings and directions for future work are presented.

4.2. Review of Motorcycle Injury-Severity Modeling Methodologies

Police data of motorcycle crashes typically report rider injury severities as no injury, possible injury, evident injury, disabling injury, and fatality. These injury-levels are discrete, necessitating the application of discrete-outcome modeling methods when developing statistical models of the probabilities of the various injury outcomes. Over the years, a wide variety of discrete-modeling approaches have been applied to model injury-outcome probabilities. For example, a traditional multinomial logit approach was used by Shankar and Mannering (1996) to investigate injury severities resulting from single motorcycle crashes in the State of Washington from 1989 to 1994. Accounting for the ordered nature of injury severities (ranging from no injury to fatality), Quddus et al. (2002) used ordered probit model to study motorcycle damage severity and injury severity resulting from motorcycle crashes in Singapore from 1992 to 2000. Savolainen and Mannering (2007b) considered a nested logit approach to study motorcyclists' injury severities resulting from single and multi-vehicle crashes in the state of Indiana from 2003 to 2004. The nested logit approach they considered addressed potential limitations of traditional multinomial logit approaches, and they found that different statistical forms of the model were valid depending on the crash type (the nested logit model was valid for single vehicle crashes whereas the traditional multinomial logit form was valid for multivehicle crashes). Regarding the choice of methodological approach, Savolainen et al. (2011) provide an extensive discussion of the potential limitations of using models that do not account for the ordered nature of injury-severity data (multinomial logit, nested logit) and those that do (ordered logit/probit). Models that do not account for the ordering of injury outcomes are not considering for information (that the severity outcomes are ordered) while those that do account for the ordering typically impose restrictions on how explanatory variables influence outcome probabilities.[15] The choice of a specific methodological approach is often data dependent, and there have been some studies that have explored empirical differences in the approaches (Rifaat et al., 2012).

Many of the previous models that have been used to study motorcycle injury severity have restricted the estimated model parameters to be the same across crash observations. However, the effects of explanatory variables could vary across the individual crash-injury observations due to factors that are not observed by the analyst. This is referred to as unobserved heterogeneity and has led to development of a variety of models that allow for the potential of some or all of the models' explanatory variables to vary across individual crash observations or groups of observations. These heterogeneity modeling approaches include the mixed logit model, random parameters ordered probit, mixed generalized ordered models, latent class models (also referred to as finite mixture models), latent class models with random parameters, Markov switching models, and bivariate/multivariate models with random parameters. In the context of vehicle injury

[15] Mannering and Bhat (2014) provide an extensive discussion of alternate methodological approaches and Balusu et al. (2018) provide numerical assessments of extensions of the ordered modeling approach.

severity, these heterogeneity models have been extensively applied in recent years. For example, Milton et al. (2008), Anastasopoulos and Mannering (2011), Morgan and Mannering (2011), Kim et al. (2013), Shaheed et al. (2013), Cerwick et al. (2014), Behnood et al. (2014), Behnood and Mannering (2016) and Xin et al. (2017) have all estimated random parameter logit models (also called mixed logit models) of crash-injury severities. In other studies, Eluru et al. (2008) and Balusu et al. (2018) estimated mixed generalized ordered response models; Shaheed and Gkritza (2014), Behnood et al. (2014), Cerwick et al. (2014), Yasmin et al. (2014), and Behnood and Mannering (2016) have estimated latent class models; and Abay et al. (2013) and Russo et al. (2014) estimated bivariate/multivariate models with random parameters. Recently, several studies developed and applied methodological approaches that can potentially capture complex layers of unobserved heterogeneity. These include Bayesian random parameters models, random thresholds random parameters ordered probability models, correlated random parameters models, grouped random parameters models, grouped latent class models with class probability functions and others (Alarifi et al., 2017; Sarwar et al., 2017; Fountas and Anastasopoulos, 2017; Fountas et al., 2018a; Marcoux et al., 2018; Fountas et al., 2018b; Wali et al., 2018).

The choice of one heterogeneity-modeling approach over another tends to be highly dependent on the data, and the structure of the unobserved heterogeneity within a specific dataset. For random parameters models, the analyst is typically required to assume a distribution of heterogeneity (normal, lognormal, logistic, etc.), and while a variety of distributional assumptions can be tested, the various parametric assumptions may limit how unobserved heterogeneity is captured. In contrast, latent class approaches do not require a distributional assumption of the heterogeneity, but estimation can be computationally cumbersome, and finding more than two or three latent classes is often difficult even though more latent classes may more accurately track the unobserved heterogeneity in the data. Approaches that combine both latent class and random parameters approaches (latent class models with random parameters within each class) have shown promise but have proven to be computationally cumbersome (Xiong and Mannering, 2013).

To provide more flexibility in capturing unobserved heterogeneity within the context of random parameters, recent research has estimated random parameters with heterogeneity in means (Behnood and Mannering, 2017), and with heterogeneity in means and variances (Seraneeprakarn et al., 2017, Behnood and Mannering, 2017, Waseem et al., 2019). By allowing heterogeneity in the means and variances, the required distributional assumption for the random parameters approach becomes less of an issue since the parameters can now vary across observations in more complex ways. While most applications of this approach have been across traditional motorized vehicle types, Waseem et al. (2019) have successfully applied it in the context of motorcycle injury severities.

For reference, Table 4.1 provides a summary of methodological approaches that have been previously used in motorcycle injury-severity research.

4.3. General Findings of Previous Motorcycle Injury-Severity Studies

Table 4.2 provides a summary of variables found to significantly influence motorcycle rider-injury severities in previous studies. The table groups variables into the following broad categories; motorcyclist characteristics, motorcycle characteristics, roadway characteristics, roadway and environmental conditions, and other variables. Motorcyclist characteristics seek to capture the effects that risk-taking tendencies and physiological characteristics of the rider may have on resulting injury severity. Examples of variables found to significantly influence injury severities

in past studies include rider age, gender, and alcohol consumption. Motorcycle

Table 1. Summary of previous methodological approaches used in the study of motorcyclist injury severities.

Methodological Approach	**Previous Research**
Binary logit model	Pai (2009)
Ordered logit/probit model	Quddus et al. (2002); Pai and Saleh (2007); Pai and Saleh (2008); Rifaat et al. (2012); Chung et al. (2014); Wang et al. (2014)
Mixed ordered logit model	Cunto and Ferreira (2017); Chang et al. (2016)
Generalized ordered logit/outcome model	Rifaat et al. (2012); Wang et al. (2014)
Heterogeneous outcome model	Rifaat et al. (2012), Wang et al. (2014)
Partially constrained generalized logit model	Rifaat et al. (2012)
Empirical Bayesian method	De Lapparent (2006)
Multinomial logit model	Shankar and Mannering (1996); Savolainen and Mannering (2007); Geedipally et al. (2011); Schneider and Savolainen (2011); Jung et al. (2013)
Nested logit model	Savolainen and Mannering (2007)
Latent class multinomial logit model	Shaheed and Gkritza (2014)
Mixed (random parameters) logit model	Shaheed et al. (2013); Xin et al. (2017)
Mixed (random parameters) logit model with heterogeneity in means and variances	Waseem et al. (2019)

Table 4.2. Summary of variables found to be statistically significant in past motorcycle injury-severity studies.

Variables	**Previous Research**
Motorcyclist characteristics	
Age	Likelihood of fatality and incapacitating injury in motorcycle crashes increases with increasing in age (Shankar and Mannering, 1996; De Lapparent, 2006; Pai and Saleh, 2007; Pai and Saleh, 2008; Pai, 2009; Savolainen and Mannering, 2007b; Schneider and Savolainen, 2011; Cunto and Ferreira, 2016) Older riders (generally more than 50 years old) have a higher likelihood of fatal and incapacitating injury in motorcycle crashes (Quddus et al., 2002; Geedipally et al., 2011; Wang et al. 2014; Xin et al., 2017) Younger riders (generally less than 25 years old have a higher likelihood of slight injury or no injury in motorcycle crashes (Geedipally et al., 2011, Shaheed and Gkritza, 2014; Wang et al. 2014; Xin et al., 2017).
Gender	Male riders have a higher likelihood of fatal and incapacitating injury in motorcycle crashes (Pai and Saleh, 2008; Wang et al. 2014; Shaheed and Gkritza, 2014). Male riders decrease the probability of severe injury in motorcycle crashes (Xin et al., 2017). Female riders have a higher likelihood of fatal injury and have a higher likelihood of incapacitating injury in motorcycle crashes (Geedipally et al., 2011; Jung et al., 2013; Shaheed et al., 2013). Female riders have a lower likelihood of non-incapacitating injury and possible injury in motorcycle crashes (De Lapparent, 2006; Savolainen and Mannering, 2007b; Schneider and Savolainen, 2011; Rifaat et al., 2012).
Alcohol	Alcohol-impaired riding increases the probability of severe and minor injury in motorcycle crashes (Shankar and Mannering, 1996; Savolainen and Mannering, 2007b; Geedipally et al., 2011; Rifaat et al., 2012; Schneider and Savolainen, 2011; Shaheed and Gkritza, 2014; Jung et al., 2013; Chung et al., 2014; Xin et al., 2017).
Motorcycle characteristics	
Engine size	Motorcycles with a larger engine sizes are associated with a higher likelihood of injury severity in motorcycle crashes (Quddus et al., 2002; De Lapparent, 2006; Pai and Saleh, 2007; Pai and Saleh, 2008; Pai, 2009; Waseem et al., 2019).
Motorcycle type	Riders on sport bikes are more likely to have non-incapacitating injuries in motorcycle crashes (Savolainen and Mannering, 2007b).

Rider actions	
Speeding	Speeding increases the injury severity in motorcycle crashes (Shankar and Mannering, 1996; Savolainen and Mannering, 2007b; Pai and Saleh, 2008; Rifaat et al., 2012; Jung et al., 2013; Shaheed and Gkritza, 2014; Wang et al., 2014; Xin et al., 2017).
Improper driving or action	Improper driving or action decrease the likelihood of severe injury in motorcycle crashes (Xin et al., 2017) Improper weaving through traffic increases the likelihood of severe injury in motorcycle crashes (Chung et al., 2014).
Roadway characteristics	
Horizontal curve	Presence of horizontal curves tends to increase injury severity in motorcycle crashes (Savolainen and Mannering, 2007b; Geedipally et al., 2011; Schneider and Savolainen, 2011). Increasing the curve radius is more likely to decrease injury severity in motorcycle crashes (Wang et al., 2014).
Rural road	Rural roads tend to increase the probability of fatal and incapacitating injury in motorcycle crashes (Shaheed and Gkritza, 2014).
Intersection	Motorcycle crashes influenced by intersections experience a lower probability of fatal, incapacitating, and non-incapacitating injury (Savolainen and Mannering, 2007b; Geedipally et al., 2011; Schneider and Savolainen, 2011).
Pavement surface condition	Good pavement-surface conditions increase the probability of fatal, incapacitating, and non-incapacitating injury in motorcycle crashes (Geedipally et al., 2011). Poor Pavement condition decreases the likelihood of severe injury in motorcycle crashes (Xin et al., 2017).
Pavement roughness	The likelihood of severe injuries in motorcycle crashes decreases as pavement roughness index increases (Xin et al., 2017).
Pavement friction	Roads with larger friction skid test numbers are associated with a higher probability of having a severe injury in motorcycle crashes (Xin et al., 2017).
Posted speed limit	Higher speed limits increase injury severity in motorcycle crashes (Shankar and Mannering, 1996; Pai and Saleh, 2007; Savolainen and Mannering, 2007b; Schneider and Savolainen, 2011; Shaheed et al., 2013; Shaheed and Gkritza, 2014; Waseem et al., 2019).
Vegetation in median	Roads with vegetation in median tend to increase the likelihood of injury severity in motorcycle crashes (Xin et al., 2017).

Roadway access control	When roads have full or partial access control, the likelihood of severe injuries in motorcycle crashes decreases (Xin et al., 2017).
Paved shoulder	Roads with paved shoulders tend to increase the probability of having severe injuries in motorcycle crashes (Xin et al., 2017).
Roadway and environmental conditions	
Road surface condition	Wet roadway surfaces tend to increase the likelihood of no injury in motorcycle crashes (Shankar and Mannering, 1996; Quddus et al., 2002; Savolainen and Mannering, 2007b; Jung et al., 2013). Dry pavement has been associated with a higher likelihood of fatality in motorcycle crashes (Shaheed et al., 2013; Shaheed and Gkritza, 2014; Xin et al., 2017).
Weather	Adverse weather (rain, fog, snow, etc.) tends to increase the likelihood of minor injury and no injury in motorcycle crashes (Schneider and Savolainen, 2011). Dry weather tends to increase the likelihood of severe injury and fatal injury in motorcycle crashes (De Lapparent, 2006; Waseem et al., 2019).
Lighting	Daylight tends to increase injury severity in motorcycle crashes (Schneider and Savolainen, 2011). Daylight tends to decrease the likelihood of fatality in motorcycle crashes (Shaheed et al., 2013; Wang et al., 2014; Cunto and Ferreira, 2016; Chang et al., 2016). Darkness tends to increase the probability of no injury in motorcycle crashes (Shaheed and Gkritza, 2014). Darkness tends to increase likelihood of fatality and incapacitating injury in motorcycle crashes (De Lapparent, 2006; Savolainen and Mannering, 2007b; Pai and Saleh, 2007; Geedipally et al., 2011; Rifaat et al., 2012; Jung et al., 2013; Shaheed et al., 2013; Chung et al.,2014; Xin et al., 2017). Darkness with streetlights increases the likelihood of severe injury in motorcycle crashes (Xin et al., 2017).

Other variables	
Hit fixed object	Fixed-object collisions increase the likelihood of fatality and incapacitating injury in motorcycle crashes (Shankar and Mannering, 1996; Quddus et al., 2002; Savolainen and Mannering, 2007b; Schneider and Savolainen, 2011; Jung et al., 2013; Shaheed and Gkritza, 2014; Xin et al., 2017).
Ejection	Rider ejection during a motorcycle crash increases the likelihood of severe injury in motorcycle crashes (Shankar and Mannering, 1996; Jung et al., 2013).
Helmet use	Wearing a safety helmet tends to decrease likelihood of fatal injury and incapacitating injury in motorcycle crashes (De Lapparent, 2006; Savolainen and Mannering, 2007b; Geedipally et al., 2011; Schneider and Savolainen, 2011; Jung et al., 2013; Shaheed et al., 2013; Shaheed and Gkritza, 2014; Wang et al., 2014; Cunto and Ferreira, 2016; Chang et al., 2016; Xin et al., 2017).
Day of week	Motorcycle crashes on weekends tend to cause more severe injuries (Pai and Saleh, 2007; Jung et al., 2013; Shaheed and Gkritza, 2014; Cunto and Ferreira, 2016; Xin et al., 2017).
Time of day	Riding in early morning hours increases the probability of fatality and incapacitating injury in motorcycle crashes (Quddus et al., 2002; Pai and Saleh, 2007; Pai and Saleh, 2008; Pai, 2009).
Passenger Presence	Passenger presence increases the likelihood of fatal and incapacitating injury in motorcycle crashes (Quddus et al., 2002). Passenger presence increases the likelihood of non-incapacitating injury in motorcycle crashes (Savolainen and Mannering, 2007b). Passenger presence increases the likelihood of property damage only in motorcycle crashes (Schneider and Savolainen, 2011).

characteristics seek to capture riders' risk-taking tendencies (with riskier riders being attracted to larger displacement engines and performance-oriented sport bike models) as well as the braking/crash avoidance capability of the motorcycle (with weight and braking performance being correlated with engine displacement). Rider actions such as speeding and improper driving act as proxies for the amount of energy that must be absorbed by the body during a crash. Roadway characteristics seek to identify areas where required rider inputs for roadway navigation could affect resulting injury severities, or riders may be altering their behavior to compensate for potentially dangerous conditions. These characteristics include the presence of a horizontal curve, riding on a rural road or intersection, pavement surface condition and roughness, pavement friction, posted speed limit, vegetation in the median, roadway access control, and the presence of paved shoulders. Roadway and environmental conditions attempt to capture the effects of road surface condition (dry or wet), environmental conditions (rain, fog, snow, etc.), and lighting on rider behavior before and during the crash. In adverse road and weather conditions, and in darkness, riders may tend to compensate by riding more cautiously. Thus, in the event of a crash, the likelihood of severe injury may be reduced if they overcompensate for these conditions.

Finally, other variables (see Table 4.2), seek to capture a wide variety of effects on motorcycle-injury severity. In this category, variables such as hitting a fixed object and being ejected from the motorcycle act as proxies for the amount of energy that will be transmitted to the body during the crash. Helmet use captures the protection afforded to the head during the crash but may also be capturing the risk tendencies of the riders in states where helmet use is not mandatory. The day of the week and time of the day capture ambient behaviors and traffic conditions that may be encountered during riding, which would affect speed selection and other factors that may influence injury severities. Passenger presence can affect injury severities by influencing rider behavior and risk taking and can alter braking distances because the weight distribution of the motorcycle is significantly altered when a passenger is present.

As shown in Table 4.2, while there is broad agreement among the findings of previous motorcycle injury severity studies in terms of the direction of the effect of explanatory variables, there are important exceptions. For example, regarding gender, some studies have found male riders to have a higher likelihood of severe injuries and other studies have found female riders to have a higher likelihood of severe injuries. And, a more detailed look at the findings of studies show that the magnitude of variables, in terms of their influence on injury severity, does vary even though the general direction of the influence may not.

There are several explanations for the observed disparity of findings across past studies. First, as shown in Table 4.1, past studies have used a wide variety of methodological approaches. These approaches can give at least slightly different results because of the various distributional assumptions that are made, and some of the approaches capture the effects of unobserved heterogeneity and others do not. Second, the various studies have had access to varying amount of data, with some studies having more explanatory variables than others. Studies that have had access to fewer explanatory variables could suffer from an omitted variables bias that could affect the magnitude of explanatory variable effects as well as the direction of their influence. While addressing the omitted variable-bias issue as unobserved heterogeneity can provide some relief from this, it is not a substitute for having more complete data (Mannering et al., 2016). Third, these studies were conducted at various locations and it is not clear that the effects of explanatory variables on motorcyclist injury severities will be the same from one study are to the next. The fourth and final point is that these studies have been conducted at different points in time, which could affect the direction and magnitude of their findings. In fact, there is ample empirical evidence from research on car/truck injury severities to suggest that the effect of explanatory variables on injury severities may change even over relatively small periods of time (a year or less) at the same location. As previously mentioned in the introduction, this fourth point will be a primary emphasis in the forthcoming empirical analysis.

4.4. Methodological Approach

In the forthcoming empirical analysis, motorcyclist-injury severities, in single-vehicle motorcycle crashes, are studied by considering three discrete motorcyclist-injury severity outcomes; no visible injury (property damage only and possible injury), minor injury (non-incapacitating injury), and severe injury (incapacitating injury and fatal). As discussed above, a wide variety of methodological approaches have been used to study crash-injury severities. In this chapter, a random parameters multinomial logit approach, with heterogeneity in means and variances, is applied to study the temporal stability of factors affecting motorcyclist injury severities in single-vehicle motorcycle crashes. Recent empirical work has shown this methodological approach to be

among the most flexible in injury-severity modeling in terms of its ability to capture unobserved heterogeneity (Mannering et al., 2016).

To begin, a function that determines the probability of motorcyclist-injury outcomes (Washington et al, 2011) is defined as;

$$S_{kn} = \beta_k \mathbf{X}_{kn} + \varepsilon_{kn} \tag{4.1}$$

where S_{kn} is a function determining the probability of motorcyclist injury-severity category k in crash n, $\mathbf{X}_{kn}$ is a vector of explanatory variables that affect motorcyclist injury-severity level k, $\boldsymbol{\beta}_k$ is a vector of estimable parameters, and ε_{kn} is the error term which is assumed to be generalized extreme value distributed. With this, a random parameters multinomial logit model of injury severity probabilities can be derived as (McFadden and Train, 2000; Washington et al, 2011),

$$P_n(k) = \int \frac{EXP\left(\boldsymbol{\beta}_k \mathbf{X}_{kn}\right)}{\sum_{\forall K} EXP\left(\boldsymbol{\beta}_k \mathbf{X}_{kn}\right)} f\left(\boldsymbol{\beta} \mid \boldsymbol{\varphi}\right) d\boldsymbol{\beta}, \tag{4.2}$$

where $P_n(k)$ is the probability that crash n results in injury category k, $f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\varphi}$ referring to a vector of parameters of the density function (mean and variance), and all other terms are as previously defined. Unobserved heterogeneity in the means and variances of random parameters is accounted for by allowing $\boldsymbol{\beta}_{kn}$ to be a vector of estimable parameters that varies across crashes defined as (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017; Waseem et al., 2019)

$$\boldsymbol{\beta}_{kn} = \beta_k + \Theta_{kn}\mathbf{Z}_{kn} + \sigma_{kn} EXP\left(\boldsymbol{\omega}_{kn}\mathbf{W}_{kn}\right) \nu_{kn}, \tag{4.3}$$

where β_k is the mean parameter estimate across all crashes, $\mathbf{Z}_{kn}$ is a vector of explanatory variables that captures heterogeneity in the mean that affect motorcyclist injury-severity level k, $\boldsymbol{\Theta}_{kn}$ is a corresponding vector of estimable parameters, $\mathbf{W}_{kn}$ is a vector of explanatory variables that captures heterogeneity in the standard deviation σ_{kn} with corresponding parameter vector $\boldsymbol{\omega}_{kn}$, and ν_{kn} is a disturbance term.

With regard to $f(\boldsymbol{\beta} \mid \boldsymbol{\varphi})$ in equation 4.2, numerous density functions can be specified, but our forthcoming empirical analysis will show that none were found to be statistically superior to the normal distribution, so this will be used in all forthcoming empirical analyses (this finding is consistent with past work including Milton et al., 2008; Moore et al., 2011; Shaheed et al., 2013). The models were estimated by simulated maximum likelihood with 1,000 Halton draws (McFadden and Train, 2000; Washington et al., 2011). To assist in the interpretation of the findings, marginal effects were also computed to capture the effect that a one-unit change in any specific explanatory variable has on the probability of an injury-severity outcome. The values of the corresponding marginal effects were calculated for each observation and were averaged over the population of observations.

4.5. Empirical Setting

Data for this chapter were gathered from the state of Florida, which offers near ideal conditions for motorcycle riding year-round,[16] and has experienced strong growth in motorcycling, with the number of registered motorcycles in the state nearly doubling since 2005, reaching nearly 600,000 in 2017 (Insurance Institute for Highway Safety, 2017). As previously discussed, two different datasets for single-vehicle motorcycle crashes are used. The first source is based on a sample of

[16] Unlike many traditional transportation modes, motorcycling is highly sensitive to weather making riding in many of the northern U.S. states unlikely for several of the winter months.

motorcyclists that passed the Florida Rider Training Program in the 2012 calendar year. The Florida Rider Training Program that offers the Motorcycle Safety Foundation's Basic Rider Course which is required to complete in order to obtain a motorcycle-only license or motorcycle-also endorsement (Florida Highway Safety and Motor Vehicles, 2018). The course is designed for beginning riders of all ages and seeks to teach course participants the essential mental and physical skills needed for safe motorcycle operations. The course offers from 8 to 10 hours classroom-style instruction on the motorcycle safety fundamentals and 10 hours of motorcycle-riding training. More than 8 million motorcyclists have graduated from basic rider course since 1974 in the United States (Motorcycle Safety Foundation, 2016). Using 2012 motorcyclists who graduated from the basic rider course in the state of Florida in 2012, graduate's information was linked to Florida police crash database from 2012 to 2016 to determine the number of 2012 Basic Rider Course graduates who had single-vehicle motorcycle crashes during this time period. Detailed information on a total 1,058 single-vehicle motorcycle police-reported crashes were obtained. For these riders specifically, the available crash data provide comprehensive information on time and location, motorcycle characteristics (such as motorcycle make, model year of the motorcycle, and the type of the motorcycle), rider attributes (such as age, gender, ethnicity, and if under the influence alcohol or drug), roadway conditions (such as traffic controls, obstacles on the road, and speed limits), roadway and environmental conditions (such as light and road surface conditions), and crash attributes (such as manner of crash and events contributing to crash).

The second dataset focuses exclusively on single-vehicle motorcycle crashes that occur on roadway curves (horizontal curves). These data include all motorcyclists (not just those who passed the Basic Riding Course and obtained their license in 2012). A total of 8,579 horizontal curves (with a 300-ft buffer at each end were identified) were identified for observation on the basis there being detailed roadway information available (horizontal curves that were influenced by signalized intersections were excluded from the dataset). On these identified curves, a total of 2,430 single-vehicle motorcycle crashes were observed between 2005 and 2015. Roadway geometrics, traffic characteristics, and pavement information for each curve were compiled from the roadway characteristics inventory database. Individual crashes were then matched to the Florida police-reported accident data that includes characteristics of crash, rider, and motorcycle.

As mentioned in the introduction of this chapter, these two databases have the potential to provide interesting temporal perspective. The new-rider data has the potential to capture the change in accident risk over time as riders accumulate experience, as well as general changes in risk that may vary over time. The horizontal-curve data can capture general changes in risk over time; changes that will likely be most noticeable on horizontal curves which can present a challenge for motorcycles as previously discussed.

4.6. Temporal Stability Tests

Attention is directed first to the analysis of the Florida new-rider data. With crash data covering 2012 to 2016 for motorcyclists initially licensed in the 2012 calendar year, some initial observations of the 1,058 police-reported crashes that these motorcyclists incurred over this period suggested a general reduction in the number of crashes over time. For example, the number of crashes in 2014 was roughly 50% less than the number of crashes in 2013 (the first full year of licensure for everyone in the sample). It is speculated that this decrease may be largely due to the effect of experience reducing crash probabilities, and one would expect a similar effect on resulting

crash severities.[17] After extensive empirical testing for possible temporal instability over all time periods, it was found that splitting the data into a 2012-13 beginning or learning period, and a 2014-16 experienced period, provided the only statistically significant temporal separation.

To statistically show that motorcyclist-injury severity models are significantly different across these specified time periods, two likelihood tests were conducted to compare learning (2012-13) and experienced (2014-16) time periods. The test statistic is written as (see Washington et al., 2011),

$$X^2 = -2\left[LL\left(\boldsymbol{\beta}_{t_2 t_1}\right) - LL\left(\boldsymbol{\beta}_{t_1}\right)\right] \tag{4.5}$$

where subscripting t_1 refers to the learning time period (2012-13) and subscripting t_2 is the experienced time period (2014-16), $LL\left(\boldsymbol{\beta}_{t_2 t_1}\right)$ is the log-likelihood at convergence of a model containing converged parameters based on using time-period t_2's data, while using data from time-period t_1, and $LL\left(\boldsymbol{\beta}_{t_1}\right)$ is the log-likelihood at convergence of the model using time-period t_1's data (with parameters no longer restricted to being time-period t_2's converged parameters as is the case for $LL\left(\boldsymbol{\beta}_{t_2 t_1}\right)$). This test was also reversed such that time-period t_1 above becomes time period t_2 and time period t_2 above becomes subset t_1 (thus giving two test results for the time-period comparisons). The resulting value X^2 is χ^2 distribution (with degrees of freedom equal to the number of estimated parameters) and can be used to determine the confidence level at which the null hypothesis that the parameters are equal in the two periods can be rejected. The test results show that using time period 2's converged parameters with time period 1's data, and comparing this to a converged model from time period 1 using variables in time-period 2's model but no longer constraining the parameters to be restricted to time period 2's converged parameters gives a χ^2 statistic of 52.01 with 13 degrees of freedom. This suggests we are more than 99.99% confident that the hypothesis that learning and experienced tome periods are the same can be rejected. Reversing this (using time period 1's converged parameters with time period 2's data, and comparing this to a converged model from time period 2 using variables in time-period 1's model but no longer constraining the parameters to be restricted to time period 1's converged parameters), gives a χ^2 statistic of 41.61 with 14 degrees of freedom, meaning that the null hypothesis that the two time periods are the same can be rejected with more than 99.99% confidence.

This result provides substantial evidence that the motorcyclist-injury severity models developed using the new-rider crash data are not temporally stable over the time periods (a more detailed discussion of individual variable findings will be provided later). The significant difference between learning and experienced models suggest that the effect of explanatory variables on injury-severity outcomes have shifted over the time. This shift could be due to a combination of riders acquiring motorcycle skills over time as well as general temporal shift that may have occurred during this time period.

To get a sense of the general temporal shifts that might be occurring, the 2005 to 2015 Florida horizontal curves data can provide some insight. Interestingly, this 2005-15 data collection period includes the great recession period that has been shown previously to be temporally unstable with regard to pedestrian injury-severities resulting from motor-vehicle crashes (Behnood and Mannering, 2016). In their work, Behnood and Mannering (2016) found significant temporal

[17] In comparing the aggregate number of crashes of these data with the second horizontal curve dataset, it is noted that the number of observed crashes on horizontal curves actually declined by 15% from 2013 to 2014.

instability that they argue resulted from the influence of economic recession as well as a long-term evolution of the influence of factors affecting pedestrian-injury severities resulting from road crashes. Using crash data from 2005 to 2011, they found statistical differences in three time periods; pre-recession, recession, and post-recession. Their pre-recession-period model was developed by using the collected data from 2005 and 2006. The year of 2007 was assumed to be the transition year between the pre-recession period and recession period and was excluded from the analysis. Their recession-period model was estimated with data from 2008 and 2009. The year 2010 was assumed to be a transition year between the recession period and post-recession period and was excluded from the analysis, and their post-recession-period model was developed by using the collected data in the year 2011.

Following these earlier findings, and after extensive statistical testing of other time periods, the random parameters approach with heterogeneity in means and variances was applied using data from 2005 and 2006, 2008 and 2009, and 2011 (consistent with Behnood and Mannering's findings). Because the data available in the current chapter goes beyond the time periods of data available to Behnood and Mannering (2016), the empirical analysis found further statistically significant differences between the years 2012 and 2013 and the years 2014 and 2015.

To statistically show that motorcyclist-injury severity models are significantly different across these specified time periods, a series of likelihood tests were conducted. As before with the new-rider data, likelihood ratio tests were applied to compare time-period models to determine if parameter estimates were stable between these periods. Equation 4.5 is applied more generally in comparing all time periods with, $LL\left(\boldsymbol{\beta}_{t_2 t_1}\right)$ is the log-likelihood at convergence of a model containing converged parameters based on using time-period t_2's data, while using data from time-period t_1, and $LL\left(\boldsymbol{\beta}_{t_1}\right)$ is the log-likelihood at convergence of the model using time-period t_1's data (with parameters no longer restricted to being time-period t_2's converged parameters as is the case for $LL\left(\boldsymbol{\beta}_{t_2 t_1}\right)$). This test was also reversed such that time-period t_1 above becomes time period t_2 and time period t_2 above becomes subset t_1 (thus giving two test results for each pair of time-period comparisons). Again, the resulting value X^2 in Equation 4.5 is χ^2 distributed and can be used to determine the confidence level at which the null hypothesis that the parameters are equal in the two periods can be rejected.

Table 4.3 presents the results of likelihood ratio tests conducted based on Equation 4.5. This table shows that the null hypotheses that time periods are the same can be rejected with very high confidence, suggesting statistically significant temporal instability. The significant difference between the 2012-13 and the 2014-15 models is consistent with the previous finding of the new-rider data, suggesting that temporal instability resulting from improvement in rider skills may be confounded by general changes in the effect that explanatory variables have on resulting injury severities.[18]

[18] Although the new-rider data ends in 2016 and the horizontal curve data ends in 2015, the new-rider data did not find temporal instability over the 2014-16 time period, so we choose to include the 2016 new-rider to improve model estimates (since the estimator is consistent, more observations will reduce the standard errors of parameter estimates).

Table 4.3. Likelihood ratio test results between different time periods based on random parameters approaches with heterogeneity in means and variances of Florida horizontal curves crash data (χ^2 values with degrees of freedom in parenthesis and confidence level in brackets).

	***t*₂** (Equation 5)				
***t*₁** (Equation 5)	**2005-2006**	**2008-2009**	**2011**	**2012-2013**	**2014-2015**
2005-2006	-	35.78 (13) [> 99.94%]	111.74 (12) [> 99.99%]	34.61 (14) [> 99.83%]	39.49 (13) [> 99.98%]
2008-2009	18.65 (10) [> 95.51%]	-	128.52 (12) [> 99.99%]	74.23 (14) [> 99.99%]	44.52 (13) [> 99.99%]
2011	16.59 (10) [> 91.61%]	26.42 (13) [> 98.51%]	-	16.53 (14) [> 71.79%]	32.24 (13) [> 99.78%]
2012-2013	43.89 (10) [> 99.99%]	33.22 (13) [> 99.85%]	117.15 (12) [> 99.99%]	-	58.12 (13) [> 99.99%]
2014-2015	20.77 (10) [> 97.73%]	39.29 (13) [> 99.99%]	107.08 (12) [> 99.99%]	32.92 (14) [> 99.71%]	-

4.7. Model Estimation Results: New-Rider Data

Turning to specific new-rider model estimates, Table 4.4 provides overall summary statistics, and Table 4.5 gives the estimation results for the model estimated using 2012-13 (learning period). Estimates shown in Table 4.5 indicate that there was one statistically significant random parameter for the variable indicating that anti-lock brakes were not present.[19] Marginal

[19] The correct test for the statistical significance of random parameters is the likelihood ratio test comparing model estimations with and without random parameters, all estimations in this paper passed this test with at least 90% confidence (at least 90% confident that the fixed parameters, random parameters, and random parameters with heterogeneity in the mean were not the same). Also note that if the standard deviation of the random parameter is significantly different from zero, the statistical significance of the mean of the random parameter is generally not important in justifying the inclusion of a random parameter. If the mean is not significantly different from zero it simply suggests that the distribution of parameters across observations are likely to have close to an equal number of positive and negative parameter values. For heterogeneity in a statistically insignificant mean, β_k in equation 3 would become zero, but $\boldsymbol{\Theta}_{kn}$ and $\boldsymbol{\omega}_{kn}$ could still have statistically significant values.

Table 4.4. Summary statistics of variables included in the models of Florida new riders' crash data.

Variable Description	All years Mean (Std. Dev.)	2012-2013 Mean (Std. Dev.)	2014-2016 Mean (Std. Dev.)
No visible/minor/severe injury	0.32/0.45/0.23	0.33/0.47/0.20	0.34/0.41/0.25
Motorcyclist characteristics			
Ethnicity of rider indicator (1 if white, 0 otherwise)	0.720 (0.448)	0.712 (0.452)	0.733 (0.442)
Condition of rider indicator (1 if rider is in normal condition and not under drug nor alcohol influence, 0 otherwise)	0.847 (0.359)	0.863 (0.343)	0.820 (0.383)
Young motorcyclist indicator (1 if motorcyclist is younger than 30 years old, 0 otherwise)	0.486 (0.499)	0.555 (0.497)	0.364 (0.481)
Older motorcyclist (1 if motorcyclist is older than 60 years old, 0 otherwise)	0.063 (0.243)	0.044 (0.205)	0.097 (0.296)
Motorcycle characteristics			
Motorcycle equipped with antilock brakes indicator (1 if no, 0 otherwise)	0.761 (0.426)	0.770 (0.420)	0.746 (0.435)
Motorcycle make indicator (1 if Harley Davidson, 0 otherwise)	0.190 (0.393)	0.163 (0.369)	0.240 (0.427)
Type of motorcycle indicator (1 if motorcycle is cruiser or chopper, 0 otherwise)	0.364 (0.481)	0.340 (0.473)	0.408 (0.491)
Roadway and environmental conditions			
Road surface condition indicator (1 if dry, 0 otherwise)	0.848 (0.358)	0.846 (0.360)	0.852 (0.355)
Weather condition indicator (1 if cloudy, 0 otherwise)	0.139 (0.346)	0.148 (0.355)	0.124 (0.329)
Other variables			
Speed limit indicator (1 if road speed limit is 50 mi/h or higher, 0 otherwise)	0.241 (0.427)	0.234 (0.423)	0.253 (0.435)
Ejection of rider indicator (1 if rider is totally or partially ejected, 0 otherwise)	0.298 (0.457)	0.300 (0.458)	0.295 (0.456)
Riding direction indicator (1 if south, 0 otherwise)	0.232 (0.422)	0.235 (0.424)	0.226 (0.419)
Driver vision obstruction indicator (1 if vision not obstructed, 0 otherwise)	0.958 (0.199)	0.964 (0.184)	0.947 (0.223)
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise)	0.628 (0.483)	0.653 (0.475)	0.583 (0.493)

Table 4.5. Random parameters approach with heterogeneity in means and variances results for single-vehicle motorcycle crash-injury severity for learning period (from 2012 to 2013) of Florida new riders' crash data (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [MI]	-1.8984	-2.46			
Constant [SI]	-1.3305	-1.99			
Random parameters (*normally distributed*)					
Motorcycle equipped with antilock brakes indicator (1 if no, 0 otherwise) [MI]	-0.2739	-0.65	-0.0144	0.0221	-0.0077
Standard deviation of motorcycle equipped with antilock brakes indicator	*2.7279*	*1.88*			
Heterogeneity in the mean of the random parameters					
Motorcycle equipped with antilock brakes indicator; older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise) [MI]	-1.7058	-1.43			
Motorcycle equipped with antilock brakes indicator; ethnicity of rider indicator (1 if white, 0 otherwise) [MI]	0.6812	1.45			
Motorcyclist characteristics					
Condition of rider indicator (1 if rider is in normal condition and not under drug nor alcohol influence, 0 otherwise) [NVI]	0.8596	2.88	0.1284	-0.0687	-0.0597
Condition of rider indicator (1 if rider is in normal condition and not under drug nor alcohol influence, 0 otherwise) [MI]	1.3446	3.21	-0.1074	0.1694	-0.0620
Young motorcyclist indicator (1 if motorcyclist is younger than 30 years old, 0 otherwise) [NVI]	0.3607	1.80	0.0351	-0.0184	-0.0167
Roadway and environmental conditions					
Road surface condition indicator (1 if dry, 0 otherwise) [NVI]	-0.6954	-2.57	-0.1007	0.0505	0.0502
Other variables					
Driver vision obstruction indicator (1 if vision not obstructed, 0 otherwise) [NVI]	-0.9990	-1.69	-0.1676	0.0848	0.0828
Ejection of rider indicator (1 if rider is totally or partially ejected, 0 otherwise) [MI]	1.1639	3.51	-0.0271	0.0498	-0.0226
Ejection of rider indicator (1 if rider is totally or partially ejected, 0 otherwise)) [SI]	0.4881	1.86	-0.0099	-0.0095	0.0194
Speed limit indicator (1 if road speed limit is 50 mi/h or higher, 0 otherwise) [SI]	0.4144	1.68	-0.0092	-0.0061	0.0153
Model statistics					
Number of observations			679		
Log-likelihood at zero			-745.957		
Log-likelihood at convergence			-684.023		

effects in Table 4.5 show that the average effect of this variable was to increase the likelihood of minor injury. However, this variable also had statistically significant heterogeneity in the mean, with the effect of not having antilock brakes varying by motorcyclists age (riders older than 60) and ethnicity (white riders). This finding shows that there is great variability in the braking skills of entry-level riders on motorcycles without antilock brakes. This is to be expected since the allocation of braking forces between front and rear brakes is among the most difficult motorcycling skills to master (Mannering and Grodsky, 1995). Antilock brakes help considerably by providing more efficient braking, and this is reflected in this finding. This random parameter did not have statistically significant heterogeneity in variance.

Variables that produced statistically significant parameters that were fixed across crash observations include an indicator variable of riding unimpaired by alcohol or drugs. This variable had a complex effect as suggested by the marginal effects in Table 4.5, but there was generally a lower probability of severe injury if the rider is riding sober.

Estimation findings show that young motorcyclists (less than 30 years old) had a higher probability of being in crashes with no visible injury relative to their older counterparts. Table 4.5 also shows that crashes occurring on dry road surfaces tended to be more severe (as indicated by marginal effects) with a 0.0502 higher probability of severe injury relative to other roadway conditions. This is quite a large increase given that severe injury crashes comprise roughly a 0.20 proportion of all crashes (see Table 4.4). The higher likelihood of severe injury on dry road surfaces may be related to over-confidence and changes in risk-taking behavior relative to other surface conditions.[20]

Other variables include an indicator for driver vision obstruction, that marginal effects in Table 4.5 show increase the probability of minor and sever injury. Having the rider being ejected from the motorcycle decreased the probability of no visible injury and riding on a roadway with a speed limit of 50 mi/h or greater increased the probability of severe injury relative to lower speed limit roads, reflecting the impact of higher speeds on injury potential.

For the experienced time period (2014-16), the estimation results shown in Table 4.6 indicate that many different explanatory variables were found to influence injury severities relative to the beginning rider period (2012-13). Table 4.6 now shows that the type of motorcycle (individuals riding cruisers and choppers) was a statistically significant determinant of injury severity, and that this varies across the crash observations (statistically significant random parameter). Also, there was significant heterogeneity in the mean with the use of a helmet reducing the mean and making severe injuries less likely (heterogeneity in the variance was not statistically significant).

In addition to the type of motorcycle, several other explanatory variables were found to be statistically significant in the experienced time period (2014-16) but not in the learning time period (2012-13). These include: a young motorcyclist indicator (1 if motorcyclist is younger than 30 years old, 0 otherwise); an older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise), although this variable also influenced the mean of the antilock-brakes indicator in the learning period; the ethnicity of rider indicator (1 if white, 0 otherwise), although this variable also did influence the mean of the antilock brakes indicator in the learning period; a

[20] For there is also the possibility of self-selectivity here, with more risky riders being more likely to ride during dry roadway-surface conditions. This self-selectivity and resulting identification issue could potentially afflict other variables as well, for example riskier riders may ride at night, etc. Please see Mannering (2018) for a detailed discussion of this possibility.

Table 4.6. Random parameters approach with heterogeneity in means and variances results for single-vehicle motorcycle crash-injury severity for experienced period (from 2014 to 2016) of Florida new riders' crash data (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [MI]	-0.4821	-1.43			
Random parameters (*normally distributed*)					
Type of motorcycle indicator (1 if motorcycle is cruiser or chopper, 0 otherwise) [SI]	-0.3331	-0.51	-0.0035	-0.0058	0.0093
Standard deviation of type of motorcycle indicator'	*1.9589*	*1.47*			
Heterogeneity in the mean of the random parameters					
Type of motorcycle indicator; Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [SI]	-1.7058	-1.29			
Motorcyclist characteristics					
Condition of rider indicator (1 if rider is in normal condition and not under drug nor alcohol influence, 0 otherwise) [NVI]	1.4050	4.41	0.2512	-0.1865	-0.0647
Condition of rider indicator (1 if rider is in normal condition and not under drug nor alcohol influence, 0 otherwise) [MI]	1.8296	4.49	-0.2428	0.3514	-0.1085
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise) [NVI]	0.4283	1.52	0.0178	-0.0118	-0.0060
Ethnicity of rider indicator (1 if white, 0 otherwise) [NVI]	-0.4282	-1.89	-0.0641	0.0446	0.0194
Motorcycle characteristics					
Motorcycle make indicator (1 if Harley Davidson, 0 otherwise) [SI]	0.7525	2.13	-0.0124	-0.0149	0.0274
Roadway and environmental conditions					
Weather condition indicator (1 if cloudy, 0 otherwise) [MI]	0.5976	1.79	-0.0112	0.0169	-0.0057
Other variables					
Riding direction indicator (1 if south, 0 otherwise). [SI]	-0.5604	-1.50	0.0075	0.0082	-0.0157
Ejection of rider indicator (1 if rider is totally or partially ejected, 0 otherwise)) [SI]	0.7055	2.10	-0.0163	-0.0181	0.0345
Speed limit indicator (1 if road speed limit is 50 mi/h or higher, 0 otherwise) [SI]	1.0615	3.16	-0.0202	-0.0244	0.0447
Model statistics					
Number of observations			379		
Log-likelihood at zero			-416.374		
Log-likelihood at convergence			-381.786		

weather condition indicator (1 if cloudy, 0 otherwise); and a riding direction indicator (1 if riding south, 0 otherwise), which is likely capturing visibility issues relating to sun angles and other unobserved factors.

To more directly compare learning and experienced model estimation findings, Table 4.7 provides a side-by-side comparison of the marginal effects by each injury-severity level. The dash values in this table indicate that the explanatory variable was not statistically significant for the time period in question (learning or experienced). Table 4.7 shows that the variables found to be significant in both time periods include the condition of the rider indicator (1 if rider is in normal condition and not under drug nor alcohol influence, 0 otherwise), the ejection of rider indicator (1 if rider is totally or partially ejected, 0 otherwise), and the speed limit indicator (1 if road speed limit is 50 mi/h or higher, 0 otherwise). However, even the marginal effects of these common variables (shown side-by side in Table 4.7) show considerable temporal instability between learning and experienced time periods.

The considerable disparity between learning and experienced periods is perhaps to be expected since motorcyclist skills rapidly evolve in the early years of riding as previously discussed. However, the role of general trends in temporal instability could also be a factor as will be explored with the Florida horizontal curves data.

4.8. Model Estimation Results: Florida Horizontal Curves Data

Table 4.8 presents the summary statistics for the variables found to be statistically significant in the Florida horizontal curves data model estimations. Tables 4.9, 4.10, 4.11, 4.12 and 4.13 provide estimation results for models using 2005-06, 2008-09, 2011, 2012-13 and 2014-15 data, respectively.

Table 4.8. Summary statistics of variables included in the models of Florida horizontal curves crash data.

Variable Description	All Years Mean (Std. Dev.)	2005-2006 Mean (Std. Dev.)	2008-2009 Mean (Std. Dev.)	2011 Mean (Std. Dev.)	2012-2013 Mean (Std. Dev.)	2014-2015 Mean (Std. Dev.)
No visible/minor/severe injury	0.19/0.41/0.40	0.17/0.42/0.41	0.15/0.41/0.44	0.18/0.44/0.38	0.21/0.43/0.36	0.24/0.40/0.36
Motorcyclist characteristics						
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise)	0.093 (0.291)	0.059 (0.236)	0.098 (0.298)	0.070 (0.256)	0.116 (0.321)	0.110 (0.314)
Middle-age motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise)	0.543 (0.498)	0.564 (0.496)	0.543 (0.498)	0.530 (0.499)	0.538 (0.498)	0.533 (0.499)
Alcohol or drugs indicator (1 if motorcycle crash is under the influence of alcohol or drugs, 0 otherwise)	0.090 (0.287)	0.145 (0.352)	0.145 (0.352)	0.039 (0.195)	0.039 (0.195)	0.049 (0.217)
Roadway and environmental conditions						
Weather condition indicator (1 if clear, 0 otherwise)	0.756 (0.429)	0.761 (0.426)	0.749 (0.433)	0.783 (0.412)	0.749 (0.433)	0.752 (0.431)
Weather condition indicator (1 if rain, 0 otherwise)	0.056 (0.230)	0.047 (0.213)	0.050 (0.219)	0.057 (0.233)	0.064 (0.246)	0.064 (0.245)
Daylight indicator (1 if light condition is daylight, dawn, or dusk, 0 others)	0.597 (0.490)	0.588 (0.492)	0.591 (0.491)	0.615 (0.486)	0.580 (0.493)	0.626 (0.483)
Road surface condition indicator (1 if dry, 0 otherwise)	0.879 (0.325)	0.907 (0.290)	0.890 (0.311)	0.831 (0.374)	0.866 (0.340)	0.880 (0.324)
Darkness indicator (1 if light condition is darkness, 0 otherwise)	0.140 (0.347)	0.130 (0.337)	0.159 (0.366)	0.141 (0.348)	0.144 (0.351)	0.119 (0.324)
Darkness with streetlight indicator (1 if light condition is darkness with streetlight, 0 otherwise)	0.257 (0.437)	0.273 (0.446)	0.242 (0.428)	0.243 (0.429)	0.269 (0.443)	0.250 (0.433)
Rider actions						
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise)	0.060 (0.237)	0.071 (0.257)	0.056 (0.231)	0.066 (0.249)	0.054 (0.226)	0.055 (0.228)

Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise)	0.224 (0.417)	0.188 (0.390)	0.181 (0.385)	0.238 (0.426)	0.240 (0.427)	0.297 (0.457)
Roadway Characteristics						
Friction indicator (1 if skid test number is larger than 45, 0 otherwise)	0.295 (0.456)	0.319 (0.466)	0.337 (0.472)	0.300 (0.458)	0.308 (0.462)	0.183 (0.387)
Flat curve indicator (1 if curve radius is greater than 4,000 ft., 0 otherwise)	0.414 (0.492)	0.383 (0.486)	0.418 (0.493)	0.371 (0.483)	0.467 (0.499)	0.399 (0.490)
Vegetation in median indicator (1 if median type is vegetation, 0 otherwise)	0.359 (0.479)	0.357 (0.479)	0.359 (0.480)	0.376 (0.484)	0.388 (0.487)	0.309 (0.462)
Road access control indicator (1 if road access is full or partial control, 0 otherwise)	0.313 (0.463)	0.297 (0.457)	0.296 (0.457)	0.340 (0.474)	0.367 (0.482)	0.262 (0.440)
Paved shoulder indicator (1 if paved, 0 otherwise)	0.805 (0.395)	0.761 (0.426)	0.802 (0.398)	0.783 (0.412)	0.862 (0.344)	0.801 (0.398)
Vertical Indicator (1 if road has a vertical grade, 0 otherwise)	0.235 (0.424)	0.238 (0.426)	0.248 (0.432)	0.199 (0.399)	0.237 (0.426)	0.233 (0.423)
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise)	0.376 (0.484)	0.400 (0.490)	0.397 (0.489)	0.358 (0.479)	0.311 (0.463)	0.419 (0.493)
Other variables						
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise)	0.587 (0.492)	0.647 (0.477)	0.612 (0.487)	0.579 (0.493)	0.530 (0.499)	0.565 (0.495)
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise)	0.442 (0.496)	0.476 (0.499)	0.454 (0.498)	0.415 (0.493)	0.469 (0.499)	0.364 (0.481)
Motorcycle's travel direction indicator (1 if right-turn, 0 otherwise)	0.477 (0.499)	0.464 (0.498)	0.462 (0.498)	0.420 (0.493)	0.505 (0.500)	0.516 (0.499)
Motorcycle's registration indicator (1 if registered in Florida, 0 otherwise)	0.091 (0.288)	0.092 (0.290)	0.096 (0.296)	0.101 (0.302)	0.081 (0.273)	0.090 (0.286)
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise)	0.104 (0.306)	0.111 (0.315)	0.115 (0.319)	0.123 (0.329)	0.091 (0.288)	0.087 (0.282)

Table 4.9. Model estimation results for 2005-06 single-vehicle motorcycle crash-injury severities on Florida horizontal curves (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [NVI]	-0.5819	-2.58			
Random parameters (*normally distributed*)					
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [MI]	-0.0620	-0.15	-0.0051	0.0239	-0.0187
Standard deviation of the helmet indicator	*3.6396*	*2.01*			
Motorcyclist characteristics					
Middle-age motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise) [MI]	0.3880	1.61	-0.0096	0.0306	-0.0210
Roadway and environmental conditions					
Darkness indicator (1 if light condition is darkness, 0 otherwise) [MI]	-1.3099	-2.41	0.0048	-0.0172	0.0124
Rider actions					
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise) [SI]	1.3992	2.34	-0.0050	-0.0080	0.0130
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise) [MI]	1.3982	2.80	-0.0103	0.0321	-0.0218
Roadway Characteristics					
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise) [NVI]	0.5768	2.02	0.0348	-0.0136	-0.0212
Other variables					
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise) [SI]	0.8304	3.30	-0.0296	-0.0370	0.0666
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise) [NVI]	-1.2028	-1.91	-0.0078	0.0024	0.0054
Model statistics					
Number of observations			420		
Log-likelihood at zero			-461.417		
Log-likelihood at convergence			-405.175		

Table 4.10. Model estimation results for 2008-09 single-vehicle motorcycle crash-injury severities on Florida horizontal curves (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [NVI]	-0.2944	-0.73			
Random parameters (*normally distributed*)					
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [MI]	-0.7495	-1.34	0.00001	0.0074	-0.0074
Standard deviation of the helmet indicator	*2.9699*	*1.96*			
Heterogeneity in the mean of the random parameters					
Helmet indicator; vegetation in median indicator (1 if median type is vegetation, 0 otherwise) [MI]	1.1864	1.61			
Motorcyclist characteristics					
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise) [SI]	0.9214	2.35	-0.0058	-0.0103	0.0160
Alcohol or drugs indicator (1 if motorcycle crash is under the influence of alcohol or drugs, 0 otherwise) [SI]	1.6452	4.78	-0.0109	-0.0255	0.0363
Roadway and environmental conditions					
Weather condition indicator (1 if clear, 0 otherwise) [NVI]	0.6708	1.65	0.0623	-0.0225	-0.0398
Road surface condition indicator (1 if dry, 0 otherwise) [NVI]	-0.8211	-1.69	-0.0834	0.0294	0.0541
Rider actions					
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise) [SI]	1.4414	2.49	-0.0035	-0.0074	0.0110
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise) [MI]	0.8324	2.08	-0.0061	0.0204	-0.0144
Roadway Characteristics					
Flat curve indicator (1 if curve radius is greater than 4,000 ft., 0 otherwise) [MI]	0.6625	2.53	-0.0123	0.0429	-0.0306
Vertical indicator (1 if road has a vertical grade, 0 otherwise) [SI]	0.5089	1.99	-0.0080	-0.0141	0.0221
Other variables					
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise) [NVI]	-0.8902	-1.59	-0.0059	0.0019	0.0040
Model statistics					
Number of observations			495		
Log-likelihood at zero			-543.813		
Log-likelihood at convergence			-462.173		

Table 4.11. Model estimation results for 2011 single-vehicle motorcycle crash-injury severities on Florida horizontal curves (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [NVI]	-0.1451	-0.42			
Random parameters (*normally distributed*)					
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [MI]	-0.6984	-0.89	-0.0095	0.0355	-0.0260
Standard deviation of the helmet indicator	*1.7605*	*1.44*			
Heterogeneity in the mean of the random parameters					
Helmet indicator; weather condition indicator (1 if clear, 0 otherwise) [MI]	1.4008	1.62			
Motorcyclist characteristics					
Middle-age motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise) [MI]	-0.9692	-2.94	0.0306	-0.0834	0.0528
Roadway and environmental conditions					
Daylight indicator (1 if light condition is daylight, dawn, or dusk; 0 others) [SI]	-0.7437	-2.40	0.0257	0.0449	-0.0706
Rider actions					
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise) [MI]	0.7649	1.71	-0.0109	0.0300	-0.0192
Roadway Characteristics					
Friction indicator (1 if skid test number is larger than 45, 0 otherwise) [NVI]	-0.9810	-1.99	-0.0236	0.0113	0.0122
Road access control indicator (1 if road access is full or partial control, 0 otherwise) [SI]	-2.2004	-3.53	0.0294	0.0810	-0.1104
Other variables					
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise) [NVI]	-1.2895	-2.26	-0.0298	0.0118	0.0180
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise) [SI]	2.1254	3.50	-0.0296	-0.1107	0.1403
Motorcycle's travel direction (1 if right-turn, 0 otherwise) [NVI]	-0.9003	-2.08	-0.0348	0.0185	0.0163
Model statistics					
Number of observations			226		
Log-likelihood at zero			-248.286		
Log-likelihood at convergence			-194.892		

Table 4.12. Model estimation results for 2012-13 single-vehicle motorcycle crash-injury severities on Florida horizontal curves (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [NVI]	0.6802	1.34			
Random parameters (*normally distributed*)					
Road surface condition indicator (1 if dry, 0 otherwise) [NVI]	-1.5618	-1.36	0.0152	-0.0083	-0.0069
Standard deviation of the Road surface condition indicator	*2.0733*	*1.43*			
Heterogeneity in the mean of the random parameters					
Road surface condition indicator; Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise) [NVI]	1.3164	1.91			
Motorcyclist characteristics					
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise) [SI]	0.8079	2.54	-0.0050	-0.0156	0.0206
Roadway and environmental conditions					
Daylight indicator (1 if light condition is daylight, dawn, or dusk; 0 others) [SI]	-0.4278	-2.39	0.0111	0.0367	-0.0478
Weather condition indicator (1 if rain, 0 otherwise) [SI]	-1.0809	-2.07	0.0035	0.0056	-0.0091
Rider actions					
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise) [SI]	1.0329	2.26	-0.0031	-0.0086	0.0117
Roadway Characteristics					
Friction indicator (1 if skid test number is larger than 45, 0 otherwise) [NVI]	-0.8843	-2.01	-0.0226	0.0130	0.0096
Paved shoulder indicator (1 if paved, 0 otherwise) [NVI]	-1.0765	-2.23	-0.0972	0.0549	0.0423
Other variables					
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [MI]	0.4878	2.60	-0.0162	0.0565	-0.0402
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise) [MI]	-0.6337	-3.22	0.0163	-0.0629	0.0467
Motorcycle's registration indicator (1 if registered in Florida, 0 otherwise) [MI]	0.5697	1.56	-0.0030	0.0101	-0.0071
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise) [SI]	-0.6969	-1.82	0.0026	0.0083	-0.0108
Model statistics					
Number of observations			479		
Log-likelihood at zero			-526.235		
Log-likelihood at convergence			-475.426		

Table 4.13. Model estimation results for 2014-15 single-vehicle motorcycle crash-injury severities on Florida horizontal curves (parameters defined for: [NVI] No visible injury; [MI] Minor injury; [SI] Severe injury).

			Marginal effects		
Variable Description	**Estimated Parameter**	**t-statistic**	**No visible injury**	**Minor injury**	**Severe injury**
Constant [MI]	-0.5295	-1.70			
Random parameters (*normally distributed*)					
Daylight indicator (1 if light condition is daylight, dawn, or dusk; 0 others) [SI]	-1.5624	-1.71	-0.0012	0.0036	-0.0024
Standard deviation of the Daylight indicator	*3.2745*	*1.75*			
Heterogeneity in the mean of the random parameters					
Daylight indicator; Older motorcyclist (1 if motorcyclist is older than 60 years old, 0 otherwise) [SI]	2.2267	1.64			
Roadway and environmental conditions					
Road surface condition indicator (1 if dry, 0 otherwise) [NVI]	-1.6612	-3.48	-0.2169	0.1556	0.0613
Weather condition indicator (1 if clear, 0 otherwise) [NVI]	0.7755	1.80	0.0920	-0.0648	-0.0272
Darkness with streetlight indicator (1 if light condition is darkness with streetlight, 0 otherwise) [MI]	0.5077	1.67	-0.0111	0.0290	-0.0179
Rider actions					
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise) [SI]	-1.4142	-2.63	0.0155	0.0290	-0.0445
Roadway Characteristics					
Friction indicator (1 if skid test number is larger than 45, 0 otherwise) [SI]	0.9240	2.07	-0.0083	-0.0167	0.0250
Other variables					
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [NVI]	1.1917	3.10	0.1172	-0.0869	-0.0303
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise) [MI]	0.8086	2.23	-0.0590	0.0939	-0.0350
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise) [SI]	0.9294	2.53	-0.0167	-0.0317	0.0485
Motorcycle's travel direction indicator (1 if right-turn, 0 otherwise) [NVI]	-0.7417	-2.72	-0.0491	0.0350	0.0141
Model statistics					
Number of observations			343		
Log-likelihood at zero			-376.824		
Log-likelihood at convergence			-340.396		

Regarding random parameters, all five time period models had one statistically significant random parameter, but the explanatory variable generating the random parameter varied by time period. Three of the time period models also had statistically significant heterogeneity in the mean of their random parameter. None of the models produced statistically significant heterogeneity in random-parameter variance. The 2005-06, 2008-09, and 2011 models all had statistically significant random parameters in the effect of helmet use on injury severities, suggesting variation in the effectiveness of helmets perhaps due to helmet design variations or being improperly used (strapped, etc.). The 2011 model also had statistically significant heterogeneity in the mean as a function of clear weather conditions, with clear weather conditions making helmet use more likely to be associated with minor injury. For the 2012-13 model (Table 4.12), the dry roadway surface indicator produced a random parameter with the overall effect being a decrease in injuries under these conditions. There was significant heterogeneity in the mean with this variable, with improper driving action making no visible injury more likely. Finally, for the 2014-15 model, the daylight indicator produced a statistically significant random parameter with the overall effect in such conditions being a decrease in the likelihood of severe injury. There was also significant heterogeneity in the mean for this variable with motorcyclists over 60 years of age being more likely to be severely injured in daylight conditions.

As mentioned in a previous footnote, some caution should be exercised in interpreting these findings because the effects of helmet use, for example, may not necessarily only be capturing the effectiveness of the helmet but may also be capturing the more cautious riding behavior of motorcyclists that chose to wear a helmet. If this is the case, having a non-helmet-wearing rider wear a helmet would not produce the same impact on injury-severity probabilities (see Mannering, 2018 for a discussion of this point). Similarly, motorcyclists riding on dry roads and in daylight may be a self-selected group of riders that differs from the riders in the comparison group (motorcyclists riding on roads other than dry and conditions other than daylight). This general issue is likely to be much more pronounced than it would be for car/truck drivers since motorcycling is impacted far more by environmental conditions than other transportation modes.

To generally compare the variables found to be statistically significant in each of the five time periods, marginal effects tables are presented. Table 4.14 provides the marginal effects for all time periods for the no visible injury-severity category, Table 4.15 for the minor injury severity category, and Table 16 for the severe injury category. All three of these tables will display a marginal effect value if the variable in question was found to be statistically significant, and a "dash" if the variable in question was not statistically significant for that time period. As an example, to see the range of variables found to be statistically significant across time periods, consider the severe injury category marginal effects displayed in Table 4.16. In this table (and the other injury severity category Tables 4.14 and 4.15), we see considerable variation in the variables found to be statistically significant from year to year. In fact, only one variable, an indicator for a motorcyclist wearing a helmet, was found to be statistically significant in all time periods. And, although the effect of the variable was to decrease the probability of severe injury in all time periods, the effect that it had on severe-injury probability ranged from -0.0074 in 2008-09 to -0.0653 in 2014-15. In addition to many specific variables being significant in some periods and insignificant in others, one significantly changed sign. The middle-aged motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise) results in a 0.0210 lower probability of severe injury in 2005-06 and a 0.0528 higher probability of injury in 2011 (and the variable is statistically insignificant in all other time periods).

Table 4.14. The marginal effects of no visible injury in all the time periods of Florida horizontal curves crash data.

	2005-06	2008-09	2011	2012-13	2014-15
Variable Description	**No Visible Injury**	**No Visible Injury**	**No Visible Injury**	**No Visible Injury**	**No Visible Injury**
Motorcyclist characteristics					
Middle-age motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise)	-0.0096	-	0.0306	-	-
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise)	-	-0.0058	-	-0.0050	-
Alcohol or drugs indicator (1 if motorcycle crash is under the influence of alcohol or drugs, 0 otherwise)	-	-0.0109	-	-	-
Roadway and environmental conditions					
Darkness indicator (1 if light condition is darkness, 0 otherwise)	0.0048	-	-	-	-
Weather condition indicator (1 if clear, 0 otherwise)	-	0.0623	-	-	0.0920
Road surface condition indicator (1 if dry, 0 otherwise)	-	-0.0834	-	0.0152	-0.2169
Daylight indicator (1 if light condition is daylight, dawn, or dusk; 0 others)	-	-	0.0257	0.0111	-0.0012
Weather condition indicator (1 if rain, 0 otherwise)	-	-	-	0.0035	-
Darkness with streetlight indicator (1 if light condition is darkness with streetlight, 0 otherwise)	-	-	-	-	-0.0111
Rider actions					
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise)	-0.0050	-0.0035	-	-0.0031	-
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise)	-0.0103	-0.0061	-0.0109	-	0.0155
Roadway characteristics					
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise)	0.0348	-	-	-	-
Flat curve indicator (1 if curve radius is greater than 4,000 ft., 0 otherwise)	-	-0.0123	-	-	-
Vertical indicator (1 if road has a vertical grade, 0 otherwise)	-	-0.0080	-	-	-

Friction indicator (1 if skid test number is larger than 45, 0 otherwise)	-	-	-0.0236	-0.0226	-0.0083
Road access control indicator (1 if road access is full or partial control, 0 otherwise)	-	-	0.0294	-	-
Paved shoulder indicator (1 if paved, 0 otherwise)	-	-	-	-0.0972	-
Other variables					
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise)	-0.0296	-	-0.0594	0.0162	-0.0167
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise)	-0.0078	-0.0059	-	0.0025	-
Motorcycle's travel direction (1 if right-turn, 0 otherwise)	-	-	-0.0348	-	-0.0491
Motorcycle's registration indicator (1 if registered in Florida, 0 otherwise)	-	-	-	-0.0030	-
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise)	-0.0051	-0.00001	-0.0095	-0.0163	0.0583

Table 4.15. The marginal effects of minor injury in all the time periods of Florida horizontal curves crash data.

	2005-06	**2008-09**	**2011**	**2012-13**	**2014-15**
Variable Description	**Minor injury**	**Minor injury**	**Minor injury**	**Minor injury**	**Minor injury**
Motorcyclist characteristics					
Middle-age motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise)	0.0306	-	-0.0834	-	-
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise)	-	-0.0103	-	-0.0156	-
Alcohol or drugs indicator (1 if motorcycle crash is under the influence of alcohol or drugs, 0 otherwise)	-	-0.0255	-	-	-
Roadway and environmental conditions					
Darkness indicator (1 if light condition is darkness, 0 otherwise)	-0.0172	-	-	-	-
Weather condition indicator (1 if clear, 0 otherwise)	-	-0.0225	-	-	-0.0648

Road surface condition indicator (1 if dry, 0 otherwise)	-	0.0294	-	-0.0083	0.1556
Daylight indicator (1 if light condition is daylight, dawn, or dusk; 0 others)	-	-	0.0449	0.0367	0.0036
Weather condition indicator (1 if rain, 0 otherwise)	-	-	-	0.0056	-
Darkness with streetlight indicator (1 if light condition is darkness with streetlight, 0 otherwise)	-	-	-	-	0.0290
Rider actions					
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise)	-0.008	-0.0074	-	-0.0086	-
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise)	0.0321	0.0204	0.0300	-	0.0290
Roadway characteristics					
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise)	-0.0136	-	-	-	-
Flat curve indicator (1 if curve radius is greater than 4,000 ft., 0 otherwise)	-	0.0429	-	-	-
Vertical indicator (1 if road has a vertical grade, 0 otherwise)	-	-0.0141	-	-	-
Friction indicator (1 if skid test number is larger than 45, 0 otherwise)	-	-	0.0113	0.0130	-0.0167
Road access control indicator (1 if road access is full or partial control, 0 otherwise)	-	-	0.0810	-	-
Paved shoulder indicator (1 if paved, 0 otherwise)	-	-	-	0.0549	-
Other variables					
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise)	-0.037	-	-0.0989	-0.0629	-0.0317
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise)	0.0024	0.0019	-	0.0083	-
Motorcycle's travel direction (1 if right-turn, 0 otherwise)	-	-	0.0185	-	0.0350
Motorcycle's registration indicator (1 if registered in Florida, 0 otherwise)	-	-	-	0.0101	-
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise)	0.0239	0.0074	0.0355	0.0565	0.0070

Table 4.16. The marginal effects of severe injury in all the time periods of Florida horizontal curves crash data.

	2005-06	2008-09	2011	2012-13	2014-15
Variable Description	**Severe injury**	**Severe injury**	**Severe injury**	**Severe injury**	**Severe injury**
Motorcyclist characteristics					
Middle-age motorcyclist indicator (1 if motorcyclist is 30 years old or older and 60 years old or younger, 0 otherwise)	-0.0210	-	0.0528	-	-
Older motorcyclist indicator (1 if motorcyclist is older than 60 years old, 0 otherwise)	-	0.0160	-	0.0206	-
Alcohol or drugs indicator (1 if motorcycle crash is under the influence of alcohol or drugs, 0 otherwise)	-	0.0363	-	-	-
Roadway and environmental conditions					
Darkness indicator (1 if light condition is darkness, 0 otherwise)	0.0124	-	-	-	-
Weather condition indicator (1 if clear, 0 otherwise)	-	-0.0398	-	-	-0.0272
Road surface condition indicator (1 if dry, 0 otherwise)	-	0.0541	-	-0.0069	0.0613
Daylight indicator (1 if light condition is daylight, dawn, or dusk; 0 others)	-	-	-0.0706	-0.0478	-0.0024
Weather condition indicator (1 if rain, 0 otherwise)	-	-	-	-0.0091	-
Darkness with streetlight indicator (1 if light condition is darkness with streetlight, 0 otherwise)	-	-	-	-	-0.0179
Rider actions					
Speeding indicator (1 if motorcycle crash cause exceeds speed limit, 0 otherwise)	0.0130	0.0110	-	0.0117	-
Proper driving indicator (1 if crash cause is improper driving or action, 0 otherwise)	-0.0218	-0.0144	-0.0192	-	-0.0445
Roadway characteristics					
Roughness indicator (1 if pavement roughness index is more than 80 in./mi, 0 otherwise)	-0.0212	-	-	-	-
Flat curve indicator (1 if curve radius is greater than 4,000 ft., 0 otherwise)	-	-0.0306	-	-	-

Vertical indicator (1 if road has a vertical grade, 0 otherwise)	-	0.0221	-	-	-
Friction indicator (1 if skid test number is larger than 45, 0 otherwise)	-	-	0.0122	0.0096	0.0250
Road access control indicator (1 if road access is full or partial control, 0 otherwise)	-	-	-0.1104	-	-
Paved shoulder indicator (1 if paved, 0 otherwise)	-	-	-	0.0423	-
Other variables					
Higher motorcycle speed indicator (1 if motorcycle speed is more than 50 mi/h, 0 otherwise)	0.0666	-	0.1583	0.0467	0.0485
Motorcycle's passenger indicator (1 if motorcycle has a passenger, 0 otherwise)	0.0054	0.0040	-	-0.0108	-
Motorcycle's travel direction (1 if right-turn, 0 otherwise)	-	-	0.0163	-	0.0141
Motorcycle's registration indicator (1 if registered in Florida, 0 otherwise)	-	-	-	-0.0071	-
Helmet indicator (1 if motorcyclist wears safety helmet, 0 otherwise)	-0.0187	-0.0074	-0.0260	-0.0402	-0.0653

The statistically significant temporal instability in the horizontal curves data suggests that the temporal instability found in the new rider data is not solely due to riders gaining motorcycling experience. As discussed extensively in Mannering (2018), there are likely fundamental behavioral reasons for this temporal variation. And, because motorcyclists' bodies are more directly exposed to potential injury without the energy-dissipating structure and safety features of cars and trucks, it is likely that any driver/rider behavioral changes over time will be more directly measured in resulting injury severities.

4.9. Summary and Conclusions

Aggregate data in the motorcycle safety field has shown that fatality rates (fatalities per mile ridden) have increase in recent years, most notably in 2015 and 2016 (National Highway Safety Administration, 2018). The reasons for this increase are not fully understood, but there is a body of research that suggest temporal instability may be the cause. This chapter presents some empirical evidence of temporal instability in motorcyclist-injury severity models. To explore this possibility, this chapter used two different datasets; the first dataset is for single-vehicle motorcycle crashes in the state of Florida from 2012 to 2016 for new riders who graduated from Motorcycle Safety Foundation training and were licensed in 2012, and the second dataset is for single-vehicle motorcycle crashes in horizontal curves in the state of Florida from 2005 to 2015. With three possible motorcyclist injury severity outcomes considered (no visible injury, minor injury, and severe injury), random parameters models that allow for possible heterogeneity in means and variances were estimated for a variety of time periods in each dataset. The models included a wide variety of factors relating motorcyclist characteristics (such as ethnicity and age), roadway and environmental conditions (such as light and road surface conditions), motorcycle

characteristics (such as motorcycle make and type of motorcycle), rider actions (such as speeding and improper driving actions) and roadway characteristics (such as obstacles on the road and speed limits).

The results show that the determinants of motorcyclist injury severities in single-vehicle motorcycle crashes have been unstable over time, and this temporal instability is confirmed in both datasets. Even though there were several common variables among the various time-period models, few variables were statistically significant in all time periods and the marginal effects for the injury-severity outcomes for some specific variables showed considerable variation between all the periods in each dataset.

The cause of the observed temporal instability is not entirely clear. In the first dataset (Florida new riders crash data), it was initially speculated that motorcyclists gaining riding skill and experience over time would cause temporal instability in the data. However, the second dataset (Florida horizontal curves crash data), which included riders that would not be in this initial-learning period, resulted in temporally unstable models over the same time period, suggesting a more fundamental temporal shift that goes beyond beginning motorcyclists learning. Following the temporal instability discussion in Mannering (2018), the findings of this chapter suggests that the effects of evolving performance and safety features of the motorcycles, changes in riders' behaviors and skills, changes induced by how riders respond to the changing behavior of other road users (whose behavior may be changing as a result of technology changes in their vehicles, evolving use of personal technologies in their vehicle, such as cell phones, etc.) and changes of the macroeconomic conditions (which could affect risk-taking behavior) may all play a role in the observed temporal instability of motorcyclist injury-severity models. In addition to these factors, there is also the possibility that police-related judgements made in recording the data could be changing over time. For the dependent variable (injury severity outcome) we have attempted to mitigate this possibility by combining the two injury severity levels with the most judgement (no-injury and possible injury) into to a single no-visible injury category. However, it is also possible that police judgments in potential explanatory variables such as opinions relating to the crash cause (speeding, improper riding, etc.) may be changing over time. This is yet another point that could be addressed in future studies that seek to untangle the temporal elements in crash injury severity analysis in an effort to improve motorcycle safety.

Chapter 5: Time-Of-Day Variations and Temporal Instability of Factors Affecting Injury Severities in Large-Truck Crashes

5.1. Introduction

Freight transportation systems play a significant role in the economic vitality of countries. The U.S. freight transportation system moves about 55 million tons of goods daily (U.S. Department of Transportation, 2017). As a dominant freight-carrier mode, trucks carry about 64% of the U.S. freight tonnage (U.S. Department of Transportation, 2017). However, due to the specific features of the large trucks[21], they impose significant safety issues on roadways. The large size and heavy weight of large trucks, while being advantageous in transporting freight efficiently, make them difficult to control, maneuver, and stop. Compared to crashes of other types of vehicles, truck crashes are associated with higher economic losses and traffic-flow disruptions. In addition, the size and weight of large trucks increase the likelihood of severe-injury crashes (Ahmed et al., 2018). According to the National Highway Traffic Safety Administration (NHTSA), in truck-involved crashes from 2007 to 2016, 72% of the fatalities were the occupants of other vehicles and 11% of the fatalities were not vehicle occupants (pedestrians, pedal cyclists, etc.) (National Highway Traffic Safety Administration, 2018). This clearly shows that large trucks significantly affect the safety of other road users. However, a review of the literature shows that, although the severity of crashes involving large trucks has been the focus of many previous studies, comparatively few studies have investigated the temporal stability of the factors influencing the injury severities of truck-involved crashes (by time of day and by year). The intent of the current chapter is to develop statistical models that consider the possibility that the effect of variables that determine resulting injury severities in large-truck crashes may vary by time-of-day and from year to year.

There are at least two reasons to suspect that the factors affecting injury severity change over the day. First, it is possible that human behavior varies by time of day (due to possible fatigue, biorhythms, etc.). In fact, there is a considerable body of literature that suggests this. For example, Leone et al. (2017) found people to be more cautious in decision making in the morning, Hasler et al. (2014) found temporal differences in people's neural responses to monetary awards, and Fabbri et al. (2008) found that people had higher subjective alertness in mid-day relative to mornings. And second, unobserved factors related to visibility, lighting, and so on, may vary, particularly throughout the day. Both suggest that time-of-day variations may be playing a significant role in resulting injury severities, and that this role may go beyond the simple use of indicator variables (indicating various time of day intervals) in statistical models. This chapter considers the possibility that the effect of all factors that determine injury severities may vary by time of day as opposed to a simple shift in probabilities that results with the use of indicator variables.

With regard to the possibility that the effects of injury-severity determinants change over time (from year to year), there is a growing body of empirical evidence that supports this possibility. For example, using a Markov switching approach, research by Malyshkina and Mannering (2009) and Xiong and Mannering (2013) found the influence of factors determining

[21] The National Highway Traffic Safety Administration (NHTSA) defines a large truck as any medium or heavy truck, excluding buses and motor homes, with a gross vehicle weight rating (GVWR) greater than 10,000 pounds (National Highway Traffic Safety Administration, 2018). According to the Federal Highway Administration (FHWA), large trucks mainly include vehicles classified as class 5 to class 13.

injury severity shifted over time. In other work, using data from Chicago, Behnood and Mannering (2015) found that the effect of factors that determined driver injury severities in single-vehicle automobile/truck crashes significantly varied from year to year, and Behnood and Mannering (2016) also found that the effect of factors influencing pedestrian-injury severities resulting from crashes with automobiles and trucks varied significantly from year to year. Mannering (2018) points out that such year to year changes are likely to result from several factors including changes in driver decision making, information processing, risk assessment, and safety attitudes that are driven by changes in vehicle, communication, and information technologies.

The remainder of the chapter is organized as follows. We begin with summarizing the findings of the current literature regarding the factors affecting the crash/driver injury severities in crashes involving large trucks. This is followed by a detailed literature review summarizing the methodological approaches used to study injury severities in large-truck crashes. The methodological approach and data used in the current chapter are then presented. Finally, a discussion on the model estimation findings is provided along with a summary and conclusions.

5.2. Review of Factors Affecting the Injury-Severity of Crashes Involving Large Trucks

A wide range of factors have been found to affect injury-severity outcomes in previous large-truck injury-severity studies. Table 5.1 presents a summary of past research findings with factors found to influence injury severity grouped by driver characteristics, driver actions, crash characteristics, truck characteristics, roadway attributes, environmental conditions, and other variables. Driver characteristics include the driver-related and physiological characteristics of large-truck drivers that significantly affect injury-severity outcomes. Examples of these variables include driver age, gender, and apparent physical condition (alcohol/drug-impaired, fatigued,

Table 5.1. Significantly affecting variables on the injury severity of truck-involved crashes: A summary of findings in previous studies.

Variables	**Findings**
Driver characteristics	
Age	Inconsistent trends have been reported regarding the effects of age on injury-severity of crashes involving large trucks. For example, Chang and Mannering (1999) reported that young drivers increase the likelihood of property damage only in truck crashes. Young drivers have also been reported to decrease the likelihood of no-injury in truck crashes (Pahukula et al., 2015), and increase the likelihood of fatalities (Zheng et al., 2018). Chen and Chen (2011) reported that old drivers (older than 50 years old) increased the likelihood of incapacitating injury/fatality in single-vehicle crashes while they had opposite effects in multivehicle crashes. The contradicting observations regarding the age might be due to the unobserved heterogeneity associated with “age” (physical and health condition of the driver). In addition, in previous research, age has been mainly treated as a categorical factor, where researchers have defined their own age categories.
Gender	Like age, gender has also been found to have complicated effects on the injury severity of large-truck crashes. However, a fair number of studies have reported that female drivers increase the likelihood of severe and fatal injuries (Chang and Mannering, 1999; Khorashadi et al., 2005; Pahukula et al., 2015). Chen and Chen

	(2011) reported that in crashes involving large trucks, female drivers increased the likelihood of incapacitating injury/fatality in single-vehicle crashes while they had opposite effects in multi-vehicle crashes. It should be noted that the number of female drivers operating large trucks are much lower than that of male drivers. This significantly affects the number of observations associated with the female drivers in large-truck crashes. Therefore, some crash-related studies may suffer from insufficient observations for female drivers.
Fatigued – asleep/fainted	Fatigued drivers increase the probability of severe injuries during peak hours (Hao et al., 2016). Fatigued drivers increase the likelihood of incapacitating injury/fatality in multi-vehicle crashes and have the opposite effects in single-vehicle crashes (Chen and Chen, 2011). Asleep/fainted drivers increase the likelihood of more severe injuries (Chen and Chen, 2011).
Alcohol-impaired	Alcohol consumption does not significantly affect the injury severity of truck crashes (Zhu and Srinivasan, 2011).
Seat-belt and air bag	In single-vehicle and multi-vehicle crashes involving large trucks, the use of seat-belts and the availability of airbags are associated with less severe injuries (Chang and Mannering, 1999; Chen and Chen, 2011; Zhu and Srinivasan, 2011).
Driver actions	
Speeding	Speeding increases the likelihood of severe and fatal injuries in truck crashes (Ahmed et al., 2018; Chang and Mannering, 1999). Speeding has also been reported to have random effects on driver-injury severities involving large trucks in both single-vehicle and multi-vehicle crashes (Chen and Chen, 2011).
Failing to grant right of way	"Failing to grant right of way" decreases the likelihood of possible injuries and increases the likelihood of property damage only and severe injuries (Chang and Mannering, 1999).
Improper passing	Improper passing as the primary collision factor decreases the likelihood of more severe injuries in both rural and urban areas (Khorashadi et al., 2005).
Crash characteristics	
Entering/leaving driveway	Crashes when trucks enter/leave the driveway are associated with higher likelihood of possible injuries (Chang and Mannering, 1999).
Right/left turn	The likelihood of severe injuries in truck crashes increases when a vehicle makes a right/left turn (Chang and Mannering, 1999). In rural/urban areas, a right/left turn is associated with decreased likelihood of more severe injuries (Khorashadi et al., 2005).
Rear end	Rear end crashes are associated with a higher probability of having a severe injury in truck-involved crashes (Chang and Mannering, 1999). In rural areas, rear end crashes increase the likelihood of complaint of pain and visible injury outcomes and decrease the likelihood of no injury and severe-fatal injury outcomes while in urban areas they only decrease the likelihood of complaint of pain outcome and increase the likelihood of other injury-severity outcomes (Khorashadi et al., 2005).
Collision with opposite direction	Collisions with opposite directions increases the likelihood of more severe injuries (Zheng et al., 2018).
Ran off the roadway	Ran off the roadway increase the likelihood of minor and severe injuries in single-vehicle and multi-vehicle truck-involved crashes (Chen and Chen, 2011).
Number of vehicles	Truck crash severity increases with an increase in the number of vehicles in the crash (Zheng et al., 2018).
Truck characteristics	

Vehicle weight	Heavy gross vehicle weight (over 20,000lb) increase the likelihood of more severe injuries (Zheng et al., 2018).
Cargo body	Cargo tank, flatbed, and grain trucks, or trucks towing another vehicle are associated with higher injury severities (Zheng et al., 2018). Single unit truck in single-vehicle and multi-vehicle crashes, respectively, decreases and increases the likelihood of incapacitating injury/fatal (Chen and Chen, 2011). Carrying hazardous materials is associated with increased likelihood of more severe injuries (Chen and Chen, 2011).
Roadway attributes	
Speed control	Speed control for truck drivers significantly reduces the truck driver's injury severity (Hao et al., 2016).
Posted speed limit	Higher speed limits increase injury severity in truck crashes (Chang and Mannering, 1999).
Stop sign/flasher	A fair number of studies has reported that stop sign/flasher decreases the likelihood of more severe injuries (Chen and Chen, 2011). In single-vehicle crashes involving large truck, stop sign/flasher decreases the likelihood of both possible injury/non-incapacitating injury and incapacitating injury/fatal outcomes.
Highway-railroad crossing	Highway-railroad crossing increases the likelihood of more severe injuries (Hao et al., 2016).
Concrete median barrier	Concrete median barrier increases the likelihood of severe/fatal injuries (Khorashadi et al., 2005).
Environmental conditions	
Visibility	Poor visibility tends to increase the likelihood of severe injuries in large truck crashes (Hao et al., 2016).
Weather condition	Bad weather such as sleet, snow, fog, rain, and cloudiness increase the likelihood of more severe injuries (Ahmed et al., 2018; Hao et al., 2016; Zheng et al., 2018). In urban areas, rain decreases the likelihood of more severe injuries (Khorashadi et al., 2005). Strong crosswind increases the likelihood of more severe injuries (Zheng et al., 2018). Good weather increases the likelihood of fatal crashes (Zheng et al., 2018).
Roadway surface condition	Dry road surface condition tends to increase the likelihood of severe injury and fatal injury in truck crashes (Chang and Mannering, 1999). Wet road surface condition tends to increase the likelihood of more severe injuries (Zheng et al., 2018). Snow/slush road surface has random effects on driver-injury severity in single-vehicle and multi-vehicle truck-involved accidents (Chen and Chen, 2011). In multi-vehicle accidents, snow/slush road surface increase the likelihood of possible injury/non-incapacitating injury severities and decrease the likelihood of incapacitating injury/fatal severities. In single-vehicle accidents, snow/slush road surface decreases both possible injury/non-incapacitating injuries and incapacitating injury/fatal injuries. Ice road surface increases the likelihood of no-injury crashes (Chen and Chen, 2011).
Darkness	Dark condition including dawn and dusk is associate with an increase in the probability of severe more severe injuries (Pahukula et al., 2015).
Other variables	
Time of crash	Peak-hours crashes increase the probability of driver's injury severity in truck-involved crashes (Chang and Mannering, 1999; Hao et al., 2016; Zhu and

	Srinivasan, 2011). Truck crashes on weekends are associated with increased likelihood of property damage only in truck crashes (Chang and Mannering, 1999).
Other party type	Truck accidents with passenger cars, small trucks, and large trucks are associated with higher likelihood of property damage only crashes (Chang and Mannering, 1999; Khorashadi et al., 2005).

asleep/fainted). Drivers' actions include variables such as speeding and failing to grant right of way. Crash characteristics include variables such as the type of crash (rollover, rear-end, etc.), movements prior to crash (turning, etc.), and number of vehicles involved in the crash. Truck characteristics include specific features of the truck involved in the crash such as size and weight of the truck, cargo type, and type of the carried goods (hazardous materials, etc.). Roadway attributes include the presence of various types of traffic-control signs and roadway geometry conditions. Environmental conditions include various weather conditions (fog, rain, snow, etc.), roadway surface conditions (dry or wet), and visibility and lightening. Other crash-related factors (other than the above-mentioned factors) are classified as "other variables" include variables such as the time of the crash (day of the week and time of the day), and characteristics of the other vehicles involved in the crash.

Note from the presentation of past findings in Table 5.1 that some variables were found to have similar effects on crash-injury severities in terms of the direction of the effect, and others have been found to have opposite effects from study to study. This observed disparity of findings could be due to several reasons such as[22]; temporal instability of the data, spatial instability of the data, insufficient number of observations, incompleteness of the data[23], variations in methodological approaches used in past research, and unobserved heterogeneity in the data.

5.3. Methodological Approaches Used in Large-Truck Injury-Severity

Previous research has used a wide variety of methodological approaches to study the injury-severity of crashes involving large trucks (Table 5.2 presents a summary). Many of the previous studies on the injury-severity of large-truck crashes have used a discrete-outcome modeling because available data on traffic-related crashes typically report discrete outcomes for injury-levels. Therefore, logit, probit, and their extension statistical models have been used in most

[22] Detailed discussion regarding the variation in the direction of explanatory variables is given in previous studies (see Alnawmasi and Mannering, 2019, Behnood and Mannering, 2016, Behnood and Mannering, 2015, Mannering et al., 2016).

[23] There are also parameters that might be reported as statistically significant factors in some studies while some other studies do not report them as significant factors. This could be the result of missing variables or multicollinearity in the data which may make it difficult to find two highly correlated explanatory variables both statistically significant.

Table 5.2. Summary of methodological approaches previously used in the study of large-truck crashes injury severities.

Methodological Approach	Previous Research
Multinomial logit model	Khorashadi et al. (2005)
Nested Logit model	Chang and Mannering (1999)
Ordered logit/probit model	Hao et al. (2016); Uddin and Huynh (2018)
Random parameters ordered probit model	Islam and Hernandez (2013a); Uddin and Huynh (2018)
Heteroskedastic ordered probit model	Lemp et al. (2011); Zhu and Srinivasan (2011)
Spatial generalized ordered probit model	Zou et al. (2017)
Random parameters (mixed) logit model	Chen and Chen (2011); Islam and Hernandez (2013b); Pahukula et al. (2015)
Gradient boosting data mining model	Zheng et al. (2018)
Bayesian binary logit model	Ahmed et al. (2018)

prior studies.[24] In an early work, Chang and Mannering (1999) used a nested logit model to study the injury-severities of the most severely injured vehicle occupant in truck-involved and non-truck-involved accidents using data from the State of Washington during 1994. To investigate the difference between rural and urban driver-injury severities in large-truck crashes in California from 1997 to 2000, Khorashadi et al. (2005) used a standard multinomial logit model. In other work, Hao et al. (2016) used ten-years of accident data starting from 2002 to develop an ordered probit model for the driver injury-severities in truck-involved accidents at highway-rail grade crossing in the United States.

Most recent studies have recognized the importance of unobserved heterogeneity in model estimation. In crash-related data, unobserved heterogeneity may arise from various sources such as unobserved driver characteristics, vehicle characteristics, roadway attributes, and environmental factors (Mannering et al., 2016). In general, previous research has shown that, depending on the nature of the data, models accounting for unobserved heterogeneity can be statistically superior. These heterogeneity models can account for observation-specific variations in the effects of explanatory variables (Behnood et al., 2014; Anastasopoulos et al., 2016; Behnood and Mannering, 2016; Sarwar and Anastasopoulos, 2017). Specifically, regarding the study of injury-severity of large-truck crashes, Chen and Chen (2011), Islam and Hernandez, 2013b, and Pahukula et al., (2015) estimated random parameters multinomial logit models, and Islam and Hernandez (2013a) and Uddin and Huynh, 2018 estimated random-parameters ordered probit models.

[24] For injury severity analysis in general (including studies not restricted to large-truck involvement), a wide variety of ordered and unordered discrete outcome methodological approaches have been used to study the crash-injury severities including ordered logit/probit models, multinomial logit models, latent class models, Markov-switching logit models, random parameters logit models with heterogeneity in means and/or variances, and others (Savolainen et al., 2011; Mannering and Bhat, 2014; Mannering et al., 2016). While modeling approaches have become more sophisticated over time, it is important to note that the choice of one modeling approach over another is often data-dependent and thus a universal statement of the methodological superiority of one method over another cannot be made.

However, in the study of large truck[25] injury severities, the authors are not aware of any research to date that has extended random parameters models to account for possible heterogeneity in the means and variance of random parameters. Such an extension allows a more generalized approach to capture unobserved heterogeneity (Mannering et al., 2016) and this has been shown to produce statistically superior models in a number of recent crash-injury-severity studies (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017b; Waseem et al., 2019; Alnawmasi and Mannering, 2019). This chapter will allow for possible heterogeneity in the means and variances of random parameters while studying various temporal aspects of injury severities in large-truck crashes.

5.4. Methodological Approach

Heterogeneity models include a wide variety of models such as random parameters logit models (Cerwick et al., 2014, Behnood and Mannering, 2015, 2017a, 2017b, Seraneeprakarn et al., 2017), latent class models (Xiong and Mannering, 2013, Behnood et al., 2014, Yasmin et al., 2014, Fountas et al. 2018a), random parameters ordered probit model (Fountas and Anastasopoulos, 2017, 2018, Fountas et al. 2018b), bivariate/multivariate models with random parameters (Abay et al., 2013, Russo et al., 2014), and Markov switching models (Malyshkina and Mannering, 2009, Xiong et al., 2014).

In this chapter, crash-injury severities (the most severely injured person[26] in a crash involving a large truck) are studied by considering three discrete crash-injury severity levels; no injury (property damage only), minor injury (possible injury and non-incapacitating), and severe injury (incapacitating or fatal). To arrive at a random parameters logit model that allows for heterogeneity in the means and variances of the random parameters, a function that determines the crash injury-severity of the most severely injured person in a crash involving a large truck is defined as;

$$S_{kn} = \boldsymbol{\beta}_k \mathbf{X}_{kn} + \varepsilon_{kn} \tag{5.1}$$

where S_{kn} is an injury-severity function determining the probability of large-truck crash injury-severity category k in crash n, $\mathbf{X}_{kn}$ is a vector of explanatory variable that affect large-truck crash injury-severity level k, $\boldsymbol{\beta}_k$ is a vector of estimable parameters, and ε_{kn} is the error term which is

[25] The injury-severity analysis could benefit from estimating separate models for different truck classes (truck class 5 to truck class 13) and/or service types (long haul vs. short haul, less-than-truckload vs. truckload, etc.). Identifying different classes of data that share common features to estimate separate models for different sub-groups of data has been the approach used by several researchers (Morgan and Mannering, 2011; Behnood et al., 2014; Anderson and Hernandez, 2017; Fountas et al., 2019). As an example, Behnood and Mannering (2016) studied the effects of occupants on drive-injury severities in single-vehicle crashes by using three different injury-severity sub-groups that were defined based on the number of occupants in the vehicles. However, careful consideration needs to be given to having a sufficient number of observations for model estimation when dealing with sub-group estimations. In the current study, to account for the unobserved heterogeneity in the data, a random parameters logit model with heterogeneity in the means and variances of the random parameters was used. The unobserved heterogeneity found with such an estimation could be capturing the effect of truck-class effects as well as other sources of unobserved heterogeneity.

[26] The crash injury-severity of the truck driver was also initially considered. However, it was observed that the "severe injury" outcome did not have a sufficient number of observations to produce reliable results. One reason for this could be due to the large size and heavy weight of trucks, which makes truck drivers less likely to be severely injured. However, crashes involving large trucks significantly affect the injury severity of other road-users. Therefore, in the current study, it was decided to statistically assess the injury-severity of the most injured person as opposed to the injury-severity of the truck driver.

assumed to be generalized extreme value distributed. The outcome probabilities of a random parameters logit model of crash injury severity, which accounts for unobserved heterogeneity in the data, can be derived as (McFadden and Train, 2000; Washington et al., 2011),

$$P_n(k) = \int \frac{EXP(\boldsymbol{\beta}_k \mathbf{X}_{kn})}{\sum_{\forall K} EXP(\boldsymbol{\beta}_k \mathbf{X}_{kn})} f(\boldsymbol{\beta} \mid \boldsymbol{\varphi}) d\boldsymbol{\beta} \tag{5.2}$$

where $P_n(k)$ is the probability of crash n having the crash injury severity k, $f(\boldsymbol{\beta}|\boldsymbol{\varphi})$ is the density function of $\boldsymbol{\beta}$ with $\boldsymbol{\varphi}$ referring to vector of parameters (mean and variance) of that density function, and all other terms are as previously defined. To account for the unobserved heterogeneity in the means and variances of random parameters, $\boldsymbol{\beta}_{kn}$ is treated as a vector of estimable parameters that varies across crashes as (Seraneeprakarn et al., 2017; Behnood and Mannering, 2017b; Waseem et al., 2019; Alnawmasi and Mannering, 2019):

$$\boldsymbol{\beta}_{kn} = \beta_k + \Theta_{kn}\mathbf{Z}_{kn} + \sigma_{kn} EXP(\boldsymbol{\omega}_{kn}\mathbf{W}_{kn})\ \nu_{kn} \tag{5.3}$$

where β_k is the mean parameter estimate across all crashes, $\mathbf{Z}_{kn}$ is a vector of explanatory variables that captures heterogeneity in the mean that affect large-truck injury severity level k, $\boldsymbol{\Theta}_{kn}$ is a corresponding vector of estimable parameters, $\mathbf{W}_{kn}$ is a vector of explanatory variables that captures heterogeneity in the standard deviation σ_{kn} with corresponding parameter vector $\boldsymbol{\omega}_{kn}$, and ν_{kn} is a disturbance term.

In this chapter, a wide range of density functions were considered in the empirical analysis including the normal, lognormal, triangular, and uniform distributions. However, the empirical analysis showed that no distribution was statistically superior to the normal distribution. The model estimation was undertaken using simulated likelihood with 1000 Halton draws (McFadden and Train, 2000). Marginal effects, which give the effect that one-unit increase in an explanatory variable has on the injury-severity outcome probabilities, were also calculated to further interpret the model estimation results (Washington et al., 2011).

5.5. Empirical setting

The data used for this chapter were collected from police-reported crashes that involved large trucks in Los Angeles over an eight-year period from January 1, 2010 to December 31, 2017. In addition to resulting injury severities, the available crash data provided comprehensive information on crash-related factors (such as primary cause of crash and events contributing to crash), driver attributes (such as age, gender, and physical condition), vehicle characteristics (such as type of the vehicle and model year of the vehicle), roadway, weather, and environmental conditions (such as road surface condition and light), and time and location of the crash.

5.6. Temporal Stability Tests

After extensive empirical testing[27], it was determined that models that produced the best statistical results were, for different times of day, morning (6:00 A.M. to 11:59 A.M.) and afternoon (12:00 P.M. to 5:59 P.M.)[28], and for the years from 2010 to 2013 and from 2014 to 2017. Table 5.3

Table 5.3. Crash injury frequency and percentage distribution by different time periods

Time period	Severe injury frequency (%)	Minor injury frequency (%)	No injury frequency (%)	Total (%)
Morning (2010-13)	35 (2.10)	449 (26.98)	1,180 (70.91)	1,664
Morning (2014-17)	31 (1.98)	453 (28.93)	1,082 (69.09)	1,566
Afternoon (2010-13)	39 (3.01)	486 (37.50)	771 (59.49)	1,296
Afternoon (2014-17)	44 (3.63)	463 (38.23)	284 (58.13)	1,211
Total (%)	149 (2.60)	1,851 (32.26)	3,737 (65.14)	5,737 (100)

presents the injury distribution in these time-of-day and time-period combinations. Table 5.4 provides the summary statistics for variables found to be statistically significant in the estimated models, and Tables 5.5-5.8 present the model estimation results for the four time-of-day/time-period combinations. To statistically test if injury-severities in crashes involving large trucks were significantly different across different times during the day (morning and afternoon) and different time periods (2010-13 and 2014-17), a series of likelihood ratio tests were conducted. The test statistic is (see Washington et al., 2011),

$$X^2 = -2\left[LL\left(\boldsymbol{\beta}_{m_2 m_1}\right) - LL\left(\boldsymbol{\beta}_{m_1}\right)\right] \tag{5.4}$$

where, $LL\left(\boldsymbol{\beta}_{m_2 m_1}\right)$ is the log-likelihood at convergence of a model containing converged parameters of time-of-day/time-period data m_2, while using data from time-of-day/time-period data m_1, and $LL(\boldsymbol{\beta}_{m_1})$ is the log-likelihood at convergence of the model using time-of-day/time-period data m_1, with the same explanatory variables but with parameters no longer restricted to the converged parameters of time-of-day/time-period data m_2. This process is repeated for all combinations of the four time-of-day/time-period data sets giving a total of 12 likelihood ratio

[27] Regarding time-of-day, we focused on the time periods to cover morning peak hours and afternoon peak hours. For yearly classification of the data, several scenarios were assumed and tested for potential temporal stability using likelihood ratio tests. The classifications used in this study included: (a) 2010-2011, 2012-2013, 2014-2015, and 2016-2017; (b) 2010-2011, 2012-2015, and 2016-2017, and (c) 2010-2013 and 2014-2017. Of these, the classification of data into the years from 2010 to 2013 and from 2014 to 2017 provided the most statistically defensible results as indicated by likelihood ratio tests.

[28] Other times of day (late evening and early morning) produced too few observations to reliably test for temporal stability.

Table 5.4. Descriptive statistics of the variables used in the estimations

Variable	Morning 2010-2013		Morning 2014-2017		Afternoon 2010-2013		Afternoon 2014-2017	
	Mean	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**	**Mean**	**S.D.**
Weekday (1 if crash occurred during the weekday; 0 otherwise)	0.938	0.242	0.934	0.249	0.892	0.310	0.903	0.295
Weekend (1 if crash occurred during the weekend; 0 otherwise)	0.063	0.242	0.066	0.249	0.108	0.310	0.097	0.295
At fault (1 if truck driver is at fault; 0 otherwise)	0.517	0.500	0.525	0.499	0.522	0.500	0.500	0.500
Male (1 if truck driver is male; 0 otherwise)	0.959	0.198	0.958	0.201	0.939	0.239	0.936	0.246
Young-age (1 if truck driver is younger than 31 years old; 0 otherwise)	0.120	0.325	0.127	0.333	0.145	0.352	0.158	0.365
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	0.560	0.496	0.493	0.500	0.525	0.499	0.486	0.500
Old-age (1 if truck driver is older than 50 years old; 0 otherwise)	0.320	0.467	0.380	0.485	0.329	0.470	0.357	0.479
Had not been drinking (1 if apparent physical condition of driver is had not been drinking; 0 otherwise)	0.949	0.220	0.923	0.267	0.927	0.259	0.898	0.302
Had been drinking, under influence (1 if apparent physical condition of driver is had been drinking and under influence; 0 otherwise)	0.002	0.049	0.003	0.050	0.011	0.103	0.008	0.091
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	0.133	0.340	0.148	0.355	0.102	0.302	0.124	0.329
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.416	0.493	0.429	0.495	0.458	0.498	0.449	0.497
Making right turn (1 if movement preceding collision is making right turn; 0 otherwise)	0.127	0.333	0.115	0.319	0.140	0.347	0.120	0.325
Making left turn (1 if movement preceding collision is making left turn; 0 otherwise)	0.092	0.289	0.080	0.271	0.100	0.299	0.089	0.285
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	0.009	0.095	0.011	0.104	0.012	0.110	0.010	0.099
Backing (1 if movement preceding collision is backing; 0 otherwise)	0.098	0.297	0.102	0.303	0.073	0.259	0.083	0.277
Asian (1 if truck driver is Asian; 0 otherwise)	0.012	0.109	0.008	0.091	0.013	0.114	0.015	0.121
Black (1 if truck driver is Black; 0 otherwise)	0.213	0.409	0.218	0.413	0.166	0.372	0.181	0.385
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	0.505	0.500	0.550	0.498	0.492	0.500	0.528	0.499
White (1 if truck driver is White; 0 otherwise)	0.216	0.411	0.156	0.363	0.258	0.437	0.183	0.387
New truck (1 if truck is less than 6 years old; 0 otherwise)	0.363	0.481	0.355	0.479	0.357	0.479	0.372	0.484
Old truck (1 if truck is above 15 years old; 0 otherwise)	0.077	0.266	0.112	0.315	0.137	0.344	0.142	0.349
Intersection (1 if intersection-related crash; 0 otherwise)	0.205	0.404	0.201	0.401	0.225	0.418	0.237	0.425
Clear (1 if weather condition is clear; 0 otherwise)	0.846	0.361	0.881	0.324	0.899	0.301	0.919	0.273
Cloudy (1 if weather condition is cloudy; 0 otherwise)	0.125	0.331	0.097	0.296	0.069	0.253	0.064	0.244
Rainy (1 if weather condition is rainy; 0 otherwise)	0.025	0.155	0.015	0.120	0.022	0.148	0.013	0.114
Driving under the influence of alcohol or drug (1 if violation category is driving under the influence of alcohol or drug; 0 otherwise	0.009	0.095	0.006	0.080	0.019	0.135	0.015	0.121
Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	0.165	0.371	0.167	0.373	0.160	0.367	0.167	0.373

Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	0.038	0.191	0.027	0.162	0.034	0.181	0.037	0.189
Improper passing (1 if violation category is improper passing; 0 otherwise)	0.084	0.277	0.073	0.260	0.052	0.223	0.042	0.201
Unsafe lane change (1 if violation category is unsafe lane change; 0 otherwise)	0.124	0.329	0.125	0.331	0.137	0.344	0.120	0.325
Improper turning (1 if violation category is improper turning; 0 otherwise)	0.150	0.357	0.178	0.382	0.133	0.340	0.160	0.367
Truck right of way (1 if violation category is truck right of way; 0 otherwise)	0.085	0.279	0.075	0.263	0.122	0.327	0.121	0.327
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	0.032	0.177	0.043	0.202	0.042	0.202	0.037	0.189
Felony (1 if crash is felony hit-and-run; 0 otherwise)	0.005	0.069	0.014	0.118	0.016	0.126	0.019	0.137
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	0.099	0.298	0.096	0.294	0.083	0.276	0.112	0.316
Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	0.897	0.304	0.890	0.313	0.900	0.299	0.869	0.338
Head-on (1 if type of crash is head-on; 0 otherwise)	0.031	0.174	0.029	0.167	0.037	0.189	0.040	0.197
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	0.488	0.500	0.462	0.499	0.408	0.492	0.403	0.491
Rear end (1 if type of crash is rear end; 0 otherwise)	0.144	0.351	0.160	0.366	0.180	0.384	0.187	0.390
Broadside (1 if type of crash is broadside; 0 otherwise)	0.152	0.359	0.144	0.351	0.181	0.385	0.191	0.393
Hit object (1 if type of crash is hit object; 0 otherwise)	0.098	0.297	0.109	0.311	0.113	0.316	0.094	0.292
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	0.023	0.149	0.025	0.156	0.033	0.179	0.026	0.160
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	0.657	0.475	0.656	0.475	0.679	0.467	0.675	0.468
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	0.132	0.338	0.142	0.349	0.100	0.300	0.131	0.338
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	0.019	0.135	0.017	0.130	0.024	0.153	0.017	0.127
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	0.118	0.322	0.123	0.328	0.127	0.333	0.120	0.325
Dry (1 if road surface condition is dry; 0 otherwise)	0.942	0.234	0.960	0.197	0.944	0.231	0.961	0.193
Wet (1 if road surface condition is wet; 0 otherwise)	0.052	0.221	0.031	0.174	0.041	0.198	0.029	0.168
Daylight (1 if light condition is daylight; 0 otherwise)	0.975	0.157	0.976	0.154	0.962	0.191	0.957	0.203
Dark - street lights (1 if light condition is dark - street lights; 0 otherwise)	0.005	0.069	0.005	0.071	0.022	0.148	0.024	0.153
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	0.225	0.417	0.226	0.418	0.214	0.410	0.249	0.433
Truck or truck tractor (1 if at fault vehicle type is truck or truck tractor; 0 otherwise)	0.518	0.500	0.526	0.499	0.523	0.500	0.501	0.500

Table 5.5. Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the morning time, 2010-2013.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	-0.672	-0.64			
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	1.319	0.62	-0.0027	-0.0013	0.0039
Standard deviation of "Hispanic"	*1.858*	*1.74*			
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	-1.412	-1.64	0.0013	0.0003	-0.0016
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	-2.205	-4.69	0.0097	0.0077	-0.0174
Daylight (1 if light condition is daylight; 0 otherwise)	-1.949	-2.34	0.0142	0.0127	-0.0269
Defined for minor injury					
Male (1 if truck driver is male; 0 otherwise)	-2.209	-3.61	0.0700	-0.0847	0.0147
Standard deviation of "Male"	*1.859*	*2.63*			
At fault (1 if truck driver is at fault; 0 otherwise)	0.441	1.79	0.3675	-0.3383	-0.0292
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	0.990	1.62	-0.0027	0.0032	-0.0005
Felony (1 if crash is felony hit-and-run; 0 otherwise)	8.530	3.57	-0.0018	0.0019	-0.0001
Head-on (1 if type of crash is head-on; 0 otherwise)	1.306	2.08	-0.0040	0.0045	-0.0005
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	1.567	2.23	-0.0023	0.0041	-0.0018
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	2.368	2.88	-0.0027	0.0046	-0.0019
Dry (1 if road surface condition is dry; 0 otherwise)	-0.808	-1.77	0.0575	-0.0629	0.0053
Defined for no injury					
Constant	-0.437	-0.40			
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	4.256	2.41	0.0049	-0.0044	-0.0005
Standard deviation of "Parked motor vehicle"	*2.941*	*1.82*			
Weekday (1 if crash occurred during the weekday; 0 otherwise)	1.615	3.28	0.1264	-0.1146	-0.0119
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	1.640	3.58	0.0182	-0.0163	-0.0019
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	2.313	3.72	0.0822	-0.0766	-0.0056
Backing (1 if movement preceding collision is backing; 0 otherwise)	4.215	4.90	0.0171	-0.0162	-0.0009
Black (1 if truck driver is Black; 0 otherwise)	1.491	3.89	0.0210	-0.0189	-0.0021
White (1 if truck driver is White; 0 otherwise)	0.621	2.10	0.0108	-0.0094	-0.0014
Intersection (1 if intersection-related crash; 0 otherwise)	-0.756	-2.86	-0.0158	0.0138	0.0020
Improper passing (1 if violation category is improper passing; 0 otherwise)	0.911	1.90	0.0042	-0.0041	-0.0002
Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	-5.069	-4.58	-0.4169	0.3785	0.0384

Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	2.375	4.95	0.0824	-0.0803	-0.0021
Hit object (1 if type of crash is hit object; 0 otherwise)	2.724	3.57	0.0075	-0.0061	-0.0013
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	3.491	4.43	0.0116	-0.0093	-0.0022
Heterogeneity in the mean of the random parameters					
Male: Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	1.621	2.66			
Hispanic: Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	1.796	2.01			
Hispanic: Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	-3.806	-2.21			
Model statistics					
Number of observations			1,664		
Log-likelihood at zero, $LL(0)$			-1,828.09		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			-724.12		
$\rho^2 = 1\text{-}LL(\boldsymbol{\beta})/LL(0)$			0.604		

Table 5.6. Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the afternoon time, 2010-2013.

Variable	**Parameter estimate**	**t-Stat.**	**Marginal effects**		
			No injury	**Minor injury**	**Severe injury**
Defined for severe injury					
Constant	-2.791	-2.69			
Weekday (1 if crash occurred during the weekday; 0 otherwise)	1.895	1.83	-0.0168	-0.0312	0.0480
At fault (1 if truck driver is at fault; 0 otherwise)	-1.107	-2.90	0.0037	0.0072	-0.0109
Old truck (1 if truck is above 15 years old; 0 otherwise)	1.083	2.81	-0.0028	-0.0052	0.0080
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	-1.452	-3.05	0.0042	0.0023	-0.0065
Rear end (1 if type of crash is rear end; 0 otherwise)	-2.435	-3.26	0.0013	0.0024	-0.0037
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	-1.727	-3.24	0.0018	0.0045	-0.0063
Defined for minor injury					
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	1.564	1.93	-0.0480	0.0847	-0.0367
Rainy (1 if weather condition is rainy; 0 otherwise)	1.865	1.91	-0.0043	0.0046	-0.0002
Automobile right of way (1 if violation category is automobile right of way; 0 otherwise)	0.818	3.41	-0.0116	0.0148	-0.0033
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	0.681	1.80	-0.0025	0.0041	-0.0016

Defined for no injury					
Constant	-1.400	-6.93			
Wet (1 if road surface condition is wet; 0 otherwise)	1.120	1.40	0.0040	-0.0039	-0.0001
Standard deviation of "Wet"	*2.373*	*2.02*			
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	0.753	2.84	0.0128	-0.0123	-0.0006
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.581	3.25	0.0378	-0.0353	-0.0025
Backing (1 if movement preceding collision is backing; 0 otherwise)	2.249	6.03	0.0162	-0.0149	-0.0012
Black (1 if truck driver is Black; 0 otherwise)	0.684	3.17	0.0147	-0.0137	-0.0011
White (1 if truck driver is White; 0 otherwise)	0.468	2.58	0.0160	-0.0151	-0.0009
Intersection (1 if intersection-related crash; 0 otherwise)	-0.353	-1.86	-0.0110	0.0101	0.0009
Improper passing (1 if violation category is improper passing; 0 otherwise)	1.236	3.19	0.0072	-0.0068	-0.0004
Unsafe lane change (1 if violation category is unsafe lane change; 0 otherwise)	0.506	2.16	0.0106	-0.0100	-0.0005
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	4.275	5.35	0.0057	-0.0053	-0.0004
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	1.473	8.09	0.0850	-0.0807	-0.0043
Hit object (1 if type of crash is hit object; 0 otherwise)	1.895	3.86	0.0100	-0.0083	-0.0017
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	2.238	5.33	0.0107	-0.0098	-0.0009
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	2.514	5.33	0.0155	-0.0136	-0.0019
Model statistics					
Number of observations			1,296		
Log-likelihood at zero, $LL(0)$			-1,423.80		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			-674.97		
$\rho^2 = 1\text{-}LL(\boldsymbol{\beta})/LL(0)$			0.526		

Table 5.7. Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the morning time, 2014-2017.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	1.053	0.91			
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	-3.262	-1.70	-0.0017	-0.0008	0.0025
Standard deviation of "Middle age"	*2.662*	*2.06*			
Weekday (1 if crash occurred during the weekday; 0 otherwise)	-1.490	-2.03	0.0061	0.0119	-0.0179
At fault (1 if truck driver is at fault; 0 otherwise)	-1.629	-3.08	0.0036	0.0051	-0.0087
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	-1.685	-2.34	0.0015	0.0016	-0.0030
Rear end (1 if type of crash is rear end; 0 otherwise)	-2.547	-2.40	0.0007	0.0014	-0.0021
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	-1.780	-3.20	0.0040	0.0088	-0.0128
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	-1.767	-1.93	0.0001	0.0018	-0.0019
Dark - street lights (1 if light condition is dark - street lights; 0 otherwise)	3.992	2.55	-0.0008	-0.0005	0.0013
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	-1.948	-2.27	0.0015	0.0036	-0.0051
Defined for minor injury					
Young age (1 if truck driver is younger than 31 years old; 0 otherwise)	1.388	4.62	0.1536	-0.1221	-0.0316
Passing another vehicle (1 if movement preceding collision is passing another vehicle; 0 otherwise)	0.738	2.56	-0.0068	0.0077	-0.0009
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	1.622	3.31	-0.0034	0.0061	-0.0027
Dry (1 if road surface condition is dry; 0 otherwise)	-1.415	-1.76	0.1085	-0.1211	0.0126
Defined for no injury					
Constant	-1.787	-2.20			
Old truck (1 if truck is above 15 years old; 0 otherwise)	-1.753	-3.91	-0.0128	0.0119	0.0009
Standard deviation of "Old truck"	*1.852*	*2.92*			
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	3.402	5.25	0.0230	-0.0223	-0.0006
Standard deviation of "Sideswipe"	*2.763*	*3.59*			
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	1.012	3.92	0.0152	-0.0147	-0.0005
Backing (1 if movement preceding collision is backing; 0 otherwise)	2.743	6.76	0.0166	-0.0152	-0.0014
Black (1 if truck driver is Black; 0 otherwise)	0.747	2.61	0.0105	-0.0099	-0.0006
New truck (1 if truck is less than 6 years old; 0 otherwise)	-0.452	-2.19	-0.0138	0.0130	0.0008
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	-1.706	-2.42	-0.0037	0.0036	0.0002
Improper passing (1 if violation category is improper passing; 0 otherwise)	3.618	2.30	0.0125	-0.0121	-0.0004

Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	-1.531	-3.40	-0.0057	0.0053	0.0004
Felony (1 if crash is felony hit-and-run; 0 otherwise)	-7.512	-2.63	-0.0017	0.0016	0.0001
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	5.113	4.87	0.0047	-0.0044	-0.0004
Hit object (1 if type of crash is hit object; 0 otherwise)	3.256	5.64	0.0116	-0.0075	-0.0041
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	3.254	5.65	0.0124	-0.0109	-0.0015
Bicycle (1 if truck is involved with bicycle; 0otherwise)	-3.623	-2.59	-0.0019	0.0018	0.0001
Fixed object (1 if truck is involved with fixed object; 0otherwise)	1.789	3.52	0.0081	-0.0060	-0.0021
Wet (1 if road surface condition is wet; 0 otherwise)	2.698	2.78	0.0064	-0.0063	-0.0002
Heterogeneity in the mean of the random parameters					
Sideswipe: Backing (1 if movement preceding collision is backing; 0 otherwise)	-4.125	-3.05			
Sideswipe: Black (1 if truck driver is Black; 0 otherwise)	1.298	1.80			
Sideswipe: Improper passing (1 if violation category is improper passing; 0 otherwise)	-2.786	-1.62			
Sideswipe: Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	-1.027	-1.96			
Model statistics					
Number of observations			1,566		
Log-likelihood at zero, $LL(0)$			-1,720.43		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			-637.04		
$\rho^2 = 1\text{-}LL(\boldsymbol{\beta})/LL(0)$			0.630		

Table 5.8. Random parameters logit model (allowing for possible heterogeneity in means and variances) results of large-truck crash injury-severities during the afternoon time, 2014-2017.

Variable	Parameter estimate	t-Stat.	Marginal effects		
			No injury	Minor injury	Severe injury
Defined for severe injury					
Constant	-0.499	-1.12			
At fault (1 if truck driver is at fault; 0 otherwise)	-0.630	-1.61	0.0022	0.0049	-0.0072
Making left turn (1 if movement preceding collision is making left turn; 0 otherwise)	1.154	2.46	-0.0015	-0.0054	0.0069
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	0.780	1.93	-0.0045	-0.0112	0.0156
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	-2.277	-3.57	0.0035	0.0035	-0.0070
Rear end (1 if type of crash is rear end; 0 otherwise)	-3.073	-3.60	0.0015	0.0031	-0.0047
Broadside (1 if type of crash is broadside; 0 otherwise)	-1.289	-2.56	0.0024	0.0089	-0.0113
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	-1.636	-2.89	0.0070	0.0171	-0.0241
Defined for minor injury					
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	0.632	3.03	-0.0245	0.0254	-0.0009
Standard deviation of "middle aged"	*0.973*	*2.13*			
Young age (1 if truck driver is younger than 31 years old; 0 otherwise)	0.702	2.63	0.4724	-0.4185	-0.0539
New truck (1 if truck is less than 6 years old; 0 otherwise)	0.327	1.77	-0.0135	0.0152	-0.0016
Rainy (1 if weather condition is rainy; 0 otherwise)	-1.353	-2.03	0.0025	-0.0031	0.0006
Automobile right of way (1 if violation category is automobile right of way; 0 otherwise)	0.923	3.17	-0.0121	0.0149	-0.0028
Head-on (1 if type of crash is head-on; 0 otherwise)	0.822	1.79	-0.0025	0.0043	-0.0018
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	-0.806	-2.06	0.0708	-0.0793	0.0084
Defined for no injury					
Constant	-1.652	-3.12			
Old truck (1 if truck is above 15 years old; 0 otherwise)	-1.356	-3.74	-0.0141	0.0127	0.0014
Standard deviation of "old truck"	*1.197*	*1.61*			
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	4.305	2.46	0.0059	-0.0044	-0.0015
Standard deviation of "fixed object"	*3.558*	*2.02*			
Had not been drinking (1 if apparent physical condition of driver is had not been drinking; 0 otherwise)	0.655	1.95	0.0677	-0.0627	-0.0050
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.339	1.78	0.0186	-0.0174	-0.0012
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	-3.330	-1.89	-0.0019	0.0015	0.0004
Backing (1 if movement preceding collision is backing; 0 otherwise)	1.987	4.61	0.0132	-0.0118	-0.0015

Black (1 if truck driver is Black; 0 otherwise)	0.959	3.81	0.0193	-0.0185	-0.0008
White (1 if truck driver is White; 0 otherwise)	0.776	3.04	0.0155	-0.0145	-0.0010
Intersection (1 if intersection-related crash; 0 otherwise)	-0.481	-2.01	-0.0129	0.0118	0.0011
Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	-1.702	-5.03	-0.0307	0.0278	0.0029
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	-1.046	-2.26	-0.0049	0.0045	0.0004
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	-1.504	-2.51	-0.0044	0.0040	0.0004
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	5.529	6.59	0.0086	-0.0081	-0.0006
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	1.453	6.31	0.0682	-0.0660	-0.0023
Hit object (1 if type of crash is hit object; 0 otherwise)	3.014	3.31	0.0123	-0.0089	-0.0034
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	3.296	5.94	0.0243	-0.0213	-0.0030
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	-2.174	-1.85	-0.0015	0.0013	0.0002
Heterogeneity in the mean of the random parameters					
Middle age: Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	-1.201	-2.81			
Model statistics					
Number of observations			1,211		
Log-likelihood at zero, $LL(0)$			-1,330.42		
Log-likelihood at convergence, $LL(\boldsymbol{\beta})$			-600.17		
$\rho^2 = 1\text{-}LL(\boldsymbol{\beta})/LL(0)$			0.549		

tests. The resulting value X^2 in Equation 4 is χ^2 distributed, with degrees of freedom equal to the number of estimated parameters, and can be used to determine if the null hypothesis that the parameters are equal between any two time-of-day/time-period data sets can be rejected. The results of these 12 tests are presented in Table 5.9. This table shows that in all cases the null hypothesis that the 12 time-of-day/time-period combinations tested produced equal parameters can be rejected with over 99% confidence, suggesting that separate models are warranted for the time-of-day and time-periods used in this analysis. These results are in line with the findings of previous research efforts that have studied of crash-injury severity models across different time periods while considering crashes involving all vehicle types, large trucks and all others (Alnawmasi and Mannering, 2019; Behnood and Mannering, 2015; Behnood and Mannering, 2016).

Table 5.9. Likelihood ratio test results between morning and afternoon in different time periods (χ^2 values with degrees of freedom in parenthesis and confidence level in brackets).

m_2 / m_1	**Morning 2010-13**	**Afternoon 2010-13**	**Morning 2014-17**	**Afternoon 2014-17**
Morning 2010-13	–	117.46 (27) [>99.99%]	183.36 (34) [>99.99%]	298.81 (37) [>99.99%]
Afternoon 2010-13	526.44 (33) [>99.99%]	–	293.18 (37) [>99.99%]	97.12 (36) [>99.97%]
Morning 2014-17	77.06 (30) [>99.99%]	101.42 (27) [>99.99%]	–	230.74 (37) [>99.99%]
Afternoon 2014-17	748.46 (33) [>99.99%]	58.00 (27) [>99.95%]	241.68 (37) [>99.99%]	–

5.7. Discussion of Estimation Results

The estimation results provided in Tables 5.5 through 5.8 show plausible parameter sign and very good overall model fit with ρ^2 values exceeding 0.60 in three of the models and exceeding 0.50 in the fourth. It should be noted that, although heterogeneity in the means of random parameters was found to be statistically significant in some of the models, heterogeneity in the variances of random parameters was not found to be statistically significant in any of the estimated models.

Tables 5.5 through 5.8 also show considerable variation in the variables found to be statistically significant in the four time-of-day/time-period combinations. To better illustrate these differences, Table 10 provides a side-by-side presentation of the marginal effects of explanatory variables (organized by variable category) for the four time-of-day/time-period models, of day and across the two time periods. A discussion of model results by variable category is presented below.

5.7.1 Driver Characteristics

With regard to driver's characteristics, black drivers consistently were involved in crashes that resulted in less severe injuries (positive marginal effects for no injury and negative marginal effects for minor injury and severe injury) in both morning and afternoon and across time periods, relative to other ethnicities (see Table 10). White drivers also tended to be involved in crashes that resulted in less severe injuries, although the white indicator variable was not statistically significant in the

2014-17 morning time period. Hispanic drivers were involved in more severe injury crashes in the 2010-13 morning period (this was a random parameter in this period) and the 2014-17 afternoon period. However, for these ethnicity results, some caution should be exercised in their interpretation because various ethnicities of drivers may be more likely to be assigned to certain routes and at certain times of day. Thus, this finding could be reflecting truck routing and delivery characteristics (some with higher or lower risk) rather than ethnicity itself.

Table 5.10. The marginal effects of the explanatory variables in different time periods of the day (italic value indicates random parameter).

Variable	No Injury				Minor Injury				Severe Injury			
	Morning 2010-13	Afternoon 2010-13	Morning 2014-17	Afternoon 2014-17	Morning 2010-13	Afternoon 2010-13	Morning 2014-17	Afternoon 2014-17	Morning 2010-13	Afternoon 2010-13	Morning 2014-17	Afternoon 2014-17
Driver characteristics												
Black (1 if truck driver is Black; 0 otherwise)	0.0210	0.0147	0.0105	0.0193	-0.0189	-0.0137	-0.0099	-0.0185	-0.0021	-0.0011	-0.0006	-0.0008
White (1 if truck driver is White; 0 otherwise)	0.0108	0.0160	-	0.0155	-0.0094	-0.0151	-	-0.0145	-0.0014	-0.0009	-	-0.0010
Hispanic (1 if truck driver is Hispanic; 0 otherwise)	*-0.0027*	-	-	-0.0045	*-0.0013*	-	-	-0.0112	*0.0039*	-	-	0.0156
Male (1 if truck driver is male; 0 otherwise)	*0.0700*	-	-		*-0.0847*	-	-		*0.0147*	-	-	0.0156
Young age (1 if truck driver is younger than 31 years old; 0 otherwise)	-	-	0.1536	0.4724	-	-	-0.1221	-0.4185	-	-	-0.0316	-0.0539
Middle age (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise)	-	-	*-0.0017*	*-0.0245*	-	-	*-0.0008*	*0.0254*	-	-	*0.0025*	*-0.0009*
Had not been drinking (1 if apparent physical condition of driver is had not been drinking; 0 otherwise)	-	-	-	0.0677	-	-	-	-0.0627	-	-	-	-0.0050
Driver actions												
Stopped (1 if movement preceding collision is stopped; 0 otherwise)	0.0182	0.0128	0.0152	-	-0.0163	-0.0123	-0.0147	-	-0.0019	-0.0006	-0.0005	-
Proceeding straight (1 if movement preceding collision is proceeding straight; 0 otherwise)	0.0822	0.0378	-	0.0186	-0.0766	-0.0353	-	-0.0174	-0.0056	-0.0025	-	-0.0012
Backing (1 if movement preceding collision is backing; 0 otherwise)	0.0171	0.0162	0.0166	0.0132	-0.0162	-0.0149	-0.0152	-0.0118	-0.0009	-0.0012	-0.0014	-0.0015
Making U-turn (1 if movement preceding collision is making U-turn; 0 otherwise)	-	-0.0480	-	-0.0019	-	0.0847	-	0.0015	-	-0.0367	-	0.0004
Making left turn (1 if movement preceding collision is making left turn; 0 otherwise)	-	-	-	-0.0015	-	-	-	-0.0054	-	-	-	0.0069
Passing another vehicle (1 if movement preceding collision is passing another vehicle; 0 otherwise)	-	-	-0.0068	-	-	-	0.0077		-	-	-0.0009	-
Crash characteristics												
Sideswipe (1 if type of crash is sideswipe; 0 otherwise)	0.0837	0.0892	0.0245	0.0711	-0.0800	-0.0784	-0.0207	-0.0625	-0.0037	-0.0108	-0.0036	-0.0093
Head-on (1 if type of crash is head-on; 0 otherwise)	-0.0040	-	-	-0.0025	0.0045	-	-	0.0043	-0.0005	-	-	-0.0018
Hit object (1 if type of crash is hit object; 0 otherwise)	0.0075	0.0100	0.0116	0.0123	-0.0061	-0.0083	-0.0075	-0.0089	-0.0013	-0.0017	-0.0041	-0.0034
Rear end (1 if type of crash is rear end; 0 otherwise)	-	0.0013	0.0007	-	-	0.0024	0.0014	-	-	-0.0037	-0.0021	-
Parked motor vehicle (1 if truck is involved with parked motor vehicle; 0 otherwise)	*0.0049*	0.0107	0.0124	0.0243	*-0.0044*	-0.0098	-0.0109	-0.0213	*-0.0005*	-0.0009	-0.0015	-0.0030
Other motor vehicle (1 if truck is involved with other motor vehicle; 0 otherwise)	0.0097	-	0.0040	0.0708	0.0077	-	0.0088	-0.0793	-0.0174	-	-0.0128	0.0084
Pedestrian (1 if truck is involved with Pedestrian; 0 otherwise)	-0.0023	-0.0025	-0.0034	-	0.0041	0.0041	0.0061	-	-0.0018	-0.0016	-0.0027	-
Bicycle (1 if truck is involved with bicycle; 0 otherwise)	-0.0027	-	0.0017	-0.0015	0.0046	-	0.0036	0.0013	-0.0019	-	-0.0019	0.0002
Fixed object (1 if truck is involved with fixed object; 0 otherwise)	0.0116	0.0155	0.0081	*0.0059*	-0.0093	-0.0136	-0.0060	*-0.0044*	-0.0022	-0.0019	-0.0021	*-0.0015*
Traffic signals and signs (1 if violation category is traffic signals and signs; 0 otherwise)	-0.0027	-	-0.0057	-0.0044	0.0032	-	0.0053	0.0040	-0.0005	-	0.0004	0.0004
Improper passing (1 if violation category is improper passing; 0 otherwise)	0.0042	0.0072	0.0125	-	-0.0041	-0.0068	-0.0121	-	-0.0002	-0.0004	-0.0004	-

Unsafe lane change (1 if violation category is unsafe lane change; 0 otherwise)	-	0.0106	-	-	-	-0.0100	-	-	-	-0.0005	-	-
Automobile right of way (1 if violation category is automobile right of way; 0 otherwise)	-	-0.0116	-	-0.0121	-	0.0148	-	0.0149	-	-0.0033	-	-0.0028
Wrong side of road (1 if violation category is wrong side of road; 0 otherwise)	-	-	-0.0037	-0.0049	-	-	0.0036	0.0045	-	-	0.0002	0.0004
Unsafe speed (1 if violation category is unsafe speed; 0 otherwise)	-	-	-	-0.0307	-	-	-	0.0278	-	-	-	0.0029
Felony (1 if crash is felony hit-and-run; 0 otherwise)	-0.0018	-	-0.0017	-	0.0019	-	0.0016	-	-0.0001	-	0.0001	-
Not Hit and Run (1 if crash is not hit-and-run; 0 otherwise)	-0.4169	-	-	-	0.3785	-		-	0.0384	-	-	-
Misdemeanor (1 if crash is misdemeanor hit-and-run; 0 otherwise)	-	0.0057	0.0047	0.0086	-	-0.0053	-0.0044	-0.0081	-	-0.0004	-0.0004	-0.0006
Passenger car/station wagon (1 if at fault vehicle type is passenger car/station wagon; 0 otherwise)	-	0.0018	0.0015	-	-	0.0045	0.0036	-	-	-0.0063	-0.0051	-
Crash time												
Daylight (1 if light condition is daylight; 0 otherwise)	0.0142	-	-	-	0.0127	-	-	-	-0.0269	-	-	-
Dark - street lights (1 if light condition is dark - street lights; 0 otherwise)	-	-	-0.0008	-	-	-	-0.0005	-	-	-	0.0013	-
Weekday (1 if crash occurred during the weekday; 0 otherwise)	0.1264	-0.0168	0.0061	-	-0.1146	-0.0312	0.0119	-	-0.0119	0.0480	-0.0179	-
Other variables												
At fault (1 if truck driver is at fault; 0 otherwise)	0.3675	0.0037	0.0036	0.0022	-0.3383	0.0072	0.0051	0.0049	-0.0292	-0.0109	-0.0087	-0.0072
Dry (1 if road surface condition is dry; 0 otherwise)	0.0575	-	0.1085	-	-0.0629	-	-0.1211	-	0.0053	-	0.0126	-
Wet (1 if road surface condition is wet; 0 otherwise)	-	0.0040	0.0064	-	-	-0.0039	-0.0063	-	-	-0.0001	-0.0002	-
Rainy (1 if weather condition is rainy; 0 otherwise)	-	-0.0043	-	0.0025	-	0.0046	-	-0.0031	-	-0.0002	-	0.0006
Intersection (1 if intersection-related crash; 0 otherwise)	-0.0158	-0.0110	-	-0.0129	0.0138	0.0101	-	0.0118	0.0020	0.0009	-	0.0011
Old truck (1 if truck is above 15 years old; 0 otherwise)	-	-0.0028	*-0.0128*	*-0.0141*	-	-0.0052	*0.0119*	*0.0127*	-	0.0080	*0.0009*	*0.0014*
New truck (1 if truck is less than 6 years old; 0 otherwise)	-	-	-0.0138	-0.0135	-	-	0.0130	0.0152	-	-	0.0008	-0.0016

In the 2010-13 mornings, male drivers (comprising 96% of all drivers) were more likely to be involved in either severe injury or no-injury crashes than their female counterparts, but this effect was from a random parameter (suggesting variability across observations) and was statistically insignificant in other time-of-day/time-period categories. As with ethnicity, this finding could also be related to different truck routing and delivery characteristics assignments that may vary by gender.

The young-age indicator, middle-age indicator and non-drinking indicator did not produce results that were consistent across time-of-day/time-period combinations. However, relative to their older counterparts, drivers younger than 31 years of age were involved in less severe crash outcomes in the 2014-17 time period. Interestingly, the marginal effect for no-injury in the afternoon was more than 2.5 times the marginal effect for no-injury in the morning, making no-injury crash outcomes involving younger drivers much more likely in the afternoon than morning (the magnitude of the afternoon marginal effect of 0.4724 is substantial, and well above other no-injury marginal effects). This finding suggests trucking firms may want to check the routes of younger drivers (morning versus afternoon) and consider that they may be more susceptible to time-of-day variations in performance relative to their older counterparts.

In 2014-17 for middle-aged drivers had a lower probability of a no-injury crash in the afternoon than in the morning, but this was a random parameter suggesting significant variation in the effect of this variable across crashes.

5.7.2 Driver Actions

Table 5.10 shows that being stopped before the collision generally resulted in less severe crash outcomes (positive marginal effects for no injury and negative marginal effects for minor injury and severe injury) in all time-of-day/time-period combinations except for the afternoons in 2014-17. Proceeding straight before the collision also resulted in less severe crash outcomes in general, except for the mornings in 2014-17 where it was statistically insignificant.

Backing (1 if movement preceding collision is backing; 0 otherwise) consistently resulted in less severe injuries (likely because of the low speed involved) in all time-of-day/time-period combinations, without much change across time-of-day/time-period combinations. Interestingly, trucks making a U-turn resulted in a higher probability of minor injury in the afternoons across years, but trucks making a U-turn did not significantly affect injury-severity probabilities in the morning. This may be a function of traffic conditions and other related factors but may be worth safety-conscious trucking companies investigating further.

Table 5.10 shows that making a left turn results in more severe crash outcomes in the afternoons of 2014-17 and passing a vehicle results in a higher probability of minor injury in the morning of 2014-17. Neither of these variables had a statistically significant effect on injury severities in 2010-13.

5.7.3 Crash Characteristics

Table 10 shows that a wide variety of crash characteristics were found to be significant in one or more of the time-of-day/time-period models. Of these, several were statistically significant in all models. Sideswipe crashes consistently resulted in less severe injuries (positive marginal effects for no injury and negative marginal effects for minor injury and severe injury) in all models. The hit-object indicator also consistently resulted in less severe crashes in all models (with little variation by time of day). A collision with a parked vehicle consistently resulted in a higher probability of no injury and lower probabilities of minor injuries and severe injuries (although this

variable produced a random parameter in the 2010-13 morning model). It is also interesting to note that the effect of this variable on injury-outcome probabilities is about twice in the afternoon as it is in the morning across the two time periods.

Collisions with fixed objects consistently resulted in less severe crashes (a higher likelihood of no injury and a lower likelihood of minor and severe injury) but produced a random parameter for the 2014-17 afternoon model. There was comparatively little difference in the marginal effects of this variable between morning and afternoon periods.

While other explanatory variables in this category mostly show considerable variation in their effect on injury severities across the time-of-day/time-period models, there are some exceptions. For example, the indicator variable for automobiles violating the right of way consistently resulted in a higher likelihood of minor injury over the years, but only in the afternoon time period. In contrast, crashes that were classified as hit-and-run felonies resulted in a higher likelihood of minor injury over the years, but only for the morning time period. These findings underscore important morning/afternoon differences even when effects are generally unstable over the years.

5.7.4 Crash Time

Table 5.10 shows the indicator variables for daylight, dark-street lights and weekdays do not generally produce consistent findings across time-of-day/time-period combinations. It is important to note here that because we consider times 6:00 a.m. to 5:59 p.m., daylight and dark streetlight will only be contrasted with non-daylight and non-dark streetlight in the late fall and winter months when the daylight time is short. Table 10 marginal effects show daylight significantly decreases severe injury crash outcomes in the mornings of 2010-13 (relative to non-daylight conditions), and in 2014-17, dark with streetlights increases severe-injury crash outcomes (relative to non-dark streetlight conditions). So, these variables are capturing the same morning effect across the two time periods in that dark mornings (occurring in late fall and winter) result in more severe crash outcomes.

The weekday-indicator marginal effects show that, in the morning, weekdays resulted in less severe morning crash outcomes in 2010-13 (a higher likelihood of no injury and lower likelihoods if minor injury and severe injury) relative to weekend crashes. But in the afternoons of the 2010-13 period, weekday crashes resulted in more severe crash outcomes (a higher likelihood of severe injury with a lower likelihood of no injury and minor injury), relative to weekend crashes. The morning time period in 2014-17 resulted in a somewhat different findings with weekdays resulting in a higher likelihood of minor injury and lower likelihoods of no injury and severe injury relative to weekend crashes. The afternoon effect of weekday crashes was statistically insignificant in 2014-17 (no significant difference between weekday and weekend crashes).

5.7.5 Other variables

Table 5.10 shows that if the truck driver was deemed to be at fault, there is a higher probability of no injury and lower probability of severe injury in all time-of-day/time-period combinations. This may suggest that truck-driver training may provide them the skills to mitigate crash consequences after they made a driving error. Interestingly, dry road-surface conditions increased the probability of both no-injury and severe injury crashes, but only in the morning time period. This may suggest a high variance in morning-driver behavior in dry-road conditions with conservative and aggressive behaviors, a finding that is consistent with earlier research that explored the effect of road surface conditions on injury severity (Morgan and Mannering, 2011). In contrast, the wet-

road condition indicator and the rain indicators were significant in several afternoon periods but did not produce consistent marginal effects (Table 5.10).

Intersection-related crashes generally resulted in more severe crash outcomes (lower probability of no injury and higher probabilities of minor and severe injuries) but were statistically insignificant in the afternoons in the 2014-17 time period. Finally, truck age was statistically significant in several time periods (and with random parameters in both daily time periods in 2014-17) but did not produce temporally stable results.

5.7.6. Heterogeneity in the Means of Random Parameters

Table 5.5 shows that, in 2010-23 morning model, two variables were found to produce random parameters with heterogeneity in means; an indicator variable for male drivers and an indicator variable for Hispanic drivers. For the male-indicator and Hispanic-indicator, proceeding straight before collision resulted in an increase in their mean, making no injuries more likely (relative to other types of movements preceding collision). For the Hispanic-indicator, non-hit-and-run crashes decreased its mean, making no injuries less likely. As indicated in Table 5.6, none of the explanatory variables were found to significantly affect the mean or variance of the random parameter in 2010-13 afternoon model.

With regard to the 2014-17 morning model (Table 5.7), the sideswipe indicator variable was found to produce a random parameter with heterogeneity in mean. For this variable, backing or improper passing resulted in a decrease in the mean (making no injuries less likely) while black drivers had an increase in the mean (making no injuries more likely). Passenger cars/station wagons, when being at fault, were also found to decrease the mean of sideswipe-indicator, making severe injuries less likely.

As shown in Table 5.8, in 2014-17 afternoon model, and indicator variable for middle age drivers (1 if truck driver is younger than 51 years old and older than 30 years old; 0 otherwise) produced a random parameter with heterogeneity in mean. Unsafe speed decreased the mean of this variable, making no injuries less likely.

5.8. Summary and Conclusions

Using data on large truck crashes in Los Angeles from January 1, 2010 to December 31, 2017, this chapter examined the effect of time-of-day and time periods on resulting injury severities in large-truck crashes. With three possible crash-injury severity outcomes (measured by the most severely injured individual in the crash) of no injury, minor injury, and severe injury, a wide range of possible factors affecting large-truck crash-injury severities such as driver's characteristics, driver' actions, crash characteristics, and roadway and environmental conditions were considered in the analysis.

Likelihood ratio tests show that the effect of factors that determine injury severity varies significantly across time-of-day/time-period combinations. However, there were several explanatory variables that do produce temporally stable effects in terms of their impact on resulting injury severities. Black drivers, crashes occurring while backing, sideswipe crashes, hit-object crashes, parked-vehicle crashes, fixed-object crashes, and truck-driver at fault crashes all consistently produced less severe crashes across all times-of-day/time-periods combinations. There are also some interesting time-of-day effects. For example, 2014-17 models show that younger truck drivers are more likely to have a no-injury crash outcome in the afternoon than they are in the morning, and the hit-object indicator variable has roughly twice the effect on injury probabilities in the afternoon time period relative to the morning time period.

The findings of this research underscore the importance of accounting for the time-dependent effect that variables have on resulting injury-severity outcomes in crashes involving large trucks. The findings of this research should be of value to decision makers and trucking companies seeking to improve truck safety, and also serve as a starting point for future research in this topic that may explore this temporal phenomenon in different regions of the country and in other parts of the world. Future research can also benefit from combining severity models with frequency models since decreasing the number of crashes (even those with less severe injuries) provides considerable economic advantages to the society and trucking companies.

Chapter 6: Non-Decreasing Threshold Variances in Mixed Generalized Ordered Response Models: A Negative Correlations Approach to Variance Reduction

6.1. Introduction

Ordered outcomes, such as those encountered in accident-injury severity (no injury, injury, fatality), measurements of satisfaction (highly dissatisfied, dissatisfied, neutral, satisfied, highly satisfied), measurements of levels of agreement or disagreement (strongly disagree, disagree, neutral, agree, strongly agree), and so on, are often modeled using ordered response models. These models have a potential advantage over unordered response models, such as the multinomial logit model and its variants, because ordered models recognize the inherent ordinal pattern of outcome responses. Standard ordered response models are based on an underlying continuous latent propensity function that is assumed to be a function of observed explanatory variables and an unobserved random component (Aitchison and Silvey, 1957; McKelvey and Zavoina, 1975; Washington et al., 2011). The latent propensity function is mapped to observed outcomes using a set of thresholds that are increasing in order. The major drawback associated with this standard ordered response (SOR) model is that it assumes the thresholds to be same for all individuals, which might not be appropriate in all applications.

To overcome this threshold restriction in the standard ordered response models, Maddala (1986) and Ierza (1985) proposed a generalized-thresholds version of the ordered response model where the thresholds were expressed as a linear function of explanatory variables. As an extension to this model structure, Srinivasan (2002) expressed the thresholds as correlated random variables with their mean as a linear function of observed explanatory variables. However, this linear specification of thresholds does not ensure the increasing order of thresholds and might result in negative probabilities (Greene and Hensher 2010a). To address this issue, Eluru et al. (2008) and Greene and Hensher (2010b) used a nonlinear specification for thresholds where each threshold was obtained by adding a non-negative term to the preceding threshold, so that the ordering of thresholds was ensured. The non-negative term was specified as an exponential function of a linear function of explanatory variables. Researchers have termed this generalized-thresholds version as the generalized ordered response model. To avoid confusion with the model names used in the literature, we term the linear-thresholds specification models as the ordered mixed response (OMR) model and the nonlinear-thresholds specification generalized ordered response (GOR) model. With regard to the GOR model, to account for heterogeneity in the parameter estimates due to unobserved factors, researchers have considered random parameters in both the propensity function and the thresholds. This model structure is referred to as the mixed generalized ordered response (MGOR) model by Eluru et al. (2008) and hierarchical ordered probit (HOPIT) model by Greene and Hensher (2010a). We use the term "MGOR" hereafter to avoid confusion with the model names. It is worth noting here that the random parameters in the thresholds are typically assumed to follow distributions with an unbounded support, such as the normal distribution.

Due to the flexibility offered by generalized ordered response (GOR) and mixed generalized ordered response (MGOR) models relative to the standard ordered response (SOR) model, many researchers (Yasmin et al. 2015a, 2015b; Forbes and Habib 2015; Fountas and Anastasopoulos 2017) have used these models in various contexts. Chiou et al. (2013) proposed a bivariate generalized ordered probit model and used it to model accident-injury severities in two-vehicle crashes. Castro et al. (2013) developed spatial random parameters generalized ordered probit model to accommodate the spatial dependencies in the accident-injury severity levels. Yasmin et al. (2014) proposed a latent segmentation based generalized ordered logit model assuming the presence of different latent groups of observations. Table 1 summarizes various

studies that have used the GOR family of models in the context of modeling traffic accident injury severity outcomes[29].

Despite the above-discussed evolution of the MGOR family of models, to the best of our knowledge, all implementations of the MGOR models to date impose an implicit restriction on the order of variances of thresholds. Specifically, as discussed earlier, the thresholds in ordered response models must be in an increasing order, which is ensured in MGOR models by specifying a higher order threshold as a sum of its preceding threshold and a non-negative random term that is typically in the form of an exponential function. Such a hierarchical specification of thresholds with random parameters leads to the restriction that the variances of thresholds are also in a non-decreasing order. However, this restriction is not necessary and can potentially lead to difficulty in the estimation of random parameters in higher order thresholds (more later).

To be sure, the MGOR model structure, in its very general form, does allow the analyst to relax the non-decreasing order of threshold variances. This can be done in at least two ways. The first approach is to allow negative correlations between the random parameters of different thresholds. Since a higher order threshold is specified as a sum of two terms (its preceding threshold with random parameters and an exponential term with random parameters), negative correlation between the two terms allows for the overall variance of the higher order threshold to

[29] Mannering et al. (2016), provide a general discussion of unobserved heterogeneity in accident injury-severity modeling. Apart from the accident injury-severity modeling, there are other research areas (sociology, psychology and economics) that have used OMR and MGOR model structures (Pudney and Shields, 2000; Boes and Winkelmann, 2006; Greene et al., 2008; Baba, 2009; Mentzakis and Moro, 2009; Boes and Winkelmann, 2010; Stanley et al., 2011; Greene et al., 2014; and Shabanpour et al., 2017).

Table 1: Summary of empirical studies that used generalized ordered response models in accident research.

Study	Abbreviation(s) of considered model(s)	Ordered outcome response representation	Estimation of random parameters (RP)		Major findings/ contributions from methodological stand point
			Propensity function	Thresholds	
Srinivasan (2002)	Standard Ordered Response Logit (SORL) and Ordered Mixed Logit (OML)	Traffic crash injury severity – four category variable	• Propensity function specification did not allow for the estimation of RP.	• Each threshold in the OML model was expressed as a linear function of explanatory variables, and RP with correlations between them were allowed over the constants. • All the correlated random parameters were found to be statistically significant. • Interestingly, the variances of thresholds were 0.013, 0.937, and 0.0026 and did not follow any order.	• OML model provided a better fit for the observed crash data than SORL model. • Prediction capability of OML model was significantly better than the SORL model.
Eluru et al. (2008)	SORL and Mixed Generalized Ordered Response Logit (MGORL)	Pedestrian and bicyclist injury severity - four category variable	• Propensity function specification allowed for the estimation of RP in MGORL model. • No RP were found to be statistically significant.	• Threshold specification allowed for the estimation of RP in MGORL model. • No RP were found to be statistically significant.	• SORL model estimation resulted in inconsistent estimates for several variables. • MGORL model provided better statistical fit over SORL model.
Clifton et al. (2009)	Ordered Mixed Probit (OMP)	Pedestrian injury severity - three category variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of RP.	• Incorporating built environment characteristics and environmental conditions significantly improved the explanatory power of OMP model.
Chiou et al. (2013)	Bivariate Generalized Ordered Response Probit (BGORP) and Bivariate Standard Ordered Response Probit (BSORP)	Injury severity of the drivers in a two vehicle crash - four category variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of RP.	• BGORP model performed significantly better than the BSORP model in terms of goodness-of-fit indices. • BGORP model had better prediction accuracy than the BSORP model.
Castro et al. (2013)	Spatial Random Parameters Generalized Ordered Response Probit (SRP-GORP) and Standard Ordered Response Probit (SORP)	Injury severity of highway crashes - four category variable	• Propensity function specification allowed for the estimation of RP in SRP-GORP model. • No RP were found to be statistically significant.	• Threshold specification did not allow for the estimation of random parameters.	• SRP-GORP model provided statistically better data fit than the Standard Ordered Response Probit (SORP). • Predicted shares of different injury severity levels from SRP-GORP model were closer to the actual shares as compared to SORP.

Eluru (2013)	GORL, SORL, and Multinomial Logit (MNL)	Four alternatives ordered variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of RP.	• SORL model was found to be restrictive as compared to MNL model for analyzing an ordered response outcome. • GORL model can act as a true ordered equivalent of MNL model. • Irrespective of aggregate shares, GORL model performed well as compared to the MNL model.
Yasmin and Eluru (2013)	SORL, GORL, MGORL, MNL, Nested Logit (NL), and Mixed Multinomial Logit (MMNL)	Passenger vehicle injury severity - four category variable	• Propensity function specification allowed for the estimation of RP in MGORL model. • Three random parameters were found to be statistically significant, and corresponding variables were 1. Restrained system use – Unrestrained (base: restrained) 2. Airbag deployment – deployed (base: not deployed) 3. Collision location: Intersection (base: non-intersection).	• Threshold specification allowed for the estimation of random parameters in MGORL model. • Two random parameters were found to be statistically significant and were in the thresholds demarcating 1. second and third injury severity levels a. Vehicle rolled over 2. third and fourth injury severity levels a. Collision with stationary object (base: another moving object).	• Elasticities obtained using the under-reported sample were incorrect in both the MGORL and MMNL models. • Both the MMNL and MGORL models had similar prediction results at the aggregate and disaggregate levels.
Yasmin et al. (2014)	SORL, GORL, and Latent Segmentation based Standard Ordered Response Logit (LS-SORL)	Pedestrian injury severity - three category variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of random parameters.	• GORL and LS-SORL models provided better data fit as compared to the SORL model. • Also, LS-SORL model provided better data fit than GORL. • In the model validation, GORL model performed marginally better than LS-SORL.
Yasmin et al. (2014)	Latent Segmentation based Generalized Ordered Response Logit(LS-GORL) and LS-SORL	Driver injury severity – three category variable	• Propensity function specification did not allow the estimation of RP.	• Threshold specification did not allow for the estimation of RP.	• At an aggregate level, LS-GORL model performed well as compared to LS-SORL on validation sample.
Hosseinpour et al. (2014)	Random Effects Ordered Mixed Probit (REOMP),	Head on crash severity injury severity - four	• Propensity function specification in REOMP model allowed for the estimation of	• Threshold specification did not allow for the estimation of random parameters.	• REOMP model was found to be statistically better than the OMP and SORP models in terms of data fit.

	Ordered Mixed Probit (OMP) and SORP	category variable	random effects parameter on the constant and was found to be statistically significant.		
Habib and Forbes (2014)	OMP with Non-Linear Thresholds specification (OMPNLT) and SORP	Bicyclist injury severity - five category variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of random parameters.	• OMPNLT model with neighborhood and land use characteristics was found to be statistically better than OMPNLT model without such characteristics and SORP model.
Yasmin et al. (2015a)	Mixed Generalized Ordered Logit Response Model (MGORL)	Severity of fatal injury - seven category variable obtained using the survival time in a fatal crash	• Propensity function specification allowed for the estimation of RP. • Two random parameters were found to be statistically significant, and corresponding variables were 1. Previous record of other harmful motor vehicle convictions 2. Speed limit above 50 mph (base: speed limit < 26mph).	• Threshold specification allowed for the estimation of random parameters. • No random parameters were found to be statistically significant.	• Endogeneity on the outcome variable due to emergency medical service (EMS) response time variable was addressed using a 2-stage model comprising MGORL for the fatality timeline and regression equation for the EMS response time.
Yasmin et al. (2015b)	Generalized Ordered Response Logit Model (GORL)	Passenger vehicle driver injury severity - eleven category variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of random parameters.	• A simple approach was developed to combine information from Fatality Analysis Reporting System (FARS) data and Generalized Estimates System (GES) data.
Forbes and Habib (2015)	OMPNLT and SORP	Pedestrian injury severity - five category variable	• Propensity function specification did not allow for the estimation of RP.	• Threshold specification did not allow for the estimation of random parameters.	• OMPNLT model performed well as compared to SORP model in terms of model fit.
Fountas and Anastasopoulos (2017)	Mixed Generalized Ordered Response Probit (MGORP), Generalized Ordered Response Probit (GORP), SORP, and Random Parameters SORP (RPSORP)	Single vehicle crash injury severity - four category variable	• Propensity function specification allowed for the estimation of RP in MGORP and RPSORP models. • Seven random parameters were found to be statistically significant in both MGORP and RPSORP models, and corresponding indicator variables were	• Threshold specification allowed for the estimation of random parameters on the constants in the thresholds in MGORP model. • Both constants in the thresholds were statistically significant at 95% confidence level.	• MGORP model was found to be statistically better than the GORP, SORP, and RPSORP models in terms of data fit. • MGORP models had better forecasting accuracy as compared to its model counterparts.

			1. Presence of vertical curve with the curve length greater than 400 feet 2. Average annual daily traffic per lane greater than 8500 vehicles. 3. Driving under the influence of alcohol or drugs 4. Vehicle crashed due to out of control 5. Vehicle exceeded a reasonable safe level or speed limit 6. Vehicle was travelling straight at the time of crash 7. Pedestrian was involved in the crash.		
Anarkooli et al. (2017)	REOMP, OMP, Random Effects Ordered Response Probit (REORP), SORP, MNL, and MMNL	Single vehicle rollover crash severity - three category variable	• Propensity function specification allowed for the estimation of random effects parameter on the constant in REOMP model and was found to be statistically significant.	• Threshold specification did not allow for the estimation of random parameters.	• REOMP model was found to be statistically better than the OMP, REORP, SORP, MNL and MMNL models in terms of model fit.
Zou et al. (2017)	SRP-GORP and RPSORP	Single-vehicle and multi-vehicle truck crash injury severity - four category variable	• Propensity function specification allowed for the estimation of RP in both SRP-GORP and RPSORP models. • One random parameter was found to be statistically significant in RPSORP model for single vehicle crash severity and corresponding variable is 1. Truck registered weight.	• Threshold specification did not allow for the estimation of random parameters.	• Spatial dependency and temporal effects have significant effect on the single vehicle and multi-vehicle truck crash severity.
Xin et al. (2017)	MGORP with Heterogeneity in Means and Variances (MGORPHMV), MGORP, GORP and ORP	Pedestrian injury severity - four category variable	• Propensity function specification allowed for the estimation of RP in MGORPHMV and MGORP models. • Two random parameters were found to be statistically significant in both MGORPHMV and MGORP	• Threshold specification allowed for the estimation of random parameters in both MGORPHMV and MGORP models. • No random parameters were found to be statistically significant.	• The order of statistical superiority (high to low) of models in terms of data fit is MGORPHMV, MGORP, GORP and ORP model.

			models, and corresponding variables were 1. Elderly pedestrian indicator 2. Very elderly pedestrian indicator. • Moreover, the random parameter on elderly pedestrian indicator had significant heterogeneity in both means and variance.		

be lower than the variance of its preceding threshold. The second approach is to use truncated distributions for thresholds, where the distribution of a higher order threshold is left-truncated by the distribution of its preceding threshold. Between these two approaches, the former is easier to implement. The latter approach is a non-trivial[30] modification of the MGOR structure, albeit it is a fruitful avenue for future research. Even in the context of the former approach, we are not aware of studies in the literature that explored correlated random parameters in MGOR models.

The intent of this chapter is to highlight the above-discussed implicit assumption made by most implementations of MGOR models that the thresholds follow a non-decreasing order of variances. In addition, the chapter explores the use of negative correlations as a variance reduction technique for relaxing the non-decreasing variances restriction in the MGOR family of models. We explore these variance and correlation issues through a simulation experiment. Specifically, we simulate ordinal outcome datasets with known negative correlation structures among an underlying true set of random parameters in threshold functions. For each of the simulated datasets, two models were estimated; one allowing correlations between random parameters and the other not allowing such correlations. The impact of ignoring correlations is then evaluated by comparing the two models using various evaluation criteria to assess the efficacy of introducing negative correlations as a variance reduction technique in the thresholds of MGOR models.

The remainder of our chapter is structured as follows. Section 6.2 presents the model structure of SOR and MGOR models. Section 6.3 provides a simple, mathematical proof for the non-decreasing order of variance of thresholds in the absence of correlation between random parameters in thresholds. In addition, this section presents a hypothetical scenario to explain how such a restriction (due to ignoring correlations) can potentially lead to difficulties in estimating random parameters in higher order thresholds. Section 6.4 describes the methodology (simulation experiments) adopted to evaluate correlations as a variance reduction technique in the thresholds of MGORL models. Section 6.5 presents the results and findings. Section 6.6 concludes the chapter.

6.2. Model structure

In this section, we present the basic model structures for the standard ordered response model (SOR) and the mixed generalized ordered response model (MGOR).

6.2.1 Standard ordered response model (SOR)

Let n (1, 2, 3...N) denote each observation and k (1, 2, 3...K) denote ordered outcomes. The latent propensity function y_n^* for observation n is expressed as

$$\boldsymbol{y_n^* = \beta X_n + \varepsilon_n} \tag{6.1}$$

where $\boldsymbol{X}_n$ is a vector of explanatory variables that influence y_n^*, $\boldsymbol{\beta}$ is a corresponding vector of estimable parameters, and ε_n is an unobserved random term which is assumed to follow a known probability distribution. Observed ordinal outcome y_n is then defined by the latent propensity function y_n^* using a set of threshold parameters as follows:

$$\boldsymbol{y_n = k, if\ \Psi_{k-1} < y_n^* < \Psi_k} \tag{6.2}$$

[30] The left truncation point of the distribution for a higher order threshold is another random variable (given by the distribution of the preceding threshold), as opposed to a deterministic value. Therefore, deriving an MGOR model structure with randomly truncated threshold distributions is a non-trivial extension and beyond the scope of this paper.

where Ψ_{k-1} and Ψ_k are a pair of estimable thresholds associated with k^{th} ordered outcome. All the thresholds are restricted to be in an increasing order, and the lower most and upper most thresholds are assumed to be negative infinity and positive infinity ($-\infty < \Psi_1 < \Psi_2 < \cdots < \Psi_{K-1} < \infty$), respectively (this is assuming that the latent propensity function y_n^* follows an unbounded distribution). For identification reasons, either the constant in the propensity function or any one of the thresholds must be fixed to zero. In this exposition, the constant in the propensity function is fixed to zero, and all the K-1 thresholds are parameters to be estimated. The log-likelihood (LL_{nk}) for observation n facing k^{th} ordered outcome is:

$$\boldsymbol{LL_{nk} = Pr(y_n = k \mid X_n) = \Gamma[\Psi_k - \beta X_n] - \Gamma[\Psi_{k-1} - \beta X_n]} \tag{6.3}$$

where $\Gamma[\cdot]$ is the cumulative distribution function of the random error term ε_n.

6.2.2 Mixed generalized ordered response (MGOR) model

The MGOR model structure is an extension of the SOR model structure with the thresholds parameterized as a function of explanatory variables, and the inherent ordering of the thresholds is ensured using a nonlinear specification for thresholds where each threshold is specified by adding a non-negative term to the preceding threshold. Moreover, to account for unobserved heterogeneity in the parameter estimates across observations, random parameters are included in the propensity function and the threshold functions as shown in Equations 6.4, 6.5 and 6.6.

$$\boldsymbol{y_n^* = \beta X_n + \gamma_n Y_n + \varepsilon_n} \tag{6.4}$$

$$\boldsymbol{\Psi_{nk} = \alpha_k U_{nk} + \theta_{nk} V_{nk}}, \text{ if k = 1} \tag{6.5}$$

$$\boldsymbol{\Psi_{nk} = \Psi_{n,k-1} + exp(\alpha_k U_{nk} + \theta_{nk} V_{nk}), \forall\, k > 1} \tag{6.6}$$

where $\boldsymbol{X}_n$ and $\boldsymbol{Y}_n$ are vectors of exogenous variables in the propensity function, $\boldsymbol{\beta}$ is a vector of fixed parameters and $\boldsymbol{\gamma}_n$ is a vector of random parameters in the propensity function. Similarly, $\boldsymbol{U}_{nk}$ and $\boldsymbol{V}_{nk}$ are vectors of exogenous variables, $\boldsymbol{\alpha}_k$ and $\boldsymbol{\theta}_{nk}$ are vectors of fixed and random parameters, respectively, in the kth threshold. For identification reasons, and without loss of generality, all the parameters in the first threshold except a constant are set to zero ($\Psi_{n1} = \alpha_1$).

As discussed earlier, the hierarchical specification of thresholds in Equation 6.6, where a higher order threshold (Ψ_{nk}) is specified as a sum of its preceding threshold ($\Psi_{n,k-1}$) plus a non-negative random term, $\exp(\boldsymbol{\alpha}_k \mathbf{U}_{nk} + \boldsymbol{\theta}_{nk} \mathbf{V}_{nk})$, ensures that the thresholds are in an increasing order.

The random parameters vectors $\boldsymbol{\gamma}_n$ and $\boldsymbol{\theta}_n$, where $\boldsymbol{\theta}_n$ is obtained by stacking the $\boldsymbol{\theta}_{nk}$ vectors across all k, are realizations from multivariate distributions $f(\boldsymbol{\gamma})$ and $f(\boldsymbol{\theta})$. The log-likelihood (LL_{nk}) for observation n facing k^{th} ordered outcome is written as,

$$\boldsymbol{LL_{nk} = \int_{\gamma}\int_{\theta} \Gamma[(\Psi_{nk}|\theta) - (\beta X_n|\gamma)] - \Gamma\big[(\Psi_{n,k-1}\big|\theta\big) - (\beta X_n|\gamma)] f(\theta) f(\gamma) d(\theta) d(\gamma)} \tag{6.7}$$

Note that $f(\boldsymbol{\gamma})$ and $f(\boldsymbol{\theta})$ are multivariate distributions. Therefore, the structure of the MGOR model allows for correlations among the random parameters, in the latent propensity function as well as in the threshold functions. However, it is a common practice in empirical research to ignore such correlations; as indicated earlier, we are not aware of empirical studies that explored correlations between random parameters in the threshold functions of ordered response models.

6.3 Non-decreasing order of variances of thresholds in MGOR models with uncorrelated random parameters

In this section, we prove the non-decreasing order of variances of thresholds in MGOR models with uncorrelated random parameters and demonstrate, through a hypothetical example, how such restriction might lead to difficulties in estimating random parameters in higher order thresholds.

6.3.1 The order of variance of thresholds

Let $VAR(\cdot)$ and $E(\cdot)$ represent the variance and the expected value of a random variable, respectively, and let $COV(\cdot)$ represent the covariance between any two random variables. Thresholds and non-negative terms are random in the presence of random parameters and the variance of a threshold Ψ_{nk} is expressed as $VAR(\Psi_{nk}) = VAR(\Psi_{n,k-1}) + VAR(\Delta_{nk}) + 2COV(\Psi_{n,k-1},\ \Delta_{nk})$, where Δ_{nk} is a non-negative term that is added to $\Psi_{n,k-1}$ to obtain Ψ_{nk}. As can be observed in Equation 6.6, the non-negative term Δ_{nk} is $\exp(\boldsymbol{\alpha}_{\mathrm{k}}\mathbf{U}_{\mathrm{nk}} + \boldsymbol{\theta}_{\mathrm{nk}}\mathbf{V}_{\mathrm{nk}})$. If the correlations between the random parameters in $\Psi_{n,k-1}$ and Δ_{nk} are ignored or restricted to zero, the covariance term, $COV(\Psi_{n,k-1},\ \Delta_{nk})$, becomes zero and forces the variance of each threshold to be either greater than or equal[31] to the variance of the preceding threshold. On the other hand, a negative correlation between the random parameters in $\Psi_{n,k-1}$ and Δ_{nk} allows for a possibility that $VAR(\Psi_{nk}) < VAR(\Psi_{n,k-1})$, depending on the level of correlation between the random parameters and the magnitude of the deterministic components.

Considering normally distributed random parameters, which are generally employed in empirical research involving MGOR models, the thresholds can be viewed as a sum of multiple log-normally distributed random variables.[32] Following the notation used in section 6.2.2, the expressions for the variance of first three thresholds with normally distributed random parameters can be written as shown below (see Appendix 6.A for a detailed derivation).

$$VAR(\Psi_{n1}) = 0,$$
$$VAR(\Psi_{n2}) = VAR(\exp\,(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2})), \tag{6.8}$$
$$VAR(\Psi_{n3}) = VAR(\exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2})) + VAR(\exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})) + C_{n23},$$

where $C_{n23} = \exp\left[\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + E(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}) + \frac{VAR(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2})+VAR(\boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})}{2}\right] \times \left[\exp\left(COV(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}, \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})\right) - 1\right]$.

If the random parameters are uncorrelated, the covariance term $COV(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}, \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})$ is equal to zero, which implies that $C_{n23} = 0$ and $VAR(\Psi_{n3}) = VAR(\Psi_{n2}) + VAR(\exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}))$. Therefore, in the presence of uncorrelated random parameters in the thresholds, the variance of thresholds are restricted to be in a non-decreasing order for a given observation. But there is no need for imposing such a restriction on the order of variance of thresholds. For example, in the ordered response model (with the linear specification for thresholds and with correlation between the random parameters in thresholds) estimated by Srinivasan (2002), the variances of the estimated thresholds do not follow any order.

This inherent restriction on the variance of thresholds can be relaxed by allowing correlations between random parameters in thresholds, which indeed makes the covariance term $COV(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}, \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}) \neq 0$. Depending on the sign and level of correlation between the random parameters, and the magnitude of the deterministic component in the thresholds, the variance of a threshold can be less than the variance of the preceding threshold. Specifically, negative correlations allow for the possibility of non-decreasing order in the variances of the

[31] The variances would be equal when the non-negative term Δ_{nk} does not have random parameters. For example, when an empirical specification does not yield statistically significant random parameters in Δ_{nk}.

[32] This is assuming that the first threshold, which is not an exponential function, is not a random parameter (for identification reasons). However, if the first threshold is a normally distributed random parameter (with other normalization restrictions for identification), then the subsequent thresholds will become a sum of normal distribution and lognormal distributions.

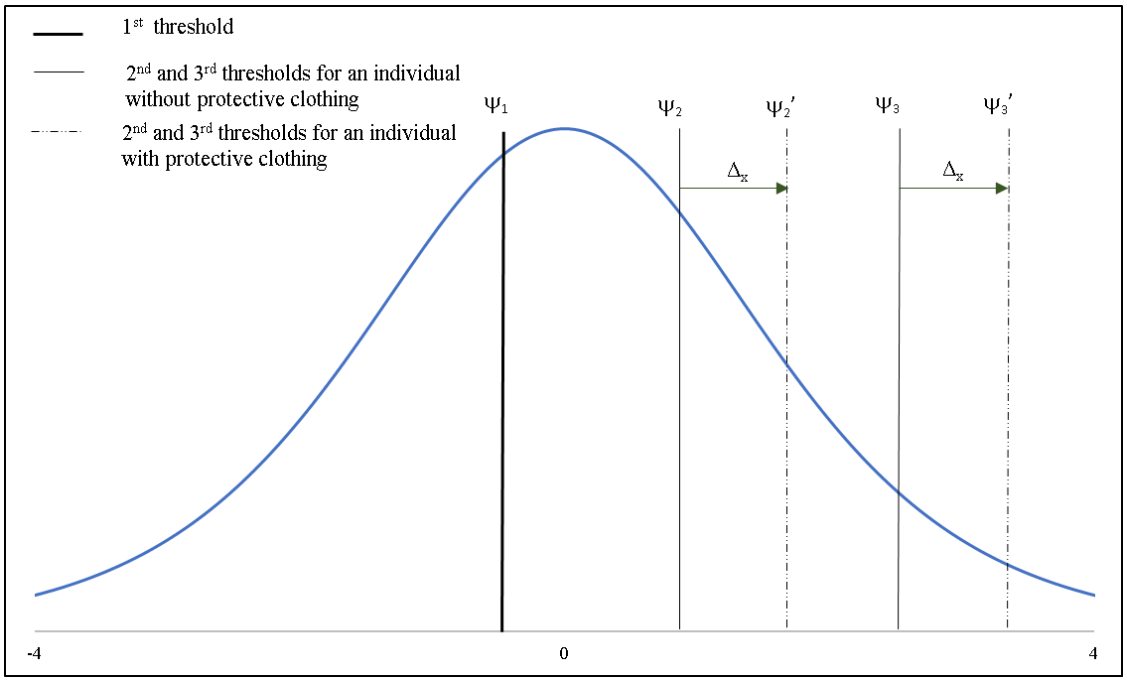
thresholds. Although we derived these expressions for normally distributed random parameters, the above-discussed restriction on the order of variance of the thresholds will occur with the other parametric distributions as well when correlations are not allowed.

6.3.2 Potential Issues with Estimation of Random Parameters in Thresholds

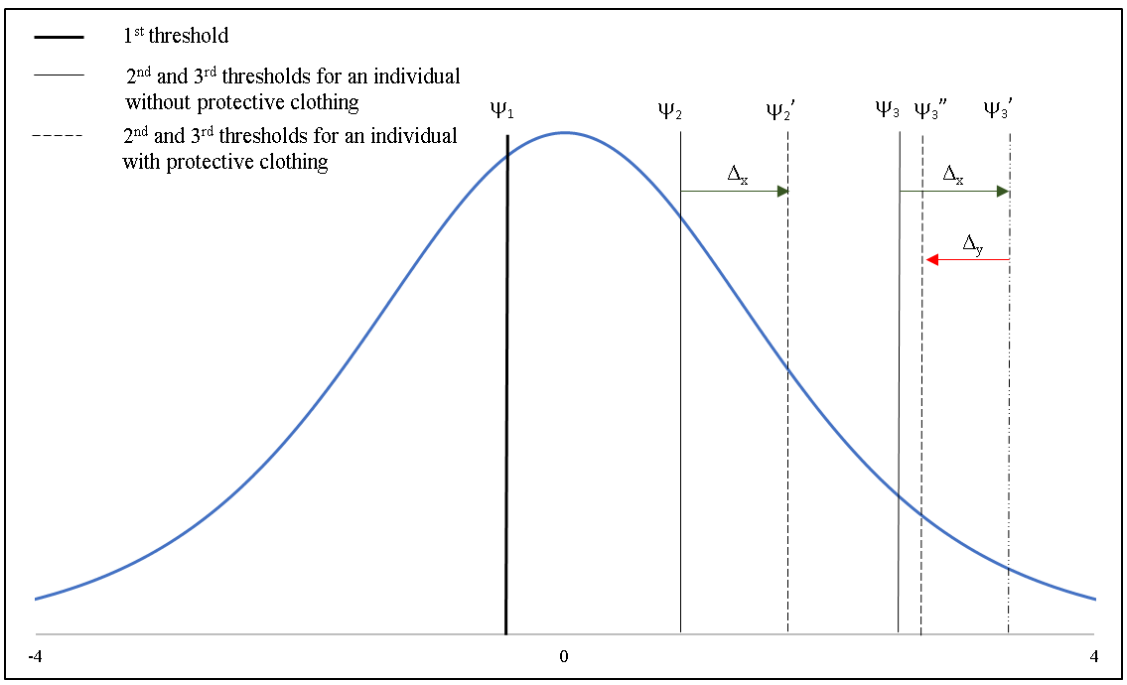
Due to the hierarchical specification of thresholds in the MGOR model, observed variables and their coefficients (along with the random components) entering the threshold function of a lower order threshold (say, the kth threshold) also enter the threshold functions of all higher order thresholds (greater than k^{th} thresholds). Therefore, an independent variable entering k^{th} threshold function influences the probabilities of the corresponding k^{th} order outcome as well as potentially all higher order outcome responses.

For example, let us consider the injury severity of motorcycle crashes on freeways. Let the outcome injury severity levels be no injury, non-incapacitating injury, incapacitating injury, and fatal injury and the corresponding thresholds are Ψ_{1n}, Ψ_{2n}, and Ψ_{3n}. Define a variable PC_n for protective clothing, which is equal to one if the motorcyclist wore protective clothing during the crash, and zero otherwise (protective clothing may include jacket, gloves, heavy pants, boots, knee pads and elbow guards). Let the threshold specifications be as $\Psi_1 = \alpha_1$, $\Psi_{2n} = \alpha_1 + \exp(\alpha_2 + \theta_2 PC_n)$ and $\Psi_{3n} = \alpha_1 + \exp\big(\alpha_2 + \theta_2(PC_n)\big) + \exp(\alpha_3)$, where, α_1, α_2, and α_3 are fixed constants and θ_2 is a positive fixed parameter on protective clothing indicator variable entering directly only in the second threshold[33]. Figure 6.1a shows the position of thresholds for two groups of individuals: (a) who wore a protective clothing during the crash and (b) who did not wear it during the crash. In the case when PC_n enters only the second threshold (Ψ_{2n}) and takes the value 1, the second and third thresholds move to the right by Δ_x (= $\exp(\alpha_2 + \theta_2) - \exp(\alpha_2)$) on the propensity scale, resulting in an increase in the probability of non-incapacitating injury and decrease in the probability of fatal injury (while all the independent variables and parameters in the propensity function remains same).

[33] Note that the protective clothing variable enters the third threshold through the second threshold but not directly.



a) Shift in the thresholds when protective clothing variable enters only the second threshold directly and takes value 1



b) Shift in the thresholds when protective clothing variable enters both the second and third thresholds directly and takes value 1

Figure 1: Influence of protective clothing variable on the shift of thresholds.

In reality, however, wearing protective clothing during a high impact crash, such as those likely to occur on freeways, will likely reduce the injury severity level from incapacitating injury to non-incapacitating injury, but may have little influence on reducing higher injury-severity levels (fatal injury level in our case). See, for example, Erdogan et al. (2013) for a supporting finding that wearing protective clothing protects from soft tissue injuries but not from severe fractures. To incorporate such differential effect of protective clothing on incapacitating and fatal injury levels, the PC_n variable should enter directly into the Δ_{nk} term of the third threshold as well (along with its entry through the second threshold), but with a negative coefficient, that is, when the third threshold is specified as $\Psi_{3n} = \exp\big(\alpha_2 + \theta_2(PC_n)\big) + \exp\big(\alpha_3 + \theta_3(PC_n)\big)$, where $\theta_3 < 0$. With such specification, when PC_n takes the value 1, the second term of Ψ_{3n} shrinks by -Δ_y (= $\exp(\alpha_3 + \theta_3) - \exp(\alpha_3)$) making the overall shift in the third threshold equal to Δ_x - Δ_y (as shown in Figure 6.1b). That is, a rightward shift of Ψ_{3n} through a positive coefficient (θ_2) will be counteracted by a leftward shift through a negative coefficient (θ_3). Naturally, the higher is the value of θ_2, the lower should be the value of θ_3 (a negative number of larger magnitude) for counteracting the influence of θ_2 on Ψ_{3n}.

Now, let us extend this discussion when we have random parameters on PC_n. Let the parameter estimates of PC_n in second and third thresholds be represented by two random parameters θ_{2n} and θ_{3n}, respectively. Analogous to the discussion above, a negative dependency can be allowed between θ_{2n} and θ_{3n} through a negative correlation between the two random parameters. Ignoring such dependency (or negative correlation), as discussed earlier, imposes that the variance of Ψ_{3n} is greater than that of Ψ_{2n}. Since variability in the influence of unobserved influences on the third threshold need not always be greater than that on the second threshold, ignoring negative correlation between θ_{2n} and θ_{3n} might make it difficult to estimate a statistically significant variance parameter for θ_{3n}. In other words, the above-discussed restriction might make it difficult to estimate statistically significant random parameters in higher order thresholds, simply because random parameters from lower order thresholds would simply carry forward to higher order thresholds.

As evident from the literature reviewed in Table 6.1, Eluru et al. (2008), Yasmin et al. (2015a) and Xin et al. (2017) tried to estimate random parameters in the thresholds without allowing correlations between them. However, perhaps due in part to the above-mentioned reasons, they were unable to find statistically significant random parameters in thresholds. Therefore, ideally, the model structure should not restrict an order on the variances of thresholds while specifying and testing the model.

6.4. Experimental Design

To evaluate the efficacy of introducing negative correlations as a variance reduction technique in the thresholds of MGOR models, we simulated motorcycle crash datasets with known negative correlation structures among an underlying true set of random parameters in threshold functions. While one may use a real data to evaluate the technique, it is difficult to control for the unobserved internal relationships which might exist between the independent variables and injury outcomes. In order to avoid such issues, a simulation-based approach is used in this chapter. For each of the simulated datasets, we estimated two models – one allowing correlations between random parameters and the other not allowing correlations. The impact of ignoring correlations was then evaluated by comparing the two models using various evaluation criteria.

The outcome injury severity levels in the simulated datasets were no injury, non-incapacitating injury, incapacitating injury, and fatal injury. We assumed that three explanatory

variables – age of motorcyclist, male indicator (1 if a motorcyclist is male, zero otherwise), and intersection indicator (1 if a crash occurred at an intersection, zero otherwise) – influence the latent injury risk propensity of a motorcyclist. Specifically, the latent propensity function is specified as:

$$y_n^* = (\beta_1 \times age_n) + (\beta_2 \times male_n) + (\beta_3 \times intersection_n) + \varepsilon_n \quad (6.9)$$

where β_1, β_2, β_3 are the parameters and ε_n is the random component of the propensity function.

To simulate data with the above propensity function, values for the age variable were drawn from a truncated normal distribution with mean 40 years, standard deviation 15 years, and 16 years and 75 years as the left and right truncation limits, respectively. Values for the indicator variables were drawn from Bernoulli distributions with mean 0.5. Values for the error term ε_n in the propensity function were drawn from a standard logistic distribution.

6.4.1 Threshold Scenarios

We simulated five different scenarios for the thresholds, as summarized in Table 6.2. The second column of the table specifies the propensity function and the threshold functions used, including the parameter values assumed, in each scenario. The parameter of the age variable in the propensity function is assumed to be positive considering that the older people tend to be susceptible to a higher injury severity levels relative to younger people (Savolainen and Mannering 2007). Literature suggests that males tend to sustain lower injury severities relative to females and therefore a negative parameter is selected for the male indicator variable (Quddus et al. 2002; Rifaat et al. 2012). Similarly, a negative parameter is considered for the intersection indicator variable assuming that the crashes occurring at intersections tend to be less severe due to driver caution and other factors (Savolainen and Mannering 2007).

Table 6.2: Summary of different scenarios[a] simulated for motorcyclist injury severity.

Scenario number[b]	Scenario detail	Scenario description	Sample size	Average percentage shares across simulated datasets			
				No injury	Non-incapacitating injury	Incapacitating injury	Fatal injury
S1	$y_n^* = 0.1 \times age_n - 0.3 \times male_n - 0.75 \times intersection_n + \varepsilon_n$ $\Psi_{1n} = 0.2$ $\Psi_{2n} = 0.2 + exp(0.25 + \theta_{n2} \times PC_n)$ $\Psi_{3n} = 0.2 + exp(0.25 + \theta_{n2} \times PC_n) + exp(0.75 + \theta_{n3} \times PC_n)$ $\theta_{n2} = N(0.5, 0.75), \theta_{n3} = N(-0.5, 0.75)$, and $\rho_{23} = -0.7$	Greater share for higher ordered outcome	5,000	4.4	18.2	27.1	50.3
S2	$y_n^* = 0.1 \times age_n - 0.3 \times male_n - 0.75 \times intersection_n + \varepsilon_n$ $\Psi_{1n} = 3.5$ $\Psi_{2n} = 3.5 + exp(0.25 + \theta_{n2} \times PC_n)$ $\Psi_{3n} = 3.5 + exp(0.25 + \theta_{n2} \times PC_n) + exp(0.75 + \theta_{n3} \times PC_n)$ $\theta_{n2} = N(0.5, 0.75), \theta_{n3} = N(-0.5, 0.75)$, and $\rho_{23} = -0.7$	Greater share for lower ordered outcome	5,000	48.2	27.4	17.8	6.6
S3	$y_n^* = 0.1 \times age_n - 0.3 \times male_n - 0.75 \times intersection_n + \varepsilon_n$ $\Psi_{1n} = 2.1$ $\Psi_{2n} = 2.1 + exp(0.06 + \theta_{n2} \times PC_n)$ $\Psi_{3n} = 2.1 + exp(0.06 + \theta_{n2} \times PC_n) + exp(0.56 + \theta_{n3} \times PC_n)$ $\theta_{n2} = N(0.5, 0.75), \theta_{n3} = N(-0.5, 0.75)$, and $\rho_{23} = -0.7$	Approximately equal shares for all outcomes	5,000	24.7	25.9	24.8	24.6
S4	$y_n^* = 0.1 \times age_n - 0.3 \times male_n - 0.75 \times intersection_n + \varepsilon_n$ $\Psi_{1n} = \alpha_{1n}$ $\Psi_{2n} = \alpha_{1n} + exp(\alpha_{2n} + 0.5 \times PC_n)$ $\Psi_{3n} = \alpha_{1n} + exp(\alpha_{2n} + 0.5 \times PC_n) + exp(0.75 - 0.5 \times PC_n)$ $\alpha_{1n} = N(3.5, 1.75), \alpha_{2n} = N(0.25, 0.75)$, and $\rho_{12} = -0.7$	Greater share for lower ordered outcome	5,000	48.2	28.4	15.8	7.6
S5	$y_n^* = 0.1 \times age_n - 0.3 \times male_n - 0.75 \times intersection_n + \varepsilon_n$ $\Psi_{1n} = 0.2$ $\Psi_{2n} = 0.2 + exp(0.25 + \theta_{n2} \times PC_n)$ $\Psi_{3n} = 0.2 + exp(0.25 + \theta_{n2} \times PC_n) + exp(0.75 + \theta_{n3} \times PC_n)$ $\theta_{n2} = N(0.5, 0.75), \theta_{n3} = N(-0.5, 0.75)$, and $\rho_{23} = -0.7$	Greater share for higher ordered outcome	10,000	4.4	18.2	27.1	50.3

[a] For each of the five scenarios, a total of 100 datasets were simulated.
[b] See text for complete scenario-number definitions.

As can be observed from the second column of Table 6.2, scenarios S1, S2, S3, and S5 simulated threshold functions based on the example discussed in Section 6.3.2. Specifically, thresholds were assumed to depend on whether a motorcyclist was wearing a protective clothing or not, using an indicator variable (PC_n) that was equal to 1 if the motorcyclist was wearing a protective clothing when the crash happened (zero otherwise). This indicator variable was assumed to be Bernoulli distributed with mean 0.5. Random parameters were allowed on the protective-clothing indicator variable in the second and third thresholds while keeping the first threshold fixed (to α_1), as in Equation 6.10 below:

$$\begin{aligned} \Psi_1 &= \alpha_1, \\ \Psi_{2n} &= \alpha_1 + \exp(\alpha_2 + \theta_{2n} \times PC_n), \\ \Psi_{3n} &= \alpha_1 + \exp(\alpha_2 + \theta_{2n} \times PC_n) + \exp(\alpha_3 + \theta_{3n} \times PC_n). \end{aligned} \tag{6.10}$$

The random parameters θ_{2n} and θ_{3n} in all the four scenarios (S1, S2, S3, and S5) were simulated from two normal distributions $N(\theta_2, \sigma_2)$ and $N(\theta_3, \sigma_3)$ with a correlation level of ρ_{23} (which was assumed to be -0.7).

In the fourth scenario (S4), however, correlated random parameters were introduced on constants in the first and second thresholds (with a correlation parameter $\rho_{12} = -0.7$)[34], while keeping the coefficients of the protective clothing variable to be fixed, as shown in Equation 6.11 below.

$$\begin{aligned} \Psi_{1n} &= \alpha_{1n}, \\ \Psi_{2n} &= \alpha_{1n} + \exp(\alpha_{2n} + \theta_2 \times PC_n), \\ \Psi_{3n} &= \alpha_{1n} + \exp(\alpha_{2n} + \theta_2 \times PC_n) + \exp(\alpha_3 + \theta_3 \times PC_n). \end{aligned} \tag{6.11}$$

Note from Table 6.2 that scenario S1 simulated a high percentage (50.3%) of fatal crashes (although empirical contexts with such a high percentage of fatal crashes are rare), S2 simulated a low percentage (6.6%) of fatal crashes, S3 simulated approximately equal shares for all injury-severity levels, S4 simulated a low percentage (7.6%) of fatal crashes, and S5 simulated a high percentage of fatal crashes. This allows us to examine the above-discussed issues in different data generation settings as defined by the percentage of different ordered outcomes. For the first four scenarios (S1, S2, S3, and S4), a sample size of 5,000 motorcyclists was generated from the assumed distributions for age_n, $male_n$, $intersection_n$, and PC_n variables. For the fifth scenario (S5), the S1 scenario was simply repeated by increasing the sample size of motorcyclists from 5,000 to 10,000. This was done to evaluate the influence of sample size, while keeping all else same.

In each of the five scenarios, the outcome injury-severity level for each observation was obtained by mapping the propensity function with the thresholds as shown in Equation 6.2. For each of the five scenarios, the data generation process was repeated 100 times to obtain 100

[34] With regard to the equation 8, the variance of higher threshold can be less than the variance of higher threshold only when there is a negative covariance between those thresholds. We considered a higher negative correlation value of -0.7 to achieve a higher negative covariance and make the variance reduction technique possible. Other correlation values of -0.5 and -0.9 were tried in the experimental design and found to produce similar findings.

different datasets by drawing different values for the random components (ε_n and random parameters) from their corresponding distributions.

For each of the 100 datasets in each of the five scenarios, two MGORL models were estimated (a total of 100×5×2=1,000 MGORL model estimations). In the first model, correlation was allowed (estimated) between random parameters in the thresholds. In the second model, the correlation term was fixed to zero. To examine the recovery of random parameters and negative correlations in the thresholds, under different severity scenarios, propensity function and thresholds specifications are forced to be the same as the ones considered during the data simulation process. All models were estimated using the maximum simulated likelihood (MSL) approach with 400 Halton draws to simulate the distribution of random parameters (Bhat, 2003). Model estimations were carried out using codes written in the Gauss matrix programming language for the MGORL model with correlated random parameters.

6.4.2 Model Performance Metrics

To evaluate the performance of MGORL models estimated with and without correlated random parameters (on simulated data with correlations), the following criteria were considered:

a. The Log-likelihood improvement in the MGORL model after allowing correlated random parameters in thresholds was evaluated using a likelihood ratio test. Here, a model without correlation was a restricted version of a model with correlation, and the number of restrictions was equal to the difference in the number of parameter estimates in both the models. Chi-square value (χ^2) which is equal to $-2\times[LL_{mwoc} - LL_{mwc}]$ was computed for each dataset and was then compared with the critical chi-square value for a given number of restrictions at 95% confidence level.

b. The Absolute Percentage Bias (APB) for each parameter was calculated as the absolute percentage difference of the mean parameter estimate from the true parameter value. The mean estimate of each parameter was the average of all estimates across 100 datasets. This metric is a measure of accuracy of parameter estimates, expressed as given below:

$$APB = \left|\frac{mean\ estimate - true\ value}{true\ value}\right| \times 100 \qquad (6.12)$$

c. The Finite Sample Standard Error (FSSE) for a given parameter was calculated as the standard deviation of that estimated parameters across 100 datasets. FSSE for a parameter may be interpreted as the empirical standard error of its estimate in finite samples. Comparison of this metric for each parameter in the two models (model with correlation and model without correlation) was used to assess the loss/gain in the precision of parameter estimate when the correlation between random parameters was allowed.

d. The Coverage Probability (CP) for each parameter was calculated using the formula: $CP = {}^{1}/_{N} \sum_{n=1}^{N} I\left[\hat{\beta}_X^n - t_\alpha \times se\left(\hat{\beta}_X^n\right) \leq \beta_X \leq \hat{\beta}_X^n + t_\alpha \times se\left(\hat{\beta}_X^n\right)\right]$, where N is the total number of datasets (100), $\hat{\beta}_X^n$ is the estimated parameter for a dataset n, β_X is the true parameter value, $se\left(\hat{\beta}_X^n\right)$ is the asymptotic standard error of $\hat{\beta}_X^n$, and $I[\cdot]$ is an indicator function which takes a value 1 if the condition inside the bracket satisfies, otherwise equals to zero, and t_α is the *t*-statistic value for a given confidence level $(1 - \alpha) \times 100$. The confidence interval in this chapter was set to 95%. If the computed coverage probability is less than the nominal coverage probability (0.95), it suggests that the confidence intervals of the estimated parameter do not provide sufficient empirical coverage of the true parameter.

e. Predicted percentage shares were calculated for each injury-severity level using the estimated parameters from each dataset and were averaged across all datasets. The predicted

percentage shares for both the models (model with correlation and model without correlation) were compared to each other to understand the impact of ignoring correlations on the predicted aggregate shares.

f. The marginal effects were calculated to understand the effect of each variable on the outcome response for the model with correlation and the model without correlation. For a continuous variable, marginal effects were calculated as the average change in the probability of injury severity levels for all individuals with a unit increase in the variable of interest from its current value. Marginal effects for an indicator variable were computed using the procedure presented by Eluru and Bhat (2007).

6.4.3 Additional Scenarios

Apart from the five scenarios discussed in Section 6.4.1, additional scenarios were simulated. Recall that all the indicator variables (such as gender) were simulated as Bernoulli distributed with mean 0.5. However, the simulated data may not always represent the actual data. Therefore, scenario S1 was repeated with a gender split of 68% males 32% females, as observed in the motorcycle crashes reported in the 2016 crash data by Fatality Analysis Reporting System (FARS), keeping all other variables same. Such a scenario is labelled S6. The overall findings from this scenario aligned with those from scenario S1 suggesting that the inferences from this chapter are applicable for simulated data based on real-world scenarios. Therefore, we retained the mean value of 0.5 for all the indicators in all other simulations.

To check the influence of number of draws on model estimation, we repeated scenario S1 by increasing the number of Halton draws from 400 to 1000 and the new scenario is termed S7. Results suggested that there is no notable change in the evaluation metrics, marginal effects, or percentage shares after increasing the number of Halton draws. Therefore, we used 400 Halton draws for all other estimations in this chapter.

Scenario S1 was repeated with a smaller sample size of 1000 (and labelled scenario S8). It was found that there is a decrease in the consistency of predictions with a decrease in the sample size. Moreover, there is a reduction in the consistency (and increase in the APB and FSSE) of parameter estimates with a decrease in the sample size. However, the comparison of models with and without correlation suggested that the new findings with regard to the evaluation of the variance-reduction technique are consistent with the S1's findings. Therefore, the results and findings of the scenario with a smaller sample size are not discussed further in the chapter.

We repeated the scenario S4 with a higher proportion (43%) of fatal injuries and the new scenario is termed as S9. Table 6.1 contains the number of datasets with converged models and significantly improved log-likelihood for S9. Table 6.2, Table 6.3 and Figure 6.1 contains the evaluation metrics, marginal effects and predicted percentage shares respectively for S9. Similar to S4, S9 results suggest that the model with correlations is superior to that of a model without correlations in retrieving the parameter estimates in higher order thresholds. Moreover, there is no notable change in the evaluation metrics, marginal effects and percentage shares for S4 even after increasing the percentage of fatal crashes in the data.

Note that the results from the additional scenarios S6, S7, S8, and S9 are not reported in the chapter to conserve space. Only the results from scenarios S1 through S5 are reported on the next section, because the overall findings from the additional scenarios are similar to those from the first set of scenarios.

6.5. Results

This section presents the results and findings of the simulation experiments to evaluate the efficacy of negative correlations as a variance reduction technique in threshold functions of MGORL models.

Table 6.3: Summary of results from simulation experiments.

Scenario number[a]	Scenario description	Number of datasets with converged models	Number of datasets with significantly improved log-likelihood[b]
S1	Greater share for higher ordered outcome	91	6
S2	Greater share for lower ordered outcome	86	4
S3	Approximately equal shares for all outcomes	94	3
S4	Greater share for lower ordered outcome	82	0

[a] See text for complete scenario-number definitions.
[b] A likelihood ratio test was carried out between the models with and without correlation between the random parameters at 95% confidence level, with 2 degrees of freedom.

6.5.1 Order of Variance in MGORL Models with Negatively Correlated Random Parameters in Thresholds

We examined the order of threshold variances in simulated MGORL data with and without correlated random parameters. Since scenarios S1, S2, S3, and S5 include random parameters on a binary variable (PC_n) entering the threshold functions, the thresholds are random only when the PC_n variable takes a value of 1. Therefore, in all these four scenarios, random parameters kick in only for 50% of the cases where the PC_n variable takes a value of 1. For all these cases, as discussed in Section 3, variances of the second and third thresholds (ψ_{n2} and ψ_{n3}) in the data without correlated random thresholds were in an increasing order, with the variance of ψ_{n2} as 5.94 and that of ψ_{n3} as 8.14. This order reversed in data with correlated random thresholds, with the variance of ψ_{n2} as 5.94 and that of ψ_{n3} as 5.02, demonstrating the use of negative correlations for relaxing the assumption of non-decreasing variances. In the scenario S4, since random parameters are associated with the constants of the threshold functions, the thresholds are random for all cases in any of the 100 datasets. Therefore, introducing a negative correlation of -0.7 rendered the order of thresholds to be decreasing for all cases.

6.5.2 Estimation Issues of MGORL Models with Negatively Correlated Random Parameters in Thresholds

During the estimation of MGORL models with correlated random thresholds (on the simulated data with correlated random thresholds), we encountered non-convergence issues for at least 10% of the datasets in each scenario. More specifically, the number of simulated datasets (out of 100) for which the MGORL models with correlated random thresholds converged in each scenario are reported in Table 6.3 (second column). For the remaining datasets in each scenario, the non-convergence issues arose due to the occurrence of maximum value for the log-likelihood (LL)

function at the boundary value (-1) of the correlation term, which was not a stationary point to satisfy the convergence criterion.

To examine this issue, we plotted the *LL* function profiles of un-converged models (in scenario S2) with respect to the correlation term while fixing the other parameter estimates. Figure 6.2 shows the variation of the *LL* function with respect to the correlation term for each of the 14 datasets on which the models did not converge in scenario S2. It can be observed that the *LL* function is monotonic in the range of the correlation term (-1 to +1). The maximum value of the log-likelihood function for all 14 profiles in Figure 6.2 is at the correlation level of -1 where the *LL* function is not stationary.

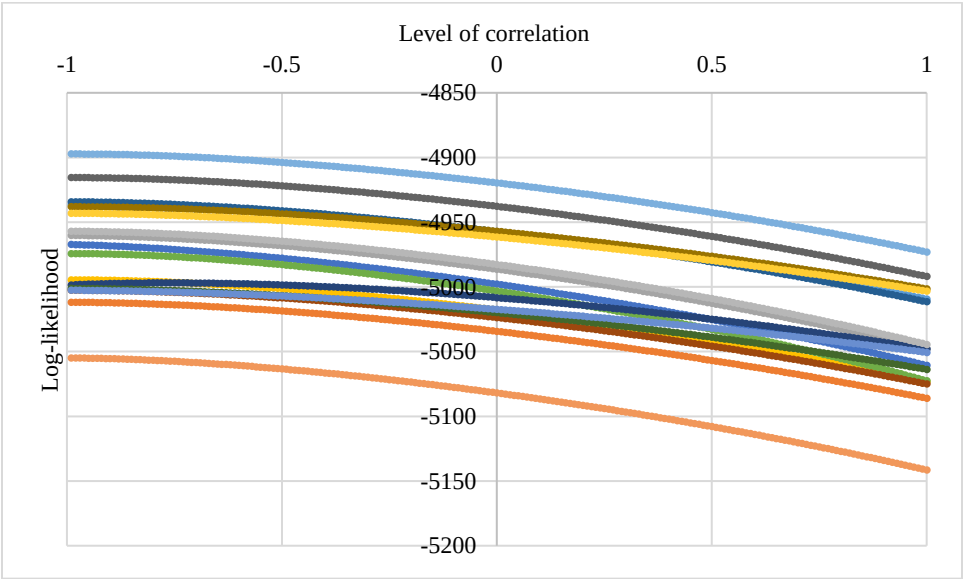


Figure 6.2. Log-likelihood profiles of unconverged models with respect to the correlation term.

Interestingly, by changing the starting values of the parameters to be estimated, convergence was achieved for 3 out of the 14 datasets mentioned above, with correlation values different from -1. However, although the parameter estimates (including those of the correlation parameter) obtained from both the converged and the corresponding un-converged models were different, the final *LL* values were not different between the converged models and the corresponding un-converged models at boundary values. This suggests a flat *LL* function profile, potentially due to identification problems in models with correlated random parameters in thresholds. Besides, the parameter estimates for the correlation term and the standard deviation of the second random parameter (σ_3, the random parameter in the higher threshold function) had high standard errors in some converged models, which again points to issues of parameter identifiability. Note also that for some of the converged models, the Hessian matrix could not be inverted at the final parameter estimates, and the *t*-statistics could not be computed using the sandwich estimator. So, the *t*-statistics were computed using the cross products of the first order derivatives. For subsequent analysis, we ignored the un-converged models and computed the evaluation measures only for the converged models in each scenario.

Interestingly, when we estimated models without correlation between random parameters in thresholds (again on simulated data with correlated random parameters), the standard deviation of the random parameter in the higher order random threshold (third threshold in S1, S2, S3, and

S5 and second threshold in S4) was statistically insignificant at 95% confidence interval in almost all datasets for all five scenarios. This suggests difficulty in estimating random parameters in higher order thresholds of MGORL models, as discussed in Section 6.3.2. Therefore, the insignificant random parameter was replaced with a fixed parameter, and the model was re-estimated with only one random parameter, instead of two correlated random parameters[35].

6.5.3 Data Fit of MGORL Models with Negatively Correlated Random Parameters in Thresholds Vis-À-Vis Those Without Correlated Random Parameters

For each dataset on which we could estimate a model with correlated random parameters without facing convergence issues (see column 3 of Table 6.3), a likelihood ratio test was conducted between the model without correlation and the model with correlation. This likelihood ratio test was associated with two degrees of freedom, since both the standard deviation of the random parameter in the higher order threshold and the correlation term were constrained to zero in the model without correlated random parameters. The results of the likelihood ratio tests are shown in Table 6.3 (last column) in the form of the number of datasets which show a statistically significant improvement in log-likelihood when correlated random thresholds were allowed. Interestingly, allowing correlated random parameters did not yield a significant improvement in data fit in a majority of the datasets in all five scenarios. Note also that increasing the sample size from 5,000 (in S1) to 10,000 (in S5) did not substantially change the results.

6.5.4 Recovery of Parameters

Table 6.4 reports, for all the five scenarios, the metrics of parameter recovery from the maximum simulated likelihood estimation technique for both the models (the model with correlated random parameters[36] and the model without correlated random parameters). Recall that these metrics (APB, FSSE, and CP) have already been defined in Section 4.

Comparing the metrics between scenario S5 and scenario S1, it can be observed that increasing the sample size did not change the APB, FSSE and CP values drastically for any of the parameters.

Comparison of mean estimates and APB values between the two models for scenarios S1, S2, S3, and S5 indicate that ignoring correlations lead to a greater rightward bias in the parameter estimate of the protective clothing variable in the third threshold. In scenario S4, ignoring correlations between random parameters resulted in a greater rightward bias in the estimates of mean values of constants for all three thresholds as well the standard deviations of random

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[35] Even in the model with correlated random parameters in second, third, and fourth scenarios, standard deviation of the second random parameter turned out to be statistically insignificant in at least 50% of the datasets. This could be due to the flat nature of the log-likelihood function and lower *t*-statistics resulting from the calculation of covariance matrix for the parameter estimates using the first order derivatives instead of using the sandwich estimator. Removing the insignificant random parameters in the model with correlation, and re-estimating the model, eliminates the need for the correlation term. We elected to keep the insignificant random parameter in the model and retain the correlation term to keep the results as general as possible.

[36] For models with correlated random parameters, we ignored the un-converged models and computed the evaluation metrics only for the converged models in each scenario.

Table 6.4. Evaluation of estimated parameters in the presence and absence of correlations between random parameters.[a]

Parameters		Performance metrics[b]	Scenario-S1		Scenario-S2		Scenario-S3		Scenario-S4		Scenario-S5	
			With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations
Propensity function	Age	True value	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1	0.1
		Mean estimate	0.1	0.101	0.1	0.1	0.1	0.1	0.112	0.28	0.1	0.101
		APB	0	1	0	0	0	0	12	180	0	1
		FSSE	0.004	0.004	0.002	0.002	0.003	0.003	0.053	0.549	0.003	0.003
		CP	0.967	0.912	0.976	0.988	0.957	0.936	0.931	1	0.966	0.933
	Gender	True value	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3	-0.3
		Mean estimate	-0.312	-0.313	-0.31	-0.309	-0.308	-0.308	-0.345	-0.774	-0.309	-0.311
		APB	4	4.33	3.33	3	2.67	2.67	15	158	3	3.67
		FSSE	0.065	0.066	0.057	0.055	0.059	0.059	0.193	1.219	0.046	0.047
		CP	0.978	0.978	0.964	0.952	0.947	0.957	0.958	1	0.944	0.944
	Intersection indicator	True value	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75	-0.75
		Mean estimate	-0.756	-0.758	-0.751	-0.749	-0.761	-0.76	-0.846	-2.122	-0.752	-0.755
		APB	0.8	1.07	0.13	0.13	1.47	1.33	12.8	182.93	0.27	0.67
		FSSE	0.067	0.067	0.05	0.05	0.054	0.053	0.397	4.219	0.045	0.045
		CP	0.967	0.978	0.988	0.988	0.957	0.947	0.972	1	0.978	0.966
First threshold	Constant	True value	0.2	0.2	3.5	3.5	2.1	2.1	3.5 (1.75)	3.5 (1.75)	0.2	0.2
		Mean estimate	0.191	0.183	3.512	3.504	2.09	2.086	3.904 (2.028)	9.846 (6.016)	0.193	0.179
		APB	4.5	8.5	0.34	0.11	0.48	0.67	11.54 (15.89)	181.31 (243.77)	3.5	10.5
		FSSE	0.132	0.129	0.108	0.106	0.104	0.104	1.811 (1.454)	19.53 (13.01)	0.104	0.102
		CP	0.934	0.956	0.976	0.964	0.968	0.957	0.944 (0.958)	1 (1)	0.933	0.944
Second threshold	Constant	True value	0.25	0.25	0.25	0.25	0.06	0.06	0.25 (0.75)	0.25(0.75)	0.25	0.25
		Mean estimate	0.247	0.247	0.255	0.254	0.071	0.07	0.277 (0.78)[c]	1.053 (-)	0.251	0.251
		APB	1.2	1.2	2	1.6	18.33	16.67	10.8 (4)	321.2 (-)	0.4	0.4

		FSSE	0.055	0.055	0.037	0.037	0.039	0.038	0.375 (1.605)	1.147 (-)	0.038	0.038
		CP	0.945	0.945	0.94	0.929	0.968	0.968	0.986 (0.856)	1 (-)	0.978	0.978
	Protective clothing	True value	0.5 (0.75)	0.5 (0.75)	0.5 (0.75)	0.5 (0.75)	0.5 (0.75)	0.5 (0.75)	0.5	0.5	0.5 (0.75)	0.5 (0.75)
		Mean estimate	0.487 (0.77)	0.488 (0.77)	0.503 (0.79)	0.502 (0.77)	0.486 (0.77)	0.488 (0.77)	0.526	0.437	0.495 (0.75)	0.494 (0.75)
		APB	2.6 (3.2)	2.4 (2.93)	0.6 (5.33)	0.4 (2.8)	2.8 (3.07)	2.4 (2.4)	5.2	12.6	1 (0.53)	1.2 (0.67)
		FSSE	0.07 (0.082)	0.069 (0.08)	0.06 (0.197)	0.06 (0.189)	0.05 (0.096)	0.05 (0.093)	0.12	0.075	0.05 (0.061)	0.05 (0.062)
		CP	0.96 (0.989)	0.96 (0.978)	0.94 (0.952)	0.94 (0.94)	0.97 (0.989)	0.97 (0.979)	0.875	0.653	0.97 (0.955)	0.98 (0.944)
Third threshold	Constant	True value	0.75	0.75	0.75	0.75	0.56	0.56	0.75	0.75	0.75	0.75
		Mean estimate	0.755	0.755	0.756	0.755	0.561	0.561	0.807	1.282	0.753	0.754
		APB	0.67	0.67	0.8	0.67	0.18	0.18	7.6	70.93	0.4	0.53
		FSSE	0.029	0.029	0.038	0.038	0.03	0.03	0.298	0.958	0.022	0.022
		CP	0.967	0.967	0.976	0.976	0.957	0.957	0.917	1	0.966	0.978
	Protective clothing	True value	-0.5(0.75)	-0.5(0.75)	-0.5(0.75)	-0.5(0.75)	-0.5(0.75)	-0.5(0.75)	-0.5	-0.5	-0.5(0.75)	-0.5(0.75)
		Mean estimate	-0.53 (0.78)	-0.175 (-)	-0.43[c] (0.85)[c]	-0.17 (-)	-0.48[c] (0.75)[c]	-0.17 (-)	-0.501	-0.514	-0.42[c] (0.56)[c]	-0.18 (-)
		APB	5.2 (4.13)	65 (-)	14.2 (12.8)	66.2 (-)	3 (0.27)	65.6 (-)	0.2	2.8	15 (24.93)	64.2 (-)
		FSSE	0.19 (0.30)	0.33 (-)	0.17 (0.25)	0.341 (-)	0.124 (0.18)	0.337 (-)	0.083	0.083	0.19 (0.41)	0.328 (-)
		CP	0.956 (0.98)	0.978 (-)	1 (1)	0.94 (-)	1 (1)	0.979 (-)	0.903	1	0.843 (0.86)	0.944 (-)
Parameters		Performance metrics[b]	Scenario-S1		Scenario-S2		Scenario-S3		Scenario-S4		Scenario-S5	
			With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations
Correlation term		True value	-0.7	-	-0.7	-	-0.7	-	-0.7	-	-0.7	-
		Mean estimate	-0.689	-	-0.632[c]	-	-0.652[c]	-	-0.76[c]	-	-0.566	-
		APB	1.57	-	9.71	-	6.86	-	8.57	-	19.14	-
		FSSE	0.198	-	0.265	-	0.208	-	0.178	-	0.351	-
		CP	0.956	-	1	-	1	-	0.931	-	0.933	-

[a] Values in parentheses represent the standard deviation of random parameters.
[b] APB = Absolute Percentage Bias; FSSE = Finite Sample Standard Error; CP = Coverage Probability.
[c] Parameter estimates are statistically insignificant (in at least 50% of datasets) at 95% confidence level.

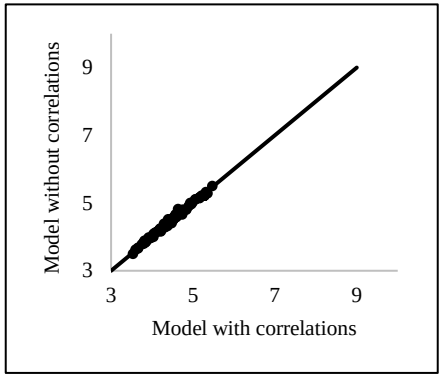
parameters. Further, coefficients of the gender and intersection dummy variables in the propensity function became biased to the left, where as the coefficient of the age variable became biased to the right.

In the context of precision (FSSE values) in parameter estimates, allowing or ignoring correlations did not have much influence in scenarios S1, S2, S3, and S5, except for the coefficient of the protective clothing variable in the third threshold. Although the parameter estimates in a model with correlation are typically expected to have better precision, probably due to the issues faced during estimation, the precision of parameters for the protective clothing variable was worse when correlations were allowed. In Scenario S4, parameters with greater bias were associated with greater FSSE values, particularly for the mean and standard deviation estimates of the first random threshold. In the context of the coverage probability (CP) values, there were not much differences between models with correlation and models without correlation.

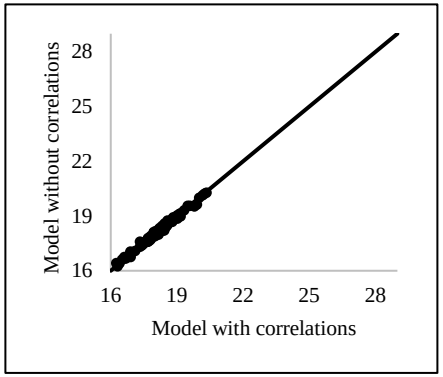
It is important not to get carried away by the above reported loss in accuracy and/or precision of parameter estimates in models without correlation. This is because a single parameter estimate does not offer much interpretation by itself in ordered response models. That is, it is difficult to use an individual parameter estimate to assess the change in probability of an outcome response when the corresponding independent variable changes. It is the combination of all parameters in the propensity and the threshold functions that determine outcome probabilities. Therefore, in the next section, we compare the predicted percentage shares and marginal effects between the model with correlation and the model without correlation.

6.5.5 Predicted Percentage Shares and Marginal Effects

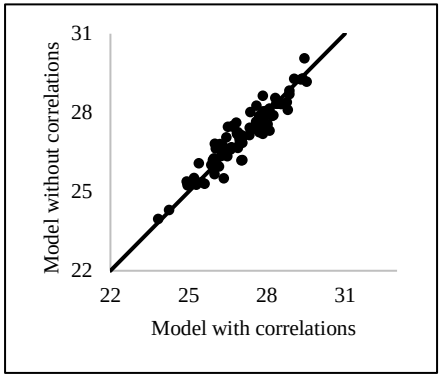
Figure 6.3 shows comparisons of predicted percentage shares for different injury severity levels by models with and without correlated random parameters for all the five scenarios. It can



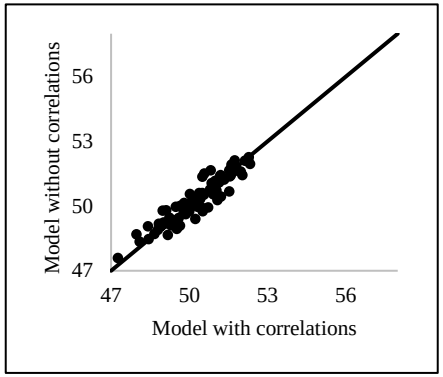
(a) No injury - S1



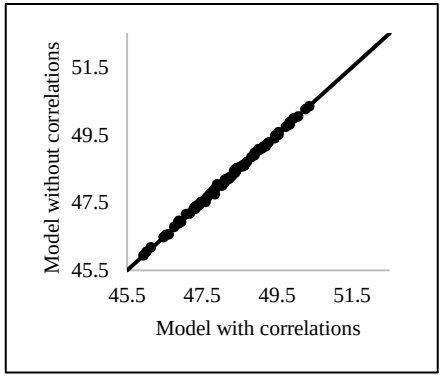
(b) Non-incapacitating injury - S1



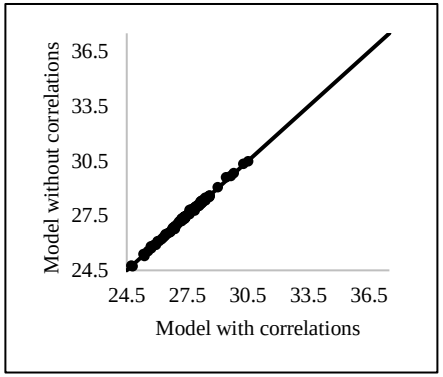
(c) Incapacitating injury - S1



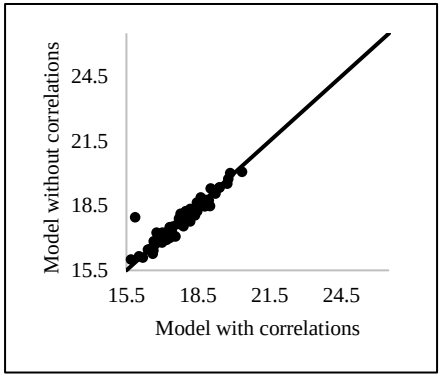
(d) Fatal injury - S1



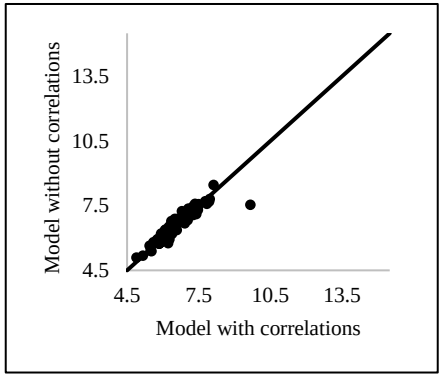
(e) No injury - S2



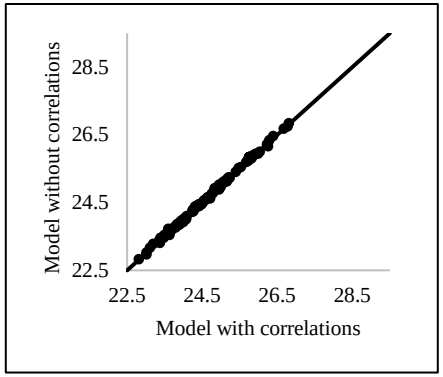
(f) Non-incapacitating injury - S2



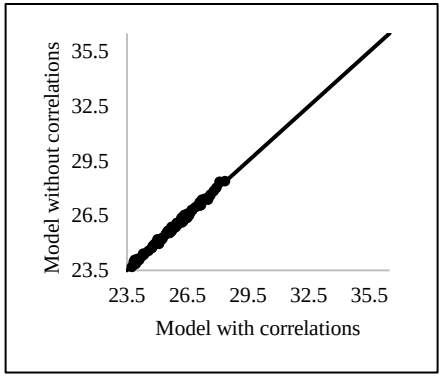
(g) Incapacitating injury - S2



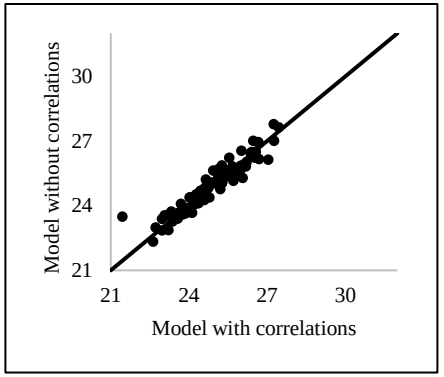
(h) Fatal Injury - S2



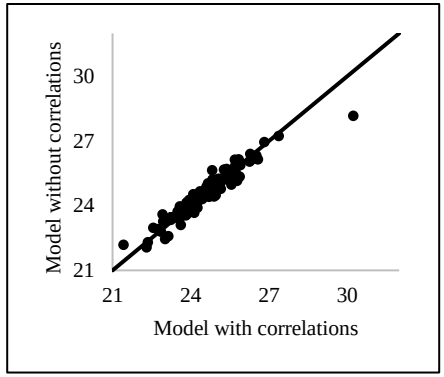
(i) No injury - S3



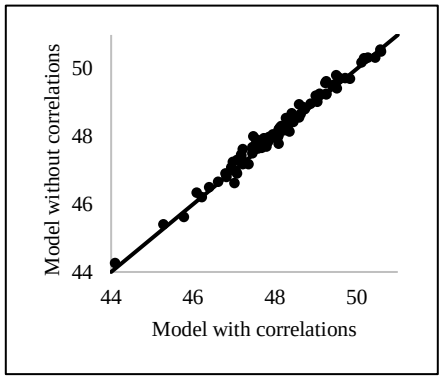
(j) Non-incapacitating injury - S3



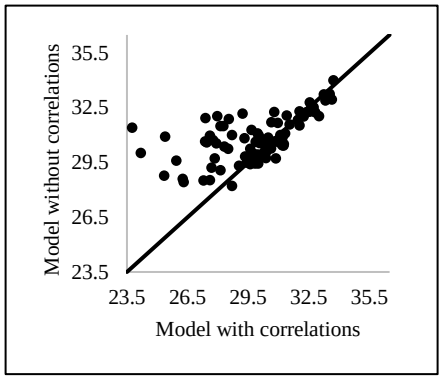
(k) Incapacitating injury - S3



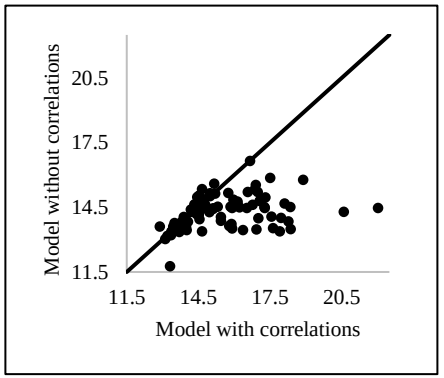
(l) Fatal Injury - S3



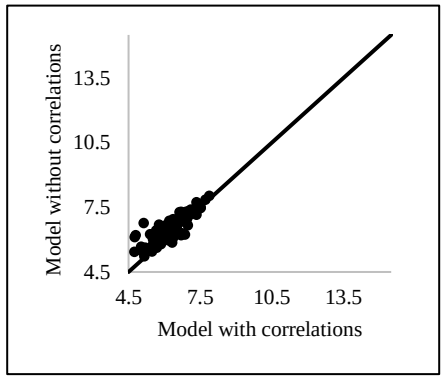
(m) No injury - S4



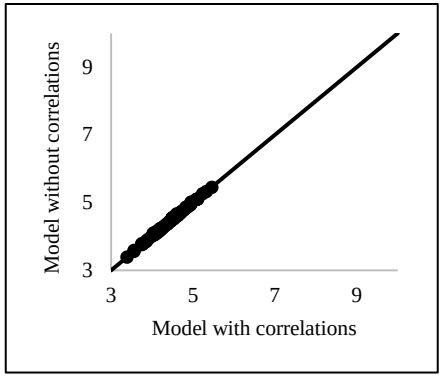
(n) Non-incapacitating injury - S4



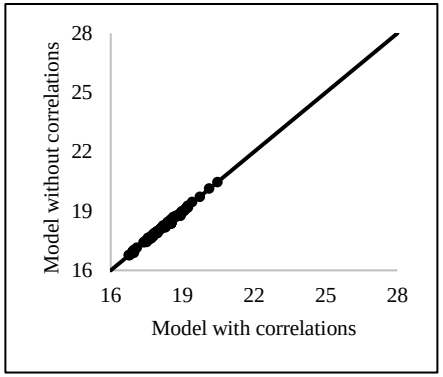
(o) Incapacitating injury - S4



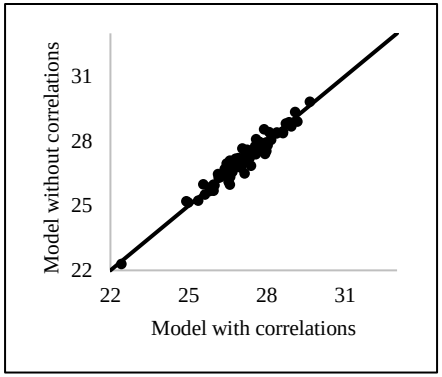
(p) Fatal Injury - S4



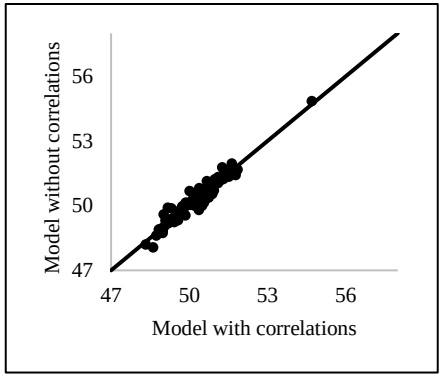
(q) No injury – S5



(r) Non-incapacitating injury – S5



(s) Incapacitating injury – S5



(t) Fatal Injury – S5

Figure 3: (Continued) Predicted percentage shares of different injury severity levels by the models with and without correlated random parameters.

be observed that the predicted percentage shares by the model with correlated random parameters and the model without correlation are close in scenarios S1, S2, S3, and S5 but differ slightly for scenario S4. Also, there is no discernible difference between the predictions in scenarios S1 and S5, which have different sample sizes but control for all other factors.

In scenario S4, the model without correlated random parameters slightly overestimates the share of non-incapacitating injuries and underestimates the share of incapacitating injuries (when compared to the model with correlated random parameters). To further examine the differences between the two models in scenario S4, we computed the root mean square error (RMSE) between predicted and actual shares for each injury severity level (for all datasets with converged models) and then averaged across all injury severity levels. The average RMSE values were 1.675 and 1.574 for the model with correlations and model without correlations, respectively. While these RMSE values are close to each other, it is interesting to note that the model without correlation has a slightly lower RMSE than the model with correlation.

Table 6.5 compares the marginal effects of each variable on different injury severity levels for the two models (the model with correlated random parameters and the model without correlated random parameters). For scenarios S1, S2, S3, and S5, the marginal effects of all the variables except the protective clothing (on which random parameters were estimated) are almost same for the two models. Even for the protective clothing variable, the marginal effects are not substantially different. In S4, the marginal effects of protective clothing variable differ slightly (but not drastically) for the incapacitating, non-incapacitating and fatal injuries.

Table 5: Comparison of marginal effects for the estimated models with and without correlation between random parameters.

Scenario	Variable description	Age		Gender		Intersection indicator		Protective clothing indicator	
	Model	With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations	With correlations	Without correlations
S1	No injury	-0.004	-0.004	0.024	0.024	0.058	0.058	0	0
	Non-incapacitating injury	-0.007	-0.007	0.041	0.041	0.101	0.101	0.397	0.396
	Incapacitating injury	-0.006	-0.006	0.035	0.034	0.087	0.085	-0.145	-0.13
	Fatal Injury	0.016	0.016	-0.1	-0.1	-0.245	-0.244	-0.252	-0.266
S2	No injury	-0.018	-0.018	0.112	0.112	0.273	0.273	0	0
	Non-incapacitating injury	0.005	0.005	-0.033	-0.033	-0.08	-0.08	0.215	0.215
	Incapacitating injury	0.008	0.008	-0.047	-0.047	-0.116	-0.116	-0.19	-0.187
	Fatal Injury	0.005	0.005	-0.032	-0.032	-0.077	-0.076	-0.024	-0.028
S3	No injury	-0.014	-0.014	0.089	0.089	0.221	0.221	0	0
	Non-incapacitating injury	-0.002	-0.002	0.011	0.011	0.028	0.029	0.329	0.33
	Incapacitating injury	0.003	0.003	-0.019	-0.02	-0.049	-0.049	-0.213	-0.204
	Fatal Injury	0.013	0.013	-0.081	-0.081	-0.201	-0.2	-0.117	-0.125
S4	No injury	-0.0183	-0.0205	0.1137	0.1274	0.2803	0.3138	0	0
	Non-incapacitating injury	0.0047	0.0093	-0.0308	-0.0596	-0.0762	-0.1486	0.2297	0.2102
	Incapacitating injury	0.0077	0.0082	-0.0475	-0.0503	-0.1178	-0.1243	-0.228	-0.2064
	Fatal Injury	0.006	0.003	-0.0354	-0.0175	-0.0863	-0.0409	-0.0018	-0.0038
S5	No injury	-0.004	-0.004	0.024	0.024	0.057	0.057	0	0
	Non-incapacitating injury	-0.007	-0.007	0.041	0.041	0.101	0.101	0.4	0.399
	Incapacitating injury	-0.006	-0.006	0.036	0.035	0.086	0.089	-0.146	-0.131
	Fatal Injury	0.016	0.016	-0.1	-0.1	-0.244	-0.246	-0.254	-0.267

Bringing together the findings in this section with those in the previous section, it appears that when correlations are ignored between random parameters in thresholds, the estimates of other parameters are adjusted in such a way that the marginal effects and predicted percentage shares are similar to those when correlation is considered.

6.6. Summary and Conclusions

This chapter highlights a potential limitation of MGOR models, as applied in most empirical research, that the variances of the random thresholds are implicitly assumed to be in a non-decreasing order. This restriction is not necessary and likely causes difficulty in estimating random parameters in higher order thresholds. To relax this restriction, we evaluated the use of negative correlations between the random parameters as a variance reduction technique. To do so, a simulation-based approach was used, where five different MGOR data scenarios were simulated with 100 datasets in each scenario using a known correlation structure between the random parameters. Two MGOR models were estimated on each simulated dataset – one allowing correlations between random parameters and the other not allowing correlations – and the performance of these two models was evaluated using various evaluation criteria.

Allowing negative correlations helped relax the non-decreasing variance property of MGOR models. However, when negative correlations were considered between random parameters in thresholds, convergence issues and parameter identification problems were encountered. In addition, for a considerable number of simulated datasets, the correlation parameter estimate was associated with a high standard error. All these issues suggest the difficulty of the maximum simulated likelihood estimation and inference method for MGOR models with correlated random parameters in thresholds.

Comparison of the models that did converge suggests that ignoring correlations leads to an estimation of fewer random parameters in higher order thresholds and results in bias and/or loss of precision for a few parameter estimates. However, when the converged models with correlated random parameters were compared with the corresponding models without correlations, we did not observe significant benefits of accounting for correlations. Neither did the data fit (as measured by likelihood ratio test) improve significantly nor did the predicted shares of different severity levels or the marginal effects differ substantially from those of the models that ignored correlations. In our experimental setup (in all five different scenarios), ignoring correlations lead to an adjustment of other parameter estimates such that overall likelihood values, predicted percentage shares, and the marginal effects were similar to those from the models with correlations. This again suggests potential identifiability issues of MGOR models with correlated random parameters in thresholds.

In summary, the technique of using negative correlation as a variance reduction technique was not effective in our experimental setup, in part due to convergence and identification issues associated with estimating MGORL models that have correlated parameters in thresholds. Therefore, more research is needed for an advanced model structure that can relax the assumption on the order of variance of thresholds in MGOR models (see Paleti and Pinjari, 2018). A relevant question in this context is whether (and to what extent) such assumption is an egregious restriction to be concerned with. Finally, the issues explored with regard to the MGOR models in this chapter add to the discussion of using ordered versus unordered models in the analysis of accident-injury data. Specifically, the tradeoff between the high-degree of model flexibility that an unordered model analysis can provide (such as the standard mixed logit and its various extensions) versus

that ability to account for the ordering of alternatives that an ordered response model allows (see Eluru, 2013; Yasmin and Eluru 2013; Mannering and Bhat 2014).

Appendix 6.A. Computation of variance of thresholds in MGOR models

Let *VAR*(.), *COV*(.) and *E*(.) represent the variance, covariance and expected value of random variables. Let the first 3 thresholds be

$\Psi_{n1} = 0,$

$\Psi_{n2} = \exp\,(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}),$

$\Psi_{n3} = \exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}) + \exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}),$

In the presence of normally distributed random parameters, variance of the third threshold is

$VAR(\Psi_{n3}) = VAR(\exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2})) + VAR(\exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})) + C_{23},$

where,

$$C_{23} = 2COV(\exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \theta_{n2}\boldsymbol{V}_{n2}), \exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}))$$

$$= 2[E(\exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}) \times \exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}))] - E(\exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2})) \times E[\exp(\boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})]$$

$$= 2 \times \exp(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\alpha}_3\boldsymbol{U}_{n3})\,[E(\exp(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})) - E(\exp\,(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}) \times E(\exp\,(\boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3}))]$$

If the mean and variance of normally distributed random variable *X* are μ and σ^2, then the expected value of exp(*X*) is exp $(\mu + \frac{\sigma^2}{2})$.

Therefore,

$$C_{23} = 2\exp\big(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + E(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})\big) \times \left[\exp\left(\frac{VAR(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2} + \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})}{2}\right) - \exp\left(\frac{VAR(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}) + V(\boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})}{2}\right)\right]$$

$$= 2\exp\left(\boldsymbol{\alpha}_2\boldsymbol{U}_{n2} + \boldsymbol{\alpha}_3\boldsymbol{U}_{n3} + E(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2} + \boldsymbol{\theta}_{n3}V_{n3}) + \frac{(Var(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}) + Var(\boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})}{2}\right) \times [\exp(COV(\boldsymbol{\theta}_{n2}\boldsymbol{V}_{n2}, \boldsymbol{\theta}_{n3}\boldsymbol{V}_{n3})) - 1]$$

Chapter 7: A Social Resources and Leisure Activity Survey: Methodology and Sample Comparison for A Trial Version

7.1. Introduction

The need for travel is often perceived as demand derived from participation in various activities. From an activity-travel perspective, most trips are categorized by purpose such as mandatory, maintenance or discretionary/leisure travel. Differentiating it from the first two purposes, leisure travel is of a social and voluntary nature. Although offering freedom and satisfaction, leisure activities also strengthen individual's relationships with friends and families and create new connections.

Gathering evidence of the linkage between social networks and activity generation, Kim and colleagues (2018) reviewed transportation articles that analyzed the impacts of individuals' social network characteristics on activity choices and travel behavior. These studies estimated the frequency of social activity participation based on three measures: network size (Carrasco et al, 2008a; Carrasco and Miller, 2006; Sharmeen et al., 2014; van den Berg et al., 2009, 2010, 2012b, 2015); relationship type (Carrasco et al., 2008a; Carrasco and Miller, 2006, 2009; Frei and Axhausen, 2008; Sharmeen et al., 2014; van den Berg et al., 2009, 2012a); tie strength (Carrasco et al., 2008a; Carrasco and Miller, 2006, 2009; Sharmeen et al., 2014; van den Berg et al., 2012a).

Regarding network size, more frequent activity participation was associated with larger networks. Regarding relationship types, there was no clear consensus on its impact on ego-alter activity frequency due to varying methodologies and classification schemes. Although relationships type can indicate tie strength, several studies asked specifically about whether respondents had strong, medium, or weak ties with their alters. Each study found that higher social activity frequency was generated by stronger ties. But there is a lack of a cohesive theory linking social network characteristics to leisure activity outcomes (Parady et al., 2019).

Lin's resource-based formulation of social capital posits that individuals invest in their social contacts and mobilize the resources within those contacts to reap instrumental (for profit and to access new resources) and expressive (to maintain access to existing resources) outcomes. To operationalize those essential outcomes flourished from embedded resources, Lin emphasized that social capital should be captured through the measurements of network characteristics and relations. Lin particularly emphasizes the hierarchical nature of social resource access through the use of the position generator instrument.

Examining tie strength effects on activity generation, Maness (2017a) theorized that larger strong ties networks and weak tie diversification and status upper reachability increases activity variety and frequency. The theory was tested by using name generator data for strong tie characteristics and a position generator for weak tie characteristics. Seeing improved model fit Maness (2017a) suggests that including these social capital measures may account for additional heterogeneity not captured by common individual and household characteristics. Maness's (2017a) study, however, was restrained by limited information on the activity space, travel mobility, and directly accessible resources.

The current study proposes to develop a survey instrument to explore the links between Lin's social capital theory and leisure activity outcomes. By including measures of social support and direct and indirect social resource access, aspects of Lin's social capital theory can be tested in a leisure activity context. Limitations of Maness (2017a) effort will be accounted for with an expansive list of leisure activities and the inclusion of a resource generator to directly measure social resource embeddedness. As a first effort, the quality of the survey instrument for self-administered web survey was tested across three varying sample sources. Particularly, the quality

of the three social capital measures (number of strong ties, position and resource generators) will be tested. Additionally, the effect of these social capital measures will be shown to positively impact the outcome: leisure activity variety. These validity analysis and outcome results suggest that the survey instrument can enable the answering of various questions related to social network characteristics, accessed social resource, and leisure activity outcomes.Ordered outcomes, such as those encountered in accident-injury severity (no injury, injury, fatality), measurements of satisfaction (highly dissatisfied, dissatisfied, neutral, satisfied, highly satisfied), measurements of levels of agreement or disagreement (strongly disagree, disagree, neutral, agree, strongly agree), and so on, are often modeled using ordered response models. These models have a potential advantage over unordered response models, such as the multinomial logit model and its variants, because ordered models recognize the inherent ordinal pattern of outcome responses. Standard ordered response models are based on an underlying continuous latent propensity function that is assumed to be a function of observed explanatory variables and an unobserved random component (Aitchison and Silvey, 1957; McKelvey and Zavoina, 1975; Washington et al., 2011). The latent propensity function is mapped to observed outcomes using a set of thresholds that are increasing in order. The major drawback associated with this standard ordered response (SOR) model is that it assumes the thresholds to be same for all individuals, which might not be appropriate in all applications.

7.2 Social Capital and Leisure Activity Behavior

This section starts by describing the interpretation of how social capital enables outcomes through the use of embedded social resources, then methods to measure social resource access, and concludes by briefly linking leisure activity behavior to embedded social resource access.

7.2.1 Social Capital and Embedded Social Resources

The concept of social capital describes how individuals acquire beneficial assets and services by using social interactions. Social capital has a variety of conceptions, but the three most prominent forms view social capital as: (1) indirect access to resources, (2) social cohesion, and (3) brokerage (Crossley et al. 2015). While the social cohesion and brokerage formulations are popularly invoked, the resource formulation has the strongest measurement traditional and methodological rigor. Specifically, Lin's defines social capital as resources embedded in a social structure that can be accessed and/or mobilized in purposive actions. In other words, social capital is equivalent to assets in one's social network (Lin et al., 2001). Under this view, the three primary elements of social capital are (1) resources embeddedness in social networks, (2) resource accessibility, and (3) resource use for action-oriented aspects. This individual-level focus of seeing social capital as embedded social resources fits in well with the individual-level basis of most activity and travel research.

Lin (2001) defines three processes involved in the creation and use of social capital: (1) investment in social capital, (2) access to and mobilization of social capital, and (3) returns of social capital. Häuberer (2011) schema (Figure 1) summarizes and clarifies Lin's theory of these three processes and thus providing a causal representation between preconditions, social capital,

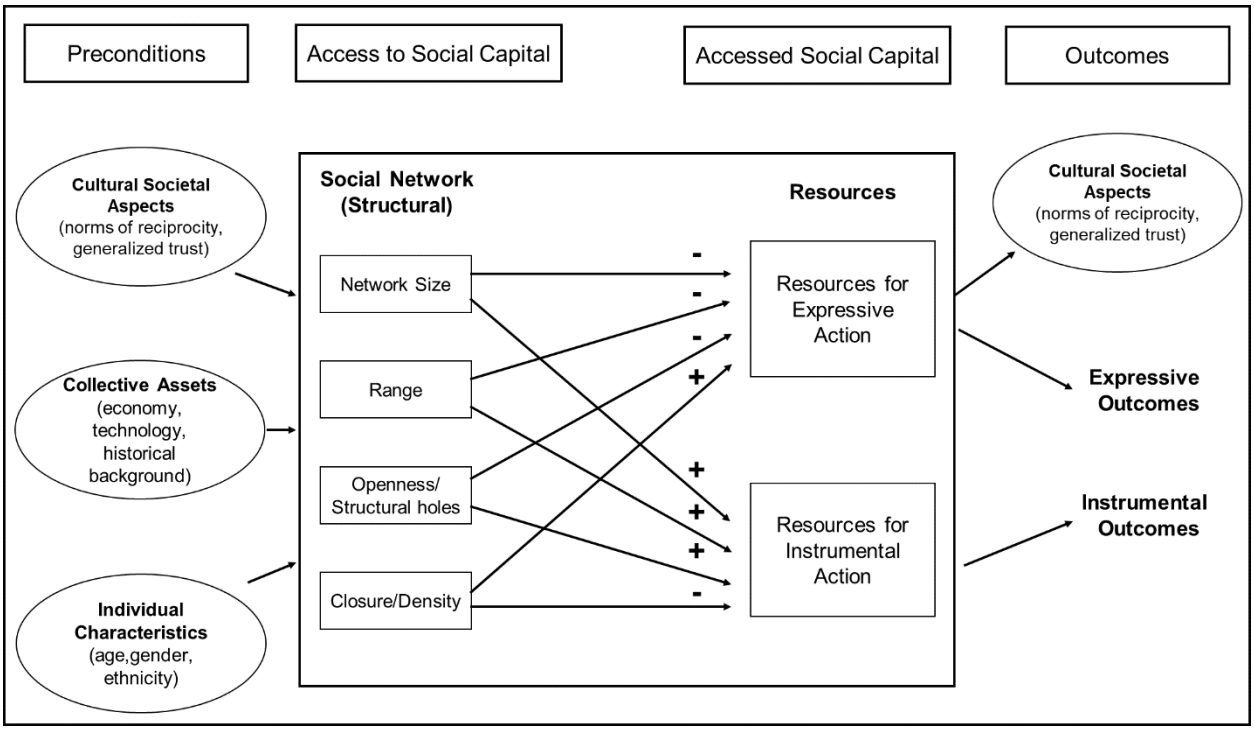


Figure 1. Häuberer (2011) Conceptual Diagram of Social Capital and Outcomes

and outcomes. Under preconditions, individuals are placed in a societal context and have access to individually owned resources and assets. These are leverage to connect with people determined by one's place in society and the assets and resource that are able to provide and leverage. Access to social resources is enabled through social networks and their structural properties. Generally, smaller, more tight-knit networks promote maintenance of social contact over brokerage between social circles. These dense networks promote continued access to group resources and promote trust and reciprocation. This leads to more resources for expressive actions and better performance of expressive outcomes. Lin (2001) classifies expressive outcomes as: mental health, physical health, and life satisfaction. In contrast, larger, wide social networks promote exploration but results in less intimate social support. These wider networks may enable to creation of new contacts and thus access to new resources for profit or resource gain. This leads to more resources for instrumental action and thus greater performance in instrumental outcomes. Lin (2001) classifies instrumental outcomes as: wealth, power, and status.

7.2.2 Measuring Social Resource Access

Lin (2001) speaks of measuring social capital as assets in social networks. A simple approach to this would involve asking individuals about their social contacts and each contacts' available resources. Called the name generator approach, this is the primary technique used in transportation studies of social capital (Kim et al., 2018). While the name generator approach provides detailed information, it is limited due to respondent burden and contact recall biases. Additionally, there are concerns about its sensitivity to survey mode, particularly self-administered formats (Joye et al. 2019).

The position generator instrument measures access to social capital indirectly. This approach focuses on hierarchal measures of people's access to resources by relating them with their contacts societal positions. Generally, those with higher societal position have more access (Lin, 2001). To determine resource access, the position generator measures a person's ties with individuals across various occupations – which have varying levels of prestige and status across society. A position generator presents an occupation list and asks respondents whether they have individuals in their social network with those occupations. "From the responses … network resource indexes [can be constructed] such as extensity (number of position accessed), range or heterogeneity (the 'distance' between 'highest' and 'lowest' positions accessed), and upper reachability ('highest' position accessed)" (Lin, 2001: p. 17). The limitation is that this indirect approach's focus on hierarchical relations may not be appropriate for all social capital related inquiries (van der Gaag and Snijders, 2005).

The resource generator approach combines the name generator/interpreter and position generator to directly measure social resource access. Using a list of specific resources, "the resource generator asks if [respondents] would have anyone to turn to should they need to access one or more of a range of resources" (Crossley et al., 2015: p. 49). This enables the resource generator flexibility in answering a range of research questions. This is particularly importance since all social capital is not equivalent and cannot be mobilized for all purposes. Van der Gaag and Snijders (2005) note that their Netherlands-focused resource generator identified four types of social resources: personal support, political and financial skills, personal skills, and prestige and education related social capital. This provides a technique to measure differences between instrumental and expressive outcomes.

By combining the position generator and resource generator approaches, an individual's social integration and network range can be measured alongside their "concrete resources available through social relations" (Joye et al. 2019: p. 23). Perry et al. (2018) also explain why the position generator is restricted to give instrumental outcomes whereas the resource generator is more leaned towards expressive outcomes but may help achieve instrumental goals.

7.2.3 Linking Leisure Activities and Social Capital

Carrasco and Cid-Aguayo (2012) and Maness (2017b) attempt to link social capital to activity behavior through measuring social network characteristics. Maness (2017a) attempts to build such theory from the basics of social tie creation (social safety, brokerage, and status). Parady et al. (2019) also links network size and club membership to social activity variety. But their efforts are limited by an unclear linkage between what the networks offer in terms of resources and what expected leisure activity behavior could result. By using Lin's social capital concept with the ability to measure structural and mobilized embedded resources, the effects of leisure activity for enabling expressive and instrumental outcomes could be explored. Lin's theory allows for clear relations between network structure and resources to test the validity of the social resource conception of social capital in the leisure activity space.

7.3 Survey Methodology

A cross-sectional survey was designed to test the validity of the social capital measures chosen to begin development of a social capital theory of leisure activity behavior. This effort focused on response differences between varying non-probability sample sources. Data collection occurred from March to June 2019. The sampling frame and design varied by sample source (details

provided in a subsection below). The survey was self-administered by web with varying personal computer and mobile browser versions.

7.3.1 Survey Layout and Design

A web-based survey instrument was developed to better understand social factors influencing the leisure activity participation. The questionnaire consists of 27 questions over five categories: 1) activity space, 2) social capital, 3) mobility/accessibility, 4) individual and household characteristics, and 5) personality traits.

Activity Space

The activity space section of the survey asks about: (1) leisure activity variety and frequency, (2) household mandatory and maintenance activities, and (3) work and school demand. Leisure activity variety and frequency were asked over a list of 87 unique activity types. Adopted from Tinsley and Eldredge (1995), 78 out of their 82 activities were adopted – with arcade games, collecting bottles, shortwave radio listening, and volunteering for crisis intervention excluded due to decreased popularity or being too dependent on specific crisis events. Nine additional leisure activities were added including: attending festivals and parades, board gaming, joyriding, gambling, gardening in community gardens, softball, singing karaoke, video games, visiting amusement/theme parks. The 87 activities list was presented alphabetically across two pages. Survey respondents were asked to choose the specific activities they participated in over the last three months. Respondents were then asked about the frequency of each selected activities in one of two formats: choice categories and open-ended. The choice categories format required respondents to select one frequency among six choices (Once, Twice, Less than once a month, 1-3 times a month, About once a week, 2 or more times a week). The open-ended format included text input fields to select an integer frequency for each activity. Future work will be performed to examine difference in response burden and frequency distribution from both formats.

The household mandatory and maintenance activity space was measured by asking respondents to recall the hours spent on ten different activities over the last week: (1) housework and chores, (2) food preparation and cleanup, (3) lawn and garden care, (4) paying bills and other household paperwork, (5) grocery shopping, (6) other shopping for the household, (7) caring for children in your household, (8) caring for children from other households, (9) caring for adults in your household, and (10) caring for adults from other households.

Work and school demand were measured by asking respondents to input their hours spent working for a job and attending school over the last week. School hours were specified as the time spent on campus, in educational building or online course content, not including the travel time to/from school.

Social Capital

The next group of questions applies the strong ties measure, position generator, and resource generator to measure respondents' social capital through their access to social resources and social support. Accessed social support was measured using the question: "From time to time, most people discuss important matters with other people. Looking back over the last three (3) months, think about the people whom you discussed matters that are important to you. How many people were you able to recall?" Respondents were free to choose any integer number of contacts between 0 and 9 or "10 or more" contacts. Selection of the number of people who they discussed important

matters over the last three months were a generalized version of Burt's name generator used in the General Social Survey (Burt 1984).

Access to social resources was measured indirectly through a position generator and directly through a resource generator. In the position generator, respondents were asked:

"This question is about types of jobs and whether people you know hold such jobs. These people include relatives, friends, and acquaintances. For each profession below, please indicate if you know someone on a first-name basis with that profession and if they are a close friend or family relative.

Example: For the job category of Nurse, if you personally know three nurses then you would check the first box ('Knows Someone'). Additionally, if at least one of these nurses is a close friend check the second box ('Close Friend / Relative')."

Two check boxes were presented for each profession corresponding to the "Know Someone" and "Close Friend or Close Relative" category. The profession list follows from that used by Hampton et al. (2009) and Maness (2017a) with the following 22 occupations:

1. Nurse
2. Farmer
3. Lawyer
4. Middle-school teacher
5. Full-time babysitter
6. Janitor
7. Personnel manager
8. Hairdresser
9. Bookkeeper
10. Production manager
11. Operator in a factory
12. Computer programmer
13. Taxi driver
14. Professor
15. Policeman
16. Chief executive officer of a large company
17. Writer
18. Administrative assistant in a large company
19. Security guard
20. Receptionist
21. Congressman or congresswoman
22. Hotel bell boy

In order to explore the availability of resources that individuals can access through their social network, a resource generator was including in the questionnaire. This questionnaire used the list refined by Foster and Mass (2016) for the US context. Respondents were asked: "For the following questions, please indicate if you know someone on a first-name basis who":

1. Knows how to fix a car
2. Give advice on using a personal computer
3. Has a professional occupation

4. Is an elected official
5. Works at City Hall
6. Can sometimes employ people
7. Knows a lot about government regulations
8. Has good contacts at TV/radio/newspaper
9. Give advice about money problems
10. Give advice on problems at work
11. Help dispose of bulky items
12. Help with small household jobs
13. Do your shopping if you are ill
14. Provide care for a serious health condition
15. Lend large sum of money
16. Lend small sum of money
17. Give career advice
18. Provide a place to stay for a week
19. Discuss politics
20. Give sound legal advice
21. Give a good job reference
22. Can babysit others' children
23. Help find someplace to live
24. Watch home or pets while away
25. Be there to talk about the day
26. Owns a car

The resource generator was implemented as a multiple answer question with check boxes used to indicate which resources respondents could access.

Mobility/Accessibility

This survey has further questions related to respondent's travel behaviors. Respondents were asked to report the number of vehicles in their household, commute mode, driver license status, and whether they have a disability, condition, or illness affecting their ability to travel. Additionally, respondents were asked about their weekly/monthly usage frequency for bicycle, transit, and ridehailing services.

Individual and Household Characteristics

There are twelve sociodemographic questions asking about the respondent's age, education, employment, gender, home type/zipcode, income, marital status, number of people in different age groups, number of workers, and race/ethnicity.

7.3.2 Sample Designs

Samples were recruited from three sources and are compared below by recruitment, sampling frame, sampling method, and target population. Descriptive statistics across each sample are described in Table 1.

Table 1 Survey Descriptive Statistics by Sample Type

Variables	Sub-description	MTurk	Qualtrics	TTE Class
Number of observations		121	134	108
Age	18-24	5.0%	12.7%	65.7%
	25-34	45.5%	14.9%	11.1%
	35-44	28.9%	18.7%	1.9%
	45-54	10.7%	14.9%	10.2%
	55-64	6.6%	18.7%	3.7%
	65-74	2.5%	17.2%	1.9%
	75 or older	0.8%	0.0%	0.0%
	Missing data	0.0%	3.0%	5.6%
Education attainment	Less than high school	0.8%	6.0%	0.9%
	High school graduate/GED	10.7%	23.1%	19.4%
	Some college	12.4%	26.1%	30.6%
	Vocational/technical training	0.8%	3.7%	0.9%
	Associate degree	9.9%	14.9%	21.3%
	Bachelor's degree	59.5%	19.4%	14.8%
	Graduate degree	5.8%	6.0%	10.2%
	Missing data	0.0%	0.7%	1.9%
Employment status	Employed full-time	75.2%	35.1%	18.5%
	Employed part-time	8.3%	15.7%	35.2%
	Retired	2.5%	21.6%	3.7%
	Student (and not employed for pay)	0.8%	5.2%	33.3%
	Disabled (and not employed for pay)	0.0%	7.5%	0.0%
	Not employed for pay	9.1%	9.7%	6.5%
	Other	4.1%	5.2%	2.8%
	Missing data	0.0%	0.0%	0.0%
Gender	Female	45.5%	49.3%	40.7%
	Male	53.7%	48.5%	58.3%
	Not listed	1.5%	0.0%	0.0%
	Missing data	0.7%	2.2%	0.9%
Household income	Under $15,000	3.3%	16.4%	26.9%
	$15,000–$24,999	9.1%	9.0%	15.7%
	$25,000–$34,999	15.7%	12.7%	10.2%
	$35,000–$49,999	24.0%	23.1%	6.5%
	$50,000–$74,999	24.0%	14.2%	9.3%
	$75,000–$99,999	14.0%	11.2%	9.3%
	$100,000–$149,999	5.0%	8.2%	10.2%
	$150,000–$199,999	3.3%	2.2%	2.8%
	$200,000–$249,999	1.7%	3.0%	1.9%
	$250,000 or more	0.0%	0.0%	1.9%
	Missing data	0.0%	0.0%	5.6%
Household people	One	29.8%	17.2%	8.3%
	Two	22.3%	36.6%	15.7%
	Three or more	47.9%	46.3%	75.9%
	Missing data	0.0%	0.0%	0.0%
Marital status	Married	34.7%	40.3%	20.4%
	Living with a partner	10.7%	11.9%	5.6%

	Widowed	0.8%	3.0%	0.0%
	Divorced	5.8%	13.4%	1.9%
	Separated	0.8%	0.7%	0.9%
	Never been married	47.1%	29.9%	69.4%
	Missing data	0.0%	0.7%	1.9%
Race/ethnicity	American Indian or Alaska Native	0.0%	0.7%	1.9%
	Asian	5.8%	2.2%	12.0%
	Black or African American	8.3%	14.9%	5.6%
	Hispanic, Latino, or Spanish origin	2.5%	5.2%	13.0%
	Middle Easterner or North African	0.0%	0.0%	8.3%
	White	79.3%	70.1%	39.8%
	Other race, ethnicity, or origin	0.0%	1.5%	3.7%
	Mixed race	4.1%	2.2%	8.3%
	Prefer not to answer	0.0%	1.5%	6.5%
	Missing data	0.0%	1.5%	0.9%
Household vehicles	No Vehicle	5.8%	13.4%	10.2%
	One	45.5%	32.8%	14.8%
	Two	34.7%	35.1%	26.9%
	Three or more	9.9%	9.7%	32.4%
	Missing data	4.1%	9.0%	15.7%

Mechanical Turk Recruitment. The recruitment consisted of a task advertised on the MTurk platform with the title: "Answer a survey about Leisure Activities (10-15 minutes)." Monetary incentive was directly advertised as $3.20 for a completed questionnaire.

Sampling Frame. The sampling frame consisted of people with internet access who are registered MTurk workers located in the United States with task approval rates greater than 90% and more than 100 approved tasks. Respondents were age 18 years and over.

Sampling Method. The MTurk sample was a non-probability convenience sample.

Target Population. The target population was US adults age 18 years and over.

Qualtrics Panels

Recruitment. The respondents were recruited via email. Incentives were provided in various forms (cash, gift cards, reward points), but the recruitment source from the panel and the form of incentive was kept anonymous and hidden from the researchers.¬¬¬¬¬

Sampling Frame. The Quatrics Panels sampling frame consisted of panel participants from various sources, but the details were not disclosed to the researchers. These participants were adults who are located in the United States with internet access.

Sampling Method. The sampling method was a non-probability sample utilizing a gender quota.

Target Population. The target population was US adults age 18 years and over.

Class and Related Contacts

Recruitment. The initial participants were recruited via an undergraduate civil engineering class at the University of South Florida. Additional participants were recruited by having these students send the survey to their friends and family. The students were offered extra credit for taking the survey and for each additional participant referred (up to four). Students were also allowed to perform an alternative homework assignment for the same amount of extra credit if desired. There was no monetary recruitment involved.

Sampling Frame. The sampling frame consisted of undergraduate civil engineering students in the course and their social contacts with internet access.

Sampling Method. This sample was a non-probability snowball (convenience) sample.

Target Population. The target population was US adults age 18 years and over.

7.4 Accessed Social Capital

Figure 2 shows the distributional difference across three social capital measures: occupational extensity, total resource variability, and social support size. Due to demographic differences between the samples, it was not expected that the social capital characteristics would be equivalent across the samples. But, the samples had variations in the experiences and ability of the respondents in taking online surveys. It was hypothesized that these additional factors could include: inattentiveness, mobile computing, and survey taking familiarity. To test the validity of the social capital survey instruments, statistical inference was performed to explore the causes of unexpected response patterns across the samples.

7.4.1 Indirect Social Resources: Position Generator

To test the validity of the resource generator, the distribution of the sampled extensity (total number of accessed occupations) for each sample is compared to that obtained in the Social Networks and Community Survey (Hampton et al., 2009; Maness, 2017a). The distribution in the Social Networks and Community Survey sample had a mean of 9.7 occupations with about 3.5% of the sample choosing zero occupations and less than 0.5% choosing more than 20 occupations. In this study, the sample distribution encountered a spike at 22 occupations whereas prior research shows no such characteristics. The general shape of the rest of the graph is similar with most people's networks containing 5-15 occupations. To explore the cause of the unexpected increase in reported extensity (occupational diversity), a logistic regression model was estimated on the dependent variable: reporting more than 20 occupations accessed.

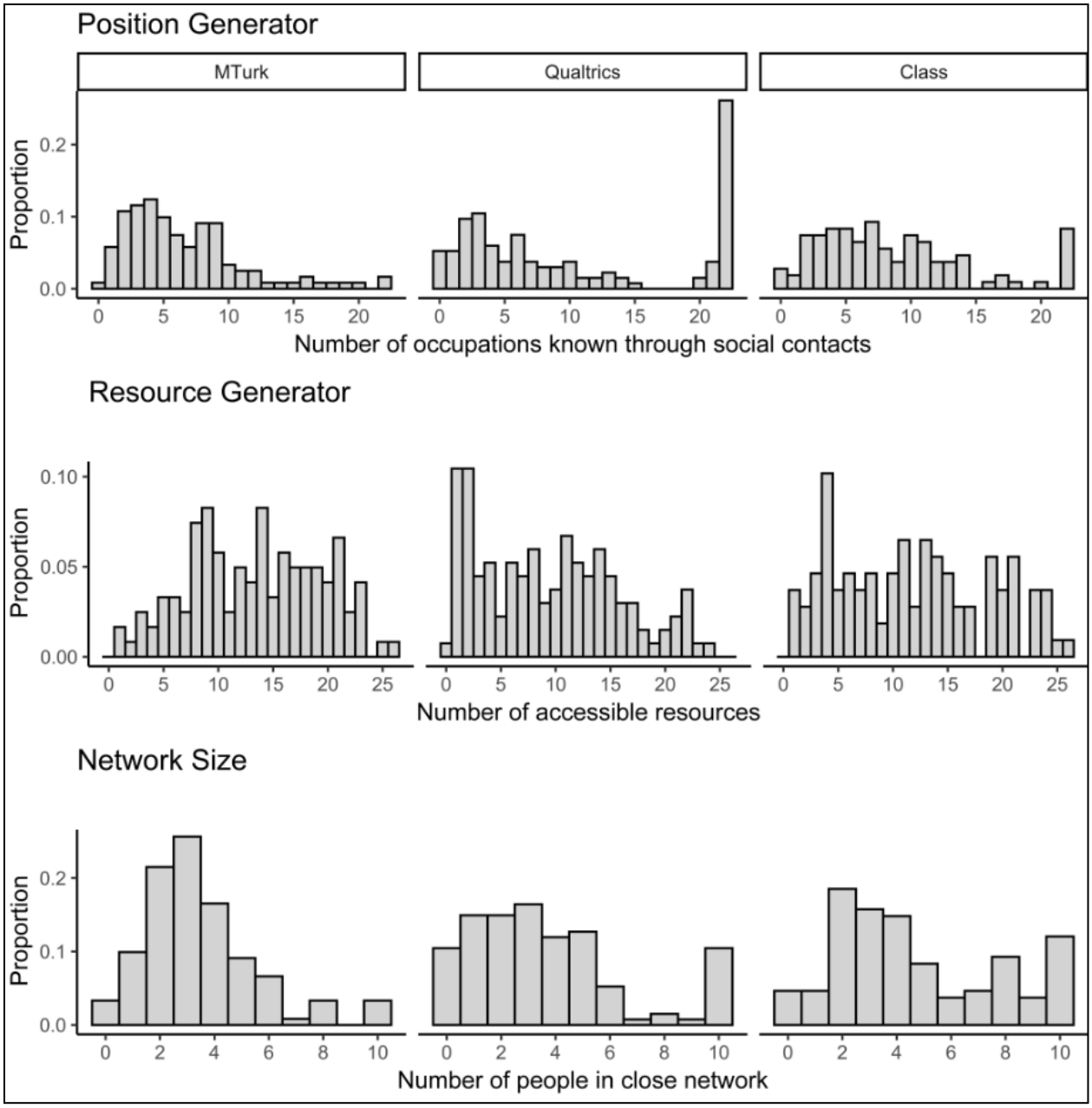


Figure 2 Distributions of Accessed Social Capital across Three Samples

To test for inattentiveness, an attention check was included for the resource generator's question: know someone who owns a car. In the United States, almost everyone knows someone with a car, and Foster and Maas (2016) observed 100% car ownership access in their dataset. Respondents who failed the attention check were more likely to report greater than 20 occupations accessed (odds ratio: 2.26, p-value: 0.02).

Due to differences in screen size, response differences between personal computer and mobile phone users may differ. Horizontal formatting of matrix questions can lead to response difficulties with mobile users, particularly due to horizontal scrolling (Couper et al. 2017). This may have lead PC users to understand that the question only entailed answering for the profession in their network due to seeing more of the question and answer format at first glance. In contrast,

mobile users may have seen fewer answer choices at once and interpreted this to indicate that each occupation needed a response. Mobile users were 2.49 times (p-value = 0.01) more likely to report excessive occupational access compared to PC users.

Online survey taking familiarity was assumed to correlate with age and formal education. Being less familiar with online forms and surveys may cause respondents to misinterpret check boxes to indicate required answers rather than multiple optional answers. Older respondents were more likely to report more than 20 occupations accessed with an odds ratio of 1.26 per decade (p-value: 0.01). College educated respondents were less likely to report excessive occupational access with a 20% chance for bachelor's degree earners (p-value: <0.01) and 58% chance for others with some college experience (p-value: 0.13).

These results follow the differences in extensity between the three samples. The Qualtrics Panels sample contained the most mobile users followed by the class sample. No MTurk respondents used a mobile device. Additionally, the Qualtrics Panels sample contained a higher proportion of users who failed the attention check – tending towards older and less formally educated respondents. Also note that the MTurk sample was quite selective as respondents were required to pass most previous assignments so attentiveness and survey taking experience was expected to be higher.

7.4.2 Direct Social Resources: Resource Generator

Foster et al. (2019) tested the importance of geographic distance on social capital by measuring network embedded resources using a resource generator tailored for the United States for social capital resources, tests the importance of geographical distance with a sample of 698 records from Atlanta. Using their analysis as a base for comparison, Foster and colleagues identified two categories of resource access: social capital via family (mean 10.55, standard deviation 6.31) and social capital via friends (mean 8.85, standard deviation 6.31). Hence this is used to check the credibility of the data collected for the current study. The mean total resource access is lower across the three samples compared to the Atlanta dataset.

The relationship between the three samples distributions is relatively similar except for the spike at the choice of 1 or 2 resources which is almost exclusive to Qualtrics Panels. Logistic regression was used to analyze which respondents were more likely to choose 1 or 2 resources accessed. Inattentiveness may cause this since respondents may lacking interest in answering this long question over a single page. Measured by the natural logarithm of page submit time in seconds, inattentiveness was found to increase the propensity to choose 1 or 2 resources (odds ratio = 0.13, p-value: <0.01). Mobile device users, who may have found the long list of check box responses also daunting, also had a higher propensity to choose 1 or 2 resources (odds ratio = 2.32, p-value: 0.06). Additionally, older respondents (odds ratio = 1.31 per decade, p-value: 0.03) and those without college education (odds ratio = 1.99, p-value: 0.13) were more likely to choose 1 or 2 resources.

7.4.3 Social Support

The social support question based on the number of network members respondents discussed important matters with is based on the question asked in Burt (1984) and also analyzed in Maness (2017a). But the modification cannot be easily compared to prior work since the majority of that work used a name generator. Name generators typically limit the number of contacts that can be named – often to 5 – 10 contacts (Burt 1984; Hampton et al. 2009). The general pattern assumed is a power law relationship with many people having a few contacts and few people having many

contacts. That relationship mostly holds but there is possibly a high proportion of respondents reporting 10 or more contacts for discussing important matters. The propensity of this occurring was tested and only mobile phone users were more likely to report 10 or more contacts. It is unclear why this would be expected of mobile phone users. The lack of results from inattentiveness and survey taking familiarity follow expectation as this question was displayed as the only question on a single page with radio button options.

7.5 Outcomes: Leisure Activity Variety

From the given list of 87 activities, 363 survey respondents selected a minimum of one (1) activity and a maximum of 41 activities. Figure 3 shows the distribution of the number of activities an individual participated in the last three months. More than half of the people reported to have done between 5 and 15 activities over the three-month period. Less than 5% of the people participated in less than 5 or more than 25 different activities.

Negative binomial models were estimated to analyze the factors influencing the number of different activities the respondents participated in over the last three months.

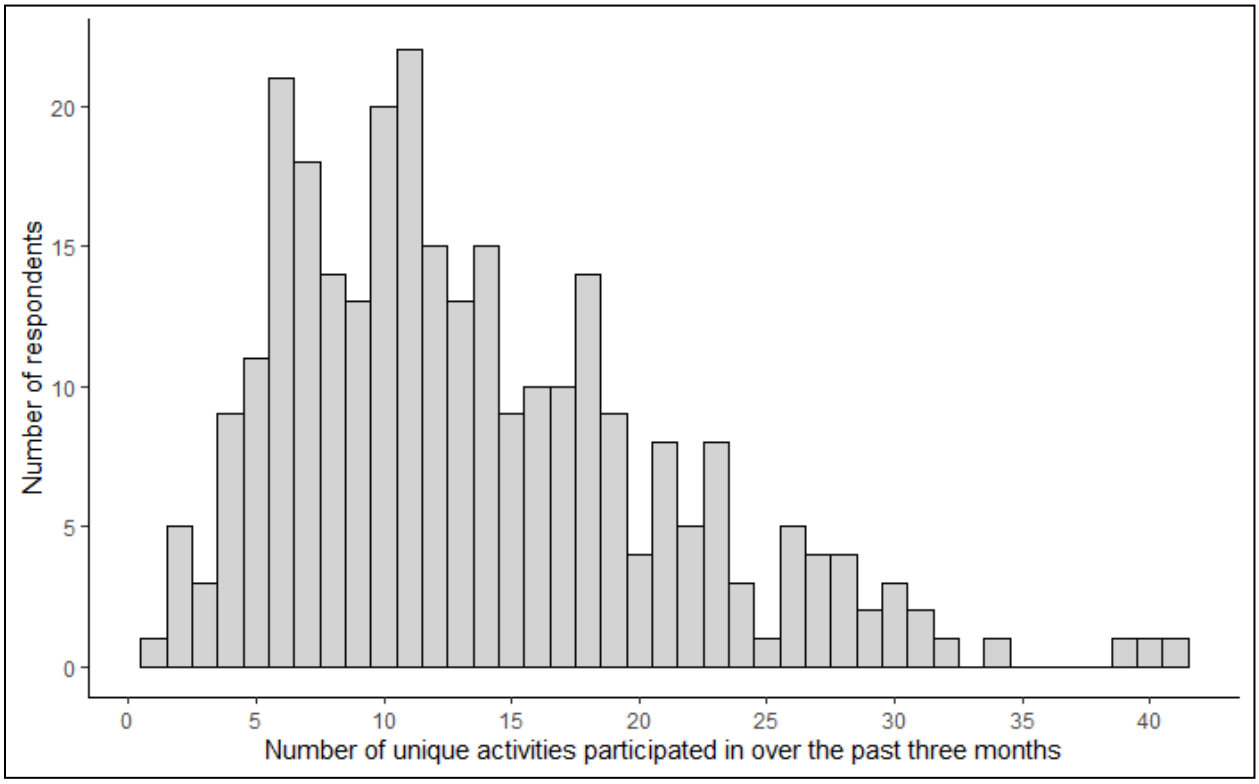


Figure 3 Activity Variety Distribution (with Cleaned Sample Used for Analysis)

7.5.1 Modeling Methodology

The dependent variable, activity variety, was the number of different leisure activities that survey takers had participated in over the last three months. With a mean of 12.9 activities and standard deviation of 8.1 activities, the over-dispersion supported use of negative binomial regression.

Activity variety was assumed to depend on individual and household factors and social capital indicators. The model is specified through the following mathematical expectation:

$$E(y_n|x_n, s_n, p_n, r_n) = \exp(\beta x_n + \alpha s_n + \delta d_n + \theta r_n)) \quad (7.1)$$

where

y_n = activity variety for individual *n*,
x_n = individual and household characteristics for individual *n*,
s_n = individual *n*'s core network size (number of strong ties),
p_n = sum of the professions known through individual *n*'s social network (as measured by the position generator),
r_n = sum of the accessible social resources in individual *n*'s social network (as measured by the resource generator), and
$\beta, \alpha, \delta, \theta$ = model parameters.

In NB regression, an individual's probability $P(y_n)$ of participating in y_n different activities is defined as follows:

$$P(y_n) = \frac{\Gamma(1/\alpha + y_n)}{\Gamma(1/\alpha) y_n!} \left(\frac{1/\alpha}{(1/\alpha) + \lambda_n}\right)^{1/\alpha} \left(\frac{y_n}{(1/\alpha) + \lambda_n}\right)^{y_n} \quad (7.2)$$

where $\Gamma(\cdot)$ is the gamma function, $\lambda_n = \exp(\beta(x_n + s_n + d_n + r_n) + \varepsilon_i)$, and $exp\ (\varepsilon_n)$ is a Gamma-distributed disturbance term with unit mean and variance given by the dispersion parameter α. Model parameters were estimated using maximum likelihood estimation.

7.5.2 Leisure Activity Variety Model

The empirical estimation results of the activity variety model are provided in Table 2. Marginal effects were calculated for each variable and averaged across each sampling source to examine sample-level differences (Table 3). The MTurk sample has the highest impact across all variables on the activity variety followed by the class sample.

Table 2 Estimation Results of Negative Binomial Regression of Activity Variety

Variable Description	Estimate	SE
Constant	1.610 ***	0.160
Position generator (number of occupations divided by 20)	0.583 ***	0.157
Resource generator (number of resources divided by 26)	0.444 ***	0.153
Network support (number of important people divided by 10)	0.328 ***	0.117
Driver license indicator (1 if yes, 0 if no)	0.233 *	0.125
Education level indicator (1 if not attending college, 0 otherwise)	-0.184 **	0.082
Income indicator (1 if household earned $100k or more, 0 otherwise)	-0.089	0.081
Employment indicator (1 if working full or part-time, 0 otherwise)	0.189 **	0.091
Number of hours spent on working per week	-0.002	0.002
Retiree indicator (1 if yes, 0 if no)	0.298 **	0.144
Age group indicator (1 if being 65 years or older, 0 otherwise)	-0.310 **	0.139
Race indicator (1 if identified as white, 0 otherwise)	0.103	0.066
Gender indicator (1 if identified as women, 0 otherwise)	-0.165 ***	0.058
Number of children under 5 years old in the household	-0.067	0.064
Home type indicator (1 if living in single-family houses, 0 otherwise)	0.126 **	0.061
Sampling source (1 if collected from MTurk panel, 0 otherwise)	0.233 ***	0.065
Number of observations	261	
Log likelihood at convergence	-818.16	
Log likelihood at constant	-952.61	
Note: SE = standard error		
* = estimate *p*-value ≤ 0.10 and > 0.05; ** = estimate *p*-value ≤ 0.05 and > 0.01; *** = estimate *p*-value ≤ 0.01.		

Sociodemographic Attributes

Regarding mobility and accessibility aspect, having a driver license results in a sample-level average activity variety increase of 2.42 to 3.29 activities. This effect direction is expected as drivers tend to have greater accessibility and flexibility thus enabling increased out-of-home activity variety and increasing a person's available activity space temporally and spatially.

Table 3. Average Marginal Effects on Activity Variety by Sample

	Average Marginal Effect		
Variable	**MTurk**	**Qualtrics**	**Class**
Position generator (number of occupations)[a]	0.46	0.34	0.38
Resource generator (number of resources)[a]	0.27	0.20	0.22
Network support (number of important people)[a]	0.51	0.38	0.43
Driver license indicator (1 if yes)	3.29	2.42	2.74
Education level indicator (1 if not attending college)	-2.88	-2.12	-2.42
Income indicator (1 if household earned $100k or more)	-1.39	-1.02	-1.17
Employment indicator (1 if working full or part-time)	2.96	2.18	2.49
Number of hours spent on working per week	-0.03	-0.02	-0.03
Retiree indicator (1 if yes)	5.41	3.75	4.53
Age group indicator (1 if being 65 years or older)	-4.85	-3.57	-4.08
Race indicator (1 if identified as white)	1.61	1.19	1.36
Gender indicator (1 if identified as women)	-2.58	-1.90	-2.17
Number of children under 5 years old in the household	-1.05	-0.78	-0.89
Home type indicator (1 if living in single-family houses)	1.98	1.46	1.66
Sampling source (1 if collected from MTurk panel)	3.65	2.68	3.06
Note: [a] are not normalized as in TABLE 2			

Individuals who have not attended college have significantly less activity variety (decrease of 2.23 to 2.88 activities) compared to college educated respondents. Joyce et al. (2019) regarded education as cultural capital and emphasized its importance on social outcomes. Higher income was expected to enable individuals to have greater activity variety because stronger financial capital can afford people's participation in more costly activities (e.g. golfing, boating). The observed effect of household income was negative but statistically insignificant. This could be due to correlation between financial and social capital as the inequalities in social capital often line up with wealth inequality. This may warrant further study to more fully differentiate financial and social capital aspects.

Working respondents averaged 2.18 to 2.96 more activities than those who were students or unemployed. But retirees can afford more time and even financial security to increase their activity space. Results reveals that the age group indicator for people who are 65 years or older and the retirees have similar parameter estimates, but with opposite signs. Older people may have health constraints that limit their ability to participate in some activities. White respondents participate in about one more activity than minorities. There is a significant gender difference on activity variety. Women participated in an average of 1.90 to 2.58 activities less than their male counterpart. It is unclear if this due to the activity list or cultural societal aspects. The number of children under the age of five in the household also decreased an individual's expected activity variety.

Individuals living in single-family houses have significantly positive effect on their activity variety. These individuals are likely homeowners and may have self-selected into locations that support their preferred activities. Finally, results also show that survey respondents in the MTurk panel had more activity variety. It is unclear what unobservable factor may cause this differentiation between samples but perhaps may relate to differing participation motivations/needs.

7.6 Discussion and Future Work

This study presents a survey designed to test for correlations between social resources and leisure activity behavior. An outcome was tested, leisure activity participation variety, which showed positive correlations with instrumental and expressive social resource access. This work motivates the use of this survey instrument with a larger sample to increase the inferential strength of this social capital theory in explaining leisure activity behavior.
It is important to note that although the Qualtrics Panel sample had the greatest issue with validity, this was partially due to greater mobile device usage. The greater diversity of that sample may outweigh this and careful consideration of survey design for mobile devices is warranted.

7.6.1 Exploring Social Capital and Leisure Activity Connections

Further study of the connections between leisure activity and social capital is motivated. In particular, it was unclear whether social activity variety is an instrumental and/or expressive outcome. The authors' first assumption is that variety is primarily instrumental and this is supported by position generator's extensity measure having the greatest impact. Additionally, the survey instrument also allows for the exploration of leisure activity frequency. The authors' interpretation of Lin's (2001) theory as applied to leisure activity behavior suggests that increasing activity frequency is used primarily to maintain social ties and this could be tested against expressive resources.
The activity list used has been group by psychological needs as determined in Tinsley and Eldredge (1995). It may be theorized that having access to a greater variety social resources may correspond increased knowledge of possible activities (types and locations) thus increasing one's activity space. Thus, increases in non-social and social activities may still be expected with greater social resource variety. But, it may be expected that having an increase in social activities are expected for those with more expressive resources but that an increase in non-social activities would not be expected. But exploring the varying psychological needs (specifically affiliation, nurturance, and status) of individuals' activities would allow for more thorough analysis of the validity of this social capital approach to leisure activity behavior.

7.6.2 Instrument Design

Recommended changes to the social capital questions include:

- **Position generator: Include another grid option: "No contacts"; change to multiple choice format for each occupation; remove the grid format for mobile users and change to an item-by-item format; separate the list into two pages**
- **Resource generator: Change to a multiple choice, grid format with "Know someone" and "Do not know someone" as options; use an item-by-item format for mobile users; separate the list into two pages**

7.6.3 Limitations

Activity lists can never be exhaustive as the activity space is nearly limitless. The activity list used may be biased and may have some limitations that could affect inference related to demographic factors. Specifically, the authors did not explore possible gender-based cultural biases in the activity list. As future research, the activity lists used for such work could analyze the tendencies for each activity to sway more towards one gender over

another. This could be done similarly to how Tinsley and Eldredge (1995) used respondents to classify activities by psychological needs. This could then be used to create a gender-weighted measure of activity variety if significant bias is found in the activity list. Another limitation is the use of a retrospective survey for understanding leisure activity behavior. Leisure activities do not occur regularly enough for one-day or even week-long surveys to get a fair assessment of one's full activity space (particularly variety). But there are issues related to recall that exist with a retrospective survey. This study chose three months, but that time period is too short to account for seasonality effects as well. This suggests that some repeated measure of leisure activity behavior could give a fuller picture. Additionally, the unit of analysis with the survey instruments develop is at the activity type and frequency level. Each activity does not have equivalent commitment requirements or time scales. This analysis did not account for those different and it may be difficult without time use and locational data. Thus, long-term activity diary data would be useful for exploring the leisure activity further and the corresponding changes and changes in social resources usage.

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